**Modeling Long-Distance BEV Charging Decisions: A Dynamic Discrete–Continuous Approach Integrating Charging Location Choice and Energy Demand**

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**Abstract**

**Objectives**

This study investigates battery electric vehicle drivers' charging decisions during long-distance trips by jointly modeling whether drivers choose to charge and the charging level they aim to achieve. Unlike conventional charging choice models focusing only on station selection, this study considers charging as a sequential decision influenced by vehicle range, station characteristics, and driver preferences.

**Methods**

A stated preference survey was conducted among electric vehicle users in the Washington Metropolitan Area to collect charging decisions under different long-distance travel scenarios. The survey included sequential charging opportunities with variations in charging station characteristics. Static binary choice models, dynamic discrete choice models with different forward-looking horizons, and a dynamic discrete–continuous model were estimated and compared.

**Findings**

The results show that incorporating forward-looking behavior provides a modest improvement over the static model, suggesting that drivers consider future charging opportunities while immediate charging conditions and range constraints remain dominant factors in en-route charging decisions. Charging price negatively affects station choice, whereas charger power and station amenities positively influence charging preferences. Range-related factors, including charging thresholds and the ability to reach future stations, significantly affect charging decisions. The dynamic discrete–continuous model further reveals that remaining range, home charging availability, and previous charging behavior influence charging levels. The estimated value of charging time at a typical fast-charging station ranges from approximately $33 per hour.

**Novelty**

This study develops a joint dynamic discrete–continuous framework that captures both the sequential decision of whether to charge and the continuous decision of desired charging level, providing a comprehensive representation of long-distance charging behavior.

**Practical Applications**

The findings provide insights for charging infrastructure planners and fast-charging operators by emphasizing the importance of charging speed, pricing, and station amenities. The proposed framework provides a foundation for future charging choice models incorporating charging level decisions alongside station selection.

## 1. Introduction

Despite the rapid growth of electric vehicle (EV) adoption, several barriers still limit their widespread use (Biresselioglu et al., 2018). Early studies identified high purchase costs, limited driving range, range anxiety, long charging times, and insufficient charging infrastructure as the main obstacles to EV adoption (Bakker and Trip, 2013; Egbue and Long, 2012; Pamidimukkala et al., 2023; She et al., 2017). Over the past decade, some of these barriers have gradually become less important. Battery technology has improved significantly, increasing the driving range of modern EVs and making them more comparable to conventional gasoline vehicles (Baik et al., 2019; Lutsey and Nicholas, 2019). At the same time, declining battery costs, lower maintenance requirements, and government incentives have reduced the total cost of EV ownership and are expected to bring EV purchase prices closer to those of conventional vehicles in the coming years (He Lau, 2024).

While these improvements have addressed some of the traditional barriers to EV adoption, the availability, accessibility, and reliability of charging infrastructure remain major challenges (Halbey et al., 2015; Satterfield and Schefter, 2022). This challenge becomes even more important as long-range battery electric vehicles (BEVs) become more common and drivers increasingly rely on them for long-distance travel. Supporting reliable long-distance travel is essential not only for improving the travel experience of current EV owners but also for encouraging broader adoption of EVs (Botsford and Szczepanek, 2009). In this context, direct current fast charging (DCFC) stations play a critical role by allowing drivers to recharge during long trips and making BEVs suitable for a wider range of travel purposes ("National Research Council: Overcoming barriers to... - Google Scholar," n.d.). Unlike conventional vehicle refueling, EV charging requires more time and involves additional planning decisions (Botsford and Szczepanek, 2009; Dorsey et al., 2022). During a trip, drivers must determine when to stop for charging, which charging station to select, and how much energy to charge before continuing their journey (Ge and MacKenzie, 2022). These decisions are influenced not only by the remaining battery level but also by factors such as charging price, charging power, station availability, and expected charging opportunities along the route (Ge and MacKenzie, 2022; Sun et al., 2016). Therefore, understanding drivers' public charging decisions is essential for accurately characterizing charging behavior and designing charging networks that better reflect users' needs (Liu and Cirillo, 2020).

A better understanding of charging behavior also helps explain how drivers interact with charging infrastructure and how their decisions influence charging demand. Although understanding public charging behavior has become increasingly important (Krause et al., 2018), collecting reliable data on charging decisions remains challenging. Because EVs still represent a relatively small share of the overall vehicle fleet, large-scale observations of real-world charging behavior remain limited (Kajanova and Bracinik, 2021). In addition, charging decisions are influenced by many factors, including driver characteristics, travel conditions, charging infrastructure, psychological factors, and the maturity of the local EV market (Du et al., 2025). Available datasets are often incomplete because they are limited to a specific charging network, operator, or geographic region, while general mobility datasets usually do not contain detailed information about charging behavior (Andrenacci and Valentini, 2023). As a result, many studies rely on either revealed travel data or stated preference (SP) surveys to better understand charging decisions.

Stated preference surveys have become one of the most widely used methods for analyzing EV charging behavior because they allow researchers to evaluate charging situations that may not yet exist in practice. In these surveys, respondents are presented with hypothetical charging scenarios that vary in attributes such as charging price, charging power, waiting time, and station amenities, allowing researchers to estimate the effect of individual charging attributes on drivers' choices (Ashik et al., 2020; Yang et al., 2016). The resulting data are typically analyzed using multinomial logit or conditional logit models to identify the factors influencing the choice among home, workplace, and public charging (Daina et al., 2017; Dong et al., 2024; Thill, 2009).

Early studies on public fast-charging behavior mainly focused on understanding when drivers decide to charge and how this decision is influenced by battery conditions and trip characteristics. One approach was to represent the driver's state of charge (SOC) as a continuous variable to examine how remaining battery level affects the decision to initiate charging during a trip (Sun et al., 2015). However, because charging decisions are also constrained by the availability and location of charging stations, considering SOC alone does not fully capture the choice of where to charge. To address this limitation, later studies incorporated the selection among feasible charging stations and examined how factors such as remaining SOC, charging cost, and detour distance influence charging location choices (Sun et al., 2016, 2015). Although these models provide a more realistic representation of public charging decisions, they mainly focus on trips involving a single charging event and do not fully capture the sequential decision-making process that occurs during longer trips.

