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Identifying electric vehicle charging styles among consumers: a latent class cluster analysis

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A R T I C L E I N F O

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A B S T R A C T

The market share of electric vehicles (EVs) is growing rapidly, making it crucial to understand the charging behaviour of current and prospective users. Such understanding is essential for designing policies that positively influence consumers' charging behaviour and facilitate EV adoption. In this study, we examined the heterogeneity in charging preferences of 994 respondents across Australia using a latent class cluster model that considers indicators of charging behaviour as outcomes of interest. We used sociodemographic characteristics, travel needs, and EV adoption status as covariates to predict class membership. Our findings indicate five segments of consumers with distinct charging preferences: *routine-focused frugals, cost-oriented deliberators, range seekers, flexibility seekers, and indifferent late adopters*. These segments differ in the importance they attach to charging attributes, their coping strategies with limited battery resources, and their risk attitude. Our results suggest that a uniform approach to EV-related policies is not appropriate, as each consumer segment has unique charging preferences and requirements. Furthermore, the study emphasizes the significance of accounting for charging behaviour heterogeneity in demand modelling, as assumptions in current models may not accurately represent the decision-making of most segments.

1. Introduction

A significant behavioural change is required for individuals to transition from internal combustion engine vehicle (ICEV) refuelling to electric vehicle (EV) charging practices. This is because EV charging decisions are more multi-dimensional and complex than refuelling choices: (1) EV charging requires careful scheduling considerations as charging takes longer than refuelling and depends on the available charger level (Level 1, Level 2, fast, or superfast chargers), (2) charging can happen at multiple types of locations (home, workplace, other destinations, or service stations), and (3) charging can have greater cost variability depending on the chosen location, time of day, and charger level used. In this sense, EV charging decisions may require higher levels of cognitive effort from users than refuelling.

The multi-dimensional decisions involved in EV charging, together with the fact that EVs use electrical grids that also supply energy to a multitude of other purposes, result in an increase in complexity in electricity supply planning. Further, it creates the need for integrated transport and energy demand analysis for policy making. Considering the difficulty in accommodating both the intricacies associated with travel behaviour and EV charging choices (and potentially other electricity use choices), models that integrate travel and charging rely on assumptions and simplifications that may not always be behaviourally realistic. For example, it is common to assume that drivers deliberate about charging before and/or after every trip based on the vehicle's battery state of charge (SOC) and charger availability at origin/destination (Muratori et al., 2020). While this behavioural assumption may represent a segment of users, other segments may base their charging choices on their daily routines or may use different heuristics to reduce the cognitive effort associated with such decisions (Heider, 2013). Capturing such heterogeneity is equally important to improve demand models and to create effective targeted (user-centred) policies.

The notion of "style", as in "lifestyle" (Talvitie, 1997), "mobility style" (Lanzendorf, 2002), "modality style" (Vij et al., 2013), has been adopted by researchers to represent behavioural patterns together with their underlying motivations and attitudes towards different aspects of life, travel, and/or modal preferences, respectively. In this sense, the idea of "charging style" can be leveraged to capture heterogeneity in user charging decision making in a way that not only has empirical value for policy making but also enables behaviourally realistic assumptions to

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be included in integrated travel behaviour and energy consumption demand models in a streamlined manner. Considering the repetitive nature of charging decisions, users can be segmented based on behavioural patterns, or styles (which reflect underlying heuristics and cues that individuals may use), measured via indicators of typical situational charging attributes and user preferences.

In this context, the objectives of this study are three-fold: (1) to identify different EV charging styles reflecting the heterogeneity in EV charging decision-making and capturing different cues and heuristics used by individuals to guide their charging choices and their preferred charging attributes; (2) to define the profiles of users associated with each charging style, and (3) to demonstrate how tailored policy recommendations can be created for each charging style and its associated user profile. We also discuss how profiles can be used to incorporate charging styles into integrated travel behaviour and energy consumption demand models.

The remainder of the paper is structured as follows. Section 2 provides the background literature relative to the idea of charging style and discusses the overall literature on consumer charging preferences. In section 3, the research framework, data, and modelling methodology are described. Section 4 presents the model results, while section 5 focuses on the discussion of implications and targeted policy recommendations. Finally, section 6 summarises the main conclusions, discusses implications to integrated energy and transport demand models, and suggests future research directions.

2. Literature review

The conventional approach to modelling individual travel behaviour through utility maximisation assumes that individuals are aware of all options and make deliberate decisions based on a rational evaluation of each alternative attribute. However, researchers in the transport field acknowledge that such rationality does not always explain travel behaviour. One approach to improve the behavioural realism of such models has been based on the concept of lifestyle (Talvitie, 1997, Plummer, 1974, William, 1963).

Lifestyle refers to an individual's internal opinions, motivations, and orientations towards various aspects of life, such as family, work, leisure, consumption, and housing. While lifestyle is an internal and unobservable phenomenon, it manifests itself in observable patterns of behaviour. For example, a family-oriented lifestyle might influence an individual's choice of travel mode, causing them to regularly commute by car instead of public transport because it facilitates picking children up from school (Van Acker et al., 2014).

There are different approaches to measuring lifestyle, such as through a behavioural typology of activity and time use patterns, or as a psychosocial orientation, including values, attitudes, and preferences, that motivate behavioural patterns (Van Acker et al., 2014). Therefore, studies can focus on collecting data on behavioural patterns and/or attitudes and preferences to better understand an individual's lifestyle. Previous travel behaviour research has incorporated lifestyle constructs in models through latent variables (for example, Lavieri and Bhat (2019), among many others) or has created classifications such as, "mobility styles" to describe the mobility aspect of an individual's lifestyle (Lanzendorf, 2002, Haustein and Kroesen, 2022), or "modality styles" to characterise the tendency of consumer groups to frequently use a particular travel mode (Vij et al., 2013).

Considering that charging choices can be complex (in terms of number of attributes to be considered) but have a repetitive nature, EV users are likely to establish patterns of charging behaviour. In this sense, as discussed earlier, instead of assuming that EV users make deliberate charging decisions weighing all available alternatives at every charging opportunity, it is plausible to expect that lifestyle and associated charging style will underlie observed charging behaviour. Yet, this notion has only been examined by a couple of studies. Instead, most studies in the charging behaviour literature have used utility maximisation theory to examine how users make trade-offs between different charging attributes, such as cost, duration, and convenience. In the following sections, we provide an overview of studies based on each one of these two perspectives. We use their results to guide our definition of EV charging style and to identify the dimensions that characterise this concept in our study.

2.1. Charging style as a coping strategy

Franke and Krems (2013) studied individual charging behaviour by proposing that EV users adopt a preferred coping strategy to interact with the limited battery resources of their EVs, which they called user battery interaction style (UBIS). UBIS was proposed as a continuum from low to high, in which an individual with high UBIS makes charging decisions mostly based on the vehicle's SOC and only charges when their preferred charge level is reached. People who have low interaction with their battery (low UBIS) use other cues to make a charging decision, such as routine or opportunity, and charge their vehicle regularly regardless of battery SOC. To measure UBIS, the authors created a factor using eight Likert scale statements about potential charging decision triggers. Four items in this list captured the importance of SOC in charging decisions and the other four items captured whether charging behaviour was driven by habit/opportunity. The resulting factor (UBIS-8) was used as an independent variable together with 'comfort range' (minimum range before range anxiety is triggered) to predict the charge level at which people typically recharge their EV.

Daina et al. (2015) built on the work of Franke and Krems (2013) by expanding the charging scope of UBIS. In addition to the eight items used by Franke and Krems (2013), they included four items to capture the role of cost as a charging trigger. These twelve items were then grouped into four distinct latent factors using factor analysis. They modelled two charging decisions, the likely SOC at the beginning of a charging event and the weekly charging frequency, using the four factors, travel patterns, sociodemographic characteristics, and EV model and range as predictors. While the factors reflecting the original scope of UBIS were significant to predict both decisions, the cost component was not a significant predictor of charging frequency.

The concept of UBIS captures the coping strategies of EV users when dealing with limited battery resources but does not define charging style as a representation of a general pattern of charging behaviour. That is, UBIS needs to be used alongside other variables to reflect charging behaviour. To develop a more comprehensive scope of charging style, we review studies that examine EV charging decisions from a utility maximisation perspective.

2.2. Deliberate charging decisions

Most changing behaviour studies have used utility maximisation theory to examine the impact of situational charging attributes (such as SOC, cost, and convenience), individual sociodemographic characteristics, travel needs, and EV adoption cohort (from early adopters to potential mainstream consumers) on charging decisions. We provide an overview of these studies and based on their results we highlight the key dimensions that are necessary to define charging styles.

