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Modeling of the Acceptable Waiting Time for EV Charging in Japan

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Abstract: The limited number of charging stations for electric vehicles (EVs) necessitates periodic charging, resulting in extended queues at charging stations as drivers await their availability. This study contributes to the existing body of literature by providing estimates of consumer preferences for allowable waiting times at charging stations, as well as furthering the understanding of the roles of the explanatory variables influencing these preferences. The study also compares the average and maximum waiting times experienced by EV drivers, with the acceptable waiting time. Responses from the stated preference survey in Japan in 2021 were analyzed using a generalized ordered logit model. The results show that (a) the sex, age, household income, employment status, and vehicle usage frequency significantly influenced the preferences for allowable waiting times, and (b) the allowable waiting time preferences were significantly associated with the charging locations. Our estimation model indicated a positive association of convenience stores, large commercial facilities, and highway locations with short and medium allowable waiting times. The results provide useful insights into the policy implications of the charging infrastructure.

Keywords: battery electric vehicle; allowable waiting time behavior; normal and fast charging; generalized ordered logit model

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1. Introduction

Electric vehicles (EVs) have emerged as a potential solution to address resource, energy, and environmental concerns, because they are energy efficient, produce minimal noise, and emit zero emissions. Consequently, EVs have been heavily promoted as a sustainable technology on the path toward net-zero emissions. In 2022, 10% of vehicles sold were EVs, marking a tenfold increase compared with that in the last 5 years [1]. The broad acceptance and utilization of EVs are contingent upon the implementation of effective policy measures and incentives [2–4]. Thus far, the penetration rate of EVs has been poor owing to multiple reasons, among which the coverage and availability of charging stations top the list of consumer concerns regarding EVs [5]. However, current research underscores the significance of establishing a sufficient charging infrastructure to facilitate the widespread adoption of EVs [6–8], as a dependable network of charging stations can boost consumers' willingness to buy an EV [9]. Owing to the substantial investment costs inherent in the development of fast-charging infrastructures, researchers have endeavored to determine the necessary number of public charging stations required to adequately support the proliferation of EVs [10]. The analysis of charging behaviors often considers time-related aspects [11], such as the possibility of EVs requiring charging even when they still have a sufficient charge under certain circumstances [12], particularly when compared with fuel vehicles, and the longer charging durations required for EVs [4]. Andreacci et al. [13] analyzed driving patterns in Rome, Italy and allocated battery EV

(BEV) users to charging stations based on the waiting time criterion. The authors proposed a charging infrastructure scenario featuring a moderate number of charging stations, which effectively eliminated waiting times at charging stations for approximately 94% of EV users. Ashkrof et al. [14] determined that an increase in the waiting time at charging stations adversely affects decision-making regarding the selection of a particular route. Bhat et al. [15] identified a higher level of dissatisfaction associated with the waiting time than with the charging time, and the duration of charging impacted the waiting time experienced by EV users. The waiting time for charging at charging stations is a primary concern among potential EV buyers. Therefore, it is imperative to investigate the charging patterns and owner preferences to determine the acceptable waiting times for charging EVs.

Several jurisdictions have fostered the development and widespread adoption of EVs through policy settings such as fuel excise taxes and EV incentives. However, the insufficiency of charging stations has created hesitancy among owners who are considering buying EVs, as well as challenges for existing EV owners, who may have to wait for a long time at charging stations [6]. Very few studies have been conducted on the willingness of EV drivers to tolerate long waiting times at different charging locations, including normal- and fast-charging stations. This study is focused on Japan, where the government aims to electrify all new passenger vehicles by 2035 [16]. Using data from 441 BEV users, we examined the waiting time behaviors of EV users, actual waiting times, and acceptable waiting times at various charging stations. Here, an acceptable waiting time refers to the time until a charging spot becomes available to the driver. Using a generalized ordered logit (gologit) model, we evaluated the no allowable waiting time, short allowable waiting times, medium allowable waiting times, and long allowable waiting times for normal- and fast-charging conditions across various locations such as homes, workplaces, convenience stores, large commercial centers, car dealerships, highway service areas, and parking areas. This study investigated the preferences of EV users for allowable waiting times at charging locations and the impacts of various sociodemographic characteristics on EV usage behaviors. This study is limited to BEV users, henceforth referred to as EVs. Understanding the allowable waiting time preferences of EV users for different charging facilities and how these preferences vary across the charging locations and EV user characteristics is crucial for the planning and deployment of charging facilities that foster the widespread adoption of EVs.