More recent studies have expanded the analysis of public charging behavior by incorporating additional station and trip characteristics. These studies demonstrate that both infrastructure attributes and drivers' trip conditions play important roles in determining charging preferences (Hoen et al. 2023). However, most existing approaches rely on a single choice situation and represent charging decisions as a static process, while in reality drivers continuously update their decisions as their battery level changes and as they receive information about available charging opportunities along the route. To better represent this dynamic decision-making process, recent research has introduced dynamic choice frameworks that model charging decisions as a sequence of interdependent choices throughout a trip. These models allow drivers to consider their current state of charge, travel progress, and expectations about future charging opportunities when deciding whether and where to charge (Ge and MacKenzie, 2022). Similarly, adaptive stated preference approaches have been developed to capture forward-looking behavior and examine how factors such as remaining range and range anxiety influence charging decisions (Thorhauge et al., 2026). Together, these studies highlight that public charging behavior is not a single isolated choice but rather a dynamic process in which drivers continuously adjust their decisions based on evolving trip conditions.

Despite these advances, most existing dynamic charging models still focus only on the discrete decision of whether to charge and which charging station to choose. Once drivers arrive at a charging station, they must also decide how much to charge before continuing their trip. This charging level depends on many factors, including the remaining trip distance, charging price, charging speed, expected future charging opportunities, and individual charging preferences. Therefore, public charging is naturally a dynamic discrete–continuous decision process (Liu and Cirillo, 2020). Ignoring the charging level may overlook an important part of drivers' decision-making process and lead to an incomplete representation of charging behavior.

To address these limitations, this study develops a stated preference survey to collect detailed information on both drivers' charging station choices and their desired charging levels at selected stations. The collected data are used to estimate and compare several modeling approaches, including a static choice model, dynamic discrete choice models with different levels of look-ahead behavior, and a dynamic discrete–continuous model that jointly captures both the selection of a charging station and the charging level chosen at that station. In addition to commonly considered charging attributes, such as charging price and charging power, the proposed framework incorporates station-specific characteristics, including expected waiting time derived from station occupancy, as well as driver-specific behavioral factors, such as charging habits and range anxiety inferred from previous charging experiences. Finally, the estimated model is used to quantify the value of charging time for EV users at public fast-charging stations. Overall, this study provides a more comprehensive understanding of public fast-charging behavior by jointly considering where, when, and how much drivers choose to charge, offering valuable implications for the planning and operation of future EV charging infrastructure.

## 2. Survey

The survey was designed to collect detailed information needed to better understand and model EV users' public charging behavior. The survey targeted EV users in the Washington Metropolitan Area who have experience using public charging stations and collected both revealed preference (RP) information from respondents' recent charging experiences and stated preference (SP) data under hypothetical charging scenarios.
The survey consisted of three main components: (1) socio-demographic characteristics, including personal, household, and vehicle information; (2) travel behavior and typical public charging usage patterns, including respondents' charging experiences and habits; and (3) a stated preference experiment designed to investigate how drivers select charging stations and determine their desired charging level during long-distance trips. This study primarily uses the SP component to estimate charging choice models because it provides controlled variation in charging attributes and allows the analysis of behavioral responses under different charging scenarios.

### 2.1 Experimental Design

The stated preference (SP) experiment was designed to investigate how EV users select public charging stations and determine their desired charging level during long-distance trips. Each scenario presented respondents with five charging stations available along their route. The charging stations were characterized by attributes that represent important factors affecting charging decisions, including charger power, charging price, access time required to reach the station, expected waiting time due to station occupancy, and available amenities. The attribute levels used in the experiment are summarized in Table 1. Charger power and charging price levels were selected based on previous EV

charging studies (Ge and MacKenzie, 2022), while other attributes were selected to represent realistic characteristics of public charging stations.

The choice scenarios were generated using Ngene, a specialized software package for developing efficient stated preference designs. A D-efficient design was selected to generate the experimental design, consisting of five choice situations with five charging station alternatives in each situation. Although the final behavioral models estimate both the decision of whether to charge and the desired charging level, the SP design presents the five charging stations as separate alternatives. This approach allows respondents to evaluate multiple realistic charging options along their route while reducing the likelihood that one alternative dominates the others.

At the beginning of each scenario, the respondent's reported vehicle range from the vehicle characteristics section was used as the initial driving range. The vehicle was assumed to start the trip with a fully charged battery. However, for respondents whose reported BEV range was less than 150 miles, a random range value between 150 and 300 miles was assigned. This adjustment avoids presenting unrealistic long-distance travel scenarios for vehicles with limited range while maintaining consistency with BEVs suitable for long-distance travel.

At each decision point, respondents were provided with their remaining driving range and information about the available charging stations. They were then asked whether they would choose to stop and charge at one of the available stations. If a charging station was selected, respondents indicated the desired charging level they would like to reach before continuing their trip. After each decision, the remaining range was updated based on the selected charging level, and respondents proceeded to the next charging decision point along the route. This sequential structure allows the survey to capture the dynamic nature of charging decisions by reflecting how drivers adjust their choices based on their current battery status and future charging opportunities.

To account for uncertainty in real-world energy consumption, the available driving range at each station was adjusted using a stochastic factor. Variations in energy consumption may result from differences in driving behavior, weather conditions, traffic conditions, and roadway characteristics. The remaining range at station (k) was calculated as:

$$R_k = R_{k-1} - D_k \cdot (1 + \alpha) \quad (1)$$

In this formulation, $R_k$ represents the remaining range (in miles) available at station k, which is derived from the remaining range at the previous decision point ($R_{k-1}$) minus the distance between the two stations ($D_k$), scaled by the stochastic factor α. The random variable $\alpha$, which typically ranges from a negative to a positive value to capture a full spectrum of consumption conditions, is incorporated to consider the variability in energy consumption; a positive simulates higher-than-expected consumption due to adverse conditions, while a negative simulates more favorable energy use.