2.2.1. Situational charging attributes

The main situational charging attributes examined in the literature are the vehicle's SOC, charging cost, and convenience. These can be associated with spatial (location) or temporal (time of the day) aspects of charging choices. Other factors included in some studies are charging duration and parking time, charger level and charging speed, and overall satisfaction with the charging facility (Ge et al., 2018, Kim et al., 2017, Wen et al., 2016, Pan et al., 2019, Wang et al., 2021, Jabeen et al., 2013, Dorcec et al., 2019).

As expected, drivers are less likely to charge when the SOC is high and/or the available range is higher than that required for the next trips

(Sun et al., 2015, Pan et al., 2019, Wang et al., 2021). However, studies involving carsharing schemes suggest that this rational behaviour may not always hold true, and users may follow a "better safe than sorry" heuristic when it comes to SOC (Hu et al., 2018, 2020). Low-cost charging options are typically preferred and tend to influence both where and when drivers choose to charge. For example, studies in Australia (Jabeen et al., 2013) and the United States (Lee et al., 2020, Tal et al., 2020) found that, when electricity rates are high at home, EV drivers are more likely to use workplace charging, especially if it is free. In China, high charging costs were found to reduce the likelihood of using public chargers (Wen et al., 2016, Pan et al., 2019, Wang et al., 2021).

Cost also affects charging time at home. That is, while people typically charge their vehicles immediately upon returning home in the evening (Hardman et al., 2018), time-of-use tariffs that offer cheaper electricity at night have shown positive effects in encouraging overnight charging (Dunckley and Tal, 2016), but may not be as effective in shifting charging demand to mid-day periods when there is an excess of solar energy (De Sa et al., 2023).

Some studies have found that there is a trade-off between charging cost and convenience in EV charging decisions (Jabeen et al., 2013, Tal et al., 2020, Wang et al., 2021). For residential charging, access to level 2 chargers is associated with an increase in perceived convenience. For workplace and public chargers, charger point congestion, swap parking rules (rules that require drivers to move their vehicles to a different parking spot once charging is completed), and time restrictions for using charger points, tend to decrease the perceived convenience counteracting monetary benefits (Tal et al., 2020, Wang et al., 2021).

While the abovementioned studies identify charging attributes that effect consumer charging behaviour, some of them also point to the impact of consumer characteristics on such decisions. They highlight the need to consider different sources of individual heterogeneity, like sociodemographic and psychosocial characteristics, to adequately capture charging choice variability.

2.2.2. Individual heterogeneity

Sociodemographic and attitudinal factors have been incorporated in EV charging choice models using direct, moderating, and indirect effect structures. For instance, age, gender, income, dwelling type and ownership, and residential solar panel ownership were found to directly impact charging location choices (Jabeen et al., 2013, Lee et al., 2020, Tal et al., 2020). At the same time, sociodemographic characteristics, such as age, gender and income, and risk related attitudinal factors were found to moderate the effects of situational charging attributes, such as SOC, cost, excess range and charging duration (Wen et al., 2016, Wang et al., 2021). For example, Wen et al. (2016) found that those with lower income put a higher weight on cost, while those with higher income and longer-range EVs gave more importance to charging speed.

Attitudinal factors have also been included as moderators of charging attributes and mediators of individual sociodemographic characteristics. For example, Pan et al. (2019) identified two groups of EV drivers with opposite charging trends: risk-averse and risk-seeking. Risk-averse drivers tended to be female, had lower incomes, and had recently purchased their EV, while risk-seeking drivers were more likely to have owned their EV for longer. Risk-averse drivers were found to make charging decisions primarily based on the range requirements for their next journey, regardless of cost or location. In contrast, risk-seeking drivers took a variety of factors into account, such as SOC, charging and parking costs. In a carsharing context in China, Hu and colleagues found that users are always risk averse, as they tend to choose vehicles with the highest SOC even for short trips where a lower charge would suffice (Hu et al., 2018, 2020).

Other sources of individual heterogeneity considered by researchers reflect travel behaviour (travel needs) and EV adoption cohort. Travel behaviour was characterised by distances driven for work and non-work purposes as well as total weekly distances driven (Daina et al., 2015, De Sa et al., 2023). Moreover, studies have shown that the charging needs and preferences of current and future EV owners differ. For example, in Australia, Lavieri and Oliveira (2023) found that future EV owners had lower travel needs (in terms of weekly distance driven and commute distance) and were less accepting of smartcharging programs compared to current EV owners. In Germany, Wolff and Madlener (2019) found that current EV owners were less sensitive to charging costs than potential later adopters. While, in Canada, Axsen et al. (2016) found that EV owners valued utilizing renewable energy for charging five times more than potential owners.

In summary, this section identified four main categories of individual heterogeneity considered in charging choice studies: sociodemographic characteristics, risk-related attitudes, travel needs, and EV adoption cohort. As discussed, different effect structures have provided unique insights into the relationship of such variables and charging choices. In this sense, these four categories of variables should be considered to either explain or characterise EV charging styles.

2.3. The current study in context

The current study leverages ideas and empirical findings from the two research streams described in Section 2.1. and 2.2 to propose a comprehensive definition of charging style. We define charging style as patterns of charging preferences and behaviours that are embedded within people's lifestyles. In this sense, charging style can be measured by a combination of indicators within three main dimensions: (1) preferred charging attributes, (2) preferred coping strategy with battery resources, and (3) preference between planned and spontaneous charging choices. The latter reflecting the risk-averse and risk-prone behavioural propensities described in Section 2.2.2. To fully describe individual heterogeneity, consumer groups can then be segmented according to their charging styles and characterised based on sociodemographic attributes, travel-related attributes, and EV adoption cohorts.

3. Methodology

We use a Latent Class Cluster Analysis (LCCA) to identify charging style latent classes of consumers based on ten indicators of charging preferences (Fig. 1) related to the three main dimensions described earlier: charging attributes, strategies to cope with battery resources, and risk propensity.

Under charging attributes, seven indicators are used to represent temporal, spatial, and cost-related preferences. The temporal and cost indicators rely on bipolar scales to capture trade-offs between opposing sides of an attribute spectrum. For example, regular charging schedules versus variable schedules, or cost versus convenience. To measure individuals' strategies to cope with battery resources, two items using bipolar scales were created based on the original UBIS scale. These measure whether individuals make choices based on battery level or opportunity, and battery level or routine. Risk propensity was approximated using one bipolar item reflecting the trade-off between planning for charging and deciding on the go. Those who plan are considered to have a risk-averse attitude by identifying potential risks and developing strategies to address them. On the other hand, those who decide on the go are considered to have a risk-prone attitude. The complete scale used to measure charging styles is available in the appendix.

While there is some similarity between the indicators measuring UBIS and risk, they represent distinct constructs and capture different aspects of charging decision-making. UBIS focuses on measuring the cognitive effort that users may put on charging decisions. That is, it contrasts deliberate decision-making based on the frequent monitoring of battery level against the reliance on daily cues as a heuristic to reduce the cognitive effort and automate the decision. The risk indicator, on the other hand, assesses whether individuals are comfortable with uncertainty. A risk-averse individual anticipates future scenarios and plans

