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Original research article



Modelling driver's response to demand management strategies for electric vehicle charging in Australia

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ABSTRACT

Electric vehicles (EVs) can help decarbonise transport as long as the energy sector successfully balances the electricity supply with the demand and maximises the use of renewable resources. For that, demand-side management strategies are necessary to encourage users to charge at certain times through time-of-use (ToU) tariffs or to control the load provided for charging (i.e., supplier-managed charging). However, adapting to different charging times can disrupt users' schedule flexibility. This study investigates consumer preferences for smart charging technology and control (user-managed or supplier-managed) and responses to progressive ToU tariff discounts for guiding changes in EV charging time in Australia. We analyse the potential of ToU tariffs in shifting demand to late-night hours and around midday when there is a peak in solar energy generation. Based on a sample of 994 drivers (including 97 EV owners), we estimated a multinomial choice model to identify key predictors of individual preference for smart charging management and a bivariate ordered model to investigate consumer response to time-of-use discounts. The results show that activity-travel behaviour is an important predictor of both demand-side management strategies. Consumers willing to change EV charging time in response to ToU tariffs are likely to have more flexible schedules, while those with more time constraints seek the practical benefits of smart charging. Current EV owners have higher propensities than potential adopters to choose supplier-managed smart charging and charge around midday in response to ToU tariffs. This indicates that trials with current EV owners may overestimate acceptance of these strategies. Our findings show that while monetary incentives can successfully shift an important share of consumers to night-time hours, these incentives are not very effective in shifting to midday charging. Synergy in formulating transport and energy demand strategies may be necessary to facilitate such a shift.

1. Introduction

Electric Vehicles (EVs) have received considerable attention in recent decades as a solution to facilitate sustainable transport transition by reducing greenhouse gas emissions that greatly contribute to climate change. However, the increasing adoption of EVs also prompts concerns in the energy sector due to challenges in balancing the supply with the electricity demand. For instance, evidence in the literature shows that EV owners tend to charge their vehicles at home in the evening (and, to a lesser extent, morning) peak, which contributes to a spike in electricity demand during the time that households already consume their largest share of energy (see Hardman et al. [1], and Lavieri and Bas Domenech [2], for reviews).

To reduce the potential grid strain that EV charging may pose,

demand-side management strategies can be used to incentivise users to charge their vehicles at different times, control the power provided for charging, or a combination of both via smart charging technologies [1]. User incentives to change charging time tend to be based on time-of-use (ToU) tariffs, which offer consumers static (fixed) or dynamic prices for their electricity depending on the time of the day, day of the week, and season [3]. Higher rates are applied during the peak hours (e.g., evening), while lower rates are available outside peak hours.

A smart charger is a type of demand-side technology (DST) that includes data connection capabilities enabling a wireless exchange of real-time data between the charger and the vehicle, the communication devices from users (e.g., smartphones and tablets), and the utility provider. This allows the charger to optimise when and how much power an EV draws from the plug based on information received from the supplier

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(i.e., price and/or load signals), settings defined by the driver (i.e., charging window and needed driving range), and other applicable information, such as solar power generation where photovoltaic installations are available [4]. In this context, supplier-managed smart charging means that the utility provider not only provides real-time information but can also exert direct load control over the charging event to balance the network operation when needed. Alternatively, user-managed smart charging is an indirect load control DST, meaning that the user has the final say on the time and power used based on the information received, without direct interference from the supplier [5].

Adjusting the time and load of EV charging based on real-time data exchange is essential to avoid events exceeding the load limit, resulting in a power outage. But more importantly, the temporal adjustment of the charging demand is essential to maximise the use of renewable energy resources in electricity generation and reduce greenhouse gas emissions [6,7]. This is because the temporal distribution of electricity generation using renewable resources is dictated by natural factors that are not demand-driven, requiring the demand to adapt instead. For instance, solar energy production peaks in the middle of the day when there is the highest insolation, suggesting that this would be a good charging period in areas with high penetration of solar installations, such as Australia, the current world leader in terms of per-capita rooftop solar panel installations [8]. However, charging during this period may only be feasible for some users based on their activity and travel patterns. In other words, people's flexibility capacity (or capital) may be constrained by social and temporal structures that will heavily influence the places and times that they can charge (see Powells and Fell [9] for a conceptualisation of flexibility capital). In this sense, charging management becomes a cross-disciplinary problem that requires integrating transport and energy demand analysis. Furthermore, EV charging management becomes an essential piece of the puzzle to enable the transport sector to transition toward net-zero emission since <30 % of the country's power generation currently relies on renewable energy sources [10].

This study aims to contribute to the body of knowledge on integrated transport and energy demand analysis by investigating consumer preferences and responses to demand-side management strategies for EV charging from two perspectives. First, we examine technology choice, that is, whether consumers would prefer a conventional charger (without a data connection) or a smart charger and if they would opt for a smart charger that allows suppliers to control the load or not. This translates into the choice between three mutually exclusive alternatives we refer to in this paper: conventional charging, user-managed smart charging, and supplier-managed smart charging. This choice is modelled using a Multinomial Probit model. Second, we investigate user response to different levels of ToU discount considering night-time and midday time windows as alternative charging times to evening and morning peaks. We estimate a bivariate ordered model of individuals' willingness to charge EVs (based on a 4-level scale from definitely not to definitely yes) late at night (11 pm or later) and midday (10 am–2 pm) in response to progressive discount levels (no discounts, 10 %, 20 %, and 50 % tariff discounts). For both analyses, we use data from an online survey with 994 Australian car owners (including 97 EV owners) and consider explanatory variables representing individual socio-demographic, dwelling-related, EV-related, and activity-travel-related characteristics. When applicable, we include attitudinal indicators reflecting attitudes toward smart technologies, the environment, and control over charging.

The remainder of this paper is organised as follows. In the next section, we present a literature review of consumers' preferences for smart charging and response to ToU tariffs and list the contributions of our analysis. Section 3 describes the methodology, which includes the analytic framework, data collection, sample description, and modelling approaches (Multinomial Probit and Bivariate Ordered Probit models). Section 4 presents the modelling results and discussions. Lastly, Section 5 comprises the conclusion of this study.

2. Literature review

This section examines transport and energy studies investigating consumer preferences for smart charging (Section 2.1) and ToU tariffs (Section 2.2). Some of these studies are within an EV charging context, while others have a broader scope and cover general residential energy consumers. We highlight the nature, the location, and the main results of the studies to both position and guide the framework adopted in the current research.

2.1. Smart charging

Despite the growing interest in understanding the motivations and barriers to user adoption of smart charging, the empirical evidence is still very limited. Past interview- and survey-based studies have implemented exploratory approaches to investigate the preferences of EV owners and potential adopters for smart charging in Europe, primarily based on descriptive statistics. Overall, exploratory studies reported that users presented a positive perception of the concept of smart charging in residential and public charging settings because of appealing practical benefits [11,12]. More specific motivations and barriers have also been explored. For instance, after interviewing 60 EV owners and drivers with previous EV experience in the United Kingdom (UK), Delmonte et al. [5] reported that their willingness to adopt user- and supplier-managed smart charging are conditional on major decreases in charging costs. Conversely, following the participation of 15 EV owners in a residential user-managed smart charging pilot in Norway, Henriksen et al. [11] concluded that user motivation goes beyond economic rationalisation and stems from the joy of using smart home technology. Regarding barriers, Libertson [12] explored consumers' perceptions of a supplier-managed smart public charging pilot in Sweden. The participants perceived the technology to contribute to feelings of uncertainty and anxiety. The authors also found that users' flexibility to deal with the consequences of direct load control was affected by external constraints, such as working patterns, financial resources, and access to charging stations.

Other studies have also conducted confirmatory analyses, primarily based on choice experiments with larger samples of EV owners and potential adopters in North America and Europe. In contrast to the abovementioned exploratory research, a study in the US revealed that the general population is still sceptical of supplier-managed smart charging programs, even with high monetary incentives [13]. Such scepticism is likely derived from concerns about privacy and loss of control [6] or fear of penalties for frequently opting out of load control during charging sessions [13].