Table 1. Attributes and Their Levels of the Experiments in the Survey

| Attribute | Levels |
|---|---|
| Number of charging stations on route | 5 (Sequential choice) |
| Charger Power (kW) | 50, 100, 150, 300 |
| Price ($/kWh) | Free, 0.5 $/kWh, 1 $/kWh |
| Access time (min) | 5, 10, 15, 30 |
| Expected Wait Time (min) | 0, 5–10, 15–25, 30+ |
| Amenities | None, Restroom only, Restroom + Food + Wi-Fi |

## 3. Data

The survey was conducted from January to March 2026, and respondents were recruited through Qualtrics. After data cleaning and quality control procedures, 932 valid responses remained from the initial 1,000 respondents. A descriptive analysis of the survey sample is presented in Table 2.

Table 2 summarizes the socio-demographic characteristics and EV-related attributes of the survey respondents. The sample includes slightly more male respondents (58.2%) than female respondents (41.3%). The majority of respondents were between 25 and 44 years old (57.0%), followed by respondents aged 45–64 (28.1%). Regarding educational attainment, approximately 57.1% of respondents held at least a bachelor's degree, including 30.0% with a bachelor's degree, 21.7% with a master's degree, and 5.4% with a professional or doctoral degree. In terms of household income, 46.5% of respondents reported an annual household income of $100,000 or higher, with the largest income group being $100,000–$149,999 (20.3%).

The EV ownership and charging characteristics of respondents indicate that the sample includes EV users with substantial access to charging infrastructure. Most respondents owned one EV (80.4%), while 17.0% owned two EVs and 2.7% owned three or more EVs. Approximately 91.3% of respondents owned high-range BEVs, while only 8.7% owned low-range BEVs. In terms of charging access, 79.2% of respondents had access to home charging. Workplace charging was also commonly available, with 39.6% of respondents reporting free workplace charging and 17.2% reporting workplace charging that requires payment.

To provide additional context regarding the characteristics of the survey sample, the demographic distributions of respondents were compared with EV owners identified in the 2022 National Household Travel Survey (NHTS). As shown in Table 2, the gender distribution of the current sample is generally comparable with the national EV owner population, although the current sample includes a slightly higher proportion of male respondents (58.2% compared with 52.2% in NHTS). The educational attainment of the sample is also comparable with NHTS EV owners, with a large proportion of respondents holding a bachelor's or graduate degree. Overall, the comparison indicates that the survey sample captures demographic characteristics commonly observed among EV users while focusing specifically on drivers who interact with public charging infrastructure.

Table 2. Description of the Sample,

| Variable | Category | This study (%) | NHTS 2022 EV owners (%) | Variable | Category | This study (%) |
|---|---|---|---|---|---|---|
| **Gender** | Male | 58.15 | 52.20 | Home charger access | Yes | 79.18 |
| | Female | 41.31 | 47.80 | | No | 20.82 |
| **Education** | Less than high school | 0.64 | — | Workplace charger access | Yes, free to use | 39.59 |
| | High school graduate | 25.00 | 15.60 | | Yes, but requires payment | 17.17 |
| | Associate degree / Trade school certificate | 17.27 | 18.50 | | No | 24.79 |
| | Bachelor's degree | 30.04 | 27.30 | Number of EVs owned | 1 | 80.36 |
| | Graduate / Professional degree | 27.03 | 38.60 | | 2 | 16.95 |
| **Annual household income** | Less than $75,000 | 40.24 | 15.10 | | 3 or more | 2.68 |
| | $75,000–$99,999 | 13.41 | 12.80 | Vehicle range category | High range | 91.31 |
| | $100,000 or higher | 46.48 | 71.40 | | Low range | 8.69 |
| **Age group** | 18–24 | 11.05 | — | | | |
| | 25–44 | 56.97 | — | | | |
| | 45–64 | 28.11 | — | | | |

| Variable | Category | This study (%) | NHTS 2022 EV owners (%) | Variable | Category | This study (%) |
|---|---|---|---|---|---|---|
| | 65+ | 3.86 | — | | | |

## 4. Methodology

### 4.1 Overview

To analyze EV drivers' charging decisions during long-distance trips, this study develops and compares three models with increasing levels of behavioral complexity using data collected from the stated preference survey. The underlying decision process is modeled as a sequential decision problem, where drivers evaluate each charging opportunity along their route and decide whether to charge at the current station or continue driving to a future charging opportunity.

At each charging station, drivers make a discrete choice between two alternatives: charging at the current station (j=1) or skipping the station and continuing the trip without charging (j=0). If a driver chooses to charge, a subsequent continuous decision is made regarding the desired charging level, represented by the amount of energy added to the vehicle. Therefore, the modeling framework captures both the decision of where and when to charge and how much to charge once a station is selected.

Three models are estimated and compared, all using the same station-level and trip-level attributes:

1. **Static discrete choice model:** A binary logit model that estimates the probability of charging at the current station without considering future charging opportunities.
2. **Dynamic discrete choice model:** A dynamic framework based on Liu and Cirillo (2017), where the charging decision at station (t) depends not only on current station characteristics but also on the driver's expectations regarding future charging opportunities along the route.
3. **Dynamic discrete–continuous choice model:** A joint model based on Liu and Cirillo (2020) that simultaneously estimates the discrete charge/skip decision and the continuous charging level decision. This framework allows the two decisions to be correlated through a shared error structure and provides a more complete representation of EV charging behavior.