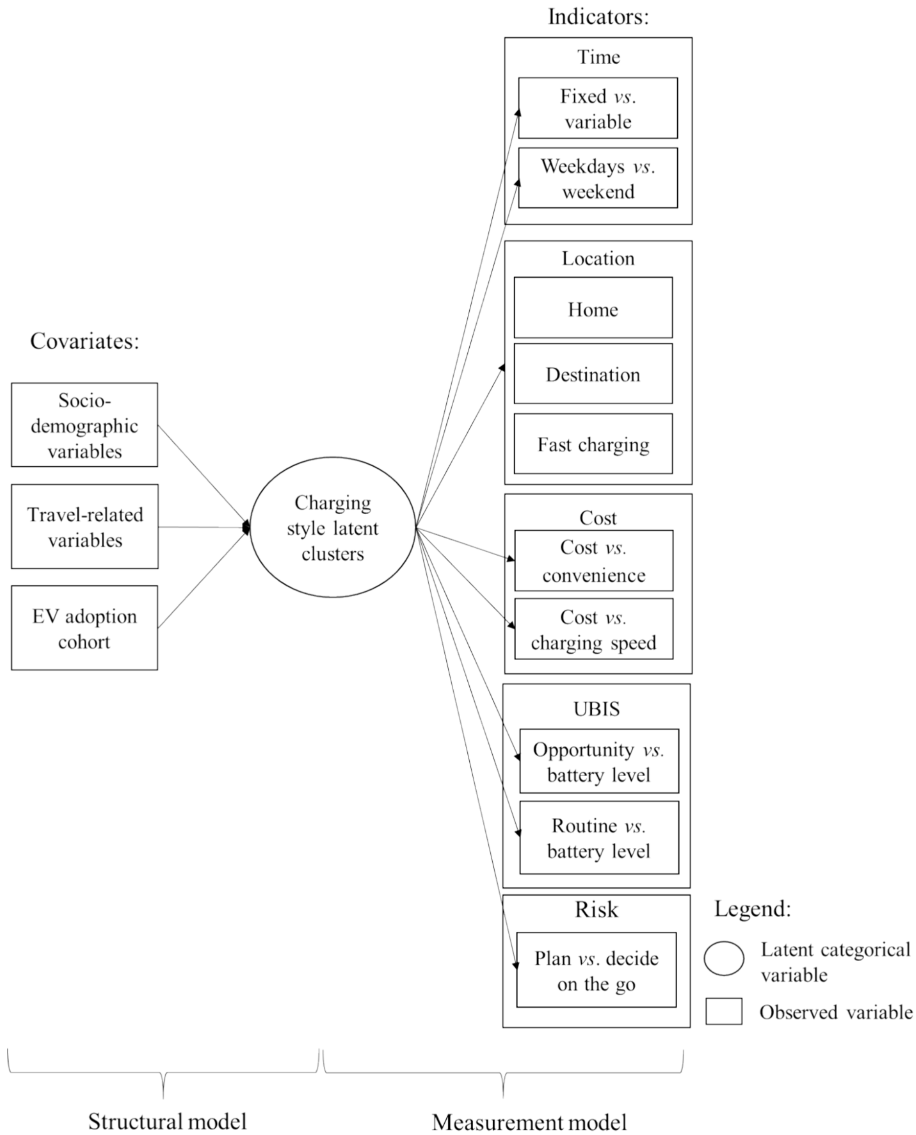

Fig. 1. Graphical representation of the Latent-Class Cluster Analysis with Covariates.

accordingly to avoid potential risks associated with running out of battery, while a risk-seeker feels comfortable with uncertainty and prefers to find charging solutions on the go. As an illustration of how these constructs work together, imagine a deliberator who follows the vehicle's SOC closely. If this individual is comfortable with risk, they may go about their day and charge as they find the SOC is insufficient to meet their next trip needs. Alternatively, if they are risk averse, they may plan in advance to charge at a higher SOC to ensure a buffer against unexpected events.

The likelihood of having a charging style (belonging to a latent class) is explained using covariates describing sociodemographic characteristics, EV adoption cohort, and travel-related variables, as justified earlier. Sociodemographic characteristics are divided into individual-level (gender, age, education, and employment status) and household-level (income, family composition, car ownership, dwelling type, dwelling ownership, residential parking type, and solar panel ownership) variables. Two travel related variables are also incorporated in the analysis, one representing travel needs (weekly distances driven) and another indicating temporal flexibility for overnight charging (overnight parking window).

EV adoption cohort is based on EV ownership and purchase intention status. Three groups are considered, those who currently own an EV, those intending to purchase an EV within five years (which we call early majorities), and those considering purchasing an EV in ten years or not having plans to own an EV (which we call late majorities). The rationale behind incorporating EV ownership status as a predictor of class membership is twofold. Firstly, current owners are early adopters of EV technology. This implies that this group is intrinsically different from mainstream consumers in terms of psycho-social characteristics, such as personality traits, motivations, economic powers, and social roles, as discussed by (Lavieri and Oliveira, 2023). Secondly, EV owners and ICEV owners are likely to differ in terms of technology experience, as the former group is already using EVs. While some ICEV owners may have trialled EV technology, they are most likely basing their responses on expectations about its operation and performance. In this sense, while for the ICEV owner group the collected data is of stated preference nature, for the EV owner group, the stated preferences may be influenced by their actual behaviour (revealed preference).

3.1. Model

The LCCA groups individuals into latent classes based on differences in the set of observed indicators. These latent classes are represented by an underlying latent categorical variable. In this sense, the LCC model has a measurement component, that links the underlying latent categorical variable to its indicators, and a structural component (also known as class membership component), that describes the relative utility of each level of the latent categorical variable based on the explanatory covariates (Magidson and Vermunt, 2004).

The measurement model assumes that how individuals respond to charging preference indicators is dependent on the unobserved class membership and groups individuals into latent classes in a way that differences in class-specific averages for these indicators are maximised across classes. The membership model computes probabilities of individual observations belonging to different classes by using selected explanatory variables (covariates). Explanatory variables that are statistically significant in the class membership estimation are called active covariates while insignificant explanatory variables are called inactive covariates and are used to help identify the unique profile of the members of each class (Linzer and Lewis, 2011).

Eq. (1) is used to identify R latent classes (r ∊ R) and calculate the likelihood that individuals are associated with these classes in a probabilistic manner. Suppose we have J indicator variables (all categorical) each of which taking a value from a set of K_j possible outcomes, for the population of size N (indexed by i, i = 1…N). Let $Y_{ijk} = 1$ if respondent i gives the k_{th} response to the j_{th} indicator, and $Y_{ijk} = 0$ otherwise. The LCCA model simultaneously computes (1) the class-conditional probability (π_{jrk}) that denotes the probability that observation in class r produces the k_{th} outcome on the j_{th} variable, and (2) the class membership probability (p_r) that denotes the probability that a respondent falls into a certain class r (Linzer and Lewis, 2011).

$$P(Y_{ijk}|\pi,p) = \sum_{r=1}^{R} p_r \prod_{j=1}^{J}\prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \tag{1}$$

The first term in Eq. (1) is for calculating class membership. The class membership probabilities are regressed from a set of observed variables (covariates) by using multinomial logistic regression. Let X_i represent the observed covariates for individual i and β_r denote the vector of class membership coefficients for the r_{th} latent class. β_r has a length of S+1 with one coefficient for the S covariates and one constant variable. One of the classes is considered as the reference class and its coefficients are set to zero. If the first class is used as the reference, $\beta_1 = 0$, then the relative probability of person i belonging to class R is calculated as:

$$ln(p_{Ri}/p_{1i}) = X_i\beta_R \tag{2}$$

Following the fact that $\sum_r \rho_{ri} = 1$, the class membership probability is obtained as follows:

$$\rho_{ri} = p_r(X_i;\beta) = \frac{e^{X_i\beta_r}}{\sum_{q=1}^{R} e^{X_i\beta_q}} \tag{3}$$

The probability function becomes (by plugging $\rho_r(X_i; \beta)$ in in Eq. (1):

$$P(Y_{ijk}|\pi,p) = \sum_{r=1}^{R} \frac{e^{X_i\beta_r}}{\sum_{q=1}^{R} e^{X_i\beta_q}} \prod_{j=1}^{J}\prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \tag{4}$$

The parameters estimated by the model are the class membership probability vector ρ_r and class conditional probabilities π_{jrk}. These parameters are computed by using maximum log-likelihood estimation using the log-likelihood function:

$$ln L = \sum_{i=1}^{N} ln \sum_{r=1}^{R} \frac{e^{X_i\beta_r}}{\sum_{q=1}^{R} e^{X_i\beta_q}} \prod_{j=1}^{J}\prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \tag{5}$$

We used poLCA (Polytomous Variable Latent Class Analysis) package to estimate the model parameters. More details about this model and estimation technique can be found in (Linzer and Lewis, 2011).

3.2. Data

This study uses data from an online survey conducted between July and August of 2021 as part of the EV Integration (2020–2022) project in Australia (University of Melbourne, 2022). In this section, we highlight the survey aspects pertinent to the present analysis, while a complete description of the questionnaire design and sampling methodology can be found in Lavieri and Oliveira (2023).

The target population for data collection was Australian EV and ICEV drivers. The sampling strategy relied on exogenous stratification to ensure around 10 % responses from EV drivers and to obtain a sample of ICEV drivers that was representative of the population of Australian drivers in terms of age, gender, and gross annual household income. Because EV ownership is still relatively low in the country, EV owners are oversampled to gain a better understanding of EV users' behaviour. A market research panel aggregator company, Qualtrics, was used to recruit and compensate participants. The final clean sample contains 994 observations, of which 97 are from EV drivers.

The survey included questions about the individual and household-level sociodemographic and travel behaviour characteristics listed in Section 3. To derive EV ownership cohorts, respondents were presented with definitions of battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) and then asked if they owned these types of vehicles. Individuals who owned and were the main drivers of either type of EV were included in the EV driver sample. Those who did not own any of these vehicles were asked about their purchase intention ranging from one to ten years in the future. Those planning to own an EV within 5 years were classified as the early majorities and the remaining individuals were classified as late majorities, based on the notions described in Rogers' diffusion of innovations curve (Rogers, 2003).