Most confirmatory analyses highlight the importance of monetary benefits as the main motivator for smart charging acceptance [6,13,14], which are usually perceived as more important than environmental benefits, such as maximising renewable energy use [6,7]. By contrast, Will and Schuller [15] reported that economic incentives did not seem to have a significant influence on the acceptance of smart charging for a sample of 237 EV adopters in Germany; grid stability (i.e., increased security of energy supply) and integration of renewable energy sources were the most influential factors for the increase of smart charging acceptance, while users' desired flexibility hindered smart charging approval.

Regarding socio-demographic characteristics, Bailey and Axsen [6] observed that people not willing to adopt supplier-managed smart charging were more likely to be older and not have tertiary education in Canada. Similarly, in the US, Wong et al. [13] observed that consumers willing to participate in a supplier-managed smart charging program were likely to be highly educated, drive-alone commuters, and the sole transportation decision-maker in their households. Women and households without children were less likely to engage in the program. Kubli [14] found very few socio-demographic differences between non- and potential adopters of supplier-managed charging in Switzerland,

contrasting with previous studies and behavioural intuitiveness. For instance, the group unwilling to adopt supplier-managed smart charging had a higher share of young individuals, while the cohort of potential early adopters had lower prior exposure to EVs.

Beyond motivations and socio-demographic factors, activity-travel behaviour may also play a relevant role in the willingness to adopt smart charging. As Daina et al. [16] highlighted, the interconnections between charging choices and activity-travel behaviour (e.g., scheduling of activities and travel) are of particular interest when modelling the effect of smart charging strategies. This is because benefiting from smart charging can cost users' flexibility, as an extension of charging time may conflict with their activity-travel needs [7,17]. For instance, Daina et al. [16] found a strong dependence between the marginal utility of the amount of energy available after charging and the planned travel driving distance. This expected result indicates that, in longer trips, where the exposure to uncertain events is higher and with worse consequences of being stranded, the utility linked to a higher available range (i.e., higher battery levels) is larger, especially if drivers perceive that public rapid chargers and super-rapid chargers are not accessible in their routes. Similarly, Lagomarsino et al. [7] suggested that tailored information about the battery state-of-charge (i.e., the translation of battery levels into travel distances, in their study) can decrease consumers' range anxiety and increase willingness to allow more temporal flexibility in the charging process, which facilitates smart charging adoption.

To our knowledge, only two studies compared users' preferences between user-managed and supplier-managed charging, both in the UK. Delmonte et al. [5] interviewed 60 EV owners and found that user-managed charging was the preferred option compared to supplier-managed charging, mainly because of perceived personal control over charging and the perceived risk of not having the vehicle charged at the desired time. Beard et al. [18] implemented a pilot with approximately 240 participants, in which they were provided with an electric vehicle for eight weeks and randomly allocated to one of three managing charging options: (1) unmanaged charging (control group); (2) user-managed charging; and (3) supplier-managed charging. Their results showed that a substantial share of trial participants indicated they would adopt smart charging if buying an electric vehicle. Those in the control group (unmanaged charging) also showed positive perceptions toward smart charging; among the managed charging options, they had stronger preferences for adopting user-managed charging. The participants were also more likely to prefer smart charging when the cost savings expected from these schemes were larger.

Considering the above review, we identify the following gaps relevant to our research:

- (1) Except for the exploratory analysis based on interviews in the study by Delmonte et al. [5] and the trial by Beard et al. [18], there is little empirical evidence about users' stated choices considering multiple types of smart charging management.
- (2) Except for Daina et al. [16] and Lagomarsino et al. [7], there has lacked attention to transport needs and activity-travel behaviour as factors affecting the preference for smart charging technology and charging control.
- (3) Most studies about consumers' preferences for smart charging were conducted in Europe and North America. In this sense, empirical studies from other contexts worldwide are highly relevant.

Therefore, the present study contributes to the literature by implementing a confirmatory analysis to investigate the factors influencing users' preferences for conventional or smart charging. Importantly, we consider two options for smart charging control: user and supplier management. Secondly, among the factors influencing consumers' preferences for smart charging, we investigate the role of activity-travel behaviour, which has not received sufficient attention in previous studies. Lastly, the present study adds to the literature by considering

consumers living in Australia, a geographical context explored sparsely in previous research.

2.2. Responses to time-of-use tariffs

Research on behavioural responses of EV drivers and potential adopters to ToU tariffs as a strategy for demand-side management is also notably limited. Even the consideration of EV ownership as a variable affecting the response to different ToU discounts is lacking in the literature. In this sense, the current literature review distinguishes (1) studies focusing on residential electricity use by the general public (i.e., general electricity use) from (2) research considering EV ownership as a relevant variable influencing ToU tariff adoption or the behaviour of EV owners and potential adopters toward ToU tariffs.

A review and meta-analysis by Nicolson et al. [19] showed that most of the studies focusing on the general electricity use and responses of the general public to ToU tariff discounts were conducted in the US and UK. Empirical evidence from other countries is scarce and usually derived from individual studies. This study reveals that ToU uptake is likely to fall between 1 % to 43 %, depending on the efforts to increase its adoption. A review by Parrish et al. [20] recently identified motivations and user characteristics linked to the adoption of residential demand response, a broader concept encompassing ToU tariffs. Overall, financial and environmental benefits served as motivation to adopt demand response. Concerning user characteristics, they reported that several studies identified time outside the home as a challenge to shifting demand while spending more time at home and flexible working hours were enablers of residential demand response adoption. In this regard, flexibility is pivotal in structuring how supply and demand relationships are developed in the longer term [9,17,21].

Torriti and Yunusov [22] used the 2014–2015 UK Time Use Survey data to cluster households based on the activities conducted during peak hours and identified households affected by ToU tariffs across different socio-demographic characteristics. Their results show that even households with different socio-economic backgrounds carry out similar activities during peak hours (e.g., cooking in the evening) and, thus, have similar temporal distributions of electricity consumption. Thus, activity-travel behaviour was the strongest predictor of how households are affected by ToU tariffs, surpassing socio-demographic characteristics.

In Australia, Burns and Mountain [23] used a comprehensive sample of 6957 household electricity bills in Victoria to investigate whether there is a change in energy consumption in response to price reductions from peak to off-peak. They observed that the ratio of peak-to-off-peak prices in ToU tariffs has minimal influence on the ratio of peak-to-off-peak electricity use; therefore, Victorians responded weakly to ToU tariffs. Interestingly, the authors reported that households adopting solar panels and households in the lowest socioeconomic areas (based on a socioeconomic ranking of each household's postcode) do not respond to ToU tariff discounts. In this regard, as stated by different authors [9,17], less affluent people are more likely to rearrange their lives to benefit from lower energy tariffs (or to avoid being penalised with higher fares) unless they do not have the flexibility capital to do so, which will likely increase the risks and severity of energy poverty [9].

We find very little empirical evidence of electric vehicle usage as a relevant factor affecting the responses to ToU. In the UK, Fell et al. [24] and Nicolson et al. [3] implemented a nationwide survey targeting a representative sample of British energy billpayers to explore their response to static ToU tariffs. They observed that a third of British consumers were willing to adopt these tariffs. The authors reported that being a financially loss-averse billpayer (i.e., that dislikes losing money more than they like gaining or saving it) negatively affects the stated willingness to adopt ToU tariffs. Contrastingly, billpayers with electric or hybrid vehicles were more willing to adopt such tariffs. While Fell et al. [24] did not observe consistent socio-demographic effects, Nicolson et al. [3] reported that those under 65 and highly educated individuals were more inclined to adopt ToU tariffs.

Considering the above review, we could observe the following research gaps:

- (1) Limited and somewhat conflicting evidence regarding the role of socio-demographics in response to ToU.
- (2) The relevance of electric vehicle adoption in consumers' willingness to switch to ToU tariffs is almost unexplored. Even less empirical evidence is available on the responses of potential adopters and current owners of electric vehicles to these tariffs and the effects of ToU tariffs on charging behaviour.
- (3) The influence of activity-travel behaviour on the response to ToU should be investigated further. This is because activity-travel behaviour is likely strongly associated with consumers' flexibility capital, affecting their ability to shift EV charging to specific off-peak periods when discounts are offered.
- (4) ToU tariffs that focus on shifting electricity consumption to the middle of the day have not been examined. Such tariff structure is particularly relevant to countries like Australia, which already faces excess solar generation in some regions.