Drivers are indexed by $i = 1, \ldots, I$, and charging stations encountered along driver i's route are indexed by $t = 1, \ldots, T_i$. At each decision point t, driver i faces two alternatives, j ∈ {0, 1}, representing the decision to skip the station (j = 0) or charge at the station (j = 1). The vector $q_{ijt}$ represents the station-specific attributes associated with alternative j at decision point t, including charging price, access time, expected waiting time, charging power, station availability, and amenities. The vector $x_i$ represents driver-specific characteristics included in the continuous charging-level model, while $y_{it}$ denotes the remaining vehicle range (or state of charge) when driver i arrives at station t.

### 4.2 Static Discrete Choice Model (Binary Logit)

As a baseline model, this study estimates a static binary logit model (McFadden, 1973) to represent the driver's charge/skip decision at each charging opportunity. In this model, the decision to charge at station *t* depends only on the current station characteristics and the driver's remaining vehicle range upon arrival. The model does not consider future charging opportunities along the route.

$$u_{i1t} = q'_{1t}\alpha + y_{it}\gamma + \varepsilon_{i1t} \quad (2)$$

$$u_{i0t} = \varepsilon_{i0t} \quad (3)$$

where $\mathbf{U_{i1t}}$ and $\mathbf{U_{i0t}}$ represent the utilities of charging and skipping station *t* for driver *i*, respectively. The vector $\mathbf{q_{i1t}}$ includes station-specific attributes associated with charging at station *t*, α is a vector of coefficients associated with

these attributes, $\mathbf{y_{it}}$ represents the remaining vehicle range (or state of charge) when driver *i* arrives at station *t*, and γ is its corresponding coefficient. The term $\boldsymbol{\varepsilon_{ijt}}$ represents the random error component, assumed to follow an independent and identically distributed Type-I extreme value distribution.

Under the random utility maximization framework, the probability that driver *i* chooses to charge at station *t* is expressed as:

$$P(Y_{it}^{disc} = 1) = \frac{\exp(q_{1t}'\alpha + y_{it}\gamma)}{1 + \exp(q_{1t}'\alpha + y_{it}\gamma)} \tag{4}$$

This static formulation assumes that each charging opportunity is evaluated independently and that the current charging decision depends only on the available information at the current station. Therefore, it does not capture the forward-looking behavior of drivers who consider future charging opportunities, remaining trip distance, or expected station conditions when making charging decisions.

### 4.3 Dynamic Discrete Choice Model

Following the generalized dynamic discrete choice framework proposed by Liu and Cirillo (2017), this study extends the static charging decision model by incorporating drivers' expectations about future charging opportunities. Unlike the static model, where each charging opportunity is evaluated independently, the dynamic model assumes that drivers consider both the utility of charging at the current station and the expected utility of continuing the trip and charging at future stations.

At each station $t$, driver $i$ evaluates two alternatives: charging at the current station or skipping the station and continuing to the next charging opportunity. The instantaneous utility associated with each alternative is defined as:

$$u_{ijt} = f(x_{it}, q_{jt}, y_{it}; \theta, \gamma, \alpha) + \varepsilon_{ijt} \tag{5}$$

where $j \in \{0,1\}$ represents the skip and charge alternatives, respectively. The vector $q_{ijt}$ includes station-specific attributes, $x_i$ represents driver characteristics, and $y_{it}$ represents the remaining vehicle range when arriving at station $t$. The parameters $\theta$, $\gamma$, and $\alpha$represent the associated coefficients, and $\varepsilon_{ijt}$ is an independent and identically distributed Type-I extreme value error term.

The maximum instantaneous utility available at station $t$ is given by:

$$v_{\mathrm{it}} = max_{\mathrm{j}} \{u_{\mathrm{ijt}}\} \tag{6}$$

Because the error terms follow an extreme value distribution, the expected maximum utility can be represented by the inclusive value:

$$r_{it} = \ln \sum_{j} \exp(f(x_{it}, q_{jt}, y_{it}; \theta, \gamma, \alpha)) = E_t[v_{it}] \tag{7}$$

The value $r_{it}$summarizes the expected utility available at the current station and serves as the state variable in the dynamic decision process. Rather than evaluating only the current charging opportunity, drivers are assumed to consider future charging opportunities within a forward-looking window of $nLook$stations. In this study, different values of nLook (1, 2, and 3) are tested to examine how the extent of forward-looking behavior affects charging decisions.

The continuation value of skipping the current station is represented using the following recursive formulation:

$$W_{it}(r_{it}) = c_{it} + \beta\, E_{t+1}\left[\, D_{i,t+1}\left(v_{i,t+1}, r_{i,t+1}\right) \mid r_{it} \,\right] \tag{8}$$

where $W_{it}(r_{it})$represents the expected utility of continuing the trip without charging at station $t$, $c_{it}$represents the immediate utility associated with continuation, and β is the discount factor. Following Liu and Cirillo (2017), β is fixed to 1, assuming that drivers do not discount future charging opportunities. The function $D_{it}$represents the maximum expected utility at station $t$:

$$D_{it}(v_{it}, r_{it}) = \max\{v_{it}, W_{it}(r_{it})\} \tag{9}$$

The probability of skipping the current charging station is then calculated as:

$$\pi_{i0t}(r_{it}) = P(v_{it} \leq W_{it}(r_{it})) = \exp(-e^{-(W_{it}(r_{it})-r_{it})}) \quad (10)$$

The probability of charging at station $t$is:

$$\pi_{i1t}(r_{it}) = 1 - \pi_{i0t}(r_{it}) \quad (11)$$

Unlike the one-time or repeated choice settings in (Cirillo et al., 2017), choosing to charge does not terminate the decision process. Instead, charging updates the vehicle's state, particularly the remaining range, and the driver continues evaluating future charging opportunities. Therefore, EV charging is modeled as a regenerative dynamic process without an absorbing state. Since the vehicle state evolves continuously rather than transitioning among discrete alternatives, a Markov transition matrix is not required in this application.