All the charging preference indicators, except for the spatial/location preference indicators, were collected using bipolar five-level scales. ICEV drivers were asked to imagine a scenario in which they owned a BEV, while EV drivers just had to consider their current vehicle. The question asked was "How would you describe your decision/preference to charge according to the attributes below?". An example of scale for one of the temporal indicators was "always charge on weekdays", "often charge on weekdays", "equally charge on weekdays and weekends", "often charge on weekends", and "always charge on weekends". The other indicators followed the same logic.[1]

For the spatial indicators, respondents were asked to rank their preferred charging locations. The options were home, work (for those who commuted), destination, and fast public charger. Workplace and destination were merged in this analysis as the sample includes both individuals who are employed and unemployed (or not in the workforce). Each one of these locations became one indicator and the ranks were converted into preference levels (1 being the most preferred, and 3 being the least preferred).

3.3. Sample description

By design, the ICEV driver sub-sample is representative of the Australian driving age population in terms of gender, age, and gross annual household income distributions. However, since EV drivers were oversampled, the complete sample is not representative. A comparison with the Australia's driving age population (Australian Bureau of

[1] For the time of day indicator, the "equal" option primary applies to individuals whose travel patterns vary across days, leading to different charging routines. For example, someone commuting to work on Tuesdays and Thursdays might charge at a fixed time (e.g., after work) on those days. However, on non-commute days when they are home more, their charging schedule may be more flexible and differ from one day to the other. The absence of an example for the "equal" option of this indicator in the survey may have introduced some ambiguity in the responses.

Statistics, 2021, Australian Bureau of Statistics, 2019) shows that the complete sample has an overrepresentation of men (53.3 % compared to 49.3 %), individuals with higher education (42 % of the sample had a bachelor's degree or higher, compared to 35 % in the population), those with household income above $100,000 (50.4 % of the sample compared to 42.7 %) and older individuals, (72.6 % of respondents were 35 years or older compared to 68.5 % of the population). Most of the respondents were homeowners (71.4 % of the sample compared to 66.0 % of the population) who lived in separate houses (69.4 % of the sample compared to 70.0 % of the population) and had access to off-street parking (87.1 % of the sample and no population statistic available). Solar panel ownership in the sample is also compatible with national averages, passing the 30 % mark (Australian PV Institute, 2021). The average annual distances driven by the sample respondents is very similar to the national average (10,857 km compared to 11,100 km), but, on average, EV drivers drive substantially more than ICEV drivers, (20,500 km compared to 9,800 km, as described in Lavieri and Oliveira (2021)(Lavieri and Oliveira, 2021).

For conciseness, the sample distributions of all the indicator and covariate variables used in the analysis are provided in the last column of Table 2 and Table 3. In terms of indicators, always charging during weekdays and having regular charging schedules are the most popular time-related preferences. Home is the preferred charging location for almost 70 % of the sample. While almost half of the sample always considers cost to be more important than convenience, 58.1 % would always select the cheapest versus the fastest charging option. In term of UBIS, opportunity and routine are usually preferred charging cues than battery level. Finally, only 13.7 % of the sample would always prefer to make charging decisions on the go (instead of planning in advance). Together, these indicators show that most of the sample is conscious about matching charging episodes with their schedules and keeping costs low. Further, most respondents are risk-averse when it comes to charging choices.

4. Results

To define the appropriate number of latent classes within the sample, models from one to six classes were estimated without any active covariates. Then goodness-of-fit measures including Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were compared for these models (Nylund et al., 2007, McCutcheon, 2002). A lower value of AIC and BIC suggests a better model fit. Table 1 presents the goodness-of-fit measures of the six models. Even though the AIC continuously decreased with the increase in number of classes, the five-class model presented the lowest BIC value. The five-class model also presented distinctive and interpretable patterns of charging style with the minimum class share of 8.6 %, which is not too small for a meaningful interpretation of results. Therefore, we selected the five-class model as the best fit for this study.

Table 2 presents the summary statistics for the indicators by class, as well as the class size and class share. Similarly, Table 3 presents the summary statistics for the active and inactive covariates by class. The class size was determined by a process known as modal assignment, where each individual is assigned to the class for which their probability of belonging to that particular class is the highest. The summary statistics reported in Tables 2 and 3 are probability-weighted mean values, and thus, take into account the probability of an individual belonging to each class. Probability-weighted mean values provide a more accurate representation of the data, as they consider the uncertainty associated with assigning individuals to latent classes. By weighting each observation by its probability of belonging to a certain class, we can better understand the characteristics of each class and their relationship with the variables of interest.

Each of the identified latent classes represents a distinct group of individuals with a unique charging style and profile. Based on the prevailing indicators within each class, the following names were chosen for each class: *routine-focused frugals, cost-oriented deliberators, range seekers, flexibility seekers, and indifferent late adopters*. In section 4.1, a detailed description of each class's charging style and profile is provided, followed by the class membership model in section 4.2.

4.1. Charging styles and class profiles

Charging styles are described based on the summary statistics of indicators for each class, which are presented in Table 2. Similarly, charging profiles are described based on the summary statistics of covariates, which are presented in Table 3. The profile of each class is explained by focusing on the variables that provide unique insights into that class, with bold values in Table 3 indicating the highest relative percentages of individuals with specific characteristics for each class. For instance, as a higher share of home ownership and access to off-street parking are common among all groups, only the classes with the highest and the lowest relative share of these characteristics are emphasized, and these variables are not discussed for the other classes.

Class 1

Routine-focused frugals make up 26.7 % of the total sample. This group favours charging based on routine and charging opportunity instead of following the battery level closely. Their routine-based choices also translate into preferring to always charge at the same time of the day and on weekdays. The charging location preference is very similar to the aggregate sample averages, with about 70 % of individuals preferring home charging. Cost is one of the major defining factors in charging decisions for individuals in this group. Therefore, most people choose the cheapest option versus the fastest or the most convenient option. As members of this group are cost-sensitive and use their routine as main charging cue, they avoid leaving charging decisions to the last minute. Hence, as expected, this group has the highest percentage of individuals that plan for charging in advance (85.8 %).

In terms of group profile, this is one of the two groups in which the share of women is larger than men. This group has the highest percentage of individuals without a bachelor's degree, individuals with part-time jobs, and households in the medium-income range ($35,000 to $99,999). On average, households in this group own the highest number of cars. Moreover, this group has the largest share of households with solar panels and those who are willing to install solar panels if they purchase an EV. This finding may seem counterintuitive if considering studies from Europe and Canada, which link high income with solar panel ownership (Hansen et al., 2022, Ameli and Brandt, 2015, Briguglio and Formosa, 2017). However, the Australian context is unique in

Table 1
Goodness-of-Fit Measure of the Latent-Class Cluster Analysis Models.

No. of classes	AIC	BIC	LL	No. of parameters	Share of each class					
					1	2	3	4	5	6
1	15759.88	15838.26	−7863.941	16	100.0 %					
2	14801.31	14962.97	−7367.657	33	54.7 %	45.3 %				
3	14188.56	14433.50	−7044.282	50	52.4 %	38.2 %	9.4 %			
4	13839.92	14168.14	−6852.961	67	32.6 %	32.0 %	26.1 %	9.3 %		
5	13691.05	14102.54	−6761.526	84	27.2 %	26.4 %	23.6 %	14.2 %	8.6 %	
6	13631.72	14126.49	−6714.859	101	25.8 %	25.7 %	16.7 %	14.6 %	9.8 %	7.4 %

Table 2
Summary Statistics for the Indicators by Class.