The remainder of this paper is organized as follows: In Section 2, a review of the literature is presented. In Section 3, the data obtained are described, and a descriptive analysis, including the average and maximum waiting times for charging the EVs, is provided. In Section 4, the modeling approach is explained, and the modeling results are provided in Section 5. Finally, in Section 6, the conclusions of this study and directions for future research are presented.

2. Literature Review

The current body of literature focusing on waiting time behaviors explores various strategies, such as optimizing the number of charging stations and managing the average waiting time at each charging spot, to reduce the overall waiting time at charging stations. Different methodologies, including ensemble machine learning methods, have been used to analyze the waiting time behaviors of consumers. The waiting time for charging may vary across charging locations and the time of visit. For example, long lines may exist if a major disaster or event occurs near a charging station. However, some delays during rush-hour congestion are simple to predict. The waiting time behavior of the fast-charging station queue affects the route choice and charging behaviors [14]. The potentially available charging locations are homes, workplaces, public locations, parking areas, shopping centers, and travel routes [17]. A previous study determined that private chargers are normally used at night, whereas public chargers are commonly used during the daytime, which may cause people to wait for a longer time at public charging stations [11]. Weldon et al. [18] found an early morning peak in the charging behavior and observed that analyses of the state of charge, charge consumption, and time and distance since the last charge suggested that EV users tend to charge more frequently than necessary. EV users have different charging preferences, such as the total time of charging and the waiting time for a charging spot to become available. A flexibility in the user schedules was observed to be beneficial for the platform [19]. Waiting times at charging stations also affect the travel decisions of users.

2.1. Overview of Charging and Waiting Time Behaviors

The duration of charging, which includes the waiting and charging times, plays a crucial role in the overall evaluation of the charging infrastructure [20]. Jabeen et al. [21] highlighted driver sensitivity to charging costs and durations, emphasizing the importance of analyzing both fast and slow charging to understand EV charging behaviors. Although fast-charging technologies can shorten the charging time, the waiting time at the charging station is uncertain, depending primarily on the charging location and time of the day [22]. Visaria et al. [23] discovered that respondents are more inclined to take a detour if there is a higher probability of finding available chargers and amenities at a charging location. The long waiting periods at charging stations can be attributed to an imbalance between the supply and demand of charging services [11]. As EVs have become more popular, the waiting times at charging stations have naturally increased. To maintain an acceptable waiting time at charging stations for existing and future EV users, we need more charging stations (increased supply) or need to make them more efficient via policies or technologies that can affect the demand.

A framework was proposed [24] that incorporates an adaptive approach in which implicit communication is facilitated through reservation systems implemented at charging stations, which was tested against a prevalent control mechanism. The experimental findings revealed the efficacy of the proposed method in suggesting a route planning strategy that significantly reduced waiting times at charging stations and overall journey times. Some studies have introduced an approach to reduce the average waiting time at charging stations and enable the optimal selection of charging stations, thereby minimizing the charging waiting time by proposing a real-time, information-sharing framework between EVs and charging stations. Additionally, the number of EV chargers (including fast and normal chargers) at a station can be adjusted to improve the charging infrastructure [12]. The choice of a charging station could be another solution to reduce the waiting time. A study was conducted [25] to observe and analyze a system for recommending charging stations in real time, specifically designed for EV taxis in Shenzhen, China. Based on previous charging instances and Global Positioning System trajectories, the ongoing operational movements at charging stations can be predicted, and a reduction in the waiting time can be observed. The popularity of EVs is steadily increasing; there were approximately 1.5 million EVs in 2015 and more than 10 million EVs in 2020 in the United States. EVs require frequent charging, which can be time consuming and may affect route planning. To address this issue [26], a simulation model was proposed to minimize the charging waiting time. Rominger et al. [27] determined that decreasing the number of charging events in favor of slow charging results in a higher probability of waiting. Nonetheless, even when the fast-charging ratio is reduced from 75% to 50%, the likelihood of a car waiting at a charging station remains at only 4%.