### 4.4 Dynamic Discrete-Continuous Choice Model

The dynamic discrete choice model captures drivers' decisions of whether to charge at a given station while considering future charging opportunities. However, once a driver decides to charge, the amount of energy added to the vehicle is also an important decision that affects subsequent charging opportunities. Therefore, the charging process is inherently a joint discrete–continuous decision problem. To jointly model the charging decision and the desired charging level, this study follows the recursive binary probit (RBP) framework proposed by (Liu and Cirillo, 2020)

At each station $t$, the driver's decision consists of two components:

$$D_{it} = (Y_{it}^{disc}, Y_{it}^{cont}) \quad (12)$$

where $Y_{it}^{disc}$represents the discrete charge/skip decision and $Y_{it}^{cont}$represents the continuous charging-level decision, which is observed only when the driver chooses to charge ($Y_{it}^{disc} = 1$).

Unlike the dynamic discrete choice model described previously, the discrete component in this framework is formulated as a binary probit model to allow correlation between the discrete charging decision and the continuous charging-level decision. The instantaneous utility of alternative $j$at station $t$is expressed as:

$$u_{ijt} = v_{ijt} + \varepsilon_{ijt}, \varepsilon_{ijt} \sim N(0, \mu^2) \quad (13)$$

Where:

$$v_{ijt} = x_{it}'\beta + q_{jt}'\alpha \quad (14)$$

where $q_{ijt}$represents station-specific attributes and $x_{it}$represents driver and trip characteristics. The driver selects the alternative that maximizes the current utility and expected future utility. The expected future utility is obtained recursively through the Bellman equation:

$$V_{it}(j) = E[\max_{j \in J_t}(v_{ijt} + \delta V_{i,t+1}(j) + \varepsilon_{ijt})] \quad (15)$$

Following Liu and Cirillo (2020), the expected maximum utility can be obtained analytically because the utilities of the charge and skip alternatives are assumed to follow a bivariate normal distribution. For two normally distributed random variables $X_1$and $X_2$:

$$E[\max(X_1, X_2)] = \mu_1 \Phi(\frac{\mu_1 - \mu_2}{\theta}) + \mu_2 \Phi(\frac{\mu_2 - \mu_1}{\theta}) + \theta\, \varphi(\frac{\mu_1 - \mu_2}{\theta}) \quad (16)$$

where:

$$\theta = \sqrt{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2} \quad (17)$$

and $\Phi(\cdot)$and $\varphi(\cdot)$represent the standard normal cumulative distribution function and probability density function, respectively. This closed-form solution allows the dynamic component to be incorporated without simulation.

The probability of choosing alternative $j$is then obtained using the binary probit formulation:

$$P(Y_{it}^{disc} = j) = \int \mathbb{I}(\tilde{v}_{ijt} + \delta\tilde{V}_{it}(k) + \tilde{\varepsilon}_{ijt} < 0)\, \varphi(\tilde{\varepsilon}_{ijt})\, d\tilde{\varepsilon}_{ijt} \tag{18}$$

where $\tilde{v}_{ijt} = v_{ikt} - v_{ijt}$; $\widetilde{V_{it}}(j) = V_{it}(k) - V_{it}(j)$; $\tilde{\varepsilon}_{ijt} = \varepsilon_{ikt} - \varepsilon_{ijt}$. The difference of two normally distributed error terms follows a normal distribution with a new mean and new variance.
Conditional on choosing to charge, the continuous charging-level decision is modeled as:

$$Y_{it}^{cont} = (x_{it}^{cont})'\beta^{cont} + \varepsilon_{it}^{cont}, \varepsilon_{it}^{cont} \sim N(0, \tau^2) \tag{19}$$

To account for the correlation between the charging decision and the charging-level decision, the error terms of the two components are jointly distributed:

$$\left(\tilde{\varepsilon}_{it}, \varepsilon_{it}^{cont}\right) \sim MVN(0, \Sigma_{2,t}) \tag{20}$$

where $\Sigma_{2,t}$is the covariance matrix estimated for each decision point. This correlation structure allows unobserved factors that influence a driver's decision to charge also affect the desired charging level. The covariance matrix across all stations is assumed to follow a block-diagonal structure:

$$\Omega = \begin{bmatrix} \Sigma_{2,t=1} & 0 & \cdots & 0 \\ 0 & \Sigma_{2,t=2} & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & \Sigma_{2,t=T} \end{bmatrix} \tag{21}$$

Finally, the joint probability of observing the discrete charging decision and the continuous charging level is expressed as:

$$P(D_{it}) = P(Y_{it}^{cont})\, P(Y_{it}^{disc} \mid Y_{it}^{cont}) \tag{22}$$

The model parameters are estimated by maximizing the joint likelihood:

$$L(\alpha, \beta, \beta^{\mathrm{cont}}, \Omega) = \prod_{\mathrm{i=1}}^{\mathrm{I}} \prod_{\mathrm{t=1}}^{\mathrm{T_i}} P(D_{\mathrm{it}}) \tag{23}$$

where $P(D_{it})$represents the joint probability of observing the discrete charging decision and the continuous charging level at station $t$for driver $i$. The likelihood is maximized over the station-attribute coefficients $\alpha$, driver- and trip-level coefficients $\beta$, continuous charging-level coefficients $\beta^{cont}$, and the covariance parameters contained in Ω, which capture the correlation between the discrete and continuous error components.

### 4.3 Value of Charging Time

To estimate the value of charging time (VOT), the estimated coefficients of electricity price and charger power are used to derive the marginal utilities of charging cost and charging time. This derivation assumes that the effect of charger power on utility arises through its impact on charging time; that is, higher-power chargers are preferred because they reduce the time required to deliver a given amount of energy.