	Class 1	Class 2	Class 3	Class 4	Class 5	Sample
Class name	Routine-focused frugals	cost-oriented deliberators	Range seekers	Flexibility seekers	Indifferent late adopters	
Class share	26.7 %	27.5 %	18.9 %	18.5 %	8.4 %	100 %
Class size	271	274	185	179	85	994
Day:						
Always/often weekdays	**84.2 %**	26.7 %	63.4 %	36.1 %	2.2 %	48.7 %
Equal	9.5 %	50.6 %	28.6 %	20.6 %	**94.4 %**	33.6 %
Always/often weekends	6.3 %	22.7 %	8.0 %	**43.3 %**	3.4 %	17.7 %
Time of day:						
Always/often the same	**91.1 %**	38.1 %	58.7 %	37.1 %	0.0 %	52.8 %
Equal	6.6 %	41.8 %	25.0 %	22.0 %	**99.3 %**	30.4 %
Always/often different	2.3 %	20.1 %	16.3 %	**40.9 %**	0.7 %	16.8 %
Charging location preference:						
Home	70.7 %	**79.0 %**	74.0 %	51.1 %	57.8 %	68.9 %
Destination charging	10.9 %	8.2 %	9.1 %	**17.9 %**	16.2 %	11.6 %
Fast charging	18.4 %	12.8 %	16.9 %	**31.0 %**	26.0 %	19.5 %
Cost vs. convenience:						
Always/often the cheapest	**90.4 %**	83.6 %	2.4 %	8.0 %	0.0 %	49.1 %
Equal	1.7 %	10.0 %	54.4 %	7.4 %	**89.0 %**	22.3 %
Always/often the most convenient	7.9 %	6.4 %	43.2 %	**84.6 %**	11.0 %	28.6 %
Cost vs. charging speed:						
Always/often the cheapest	95.3 %	**97.5 %**	19.7 %	11.6 %	0.5 %	58.1 %
Equal	2.9 %	2.5 %	61.9 %	12.3 %	**92.4 %**	23.3 %
Always/often the fastest	1.8 %	0.0 %	18.4 %	**76.1 %**	7.1 %	18.6 %
Opportunity vs. battery level:						
Always/often opportunity	**80.2 %**	17.9 %	43.1 %	30.1 %	2.2 %	40.2 %
Equal	13.9 %	46.0 %	32.5 %	17.0 %	**94.5 %**	33.6 %
Always/often battery level	5.9 %	36.1 %	24.4 %	**52.9 %**	3.3 %	26.2 %
Routine vs. battery level:						
Always/often routine	**96.1 %**	32.0 %	57.9 %	18.6 %	0.0 %	48.9 %
Equal	2.8 %	29.4 %	17.0 %	10.0 %	**95.6 %**	21.9 %
Always/often battery level	1.1 %	38.6 %	25.1 %	**71.4 %**	4.4 %	29.2 %
Plan vs. decide on the go:						
Always/often plan	**85.8 %**	61.5 %	51.3 %	36.8 %	0.0 %	56.3 %
Equal	10.0 %	34.3 %	35.3 %	15.8 %	**98.7 %**	30.0 %
Always/often decide on the go	4.2 %	4.2 %	13.4 %	**47.4 %**	1.3 %	13.7 %

Note: Bold numbers indicate the highest value in each row.

terms of substantial government subsidies for solar panel adoption, including purchase rebates and feed-in tariffs. Rebates often have income caps, increasing access to solar panels for middle- to low-income households. For example, Victoria's combined annual household income threshold for rebates initially stood at $180,000 and has just recently increased to $210,000. Additionally, around 61 % of the subsidies are reserved to households with combined incomes under $100,000 (Solar Victoria, 2023). In this sense and expectedly, several studies indicate that income is not a strong predictor of solar panel adoption in Australia (Sommerfeld et al., 2017, Bondio et al., 2018, Hajhashemi et al., 2024a). In terms of EV adoption cohort, this group is above the sample averages for both potential early and late majority individuals. This result is expected based on both the sociodemographic characteristics and the risk averse preferences of such consumers (Plananska and Gamma, 2022).

Class 2

Comprises 27.5 % of the sample and contains the *cost-oriented deliberators*. Like Class 1, their charging decisions are primarily guided toward monetary savings. However, the temporal and UBIS-related preferences of this group are significantly different from Class 1. Consumers in Class 2 are clearly willing to invest more cognitive effort to deliberate on scheduling (days of week and time) and battery level attributes to minimise costs (instead of following simple routine cues and having fixed schedules). Yet, they show the highest propensity to charge at home across the five classes. Their calculated behaviour is also evident in the preference to always plan to charge in advance (this group shows the second highest share of individuals with this preference).

The profile of this groups shows the highest potential for residential charging, which justifies their strong preference for charging at home. That is, this group contains the highest percentage of homeowners and individuals living in detached houses with off-street parking. Further, the lowest average weekly travel distances and the second highest overnight parking time window are observed within Class 2. This provides them with the flexibility to charge their vehicles whenever they find a cost-effective option based on their battery needs. Despite the favourable conditions for residential charging, this group presents a large fraction of retired men with no current interest in EV purchase and the lowest share of current EV owners. Considering that EV upfront purchase costs are still significantly higher than those of ICEV vehicles, the late EV adopter profile associated with this class may be explained by their cost-continuousness together with a lack of technology interest, usually observed among older and retired segments of the population (Daley et al., 2018, Hajhashemi et al., 2024a, Helsper and Eynon, 2010, Bondio et al., 2018).

Class 3

This class was named *range seekers* and makes up 18.9 % of the sample. They present the most even distribution of preferences for all indicators, showing that there is no one-size-fits-all within this group. Nevertheless, they show a slight inclination toward at home planned and routine-based charging, happening on weekdays always at the same time. Contrary to the previously described classes, this group puts equal or higher value on convenience over charging cost. They also tend to weigh cost and charging speed equally.

The routine-based weekday charging behaviour is probably a coping strategy used to meet this group's travel needs, as they revealed the highest average weekly distances travelled across all classes. This class also presents the highest proportion of women and households without children compared to other classes. More than 50 % of people in this class are in the highest income bracket, which probably justifies the reduced emphasis on cost in their charging decisions. This class has the

Table 3
Summary Statistics for the Covariates (active and inactive) by Class.

Covariates	Class 1	Class 2	Class 3	Class 4	Class 5	Sample
Gender:						
Female	52.9 %	43.4 %	**55.5 %**	32.1 %	49.7 %	46.7 %
Male	47.1 %	56.6 %	44.5 %	**67.9 %**	50.3 %	53.3 %
Age:						
18 to 34	29.7 %	20.0 %	23.1 %	**36.3 %**	33.7 %	27.4 %
35 to 54	33.8 %	35.7 %	38.5 %	**42.1 %**	27.5 %	36.2 %
55 and older	36.5 %	**44.3 %**	38.4 %	21.6 %	38.8 %	36.4 %
Education: *<Inactive>*						
Bachelor and higher	35.8 %	40.6 %	37.9 %	**59.1 %**	38.5 %	42.1 %
Below bachelor	**64.2 %**	59.4 %	62.1 %	40.9 %	61.5 %	57.9 %
Employment status: *<Inactive>*						
Part-time	**24.5 %**	23.0 %	21.2 %	8.7 %	14.4 %	19.7 %
Full-time	40.2 %	36.0 %	44.0 %	**65.4 %**	43.3 %	44.7 %
Not in workforce	35.3 %	41.0 %	34.8 %	25.9 %	**42.3 %**	35.6 %
Gross annual household Income:						
$100,000 or more	41.0 %	43.9 %	52.5 %	**73.4 %**	46.3 %	50.4 %
$35,000 to $99,999	**42.2 %**	41.6 %	31.4 %	14.1 %	36.1 %	34.3 %
Less than $34,999	16.8 %	14.5 %	16.1 %	12.5 %	**17.6 %**	15.3 %
Family composition:						
Have children	43.4 %	32.3 %	27.3 %	**52.8 %**	30.1 %	37.9 %
No children	56.6 %	67.7 %	**72.7 %**	47.2 %	69.9 %	62.1 %
Average number of cars in household	**1.81**	1.78	1.77	1.54	1.43	1.71
Dwelling ownership: *<Inactive>*						
Own	67.4 %	**74.6 %**	74.1 %	72.8 %	65.0 %	71.4 %
Rent	32.6 %	25.4 %	25.9 %	27.2 %	**35.0 %**	28.6 %
Dwelling type: *<Inactive>*						
Flat or apartment	10.3 %	7.2 %	9.8 %	**15.2 %**	10.4 %	10.3 %
Separate house	69.7 %	**76.5 %**	66.1 %	59.4 %	74.7 %	69.4 %
Townhouse	9.8 %	7.8 %	12.8 %	**17.2 %**	8.4 %	11.1 %
Other	10.2 %	8.5 %	11.3 %	8.2 %	6.5 %	9.2 %
Having off-street parking:						
No	10.2 %	7.1 %	15.9 %	17.3 %	**23.9 %**	12.9 %
Yes	89.8 %	**92.9 %**	84.1 %	82.7 %	76.1 %	87.1 %
Solar Panel ownership:						
Already have	**36.9 %**	32.3 %	35.2 %	27.0 %	25.0 %	32.5 %
Will adopt if buy an EV	**22.5 %**	18.5 %	17.4 %	16.4 %	5.8 %	17.9 %
Do not have	40.6 %	49.2 %	47.4 %	56.6 %	**69.2 %**	49.6 %
EV adoption cohort:						
EV owners	4.2 %	1.9 %	12.8 %	**29.3 %**	3.5 %	9.8 %
Early majority	39.9 %	35.5 %	**40.6 %**	31.8 %	33.6 %	36.8 %
Late majority	55.9 %	62.6 %	46.6 %	38.9 %	**62.9 %**	53.4 %
Average typical weekly distance travelled (km)	229	154.3	**246.8**	237.2	174.4	208.8
Average overnight parking time window (hours)[a] *<Inactive>*	25	28.3	25.5	23.8	**29**	26.1
Residential location: *<Inactive>*						
Living in a metropolitan area	64.6	66.4	70.3	**79.9**	71.8	69.5
Not living in a metropolitan area	**35.4**	33.6	29.7	20.1	28.2	30.5

Note: Bold numbers indicate the highest value in each row.