In this sense, we reiterate the relevance of the present study in exploring consumers' responses to ToU tariff discounts for two different periods of the day while analysing several individual-level and household-level characteristics, such as socio-demographics, attitudinal factors, activity-travel behaviour, and EV ownership.

3. Methodology

In the methodology, we first present the analytic framework (Section 3.1), in which we identify the set of explanatory variables and hypothesise their influence on smart charging technology and control choice, as well as on the responses to ToU tariffs in changing EV charging behaviour. Then, we describe the modelling framework (Sections 3.1.1 and 3.1.2), data collection (Section 3.2), and sample characteristics (Section 3.3).

3.1. Analytic framework

In this paper, consumer preferences for EV smart charging technology and control, and their willingness to change EV charging time in

response to ToU tariff discounts are examined using two separate models based on a common set of explanatory variables, as illustrated in the analytic framework diagram in Fig. 1 and explained next.

First, socio-demographic characteristics are expected to influence the preferences for smart charging technology and control and responses to ToU tariff discounts. For instance, although household income does not appear as a significant predictor in the ToU tariff and smart charging literature, we expect lower-income households to be more sensitive to monetary discounts and, thus, more likely to respond positively to ToU tariffs and smart charging. Indeed, as conceptualised by Powells and Fell [9] and Libertson [17], affluence has the most evident interaction with flexibility capital among the socio-demographic characteristics.

Activity-travel behaviour variables can serve as proxies of time constraints and indicators of flexibility capital, which could significantly influence the relinquishment of charging control (e.g., through supplier-managed smart charging) and reduce the willingness to change EV charging time. We utilise employment status, commute mode (including telecommuting), and distance travelled per week as activity-travel behaviour variables that serve as time constraints.

In line with previous research, we hypothesise that attitudinal indicators will play a major influence on the preferences for adopting smart charging technology and control and, in some instances, the responses to ToU tariffs. Specifically, attitudinal indicators of privacy concerns and desire to control could result in lower probabilities of accepting smart charging [6]. Beyond these factors, we expect that pro-environmental attitudes influence the preferences for smart charging technology and control and the responses to ToU tariffs. This is because smart charging and ToU tariffs can reduce peak demand (which requires higher energy generation) and orientate charging behaviour toward periods of the day when renewable energy use is maximised. We also expect that technology enthusiasts will have a higher acceptance of smart technologies [25,26].

Current ownership and intentions to adopt electric vehicles are anticipated to affect both choices because EV charging significantly increases the energy consumption of households. Indeed, earlier research reported that EV owners had a stronger willingness to adopt ToU tariffs [3,24], which is the expected behaviour in the current study.

Lastly, dwelling features like parking arrangements, current utility plans, and residential solar panel installations are also expected to impact both choice dimensions. In particular, solar panel installations

EXPLANATORY VARIABLES

CHOICES

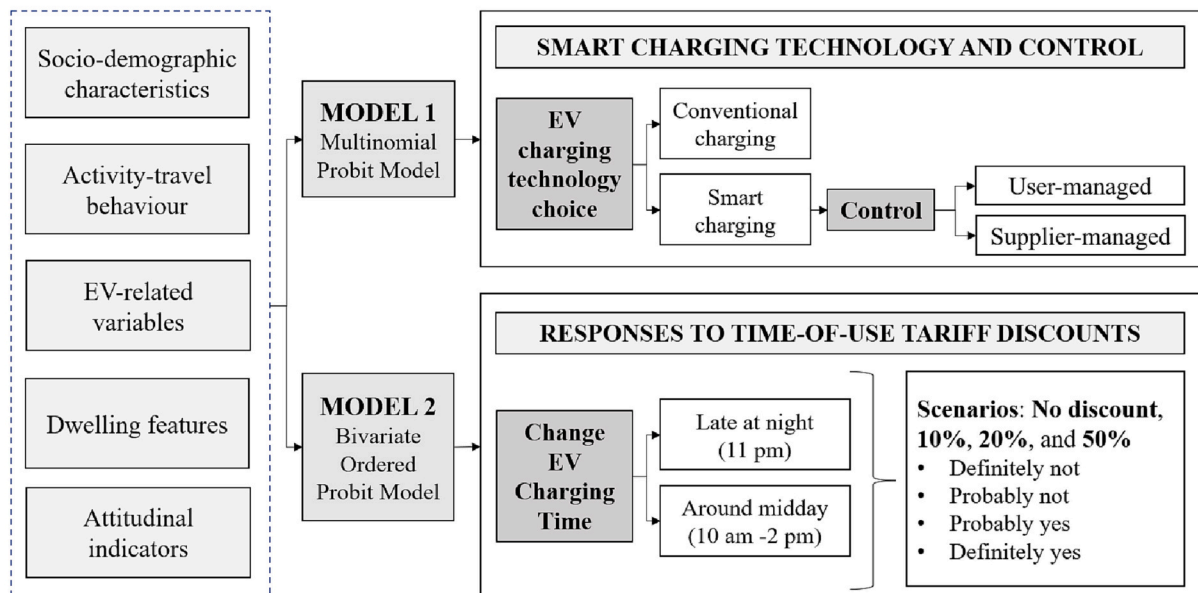


Fig. 1. Analytic framework diagram showing the structure of both models.

are expected to be positively associated with accepting smart charging (especially supplier-managed because users have some level of grid independence) and with interest in charging EVs during the day, when solar energy is generated.

3.1.1. Model 1: smart charging technology and control choice

We use a Multinomial Probit (MNP) model to analyse consumer preferences for smart charging technology and control. As discussed earlier, the choice of interest involves three mutually exclusive alternatives: conventional charging, user-managed smart charging, and supplier-managed smart charging. Because two alternatives require smart technology, we expect that common unobserved factors (variables not captured in our model specification) may simultaneously impact the preference for both options. In this regard, a positive covariance may exist between the user-managed and supplier-managed charging alternatives. For a detailed description of MNP, see Train [27]. The code was developed in GAUSS matrix programming language and utilises Bhat's analytic approximation method to evaluate the multivariate normal cumulative distribution [28].

3.1.2. Model 2: bivariate response to ToU midday and night tariff discounts

We simultaneously model users' willingness to charge EVs in two off-peak windows (a) late at night (11 pm onwards) or (b) around midday (10 am–2 pm). Participants answered separately whether they would agree to change their EV charging time to each of these windows considering progressive discount levels (no discounts, 10 %, 20 %, and 50 %). They answered these scenarios based on a 4-level scale ranging from 'definitely not' to 'definitely yes', as described in Section 3.2. Considering these are two interdependent outcomes with an ordered nature, we adopt a bivariate ordered probit modelling framework to jointly estimate these propensities. This modelling framework is presented in detail by multiple authors, such as Ferdous et al. [29] and Hirk et al. [30]. We use the **mvord** package developed in the R programming language to estimate the model parameters [30].

In summary, using the bivariate ordered probit modelling framework, we can consider that f_q and g_q represent the aforementioned (a) and (b) dependent variables for individual q . These are translated into latent variables (f_q^* and g_q^*) that indicate the propensity of a consumer to shift their charging to each one of the charging windows. Using m and n to represent the indices for the ordered outcomes, we have $m = 0$ or $n = 0$ symbolising "definitely not" to $m = 3$ or $n = 3$ symbolising "definitely yes". The propensity equations can then be written as shown in Eq. (1):

$$\begin{aligned} f_q^* &= \alpha'x_q + \nu_q \cdot f_q = m \text{ if } \delta_{m-1} < f_q^* < \delta_m \\ g_q^* &= \beta'y_q + \eta_q \cdot g_q = n \text{ if } \varphi_{n-1} < g_q^* < \varphi_n \end{aligned} \quad (1)$$

x_q and y_q are vectors containing all exogenous variables; α and β are vectors of the coefficients to be estimated; δ_m and φ_n are the thresholds that subdivide the latent variable into the same number of categories as the outcome levels. Since the model does not include a constant, we estimate three thresholds per propensity equation. ν_q and η_q are standard normal error terms. These error terms are assumed to be independent and identical across observations, with their variance normalised to 1 for identification. However, correlations across the error terms are allowed and follow a bivariate normal distribution. The estimation is performed using a maximum composite likelihood estimation approach, as described in Hirk et al. [30]. The model does not account for intraindividual correlation, which is a limitation that can affect the model's ability to capture unobserved heterogeneity and lead to some bias in standard error estimates.