Let $E$denote the amount of energy delivered (kWh), $C$the total charging cost ($), $T$the charging time (hours), and $P$the charger power (kW). Since electricity price is measured in $/kWh and charger power in kW,

$$Price = \frac{C}{E} \tag{24}$$

And

$$P = \frac{E}{T} \tag{25}$$

The marginal utility of charging cost is therefore

$$\frac{\partial U}{\partial C} = \frac{\beta_{\text{Price}}}{E} \tag{26}$$

where $\beta_{\text{Price}}$is the estimated coefficient of electricity price.

The marginal utility of charging time is obtained by applying the chain rule:

$$\frac{\partial U}{\partial T} = \frac{\partial U}{\partial P} \cdot \frac{\partial P}{\partial T} = -\beta_{Power} \frac{E}{T^2} \tag{27}$$

where $\beta_{\text{Power}}$is the estimated coefficient of charger power.

The implied value of charging time is calculated as the ratio of the marginal utility of charging time to the marginal utility of charging cost:

$$VOT = -\frac{\partial U/\partial T}{\partial U/\partial C} = \frac{\beta_{Power} E/T^2}{-\beta_{Price}/E} \tag{28}$$

Since

$$\frac{E}{T} = P \tag{29}$$

the expression simplifies to

$$VOT = \left(\frac{\beta_{\text{Power}}}{-\beta_{\text{Price}}}\right) \cdot P^2 \tag{28}$$

where VOT is expressed in dollars per hour ($/h). The estimated value therefore depends on the charging power of the station, implying that the monetary value of reducing charging time increases for higher-power chargers.

## 5. Results

Table 3 presents the estimation results for the models developed in this study. The first five models represent the charging decision as a binary choice between charging at the current station and continuing the trip without charging. These models include a static binary logit model and four dynamic discrete choice (DDC) models with different forward-looking horizons, ranging from considering one to four downstream charging stations ($nLook = 1$–$4$). The final model is a dynamic discrete–continuous model that jointly estimates the charging decision and, conditional on charging, the desired charging level. Since the static and DDC models share the same utility specification, differences among these models primarily reflect the effect of incorporating forward-looking behavior into drivers' charging decisions.

The explanatory variables included in the models capture two main aspects of public charging decisions: station attributes and driver-related characteristics. Station attributes describe the characteristics of available charging options, including charging price, charger power, access time, expected waiting time, and station amenities. Driver-related variables represent individual charging preferences and behavioral characteristics, including the remaining driving range at each charging opportunity, home charging availability, and self-reported charging habits. These charging habit variables capture drivers' typical charging behavior, including the battery level at which they usually initiate charging and their preferred charging level. Together, these variables allow the models to capture how both the characteristics of available charging stations and individual charging preferences influence public charging decisions.

Among station-related attributes, charging price, charger power, and station amenities consistently influence BEV drivers' charging decisions across model specifications. The coefficient of charging price is negative and statistically

significant in all models ($\beta \approx -0.55$ to $-0.69$), indicating that drivers are less likely to select stations with higher charging costs. In contrast, charger power has a positive and significant effect, suggesting that drivers prefer faster charging options during long-distance trips.

Station amenities also play an important role in charging station selection. In the discrete choice models, stations offering a combination of restrooms, food, and Wi-Fi have a strong positive effect on charging decisions ($\beta \approx 0.42$–$0.54$), while stations offering only restroom facilities have a smaller but still significant effect ($\beta \approx 0.18$–$0.23$) compared with stations without amenities. However, in the joint discrete–continuous model, the coefficient of restroom-only amenities becomes insignificant, suggesting that when the charging location decision is modeled jointly with the amount of energy added, only stations providing a broader set of amenities significantly affect the decision to charge. This finding indicates that drivers may particularly value charging locations that provide opportunities to use their charging time productively during longer stops.

In contrast, access time and expected waiting time show limited effects across model specifications. Both variables are generally insignificant, suggesting that within the range of values presented in the stated preference scenarios, drivers place greater emphasis on charging cost, charging speed, and station amenities than on differences in detour time and waiting time. This finding may be related to the long-distance travel context considered in this study. Unlike routine charging decisions, where drivers have more flexibility in selecting when and where to charge, drivers on long-distance trips may face greater constraints due to their remaining range and the availability of charging opportunities along the route. As a result, once a charging stop is needed, moderate differences in access time or waiting time may have a smaller influence on the station selection decision compared with attributes that directly affect the charging experience, such as price, charging speed, and amenities.

with variables representing drivers' perceived need to maintain sufficient range during the trip. The coefficient of BelowTrigger, which indicates that the remaining range falls below the driver-reported charging threshold, is positive and significant across all model specifications ($\beta \approx 0.15$–$0.20$). Similarly, CantReachNext, which represents situations where the remaining range is insufficient to reach the next available charging opportunity, has a positive effect and becomes particularly significant in the joint discrete–continuous model ($\beta = 0.345$). These results indicate that charging decisions are strongly influenced by drivers' perceived range constraints and the need to maintain a safety buffer during long-distance travel. Previous studies have shown that EV drivers generally avoid reaching very low battery levels and tend to initiate charging before depletion, reflecting the influence of range anxiety and risk management behavior on charging decisions (Franke and Krems, 2013; Rauh et al., 2015; Sun et al., 2016). Therefore, the results suggest that the need to ensure trip completion and avoid range-related risk plays a dominant role in determining when drivers choose to charge.

The continuous component of the discrete–continuous model provides additional insights into charging behavior by explaining the amount of energy added conditional on the decision to charge. The results show that drivers arriving at a station with higher remaining range tend to add less energy, indicating that charging levels are adjusted based on the immediate battery state. This behavior is consistent with observed EV charging patterns, where drivers often charge only the amount needed to maintain sufficient range for the trip rather than always charging to the maximum level (Hardman et al., 2018; Sun et al., 2016).