[a] Overnight parking time window measures the duration between a car's last trip of day x and its first trip of day x+1, indicating users' temporal flexibility for home charging. The average value of this measure was still under the impact of COVID-19 and its influence on work from home (or stay at home) mandates, which resulted in high window values. Nonetheless, relative comparisons of these values still provide valuable insights into the characteristics of each group.

highest share of early majorities and the second-highest share of current EV drivers.

Class 4

Flexibility seekers make up 18.5 % of the total sample. This group prefers to follow the battery level closely instead of using routine and opportunity cues. They prioritize charging convenience and speed over cost. Since they make charging decisions based on battery level, they are more likely to charge at different times of the day and make on-the-go decisions. They also display the highest probability of charging during weekends, as opposed to people who charge based on routine and might usually charge every weekday after work. While home charging is still the preferred option for more than half of the individuals in Class 4, this class has the highest share of people who prefer destination and fast charging.

The profile of this class is very well delineated, with the highest proportion of men and prevalence of young to middle-aged individuals (78 % of the group is between 18 and 54 years old). This class also has the largest share of high-income earners, highly educated individuals in the workforce, and households with children compared to other classes. Their preference for out-of-home charging is probably associated with the fact that Class 4 displays the highest share of people living in apartments and townhouses, the second-largest weekly travel distances, and the shortest overnight charging time window across all classes. This finding is aligned with other study from Australia that found that those living in townhouses and apartments are more likely to use fast charging (Philip et al., 2022). Interestingly, this class has the highest proportion of current EV drivers and the lowest share of potential late majority consumers of all classes. Despite their high income, class 4 exhibits the highest share of apartment and townhouse dwellers among all classes, indicating a strong preference for urban lifestyle. This preference is further supported by the highest proportion of people residing in metropolitan areas being within this group. While this class still includes a significant share of individuals living in detached houses, living in a metropolitan area likely provides easier access to public charging infrastructure for those who live in townhouses and apartments within this group. This accessibility to public charging, coupled with reduced sensitivity to charging costs due to their high income is likely mitigating the absence of home charging as a barrier to EV adoption. However, it is important to note that this may differ for townhouse/apartment dwellers in other clusters with a lower share of high-income individuals and people living in metropolitan areas.

Class 5

The remaining respondents in the sample (8.4 %) fall under the group of *indifferent late adopters*. This is because between 89 % and 99.3 % of the members of this group selected the "equal" option in all bipolar scale indicators, which shows they do not have specific preferences and their charging behaviour is far from being defined. Following the general sample trend, home is the preferred charging location for more than half of the group members and they display the second highest share of respondents who have fast public chargers as their preferred option. This could indicate a potential desire for charging to be similar to current refuelling practices.

The profile of this group is interesting in the sense that it likely contains two distinct types of individuals, young adult renters that do not own cars and retired individuals. That is, this class has a prevalence of individuals below 35 and above 54 years old, while also showing the highest proportion of renters and individuals not in the workforce, and the lowest vehicle ownership rates. Furthermore, solar panel ownership and off-street parking access are also low in this group. All these features are not propitious for residential EV charging and, consequently, EV ownership (Lee et al., 2019). Therefore, it is not surprising that this class displays the highest share of potential late majorities.

4.2. Class membership model

The probabilities used to compute the results in Table 2 and Table 3 were derived from the discrete choice component of the LCC model, the membership model. Since the main characteristics of each class has already been discussed, we provide a brief overview of the membership model results shown in Table 4. Class 1, the *routine-focused frugals* class, served as the reference category for the model. Therefore, all coefficients indicate the relationship between Classes 2–5 and Class 1. We briefly report the statistically significant coefficients, which are identified in bold in Table 4.

Among individual-level sociodemographic characteristics, gender and age are significant factors. Men are more likely than women to belong to the *flexibility seekers* class. Furthermore, individuals aged 35 years and older are more likely (than those aged 18 to 34) to belong to the *range seekers* class. Regarding household-level characteristics, income, family composition, car ownership, residential parking type, and solar panel ownership have been identified as significant variables. Individuals living in households with an income between $35,000 to $99,999 are less likely (than those with higher incomes) to belong to the *range seekers* class and the *flexibility seekers* class, whose members have a lower inclination toward monetary savings. Families without children are more likely to belong to the *cost-oriented deliberators* class and the *range seekers* class. Households with a higher number of cars are less likely to belong to the *flexibility seekers* class and the *indifferent late adopters* class. Those with off-street parking are also less likely to belong to the *indifferent late adopters* class. While those living in households with solar panels are less likely to belong to the *flexibility seekers* class compared to the *routine-focused frugals* class.

Furthermore, EV adoption cohort and weekly distance travelled were also found to be significant predictors of class membership. EV owners are more likely to belong to the *range seekers* and the *flexibility seekers* class. Finally, an increase in typical weekly distances driven is associated with a decrease in the likelihood of belonging to the *cost-oriented deliberators* class.

Table 4
Class Membership Model (base: routine-focused frugals).

Covariates (reference)	*Cost-oriented deliberators* Coef. (t-stat)	*Range seekers* Coef. (t-stat)	*Flexibility seekers* Coef. (t-stat)	*Indifferent late adopters* Coef. (t-stat)
Intercept	−0.690 (−1.057)	−0.621 (−0.848)	1.805 (2.814)	1.343 (2.002)
Gender *(female)*				
Male	0.358(1.444)	−0.370 (−1.356)	**0.700 (2.475)****	0.019 (0.058)
Age *(18 to 34)*				
35 to 54	0.530(1.603)	**0.787 (2.067)****	−0.631 (−1.930)*	−0.544 (−1.290)
55 and older	0.394(1.132)	**0.819 (1.996)****	−0.476 (−1.164)	−0.408 (−0.940)
Gross annual household Income: *($100,000 or more)*				
$35,000 to $99,999	−0.349 (−1.266)	**−0.626 (−2.002)****	**−1.497 (−3.862)*****	−0.623 (−1.680)*
Less than $34,999	−0.658 (−1.767)*	−0.620 (−1.437)	−0.784 (−1.689)*	−0.794 (−1.545)
Family composition *(have children)*				
No children	**0.532 (2.021)****	**1.075 (3.626)*****	−0.279 (−0.946)	0.442 (1.277)
Average number of cars in household	0.109(0.782)	0.057 (0.345)	**−0.407 (−2.306)****	**−0.659 (−2.533)****
Having off-street parking *(no)*				
Yes	0.339(0.819)	−0.663 (−1.765)*	−0.706 (−1.905)*	**−0.949 (−2.314)****
Having solar panel *(no)*				
Yes	−0.158 (−0.673)	−0.216 (−0.799)	**−0.763 (−2.544)****	−0.321 (−0.932)
EV adoption cohort *(early majority)*				
EV owners	−0.338 (−0.468)	**1.174 (2.268)****	**2.269 (4.530)*****	0.267 (0.302)
Late majority	0.197(0.824)	−0.345 (−1.260)	0.177 (0.572)	0.371 (1.023)
Average typical weekly distance travelled (km)	**−0.002 (−3.167)*****	0.000 (0.355)	−0.001 (−1.907)*	−0.001 (−1.274)

Note: * indicates significance at the 10 % level ($p \le 0.10$), ** at the 5 % level ($p \le 0.05$), and *** at the 1 % level ($p \le 0.01$).

5. Implications

We discuss the implications of the results of this study by exploring the applicability of charging styles in two fronts. First, in the development of tailored policy recommendations that can encourage the adoption of EVs, assist users in satisfying their charging needs, and lead to sustainable charging practices. Second, as an approach to bring behavioural realism and keep parsimony in models that integrate travel and charging behaviour or transport and energy consumption.