While the estimated coefficients of the bivariate ordered model allow for a qualitative discussion of the relationships between the explanatory variables and the outcomes, they do not provide a good perspective on the magnitude of the effects. A quantitative evaluation of effects is

particularly relevant to analyse the effect of discounts on charging behaviour. Therefore, we estimate average treatment effects (ATEs) to quantify the marginal effect of tariff discounts in terms of the probability of changing the charging schedule. The ATE measures the mean outcome difference between the treatment (discount levels) and control groups (no discount).

First, we identify the average probability associated with each threshold. Then we compare these values with the fitted (predicted) probability for each outcome from the model under the control and treatment situations. To obtain the mean and standard errors, the fitted probability and ATE computation uses 200 bootstrap draws taken from the sampling distributions of the estimated parameters.

Based on the properties described in Eq. (1), the average fitted probability of the two outcomes and the ATEs are:

$$\text{Average fitted probability of changing to 11pm} = \frac{1}{Q} \sum_{q=1}^Q Pr[f_q^*] \quad (2)$$

$$\text{Average fitted probability of changing to 10am} - \text{2pm} = \frac{1}{Q} \sum_{q=1}^Q Pr[g_q^*] \quad (3)$$

$$\text{ATE of changing to 11pm} = \frac{1}{Q} \sum_{q=1}^Q Pr_1[f_q^*] - \frac{1}{Q} \sum_{q=1}^Q Pr_0[f_q^*] \quad (4)$$

$$\text{ATE of changing to 10am} - \text{2pm} = \frac{1}{Q} \sum_{q=1}^Q Pr_1[g_q^*] - \frac{1}{Q} \sum_{q=1}^Q Pr_0[g_q^*] \quad (5)$$

To further appraise the marginal effect of increasing tariff discounts, we also compute elasticities. The elasticity is calculated as the difference between the fitted probability of a discount level and the base (i.e., no discount) divided by the fitted probability of the base.

3.2. Data collection

The data used in this study was collected in an online survey held between July and August 2021 as part of the EV Integration (2020–2022) project in Australia [31]. A complete explanation of the questionnaire design, sampling methodology, survey distribution, and descriptive analysis can be found in Lavieri and Oliveira [32,33]. Here, we summarise the most relevant aspects to the current analysis.

The survey was targeted at the population of Australian car owners, with an oversampling of EV owners because this technology still faces low market penetration in the country. While sampling quotas were used to ensure that the share of internal combustion engine vehicle (ICEV) owners represented the population in terms of gross household income, age, and gender, no quotas were established for EV owners. Participant recruitment and compensation were managed by the online panel aggregator company, Qualtrics. This company relies on multiple sample providers that maintain lists of potential survey participants (email or user-id list) and utilise weighted randomization techniques (based on the desired socio-demographic attributes) to send out survey invitations to potential respondents. The recruitment strategies aimed at minimising self-selection bias by omitting any information about the survey topic from the recruitment material and responses were verified to remove potential duplicates. While using online survey tools and sample providers cannot be considered a probabilistic sampling approach, it is a cost-effective strategy that allows for better socio-demographic distribution coverage than other convenience sampling techniques.

As described in Lavieri and Oliveira [33], the survey questionnaire contained six main sections, including (1) filter questions and socio-demographic characteristics, (2) travel behaviour, (3) EV ownership and purchase intention, (4) residential and workplace parking and charger availability, (5) general charging preferences, and (6) residential charging management preferences and attitudes. Prior to answering

sections 5 and 6, respondents who did not own an EV were requested to consider a hypothetical scenario where they owned a battery electric vehicle and were able to charge it in their houses. In section 5, participants selected their preferred residential charging start time. Then, they were asked about their willingness to switch their charging start time to (1) between 10 am and 2 pm, and (2) after 11 pm considering different levels of tariff discount (No discount, 10 % discount, 20 % discount, and 50 % discount). Respondents whose preferred charging time was already within one of these windows were automatically considered to accept the respective “switch” for all levels of discount. Finally, in section 6, respondents were introduced to the idea of smart chargers and charging control. The following definitions were provided to respondents:

- Types of chargers (Charging technology)
 - Conventional chargers: do not include a data connection.
 - Smart chargers: include a data connection.
- Options for controlling the charging and managing your costs and electricity demand (Charging control)
 - Conventional charging: Charging is monitored and controlled only by you. Your car is charged from the moment it is plugged in (or based on a simple timer). The rate of charge is fixed based on your charging point specification (ex: 20 km per hour of charge), and costs depend on your electricity plan and the times you choose to charge.
 - User-managed smart charging: Charging is optimized by an automatic system that is monitored and controlled only by you. You provide the system with the desired level of charge and your next departure time, and the system will automatically select the cheapest time to charge your car based on time-of-use tariffs. The rate of charge may be lower than your charging point specification to minimise costs. If you need to use your car before your set departure time, it may not have the desired level of charge.
 - Supplier-managed smart charging: Charging is optimized by a centralized system that communicates and coordinates with the electricity supplier to determine the best schedule for your charge considering real-time electricity demand in your area. You provide the system with the desired level of charge and your next departure time, and the system will automatically select the cheapest time to charge your car based on discounts that vary to help balance the overall demand for power in your area and increase the share of renewable energy used. The rate of charge may be lower than your charging point specification to minimise costs and balance the demand. If you need to use your car before your set departure time, it may not have the desired level of charge.

Respondents had first to select their preferred charging control option and then answer attitudinal questions (five-point Likert scale) regarding perceived risks and benefits of supplier management. Attitudes toward environmental responsibility were also elicited. To avoid respondent learning bias, the questionnaire was designed with a gradual degree of question specificity. The most general questions were presented at the beginning, and the most specific ones at the end.

3.3. Sample description

The final clean sample used in this study comprises 994 respondents. These translate into 994 responses regarding the charging technology and control choice and 3974 responses (994 × 4) for each midday and night ToU tariff adoption scenario. **Table 1** presents the frequency distribution of these three dependent variables. We observe that smart charging technology was the preferred option (72 %), surpassing conventional charging (28 %). Among the smart charging control options, user-managed charging was the favourite (45.3 %), while supplier-managed charging was the least preferred (26.7 %), in line with the findings of Delmonte et al. [5]. Regarding charging time, the sample is more willing to change EV charging to late at night (11 pm) than around

Table 1
Sample frequency distribution of dependent variables.

Smart charging technology and management					
Variables		Count	%		
Conventional charging		279	28.1		
User-managed smart charging		450	45.3		
Supplier-managed smart charging		265	26.7		
Change EV charging time in response to ToU tariff discounts					
Scenario	Answer	Change to late-at-night (11 pm)		Change to around midday (10 am–2 pm)	
		Count	%	Count	%
No discount	Definitely not	276	27.8 %	398	40.0 %
	Probably not	350	35.2 %	287	28.9 %
	Probably yes	234	23.5 %	150	15.1 %
10 % discount	Definitely yes	134	13.5 %	159	16.0 %
	Definitely not	83	8.4 %	273	27.5 %
	Probably not	280	28.2 %	236	23.7 %
20 % discount	Probably yes	427	43.0 %	279	28.1 %
	Definitely yes	204	20.5 %	206	20.7 %
	Definitely not	50	5.0 %	248	24.9 %
50 % discount	Probably not	132	13.3 %	120	12.1 %
	Probably yes	461	46.4 %	316	31.8 %
	Definitely yes	351	35.3 %	310	31.2 %
50 % discount	Definitely not	30	3.0 %	228	23.0 %
	Probably not	36	3.6 %	40	4.0 %
	Probably yes	176	17.7 %	171	17.2 %
	Definitely yes	752	75.7 %	555	55.8 %

midday (10 am–2 pm), potentially due to time constraints, as anticipated in the analytic framework. As expected, the higher the ToU tariff discount, the higher the willingness to shift the EV charging time. The response to discount is more pronounced in changes to late at night than around midday, suggesting again the potential schedule constraints associated with the latter.