Another factor influencing charging level is access to home charging. The negative and significant coefficient of home charging availability indicates that drivers with access to home charging are less likely to add large amounts of energy at public charging stations. This result is reasonable because drivers with reliable home charging opportunities have less need to maximize energy gained during public charging events and may use public chargers primarily for short-term travel needs or trip continuation. Previous studies have shown that home charging is the dominant charging location for EV users and that public charging is often used as a complementary option when home charging is unavailable or insufficient (Hardman et al., 2018)

Finally, self-reported charging habits significantly influence the amount of energy added. Drivers who typically charge their vehicles to higher battery levels are more likely to select higher charging levels in the stated preference scenarios. This finding suggests that individual charging preferences and habitual behavior play an important role in determining charging intensity. Previous research has shown that EV charging behavior is heterogeneous across users and is influenced by individual preferences, driving patterns, and personal charging strategies (Lee et al., 2020; Sun et al., 2016).

1 Table 3. Results of the models on charging choices.

| Variable | Static Logit | DDC nLook=1 | DDC nLook=2 | DDC nLook=3 | DDC nLook=4 | Discrete-Continuous |
|---|---|---|---|---|---|---|
| **Discrete Part** | | | | | | |
| ASC | -0.442** | -0.578 | -0.568*** | -0.654*** | -0.666*** | -0.084 |
| Charging Price ($/kWh) | -0.685*** | -0.588*** | -0.617*** | -0.599*** | -0.582*** | -0.457*** |
| Access Time (min) | 0.002 | 0.0003 | 0.0003 | 0.001 | 0.0003 | 0.0009 |
| Full Amenities | 0.541*** | 0.472*** | 0.469*** | 0.430*** | 0.422*** | 0.253*** |
| Restroom Only | 0.226*** | 0.189*** | 0.200*** | 0.195*** | 0.161** | 0.042 |
| Waiting Time (min) | -0.004 | -0.0047*** | -0.006 | -0.004 | -0.0045 | -0.0042 |
| Charging Power (kW) | 0.001*** | 0.109*** | 0.001*** | 0.001*** | 0.00102*** | 0.000346 |
| Remaining Range (%) – Discrete | -0.0031* | -0.0036*** | -0.0038** | -0.0033** | -0.0038*** | -0.0023 |
| Below Threshold | 0.174** | 0.171*** | 0.166** | 0.168*** | 0.162** | 0.198*** |
| Cannot Reach Next Station | 0.228* | 0.152** | 0.178 | 0.157 | 0.141 | 0.352*** |
| **Continuous Part** | | | | | | |
| Home Charger Access | — | — | — | — | — | -0.057** |
| Remaining Range (%) – Continuous | — | — | — | — | — | -0.0056*** |
| Usual Charge Level 30–50% | — | — | — | — | — | 0.846*** |
| Usual Charge Level 50–80% | — | — | — | — | — | 0.869*** |
| Usual Charge Level 80–90% | — | — | — | — | — | 0.897*** |
| Usual Charge Level 90–100% | — | — | — | — | — | 0.990*** |
| Usual Charge Level Full | — | — | — | — | — | 1.049*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| Initial Log-Likelihood | -3230.07 | -3660.17 | -3660.17 | -3660.17 | -3660.17 | -6240.20 |
| Final Log-Likelihood | -3048.595 | -3043.428 | -3043.672 | -3045.376 | -3041.932 | -4310.83 |
| Number of Parameters | 11 | 11 | 11 | 11 | 11 | 29 |
| AIC | 6119.19 | 6108.86 | 6109.34 | 6112.75 | 6105.86 | 8679.66 |
| BIC | 6190.10 | 6179.77 | 6180.26 | 6183.67 | 6176.77 | 8866.62 |
| Number of Observations | 4,660 | 4,660 | 4,660 | 4,660 | 4,660 | 4,660 discrete; 1,847 continuous |

*p<0.1, **p<0.05, ***p<0.01

## 6. Discussion

### 6.1 Model Comparison

Across all discrete model specifications, the estimated coefficients remain remarkably stable. The charging price coefficient ranges from −0.58 to −0.69, the coefficient for stations offering full amenities ranges from 0.42 to 0.54, and charging power remains positive and statistically significant across all models. Similarly, the effects of remaining range and charging-threshold variables change very little with the assumed look-ahead horizon. This stability indicates that the key determinants of charging station choice and the implied behavioral measures such as willingness to pay and value of charging time are robust to different assumptions about drivers' planning horizons.

Model fit comparisons, however, suggest that incorporating forward-looking behavior provides a modest but consistent improvement over the static specification. All dynamic discrete choice models achieve higher log-likelihood values and lower AIC values than the static binary logit model, with the four-station look-ahead model providing the best overall fit. Although the improvement is relatively small, it indicates that drivers do consider future charging opportunities when making en-route charging decisions.

This finding differs from that of Ge and MacKenzie (2022), who found that a static discrete choice model outperformed a dynamic specification and concluded that long-distance BEV drivers primarily operate in a "survival mode," with charging decisions dominated by immediate range constraints. In contrast, our results suggest that incorporating forward-looking behavior provides a modest improvement in model performance. One possible explanation is the substantial expansion of the public DC fast-charging network in recent years, which has increased the number of charging opportunities available to drivers. Based on the U.S. Department of Energy Alternative Fuels Data Center database, the cumulative number of public DC fast-charging stations approximately tripled between 2022 and 2026. A denser charging network provides drivers with more feasible alternatives along their routes, potentially increasing the relevance of evaluating downstream charging opportunities when selecting where to charge. However, differences in survey design, sample characteristics, and model specification may also contribute to the differences between the two studies. Overall, our results indicate that although immediate charging conditions remain the dominant determinants of charging decisions, accounting for future charging opportunities provides additional, albeit limited, explanatory power.