5.1. Tailored policy recommendations

We identified in the literature five main categories of policies that are being proposed and implemented worldwide to facilitate EV uptake and charging. Considering this study's geographical context, we also introduce the specific policies available in Australia and then we discuss which policies are particularly beneficial to each one of the charging styles and consumer profiles identified in our analysis.

a) Regulatory/prescriptive actions designed to facilitate residential charging (and solar residential charging) for individuals with living arrangements that hinder their access to home charging, such as multi-unit building residents, renters, and those without off-street parking. Examples of such policies include "right-to-install" laws, which empower tenants to install charging stations without requiring approval from building owners, and electric vehicle-ready building codes mandating the installation of charging points or necessary wiring during construction or major renovation (Hall and Lutsey, 2020). For those lacking access to dedicated residential parking, shared stations or communal charging in multi-unit residential buildings could be implemented, with regulations governing their usage (Hall and Lutsey, 2017). Policies are also required to address the challenges faced by apartment residents in accessing solar charging. Shared solar is a viable solution, allowing customers to purchase or lease part of a larger photovoltaic system. New policies and business models, such as third-party-owned photovoltaic systems or building-integrated photovoltaics, must be developed to regulate shared solar (Horváth and Szabó, 2018, Zander, 2020).

While Australia has a national EV-ready building code for new construction, retrofitting existing multi-unit buildings and rentals with charging infrastructure remains a challenge. The lack of a federal "right-to-install" law can make the approval process for tenants and multi-unit building dwellers seeking EV charger installations time-consuming and difficult. Among Australian states, New South Wales (NSW) and the Australian Capital Territory (ACT) are at the forefront of law reforms to simplify the charger installation process for both owners and tenants (NSW Government, 2023a, ACT Government, 2023a). Additionally, the Australian government is collaborating with states and territories to implement a shared solar program within the next two years, benefiting over 25,000 households. This initiative offers a viable solution for individuals residing in apartments, rental units, and those unable to afford their own solar panels, allowing them to access renewable energy through a community solar bank. As of now, the Australian government has partnered with NSW, Victoria (VIC), Western Australia (WA), ACT, and Northern Territory (NT) in this project (Australian Government, 2024).

b) Financial incentives to install residential chargers and/or residential solar panels involve providing rebates, tax credits, and discounted loans to help alleviate the cost associated with installing charging infrastructure and/or residential photovoltaic systems (Lopez-Behar et al., 2019). While these policies usually benefit homeowners, renters (particularly in multiunit buildings) can also make use of such incentives if financial aid to install charging stations and/or solar panels is provided to landlords and strata councils (for multiunit buildings).

In Australia, financial incentives predominantly focus on reducing upfront EV purchase costs through rebates and stamp duty (transfer tax) exemptions. Only two states are subsidising residential charging infrastructure, ACT and NT (ACT Government, 2023b, NT Government, 2023). For over a decade, substantial subsidies like rebates and feed-in tariffs have driven residential solar uptake to world-leading levels in Australia (Australian PV Institute, 2021). Furthermore, supports for renters, such as the solar rebate policy implemented in Victoria, enable equitable sharing of costs and benefits between landlords and tenants. That is, landlords can apply for the rebate for the installation of solar panels, and renters can benefit from savings on their electricity bills (Solar Victoria, 2019). While these incentives have been serving their purpose, policies supporting EV charger installation and solar energy were developed in isolation and should be integrated for greater effectiveness, especially as EV penetration increases.

c) Temporal management of electricity demand through time-of-use (TOU) tariffs and smart charging can increase consumers monetary savings when charging while also benefiting the grid by increasing energy use efficiency and reducing peaks. While TOU tariffs incentivize users to charge during off-peak hours, smart charging manages charging load based on real-time supply, demand, and range requirements (Hardman et al., 2018). Both strategies may be perceived as inconvenient for those looking for flexible charging schedules (De Sa et al., 2023). However, smart charging also tends to be rejected by those who have high desire for control and are averse to uncertainty. To encourage adoption among such groups, overriding options and a guaranteed minimum charge by the required departure time have been incorporated to smart charging programs (Delmonte et al., 2020, Hajhashemi et al., 2024b).

In Australia, energy providers are starting to offer TOU tariffs specifically for EV charging. One company offers a very low overnight rate for EV charging (without an increase in peak rates), while another offer free midday charging for those who subscribe for the EV subscription plan (AGL, 2023, Origin Energy, 2023). Both companies are also currently trialling smart charging programs (Electric Vehicle Council, 2023). While these actions are positive starting points, broader rollout would require more targeted plans that cater to diverse consumer preferences.

d) Public charging infrastructure deployment is a strategy that can increase EV visibility by consumers, reduce range anxiety, and act as an alternative for those who cannot charge at home (Hardman et al., 2018). In particular, the construction of public kerbside charging stations in regions with predominant on-street parking has been successfully implemented in Amsterdam and the United Kingdom (Hall and Lutsey, 2017). In high density areas where a fast turnaround is necessary, fast public charging infrastructure is a critical to serve those who lack access to home charging (Nicholas and Tal, 2017, Sun et al., 2016).

Australia has made significant efforts and investments to expand the number of fast and public chargers. In 2023, there was a 75 percent increase in fast/ultra-fast public charging stations compared to 2022. However, continuous efforts are needed to fulfill the charging requirements of users (Electric Vehicle Council, 2023). Particularly, NSW stands out for its leadership in charging infrastructure provision through initiatives like the NSW EV Kerbside Charging Grant (NSW Government, 2023b). This grant co-funds installations of kerbside chargers in areas with limited off-street parking.

e) Educational campaigns are an effective way to increase consumer familiarity with EV charging and accelerate EV uptake. Despite growing awareness of EVs, many individuals lack knowledge about the availability of public charging infrastructure and the requirements for residential charging (Long et al., 2019). To address this, educational campaigns including events, test drives, trials, and rental opportunities can be used to help consumers become more comfortable with EVs and their charging requirements (Jin and Slowik, 2017). Media campaigns can complement these initiatives by raising consumer awareness about EV ranges and charging options (Jin and Slowik, 2017).

While existing initiatives such as EV festivals and drive days in Australia provide valuable learning opportunities, the true challenge lies in effectively reaching individuals who are not actively considering EVs and may lack interest in technology. To address this, future education campaigns should adopt broader outreach strategies tailored to diverse audiences. Additionally, there should be a focus on increasing interest in technology and educating people about how EVs function and their charging requirements (Salari, 2022, Hajhashemi et al., 2024a).

Routine-focused frugals not only display the highest rate of rooftop solar ownership and willingness to install such technology when purchasing EVs, but they also tend to be employed on a part-time basis and own multiple vehicles, which suggests enough flexibility to be able to rely on residential solar charging. Considering that they value monetary savings, this group can benefit from rebates or tax credits for residential charging installations or for joint EV charger-rooftop solar installations. While they may be attracted by the monetary savings associated with TOU tariffs and smart charging, they are more likely to choose the former due to their risk-averse nature and planning-ahead preferences.

The group of *cost-oriented deliberators* is highly fit for residential charging due to the high percentage ownership of detached houses with off-street parking. Access to home charging is known to be one of the primary factors in enabling EV adoption (Hardman et al., 2018, Lee et al., 2019). Yet, this group displays the lowest share of EV owners. While high purchase costs may be hindering EV adoption among this group of cost-sensitive consumers, educational campaigns highlighting the ease and affordability of residential charging and installation rebates could increase purchase assurance among this group. With high mobility flexibility displayed by their low average weekly distances travelled, high overnight time window, and a significant proportion of members not in the workforce, this group can also save on charging by installing solar panels or adopting TOU tariffs and smart charging. Considering their willingness to deliberate about charging decisions to reduce costs, they are likely to be interested in time management, especially TOU tariffs, as long as the opportunity for monetary savings is clear.

Range seekers cover the greatest distances on a weekly basis and attribute equal or higher value on convenience and speed over charging cost. Fast destination charging infrastructure (at workplace, malls, and other activity hubs) is likely the measure of greatest appeal to this group. The highest share of potential early majority consumers is in the *range seeker* class, which indicates that media campaigns advertising new destination fast charging facilities could be the turning point for their EV adoption. Another group who is likely interested in easy access to fast charging infrastructure are the *flexibility seekers*. This is because members of this group prioritize charging convenience and speed over cost as they have high incomes and limited temporal flexibility due to their full-time work, child-bearing responsibilities, higher weekly distance travelled, and lower average number of cars. Regulatory actions that facilitate charger installations in multi-unit buildings as well as kerbside charging infrastructure may also benefit flexibility seekers, who are likely to be apartment and townhouse dwellers. This group is not risk-averse, which could lead to high acceptance of smart charging. However, guaranteed minimum charge and weekend benefits may be necessary to fit their busy schedules.