Table 2 shows the sample distribution for each explanatory variable. Regarding socio-demographic characteristics, the sub-sample of ICEV drivers is representative of Australia’s driving age population by design in terms of age, gender, and income. However, because we oversampled EV owners, the final sample is not representative of the population. Respondents living in Greater Sydney or Melbourne correspond to 42 % of the sample (compared to 40.4 % in the population). A comparison of our total sample with Australia’s driving age population indicates that the sample has an overrepresentation of men (53.3 % in the survey compared to 49.3 % in the population), individuals with bachelor’s degree or higher qualification (42.0 % in the survey compared to 35 % in the population), individuals with an income level of \$100,000 or more (50.4 % in the survey compared to 42.7 % in the population), individuals older than 34 (72.6 % in the survey compared to 68.5 % in the population).

Regarding activity-travel behaviour, the average annual distance driven (10,857 km, i.e., 209 km per week) is below but similar to the national average (11,100 km, i.e., 211 km per week) [34]. Full- and part-time workers driving their car to work correspond to 47.2 %, workers commuting by other modes correspond to 13.3 %, and telecommuters represent only 3.9 %. People not in the workforce (e.g., retired) or unemployed comprise 35.6 %. Concerning EV ownership and purchase intention, 9.8 % are actual EV owners (97 respondents), 6.8 % are consumers currently doing research to buy an EV or planning to buy it within the next 5 years, and the remaining 53.4 % are individuals who would only buy an EV in the next 10 years or who would not buy it. Concerning dwelling features, about 64.9 % and 49.6 % of respondents do not have attached garages and solar panels in their households, respectively. Most respondents do not have nor plan to adopt EV-specific tariffs (73.9 %) and time-of-use tariffs (59.9 %).

In terms of attitudinal indicators (**Table 3**), we observe a general

Table 2
Sample frequency distribution of explanatory variables.

Variable	Count	%	Variable	Count	%
Socio-demographics					
Location					
Greater Sydney or Melbourne	417	42.0	Activity-travel behaviour		
Rest of Australia	577	58.0	Employment status vs. work from home vs. commute mode		
			Full-time, Not working from home, car driver	333	33.5
			Full-time, Not working from home, other modes	83	8.4
			Part-time, Not working from home, car drive	136	13.7
			Part-time, Not working from home, other modes	49	4.9
			Working from home	39	3.9
			Not in the Workforce & Unemployed	354	35.6
			Distance travelled per week		
			<150 km	475	47.8
			150–290 km	275	27.7
			>290 km	244	24.5
Gender					
Male	530	53.3			
Female	464	46.7			
Annual household income					
Less than \$34,999	152	15.3	Dwelling features		
\$35,000 to \$99,999	341	34.3	Garage type		
\$100,000 or more	501	50.4	Do not have attached garage	645	64.9
			Have attached garage	349	35.1
Education level					
Below bachelor's degree	576	58.0	Solar panel		
Bachelor's degree or higher	418	42.0	Do not have	493	49.6
Car ownership					
One car	487	49.0	Currently have	323	32.5
Two cars	356	35.8	Will adopt if buy EV	178	17.9
Three or more cars	151	15.2	EV-specific tariff		
			Do not have	735	73.9
EV ownership					
EV owners	97	9.8	Currently have	31	3.1
			Will adopt if buy EV	228	22.9
Currently doing research to buy an EV or planning to buy it within the next 5 years					
Would only buy an EV in the next 10 years, or would not buy an EV	531	53.4	Time-of-use tariff		
			Do not have	595	59.9
			Currently have	219	22.0
			Will adopt if buy EV	180	18.1

tendency toward a desire for control and interest in the sense of community and environmental responsibility. Regarding technology adoption, around 30 % tend to buy new technologies first or before most others, while most prefer waiting to acquire them.

4. Results and discussion

In the following subsections, we describe the estimation results of Model 1 (Section 4.1) and Model 2 (Section 4.2). Results are discussed within the context of our analytic framework and compared with previous studies.

Table 3
Sample frequency distribution of attitudinal indicators (explanatory variables).

Attitudinal indicators	Count	%
It's my moral obligation to reduce emission of greenhouse gases.		
Strongly agree	257	25.8
Somewhat agree	410	41.3
Neutral or disagree	327	32.9
In all my daily decisions, being environmentally responsible should be a top priority.		
Strongly agree	213	21.4
Somewhat agree	405	40.7
Neutral or disagree	376	37.9
It is my responsibility to help balance the demand for electricity and reduce the use of non-renewable energy.		
Strongly agree	190	19.1
Somewhat agree	465	46.8
Neutral or disagree	339	34.1
Smart technologies endanger my privacy.		
Strongly agree	146	14.7
Somewhat agree	352	35.4
Neutral or disagree	496	49.9
I feel comfortable passing over the control of when my car will be charged to a supplier-managed smart-charging system.		
Strongly agree	90	9.1
Somewhat agree	290	29.2
Neutral or disagree	614	61.7
I am concerned about third parties managing my car charging, even if my car is always ready to go when I need it.		
Strongly agree	210	21.1
Somewhat agree	427	43.0
Neutral or disagree	357	35.9
Technology adoption cohort		
I like to be one of the first people to have a new technology/gadget.	113	11.4
I'm not always the first to buy a new technology/gadget, but I tend to buy it before most others.	205	20.6
I prefer for other people to test out the technology/gadget before I buy it myself	295	29.7
I prefer to wait until the price drops to buy a new technology/gadget.	231	23.2
I'm usually one of the last people I know to buy a new technology/gadget.	150	15.1

4.1. Model 1: smart charging technology and control choice

The final model specification (Table 4) was achieved after systematically testing combinations of explanatory variables, eliminating statistically insignificant ones, merging variables' levels, and fixing equivalent coefficients across alternatives. The latter was particularly important to correctly identify effects associated with smart technology adoption rather than differences in perceived control. These effects have been underlined in Table 4 for easy identification. Also, some variables that were not statistically significant at a 95 % confidence level were kept in the final model specification because of their intuitive interpretations and relevant empirical implications.

We find that socio-demographic characteristics are relevant factors influencing the choice of charging technology and control. Young individuals aged below 54 years old have preferences for user-managed smart charging. Among them, people aged 25–54 had the highest probability of choosing this option. This result is consistent with findings indicating that younger people are more open to adopting smart technologies in general [35] and smart charging [6,13]. At the same time, middle-aged consumers (45–54) presented the lowest probability of choosing supplier-managed smart charging. Controlling household composition variables could potentially provide more insights into this

Table 4
Model 1 results: Smart charging technology and control choice.

Variables (base category)	Charging choice (base: conventional charging)			
	User-managed smart charging		Supplier-managed smart charging	
	Coeff	t-Stat	Coeff	t-Stat
Socio-demographic characteristics				
Age (>54)				
18–24	0.374	3.01	–	–
25–44	1.255	2.68	–	–
45–54	1.255	2.68	–0.258	–1.99
Employment status (Part-time, unemployed, or not in the workforce)				
Full-time worker	<u>0.242</u>	2.58	<u>0.242</u>	2.58
Annual household income (<\$150,000)				
\$150,000 or more [high income]	–	–	–0.198	–1.69
Household vehicle ownership (1 car)				
2 or more cars	–	–	–0.174	–2.00
EV ownership (Does not own an EV nor is doing purchase research)				
Currently owns an EV or is doing research to purchase shortly	–	–	0.212	1.92
Activity-travel behaviour				
Distance travelled per week (>150 km)				
150 km or less	<u>–0.295</u>	–3.11	<u>–0.295</u>	–3.11
Preferred EV charging start time (Before 3 pm or after 6 pm)				
Between 3 pm–6 pm	<u>0.256</u>	2.43	<u>0.256</u>	2.43
Dwelling features				
Time-of-use tariff (No, I don't have it now)				
Yes, I have it now	–	–	0.296	2.87
Residential solar panel (No, I don't have it now)				
Yes, I have it now	–	–	0.197	2.20
Attitudinal indicators				
It's my moral obligation to reduce emission of greenhouse gases. (Neutral or disagree)				
Strongly agree or somewhat agree	0.192	2.30	–	–
In all my daily decisions, being environmentally responsible should be a top priority & It's my moral obligation to reduce emission of greenhouse gases. (Somewhat agree, neutral or disagree)				
Strongly agree	–	–	0.327	2.82
I feel comfortable passing over the control of when my car will be charged to a supplier-managed smart-charging system (Neutral or disagree)				
Strongly agree or somewhat agree	–	–	0.692	7.69
I am concerned about third parties managing my car charging, even if my car is always ready to go when I need it (Neutral or disagree)				
Strongly agree or somewhat agree	–	–	–0.289	–3.16
Smart technologies endanger my privacy (Neutral or disagree)				
Strongly agree or somewhat agree	<u>–0.181</u>	–2.14	<u>–0.181</u>	–2.14
Technology adoption cohort (Innovators, early adopters, and early majorities)				
Late majorities – I prefer to wait until the price drops to buy a new technology/gadget.	<u>–0.261</u>	–2.57	<u>–0.261</u>	–2.57
Laggards – I'm usually one of the last people I know to buy a new technology/gadget.	–0.432	–3.20	–0.333	–2.20
Constant	0.139	1.14	–0.244	–1.78

“–” means that the variable was removed from the specification due to a lack of statistical significance.