Unlike the discrete choice models, which explain only whether drivers choose to stop and charge, the dynamic discrete–continuous model additionally captures the charging level selected after a charging stop is made. Because the model jointly estimates a binary charging decision and a continuous charging-level decision, its likelihood function differs from that of the discrete choice models. The continuous component is observed only for charging events, and the joint likelihood incorporates both discrete and continuous outcomes. Consequently, goodness-of-fit measures such as log-likelihood, AIC, and BIC are not directly comparable with those of the discrete models. The objective of the joint model is to represent the complete charging decision process by jointly modeling both whether drivers choose to charge and to what level they charge. This richer behavioral representation enables the model to

capture heterogeneity in charging demand that cannot be identified using conventional discrete choice models and provides a more realistic framework for applications such as charging demand estimation, infrastructure planning, and charging station operations.

### 6.3 Value of Time

The value of time (VOT) during long-distance EV charging may include multiple components, including access time to the charging station, waiting time before charging begins, and charging duration. In this study, access time and expected waiting time do not show statistically significant effects across model specifications. Therefore, consistent with previous studies identifying charging speed and charging duration as important factors affecting EV users' preferences for public charging infrastructure (Hardman et al., 2018; Philipsen et al., 2016), the VOT calculation focuses on the time spent charging at the station. Since higher charging power reduces charging duration, the implied value of charging time increases substantially with charger power. Using the static model estimates, the value of charging time is approximately \$3.7/hour for a 50 kW charger, \$14.6/hour for a 100 kW charger, \$32.9/hour for a 150 kW charger, and \$131/hour for a 300 kW charger. Across the discrete choice specifications, the estimated value of charging time at a typical 150 kW fast-charging station ranges from approximately \$33–\$41/hour, which is in a similar range but somewhat higher than the approximately \$24/hour reported by Ge and MacKenzie (2022). Differences in survey design, model specification, and sample characteristics may contribute to the variation between these estimates.

The estimated coefficients also provide insights into users' willingness to pay for charging station attributes. Assuming a typical 30 kWh charging session, EV users are willing to pay approximately \$23.70 per charging session for stations offering a full amenity package, including restrooms, food, and Wi-Fi, compared with stations without amenities. Similarly, access to basic restroom facilities alone has an estimated willingness to pay of approximately \$9.90 per charging session. These results highlight that both charging speed and the quality of the charging experience influence EV users' preferences during long-distance travel and provide useful information for charging infrastructure planners and DC fast-charging operators.

## 7. Conclusion

This study investigates BEV drivers' charging decisions during long-distance trips by modeling charging as a sequential decision process involving both the decision of whether to charge and the amount of energy added during a charging event. A stated preference survey was conducted to collect information on drivers' charging preferences under varying route, battery, and charging station conditions. Using the collected data, three modeling approaches were evaluated: a static binary logit model, dynamic discrete choice models with different look-ahead horizons, and a dynamic discrete–continuous model that jointly captures charging station choice and charging level decisions.

The results provide several important insights into BEV charging behavior. First, the comparison across discrete choice models shows that incorporating forward-looking behavior provides a modest but consistent improvement in model performance compared with the static specification. Although the improvement is relatively small, the results suggest that drivers consider future charging opportunities when making en-route charging decisions. However, the stability of estimated coefficients across model specifications indicates that immediate charging conditions remain the dominant determinants of charging choices. Range-related factors, including approaching preferred charging thresholds and insufficient range to reach downstream charging opportunities, continue to play a critical role, highlighting the importance of range constraints and range anxiety during long-distance travel.

Second, charging station characteristics significantly influence drivers' choices. Charging price negatively affects station selection, while charging power and station amenities increase the likelihood of choosing a charging location. In contrast, access time and expected waiting time do not exhibit statistically significant effects within the range of scenarios considered. These findings suggest that improving charging speed and enhancing the overall charging experience may be more effective strategies for attracting long-distance EV travelers than focusing solely on reducing small differences in access or waiting times.

The dynamic discrete–continuous model further demonstrates the interconnected nature of charging decisions. Unlike discrete choice models that only explain whether drivers choose to charge, the joint model captures both the charging decision and the selected charging level. The results indicate that drivers arriving with higher remaining battery levels tend to add less energy, while previous charging behavior and individual charging preferences influence the amount of energy added. Furthermore, access to home charging significantly affects public charging

behavior, with drivers who have reliable home charging availability exhibiting different charging-level preferences compared with those without home charging access. These findings highlight the importance of jointly modeling charging participation and charging demand when estimating future charging requirements.

The estimated value of charging time demonstrates that EV users place substantial value on reducing charging duration, particularly at higher-power charging stations. For a typical 150 kW fast-charging station, the estimated value of charging time ranges from approximately $33–$41/hour across discrete choice specifications. In addition, users exhibit positive willingness to pay for improved charging experiences, including amenities such as restrooms, food, and Wi-Fi. These results provide practical implications for charging infrastructure planners and DC fast-charging operators by emphasizing that both charging speed and station quality are important factors in supporting long-distance EV adoption.

Overall, this study provides a comprehensive framework for understanding long-distance BEV charging behavior by jointly considering charging station choice and charging-level decisions. The findings show that while drivers consider future charging opportunities, immediate range constraints, charging cost, charging speed, and station experience remain the primary factors influencing en-route charging decisions. By capturing both charging location choice and energy demand, the proposed framework provides valuable insights for charging infrastructure planning and demand forecasting. Future research could examine different look-ahead horizons in dynamic discrete choice models and integrate revealed preference data to compare actual charging behavior with stated preferences.

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**Author Contribution**

The authors confirm contribution to the paper as follows: study conception and design: Asal Mehditabrizi, Cinzia Cirillo.; data collection: Cinzia Cirillo, Asal Mehditabrizi; analysis and interpretation of results: Asal Mehditabrizi,Cinzia Cirillo; draft manuscript preparation: Asal Mehditabrizi,Cinzia Cirillo. All authors reviewed the results and approved the final version of the manuscript.

**Declaration of Conflicting Interests**

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

**Declaration of Generative AI and AI-Assisted Technologies In The Writing Process**

During the preparation of this work the author(s) used Chat-GPT in order to improve readability and correct grammatical errors. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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