The charging behaviors among EV drivers vary based on driver characteristics, as highlighted by Helmus et al. [28]. The heterogeneity observed among drivers, as noted by Franke and Kerms [29], means that charging decisions are significantly influenced by factors such as vehicle attributes, charging station characteristics, price, and trip features. Forecasting the charging habits of drivers is essential for identifying the optimal locations for charging stations.

Chaudhari et al. [30] studied how factors, such as the driver behavior, charging station location, electricity pricing, and the presence of other EVs, influence the EV charging demand. The authors stressed the importance of considering all these factors when designing an optimal charging infrastructure to efficiently meet the EV demand. Longer charging and waiting times, higher charging costs, greater distances to charging stations, and higher emissions are less favorable for individuals when making charging decisions [15]. A cloud model was employed [31] to forecast the charging behaviors of drivers, and the researchers proposed utilizing the waiting time as the basis for an optimization model for charging stations. The study found that the total cost in terms of time without driver behavior prediction was 27.28% higher than that when driver behavior prediction was considered. Wolf and Madlener [32] determined the required number of fast-charging stations and the necessary power communication to ensure the profitability of a charging location. Modeling evidence revealed that respondents were willing to pay a significant amount to reduce waiting times and the uncertainty of available charging spots. These studies emphasized the consideration of the waiting time to identify congestion issues with EVs and explore strategies to mitigate congestion at charging stations.

2.2. Overview of the Waiting Time for Charging at Charging Stations

The congestion caused by lengthy charging lines is inconvenient and incurs a high social cost. Oda et al. [33] depicted the demand for quick-charging units (QCUs) and explored how adding more QCUs would shorten the charging wait times. Because the usage factor of QCUs is increased, a charging station that permits parallel QCU installations can decrease EV waiting times and the social cost of adding another QCU. Gareau et al. [34] pointed out that by considering the charging station occupancy in advance through graph relabeling, waiting times could be reduced by more than 75%, with a minimal impact on the driving times. In addition, creating alternate routes proved to be effective in further reducing the waiting and overall travel times. Keskin et al. [35] studied the uncertainty of waiting times at charging stations. They simulated the Electric Vehicle Routing Problem with Time Windows by considering time-dependent queuing periods at stations. The objective was to reduce the costs related to vehicles, drivers, energy consumption, and fines for delayed arrivals. The findings revealed that waiting at stations, depending on the situation and queue length, could increase the overall expenses by 1% to 26%. The study also found that EV recharging tends to occur more frequently during less congested midday hours owing to the time-dependent waiting times at charging stations. Recent studies have focused on determining the best layout for EV charging stations in terms of their capacity and location. Chen et al. [36] designed a bi-level mathematical model that considers the equilibrium of route selection and the charging wait time to reduce the combined cost of facility construction as well as the network travel and waiting times of EV drivers.

Ma et al. [19] introduced a waiting time policy and user utility as metrics for assessing user retention, assuming that users are willing to wait for EVs to be charged to satisfy trip demands. To optimize the assignment and waiting decisions, a bilevel electric car assignment model was used with a waiting time policy. The numerical outcomes demonstrate that with a waiting time policy, the profitability, trip fulfillment rates, and vehicle usage can be significantly increased. One potential solution is to enhance the charging infrastructure by increasing the number of available chargers [37]. However, Ullah et al. [38] demonstrated that owing to physical space constraints and the demand for power systems, the straightforward solution of building new charging stations to increase the charging capacity may not be effective. Ensemble machine learning algorithms were used to predict the charging times for various charging modes, including quick and normal charging. Vanitha et al. [39] provided another solution by introducing a booking system for charging stations using a machine learning-based app. According to Philipsen et al. [40], users are unwilling to wait for charging, and they discovered that the waiting time at an available charging station, the required detour, and the charging costs rank the highest among the attributes influencing the selection of a charging location [41]. Sun et al. [42] observed the charging time choice behaviors of EV users in Japan and demonstrated that consumers have a high heterogeneity in the charging time choice behaviors, such as night-time charging, evening-time charging, and charging after the last trip of the day; these behaviors are primarily concerned with charging types and peak factors. Keskin et al. [43] investigated the anticipated duration of waiting at charging stations, and Hoen et al. [22] focused on estimating the willingness to pay to reduce the waiting time for charging and explored how various explanatory variables influence charging decisions, particularly for longer trips. Given the current scarcity of charging stations, identifying the optimal location and capacity of charging stations poses a complex challenge [44].