Finally, educational campaigns to increase the knowledge about EVs is the foremost prerequisite for the group of *indifferent late adopters*, which does not even consider EV adoption and does not display any formed preference regarding charging. As mentioned earlier, this class likely contains two distinct types of individuals, young adult renters that do not own cars and retired individuals. Policies and incentives should be planned in a way that avoids increase in motorisation rates. Therefore, among the *indifferent late adopters*, retired individuals should be the target of campaigns in form of festivals, test drives, and trials that increase consumer familiarity with EV technology. However, even after raising awareness, financial support is necessary to facilitate EV adoption and charging because many individuals in this group have financial limitations.

As introduced earlier, in Australia, significant efforts are underway to incentivize EV purchase, solar panel installation, and the deployment of public and fast charging infrastructure. However, the current approach typically involves separate policies for EVs, solar energy, and charging infrastructure, highlighting the need for integration. Integration of these policies can streamline processes, reduce administrative burden, and ensure a more cohesive and effective strategy for achieving sustainable charging practices. Additionally, existing policies tend to be general and not consider the diversity in user preferences and needs. The benefit of integration (across sectors) and customization (toward user needs) can be illustrated by looking into the *routine-focused frugals* and the *cost-oriented deliberators*. Both groups have ideal conditions for solar-based home charging but are yet to consider EV adoption. Offering bundled incentives for EVs, solar panels, and home chargers could increase the appeal of EV adoption for those groups by streamlining the subsidy application process and helping consumer understanding of the savings opportunities derived from this bundle. Also, considering that the *routine-focused frugals* prefer simpler and habitual charging, introducing these options together can enable the formation of sustainable charging habits from the start.

For *range seekers* and *flexibility seekers,* who require less financial support for EV adoption and have high travel needs, the focus of policies should be more on facilitating their charging needs. For instance, range seekers require readily available kerbside charging and faster deployment of fast-charging infrastructure to expedite their transition. Therefore, other states should consider implementing initiatives like the EV Kerbside Charging Grant in NSW. Similarly, policy reform is needed to streamline apartment and townhouse retrofitting processes, mirroring initiatives like NSW's strata law reform, which would particularly benefit *flexibility seekers.* Public outreach events are valuable but analysing attendance demographics are important to understand how to target non-engaged groups like *indifferent late adopters*. By connecting current reluctant ICEV drivers with customized, bundled policies that simplify the EV adoption and charging process, these individuals can be encouraged to switch to EVs and adopt a sustainable charging practice.

5.2. Modelling recommendations

Integrated travel behaviour and energy consumption demand models often overlook the heterogeneity of charging behaviour among EV users. They assume that all users follow similar charging decision rules. For instance, some models assume that all users will charge their EVs when their SOC reaches a specific level (Marmaras et al., 2017, Arias et al., 2017), or when the vehicle does not have enough charge to reach the next destination (Xing et al., 2019). Other models assume that all users will charge their vehicles after their last trip of the day (Harris and Webber, 2014), or make charging decisions after each trip based on cost and SOC (Olivella-Rosell et al., 2015). These assumptions do not accurately reflect the diverse charging preferences and decision-making processes of EV users.

Our research findings suggest that incorporating the concept of charging style can provide a valuable framework for addressing consumer heterogeneity in charging models. By using this approach, EV users can be divided into segments based on their sociodemographic and travel needs characteristics, and specific decision rules can be considered for each class based on their charging style. For instance, our results show two groups of consumers who are likely plan to charge at home and give significant value to monetary cost minimisation, while other two groups will favour convenient and fast charging options. In this sense, the charging style concept can be used to incorporate distinct decisions rules for each group in the models, making them more accurate and behaviourally realistic.

6. Conclusions

This study sheds light on the heterogeneity of charging behaviour among current and prospective EV users in Australia by exploring and modelling the concept of charging style. We conducted a LCCA and identified five distinct charging style consumer groups: *routine-focused frugals*, *cost-oriented deliberators, range seekers, flexibility seekers, and indifferent late adopters*. Our results indicate that members of *routine-focused frugals* and *cost-oriented deliberators* groups prioritize cost savings and home charging, with the second group being more deliberative about their decisions. *Range seekers* have the highest travel needs and tend to weigh cost and convenience equally when planning their routine-based charging. *Flexibility seekers,* on the other hand, are more spontaneous about their charging decisions, following closely their vehicles' SOC and prioritizing speed and convenience over cost. Lastly, *indifferent late adopters* do not exhibit any charging preferences.

Our findings suggest that a uniform approach to EV-related policies is not appropriate, as the socio-demographic profile, charging needs, and preferences of each charging style class are unique. Therefore, policy interventions must be customized to meet the specific needs of each class. For example, while financial incentives for home charging installation may be ideal for *routine-focused frugals*, *flexibility seekers* may need fast public charging infrastructure. Furthermore, our study highlights the significance of accounting for charging behaviour heterogeneity in demand modelling. Most of current models assume that EV users make charging decisions based on the vehicle's SOC. However, our findings indicate that only members of the *cost-oriented deliberators* and the *flexibility seekers* classes are likely to be deliberative and use this strategy. Most other groups prefer planned routine-based charging at their residences. Therefore, it is essential to improve the charging decision rule assumptions in demand models and adopting the notion of charging styles is a feasible approach to do so.

This study has some limitations and suggests the need for further investigation in several fronts. Firstly, the sample used in this study was drawn from Australia, which is currently lagging behind in EV adoption when compared to other developed economies. As a result, a significant portion of the sample (ICEV owners) answered the charging behaviour questions by assuming their charging preference, which may not accurately reflect their actual behaviour in the future. Secondly and related to the previous limitation, panel data would be necessary to investigate how charging behaviour evolves over time with EV ownership experience. This will help the understanding of the process of charging style formation and how it changes as people become more familiar with the technology. These limitations and the implications of sample differences are further elaborated in (Lavieri and Oliveira, 2023). Thirdly, while this study focused on socio-demographic and travel needs variables for predicting the class membership of each charging behaviour class, future research could focus on understanding the personality, lifestyle and values that drive charging style. This will provide a more comprehensive understanding of the underlying factors that influence charging behaviour. Finally, the actual operationalisation and calibration of integrated transport and energy demand models is likely to require additional empirical examinations than the one provided herein.

CRediT authorship contribution statement

Elham Hajhashemi: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Patricia Sauri Lavieri:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Validation, Writing – review & editing. **Neema Nassir:** Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Patricia Sauri Lavieri reports financial support was provided by Energy Networks Australia. Patricia Sauri Lavieri reports financial support was provided by Centre for New Energy Technologies (C4NET). Patricia Sauri Lavieri reports a relationship with Victorian Department of Energy, Environment and Climate Action in Australia that includes: consulting or advisory.

Data availability

The data that has been used is confidential.

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Appendix 1

Table 5
Electric vehicle charging style scale.

How would you describe your decision/preference to charge according to the attributes below?

Category	Indicators	Scale (Bipolar five-level)
Time	Fixed vs. variable	Always charge at the same time
		Often charge at the same time
		Equally charge at the same and different times
		Often charge at different times
		Always charge at different times
	Weekdays vs. weekends	Always charge on weekdays
		Often charge on weekdays
		Equally charge on weekdays and weekends
		Often charge on weekends
		Always charge on weekends
Cost	Cost vs. convenience	Always prefer the cheapest charging option
		Often prefer the cheapest charging option
		Equally prefer the cheapest and the most convenient charging option
		Often prefer the most convenient charging option
		Always prefer the most convenient charging option
	Cost vs. charging speed	Always prefer the cheapest charging option
		Often prefer the cheapest charging option
		Equally prefer the cheapest and the fastest charging option
		Often prefer the fastest charging option
		Always prefer the fastest charging option
UBIS	Opportunity vs. battery level	Always charge based on opportunity
		Often charge based opportunity
		Equally charge based on opportunity and battery level
		Often charge based on battery level
		Always charge based on battery level
	Routine vs. battery level	Always charge based on routine
		Often charge based on routine
		Equally charge based on routine and battery level
		Often charge based on battery level
		Always charge based on battery level
Risk	Plan vs. decide on the go	Always plan for charging
		Often plan for charging
		Equally plan for charging and decide on the go
		Often decide on the go
		Always decide on the go

Please rank the charging locations below from the most to least convenient with 1 being the most convenient.

Category	Indicators	Scale (rank)
Location	Home	1 to 3: from most convenient to least convenient

(*continued on next page*)

Table 5 (*continued*)

How would you describe your decision/preference to charge according to the attributes below?		
Category	Indicators	Scale (Bipolar five-level)
	Destination	1 to 3: from most convenient to least convenient
	Dedicated fast-charging station	1 to 3: from most convenient to least convenient

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