Log-likelihood Constants Only Model: –1061.43 (2 parameters); Log-likelihood Fitted Model: –931.85 (21 parameters); Adjusted rho-squared: 0.104.

result, as it may suggest higher range anxiety associated with busy and car-dependent lifestyles.

Compared to other employment statuses, full-time workers were more likely to choose smart charging technology in general. A possible explanation for this result is that full-time workers have more time constraints and potentially lower flexibility capital, which influences them to choose alternatives that release them of the responsibility of monitoring and managing the best charging time, thus bringing practical benefits. As hypothesised in our framework, employment status can be considered a proxy of time constraints.

Consumers in high-income and multiple-car-owning households have a lower probability of choosing supplier-managed smart charging than the other two options. A potential reason is that affluent households owning multiple cars may be less sensitive to the financial benefits of smart charging. In addition, the reason for owning multiple cars may arise from the complex schedules of individuals in a household. These individuals may value temporal flexibility in travel decisions and may not be willing to accept constraints associated with a charging schedule defined by the utility company.

Current EV owners and consumers doing research to purchase an EV in the near term have a greater probability of choosing supplier-managed smart charging compared to other ICEV drivers. Although a prior study found that the segment most willing to adopt supplier-managed had lower exposure to EVs [14], it is discussed in the literature that higher familiarity with EV technology is associated with a better understanding of the supplier-managed smart charging concept [36]. Also, greater EV experience is linked to decreasing driving range preferences [37] and lower range anxiety than non-EV adopters [38]. It is possible that, with higher familiarity with the concept of supplier-managed smart charging and lower range anxiety due to EV experience, EV owners could better appraise the benefits of supplier-managed smart charging beyond its frequently perceived shortcomings (e.g., concerns about losing charging control arising from range anxiety).

In terms of activity-travel behaviour, while we do not observe a significant effect of commute mode on the choice of charging technology and control, consumers travelling low weekly distances (<150 km) have a lower tendency to choose smart chargers (both user-managed and supplier-managed) compared to those travelling longer distances. A possible explanation is that individuals travelling low distances would incur lower financial benefits from adopting this technology, while long-distance travellers may see a greater value in decreasing charging costs. An important finding is that those individuals whose preferred EV charging time is the early evening peak are in the group of consumers most willing to adopt smart charging technologies. Since long-distance commuters have lower flexibility capital (due to time constraints imposed by their commute trips), technological solutions, such as smart charging, are appealing to lower their charging costs.

Dwelling features such as the current adoption of ToU tariffs and solar panels are associated with an increased likelihood of adopting supplier-managed smart charging. ToU tariff and solar panel adopters may be already used to adapting their charging behaviour to receive the economic and environmental advantages of charging off-peak while still achieving their desired charging levels, which are the premises behind smart charging. In this sense, smart charging is the expected choice for these individuals, who may benefit from adopting supplier-managed charging as it automatically determines the best charging schedule based on real-time electricity demand while maximising the use of renewable energy sources. Parking arrangements did not show a statistically significant impact on the model.

As anticipated, attitudinal indicators have an important role in smart charging technology and control choice. Pro-environmental attitudes are associated with a higher willingness to adopt smart chargers and accept supplier control. Our specification shows that those who opted for supplier-managed smart charging, which can maximise the use of renewable energy, not only were likely to strongly believe that reducing greenhouse gases is their moral obligation, but they also take this

responsibility as a priority in their daily decisions. In other words, consumers who are more actively engaged in fighting climate change will likely be the early adopters of controlled charging, as discussed by Sovacool et al. [36].

Unsurprisingly, consumers comfortable with passing over the control of when their EV will be charged to the supplier presented a higher willingness to adopt supplier-managed smart charging. Contrastingly, individuals concerned about third parties managing their charging had a lower probability of accepting supplier control. Indeed, the need for suppliers to improve consumer trust has appeared as an important recommendation in previous studies [5,36].

In terms of attitudes toward emerging technologies, we observe that privacy concerns appear as an equal barrier to both smart charging options, which corroborates the findings from Bailey and Axsen [6], Delmonte et al. [5], and Wong et al. [13]. Additionally, individuals classified as late majorities and laggards in terms of technology adoption also presented lower probabilities of adopting smart charging technology. Similarly, Henriksen et al. [11] observed that consumers that signed up for a user-managed smart charging program had a keen interest in technology.

The MNP model allowed us to estimate the covariance matrix of error differences between utilities. While we observed these covariances as positive, they were not statistically significant, suggesting that the covariates already captured all the taste commonalities.

4.2. Model 2: bivariate response to midday and night ToU tariff discounts

The results of the bivariate ordered probit model estimation are shown in Table 5. The final specification was obtained after systematically adding and removing explanatory variables depending on their statistical significance and empirical relevance. We tested for moderating effects of the five groups of explanatory variables on the individuals' sensitivity to discount and found one meaningful relationship.

As expected, an increase in discount is positively associated with an increase in the propensity to change charging time to both off-peak time windows. For the midday window, we observe that individuals with low annual household incomes (<\$34,999 per year) are more responsive to any discount level than the medium- and high-income groups. This result is expected, considering that savings have a higher marginal value for those who earn less. In this regard, less affluent people provide flexibility capital by rearranging their lives; otherwise, they would have to afford higher energy tariffs, thus increasing the tensions between comfort and energy costs [9].

Different socio-demographic characteristics influence individuals' willingness to switch to each one of the off-peak time windows. Younger individuals (aged 18 to 44), men, those living in low-income households, and those with tertiary education are more likely to change EV charging time to late at night. On the other hand, location and car ownership are associated with the propensity to change EV charging time to midday. Consumers living in Melbourne or Sydney are more likely to shift the charging time to midday than in the rest of Australia. Considering that these are the largest metropolitan areas in the country, consumers may find more flexible work opportunities (which allow working from home, for example) in these locations that enable them to change the charging time more easily to this period. Concerning car ownership, multiple-car owners are less willing to change their charging time to midday, especially those owning three or more cars. Like the effects observed in the smart charging model, a possible explanation for this effect is that households may own multiple cars to cater to individuals' complex schedules. Thus, these consumers may have lower flexibility capital to change their charging time, even with tariff discounts.

EV-related variables also affected the willingness to change the EV charging time in response to ToU discounts. Consumers who currently own an EV show a higher propensity of changing their charging time to around midday compared to individuals currently doing research to buy an EV or planning to buy it shortly. In this regard, early EV adopters may

Table 5

Model 2 results: response to ToU tariff discounts.

Variables (base category)	Change to late-at-night (11 pm)	Change to around midday (10 am–2 pm)
	Coef. (t-stat)	Coef. (t-stat)
Discount levels		
10 %	0.593 (11.844)	0.303 (5.595)
20 %	1.030 (20.386)	0.555 (10.518)
50 %	1.963 (38.038)	0.993 (19.535)
Interactions		
Discount × Annual household income less than \$34,999	–	0.141 (2.119)
Socio-demographic variables		
Location (Rest of Australia)		
Melbourne or Sydney	–	0.108 (2.786)
Age (>44)		
18–34	0.161 (3.301)	–
35–44	0.126 (2.462)	–
Gender (Female)		
Male	0.077 (2.051)	–
Annual household income (More than \$34,999)		
Less than \$34,999	0.159 (2.882)	–
Education Level (Bachelor's or Graduate degree)		
Below Bachelor's degree	–0.147 (–3.618)	–
Car Ownership (One car)		
Two cars	–	–0.149 (–3.568)
Three or more cars	–	–0.307 (–5.693)
EV ownership (Currently doing research to buy an EV or planning to buy it within the next 5 years)		
EV owners	–	0.235 (3.158)
Would only buy an EV in the next 10 years, or would not buy an EV	–0.146 (–3.617)	–0.128 (–3.069)
Activity-travel behaviour		
Distance travelled per week (<150 km)		
>150 km	0.146 (3.487)	–0.123 (–2.713)
>290 km	–	–0.372 (–7.441)
Employment Status × Commute Mode (Not in the workforce and unemployed)		
Full-time worker × car driver	–	–0.571 (–11.324)
Full-time worker × other modes	–	–0.203 (–2.845)
Part-time worker × car driver	0.128 (2.264)	–0.243 (–4.166)
Part-time worker × other modes	–	–0.336 (–3.670)
Full-time and Part-time workers x working from home	–	0.273 (3.566)
Dwelling features		
Garage type (Other)		
Attached	0.206 (5.325)	–
Solar panel (No, I don't have)		
Want to have	0.252 (4.807)	0.161 (3.060)
Currently have	–	0.089 (2.119)
EV-specific tariff (No, I don't have)		
Want to have	–	0.169 (3.747)
Currently have	–	0.517 (4.325)
Attitudinal indicators		
It's my moral obligation to reduce emission of greenhouse gases. (Somewhat agree, neutral or disagree)		
Strongly agree	–0.142 (–3.459)	–
In all my daily decisions, being environmentally responsible should be a top priority (Neutral or disagree)		
Strongly agree or somewhat agree	–	0.089 (2.405)
Intercept	0.529 (8.312)	0.451 (6.398)
Threshold parameters		
Threshold 0 1	Fixed	Fixed
Threshold 1 2	0.893 (30.808)	0.515 (27.400)
Threshold 2 3	1.965 (56.677)	1.198 (46.763)
Correlation between dependent variables		Coef. (t-stat)

(continued on next page)

Table 5 (continued)

Variables (base category)	Change to late-at-night (11 pm)	Change to around midday (10 am–2 pm)
	Coef. (t-stat)	Coef. (t-stat)
Correlation between ‘Change to 11 pm’ and ‘Change to 10 am–2 pm’		0.146 (7.281)

Log-likelihood Thresholds Only Model: -10,461.360 (4 parameters); Log-likelihood Fitted Model: -9423.59 (40 parameters); Log-likelihood Independent Model: -9702.357 (39 parameters); Adjusted rho-squared: 0.096; Likelihood Ratio vs. Null: 2056.608 ($p < 0.000$); Likelihood Ratio vs. Independent: 538.602 ($p < 0.000$).

consider other factors beyond the monetary benefits of changing the charging time to midday, especially environmental benefits, since they can maximise the use of solar energy during this period, for example. Conversely, consumers who would only buy an EV within the next 10 years or would not buy it have a lower willingness to switch charging time to late at night or around midday.

The effects of the distance travelled in a week variable highlight the relationships between activity-travel behaviour and the ability to charge off-peak. People travelling between 150 and 290 km per week (around the national average) are more willing to shift the charging schedule to late at night than those who travel shorter or longer distances. While those travelling shorter distances may not derive much monetary benefit from switching charging times, those who travel long distances may believe that delaying the charge start time will affect the battery range available for their next trip. The propensity to switch charging to midday decreases with an increase in weekly distances travelled. This result is expected as it indicates that high-distance travellers are less likely to be home in the middle of the day. As suggested in the smart charging results, those long-distance commuters have lower flexibility to rearrange their schedules to adapt to other charging times. Yet, they may utilise technological solutions, such as smart charging, to maximise their flexibility capital when they are home and generate financial benefits.

The interactions between employment status and commute mode provide further insights into potential constraints that activity-travel behaviour brings to residential charging schedules. Full-time and part-time workers not working from home are less willing to shift their charging time to midday. Among them, full-time workers who drive their cars to work presented the lowest propensity. By contrast, individuals working from home are more willing to shift their charging schedule to midday, as this arrangement allows them to be more flexible.

Among the dwelling features, we find that households with an attached garage present an increased propensity to shift the charging time to late at night, compared to households with other garage types or off-street parking. This probably reflects the lower inconvenience of checking your vehicle during the night if you have an attached garage compared to other parking settings. As expected, consumers who currently have or want to have solar panels in their homes present a higher probability of changing their EV charging time to around midday. Individuals who want to have solar panels are also more willing to change their charging time to late at night (11 pm) in response to ToU tariffs. This result contrasts with the observed by Burns and Mountain [23] in Australia, where they found that Victorians who have solar panels were not responsive to ToU tariff discounts. Additionally, consumers who currently have or want to have EV-specific tariffs show an increased propensity to shift their charging time to around midday.

Among the attitudinal indicators, we find that pro-environmental attitudes are negatively associated with the propensity to charge late at night and positively associated with midday charging. Environmentally conscious consumers may prefer charging their EVs during the day (or avoid charging at night) to maximise the use of solar energy, a

renewable energy resource. While regions with wind energy generation usually have excess energy during night hours [39], Australian consumers are probably less aware of this energy resource.

The positive correlation between the outcomes ‘Change to late at night (11 pm)’ and ‘Change to around midday (10 am–2 pm)’ indicates that unobserved factors increase the consumer’s propensity to change their EV charging time to both periods in response to ToU tariff discounts. Examples of such unobserved factors could be activity-travel behaviours reflecting users’ flexibility and time scarcity not captured in our survey design.

4.2.1. Average treatment effects

The lower average threshold probabilities (Table 6) for charging late at night indicate that consumers are more willing to change to this period than midday, as shown in the sample description.

Based on the ATEs and elasticities (Table 7 and Fig. 2), we observe that the higher the discount, the higher the probability of change to charging time, especially late at night. However, the marginal effect of tariff discounts decreases as the discount increases. The effects of discounts are much less pronounced for changing the EV charging time to midday (Table 7 and Fig. 2). That is, providing discounts does not seem to motivate many consumers to charge EVs around midday, compared to the effects observed for shifting to late at night. In this sense, other incentives may be necessary to shift EV charging demand to use solar energy generation.

5. Conclusions

This study brings relevant insights into the consumer preferences for EV smart charging technology and control, and users’ responses to ToU tariff discounts as a promoter of charging time change. Importantly, the present research is one of the pioneering studies to analyse these topics with a specific focus on EV charging and to investigate charging preferences in Australia. We examined the influence of a wide range of variables, such as activity-travel behaviour, EV ownership, and attitudinal indicators, which are crucial to identify market segments and profiling potential consumers of smart charging and ToU tariff discounts. Therefore, the findings in this paper are valuable for academia, industry, and policymaking in setting the target population for future trials and program implementation. The main findings and implications are underlined as follows.

First, we highlight activity-travel behaviour serving as a proxy of time constraints and impacting both the smart charging choice and EV charging behaviour in response to ToU tariffs, contributing to filling a noticeable gap in previous research. Remarkably, we find that individuals with more time constraints (e.g., full-time workers commuting by car and travelling longer distances per week) are among the consumers with a lower willingness to change EV charging time in response to ToU tariffs. Smart charging technology seems less appealing to low-distance travellers (and potentially with fewer time constraints), possibly because financial and practical benefits are outweighed by other concerns (e.g., privacy and loss of charging control). These results

Table 6

Average threshold probability extracted from the cumulative probability of the estimated model.

Outcome variable	Average threshold probability		
	Definitely not Probably not 0 1	Probably not Probably yes 1 2	Probably yes Definitely yes 2 3
Change to late at night (11 pm)	0.1105	0.3112	0.6368
Change to around midday (10 am–2 pm)	0.2870	0.4577	0.6904

Table 7
Average treatment effects and elasticities.

Discount level	Probability (t-stat)	ATE (t-stat)	Elasticity (t-stat)
Change to late at night (11 pm)			
0 % (Base for ATE and elasticity)	0.2384 (134.796)	Base	Base
10 %	0.2862 (183.988)	0.0479 (26.728)	0.2012 (23.703)
20 %	0.3148 (144.672)	0.0763 (23.580)	0.3214 (22.471)
50 %	0.3500 (71.06)	0.1110 (18.187)	0.4637 (15.109)
Change to around midday (Low-income)			
0 % × low income (Base for ATE and elasticity)	0.2861 (108.878)	Base	Base
10 % × low income	0.2874 (167.167)	0.0012 (0.671)	0.0056 (0.839)
20 % × low income	0.2890 (144.331)	0.0029 (0.988)	0.0094 (0.962)
50 % × low income	0.2933 (87.894)	0.0072 (1.618)	0.0237 (1.456)
Change to around midday (Higher income)			
0 % × higher income (Base for ATE and elasticity)	0.2861 (108.878)	Base	Base
10 % × higher income	0.2867 (154.662)	0.0006 (0.427)	0.0042 (0.656)
20 % × higher income	0.2880 (163.116)	0.0020 (0.862)	0.0117 (1.145)
50 % × higher income	0.2918 (101.860)	0.0058 (1.376)	0.0260 (1.448)

suggest that expanding the strategies of ToU tariff discounts and smart charging beyond home charging could be beneficial, especially at the workplace, which can also help balance electricity demand spatially and potentially reduce the evening peak.

Second, we observe that current EV owners are more prone to adopt supplier-managed smart charging and change EV charging time to around midday than other consumers (later EV adopters). These preferences reveal that current EV owners may have a strong desire to maximise the use of renewable energy, which is one of the main premises behind supplier-managed smart charging. This desire to maximise renewable energy use is also reflected in the choice to change EV charging time to around midday (10 am – 2 pm) when sunlight is prevalent, and solar panel performs best. This finding is especially remarkable in Australia, the current world leader in per-capita rooftop solar panel installations [8], and reassuring for initiatives planning to implement supplier-managed smart charging trials targeting EV owners in the near future. However, results from such trials need to be evaluated with caution, as they will probably overestimate consumer acceptance and response to such programs. Nevertheless, it should also be emphasised that mainstream consumers may increase their acceptance of supplier-managed smart charging over time as they have greater exposure to EV technology and gain a better understanding of battery range and charging.

Third, attitudinal indicators are key predictors of smart charging technology and control adoption, especially while consumers are still sceptical about these technologies. In this sense, we find that environmental attitudes, technology adoption cohort, privacy concerns and fear of losing control over charging are important factors influencing the willingness to use smart charging. Environmental attitudes also show a significant impact in predicting responses to ToU tariffs. These factors should be addressed in current and future trials and programs. For instance, while environmental benefits have often appeared in the smart charging literature and trials, a similar narrative could be used to encourage users with pro-environmental attitudes to adopt ToU tariffs and shift charging time to around midday.

Fourth, ToU tariff discounts seem to be more efficient in motivating behavioural changes toward late-at-night EV charging, compared to around midday. In this sense, when promoting midday EV charging,

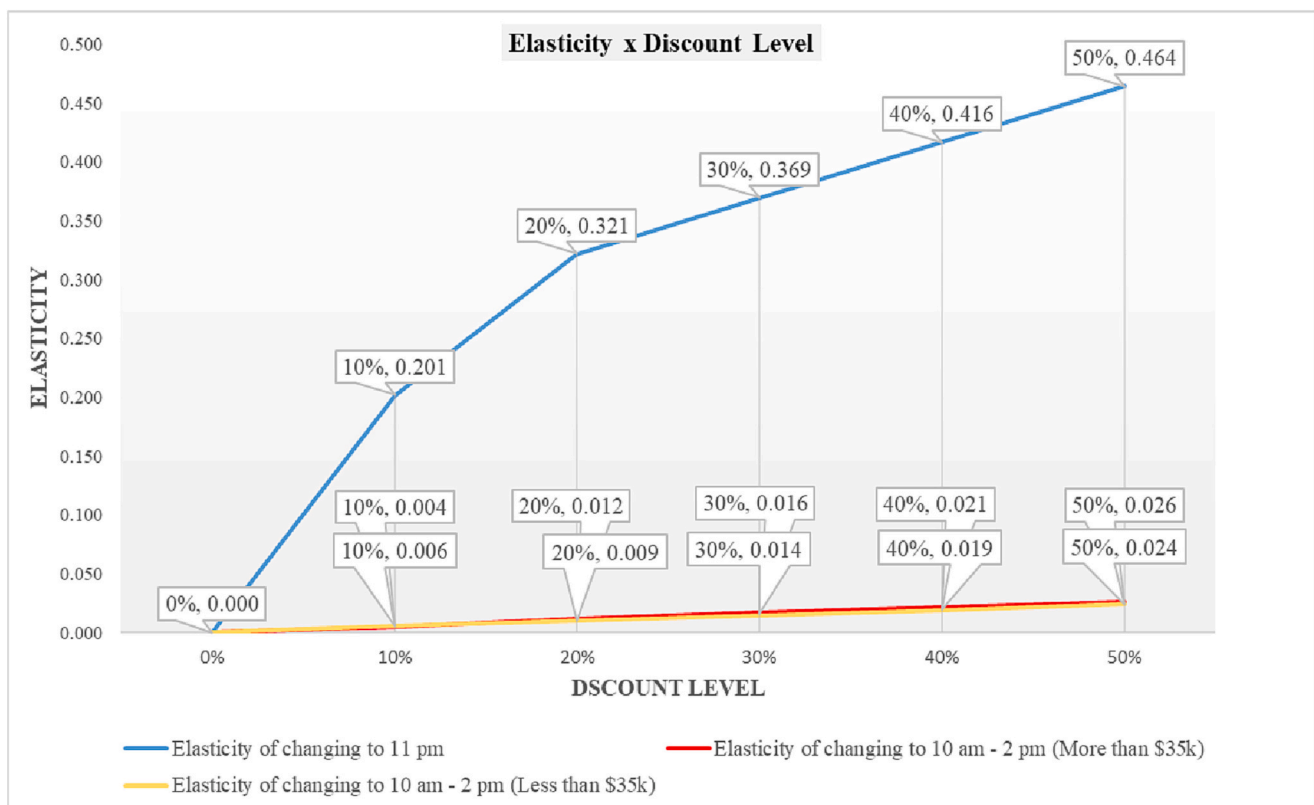


Fig. 2. Graph of the elasticities versus discount levels.

other strategies beyond tariff discounts are encouraged. While emphasising environmental benefits may be one approach, as discussed above, acting upon individuals' activity-travel schedules to increase their flexibility capacities will probably be inevitable. In this sense, there is a major need for future research and programs to investigate the integration of transport demand management strategies with energy demand-side management. Examples of such an integrated approach could involve the planning of telecommuting and workplace parking management programs that not only aim to improve sustainable travel choices but also facilitate access to renewable-energy EV charging.

The current study presents some data and modelling limitations that should be addressed by future research. While we analyse the effects of some explanatory variables representing activity-travel behaviour, analysing diary data containing actual time-use and parking patterns will be essential to fully measure individuals' charging scheduling flexibility. Another aspect that requires further measurement is consumer attitudes. Because of the limited number of attitudinal indicators available in our study, these were included directly as explanatory variables in our models. However, further attitude elicitation would allow such psychological constructs to be more accurately portrayed as latent factors. As identified in Section 3.1.2, the bivariate ordered probit model estimated in our analysis did not accommodate for intra-individual correlation associated with the repeated choice scenarios. Even though this limitation may have caused some inaccuracy in the computed standard errors, they do not affect the main findings and implications of our study. Our sample represents only the Australian market, which is lagging behind in terms of EV adoption. Future comparisons with results from studies from more developed markets are essential to derive generalisable conclusions. Finally, beyond the data and modelling limitations, future research should also address other relevant topics to understand the relationships between electric vehicle adoption and charging and demand-side management. For instance, future research could explore the effects of available managed charging schemes on consumers' willingness to adopt electric vehicles.

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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