Based on previous discussions, there are some notable shortcomings in understanding the perception of allowable waiting times at charging stations and the factors that affect the preferences of allowable waiting times. Therefore, in this study, we focused on the following research gaps:

(1) There is no clarity on the extent to which EV users are willing to wait at charging stations until a charging spot becomes available, particularly concerning both fast- and slow-charging facilities.

(2) There is a dearth of knowledge regarding the sociodemographic characteristics, the impact of vehicle frequency usage on the allowable waiting time preferences, and the association of allowable waiting times with respect to the charging location.

To address these challenges, we explored consumer preferences for the allowable waiting time behaviors of BEVs at charging stations using a generalized ordered logit model on the stated preference (SP) data collected from 441 BEV users in Japan. The findings are expected to offer policymakers valuable insights for crafting effective policies to advance the development of the charging infrastructure.

3. Survey Design

A questionnaire survey targeting EV owners in Japan was designed and administered to collect data on the user experiences of using EVs, including the locations, frequency, and time required to charge their vehicles. A research marketing company conducted the survey in November 2021. In total, 60,000 respondents were recruited via email invitations with embedded screening questions. Some of the screening questions regarding the vehicles were as follows: (1) Do you have your own car? If so, how many private vehicles do you use? (2) What is your household's car model? (3) How often do you use your car? (4) What is the purpose of using your car? (5) What is your annual mileage of your own car? (6) Please enter the model number of your car. Subsequently, 441 respondents who owned EVs were invited to participate in the full survey, which consisted of two main parts: the first part sought information on sociodemographic characteristics of the respondents, such as their sex, age, household income, residential area, and employment status, as well as the revealed preference (RP) data regarding the information on EVs and EV usage behaviors. This included data on the frequency of EV usage, charging frequency, and waiting times at charging stations. The second part of the questionnaire included a stated-choice (SC) experiment to explore preferences for charging station locations. The respondents were asked to select their preferred charging location, with options for slow or fast charging, based on factors such as the remaining battery level, expected distance for the next trip, and charging costs in the hypothetical scenarios. However, the data collected in the first part were primarily aimed at investigating the impacts of sociodemographic characteristics and EV usage behaviors on the frequency of charging at charging stations and allowable waiting time preferences. Specifically, the experienced waiting times focus on the average and maximum waiting times at charging stations to understand the influence of preferences on the allowable waiting times. However, the preferred charging locations, charging intentions, and charging frequency were beyond the scope of this study. Table 1 presents the description of the SP scenario and a full list of 12 sub-scenarios, each asking them to indicate their tolerable waiting times at various charging stations, defined by the charging facility and location; nine selectable options for tolerable waiting times are presented as a choice list. The respondents were asked to choose from the list of 12 sub-scenarios.

Table 1. Allowable waiting times in SP scenarios.

Scenario
Regarding the waiting time for charging that you can tolerate when the charging facility is busy (someone is charging when you arrive at the charging location)
Sub-Scenario
Allowable waiting time for normal charging at home
Allowable waiting time for normal charging at work
Allowable waiting time for normal charging at convenience stores
Allowable waiting time for normal charging at large commercial facilities
Allowable waiting time for normal charging at a car dealer
Allowable waiting time for normal charging at highway service areas/parking areas (SA/PA)
Allowable waiting time for quick charging at home
Allowable waiting time for quick charging at work
Allowable waiting time for quick charging at convenience stores
Allowable waiting time for quick charging at large commercial facilities
Allowable waiting time for quick charging at a car dealer
Allowable waiting time for quick charging at highway SA/PA
Choice List
I cannot tolerate any waiting time
Less than 5 min
5 min or more and less than 10 min
10 min or more and less than 15 min
15 min or more and less than 30 min
30 min or more and less than 45 min
45 min or more and less than 60 min
60 min or more but less than 90 min
90 min or more

The data were collected from private households in the Kanto and Chubu regions, covering 16 prefectures in central Japan. The Kanto region includes the Tokyo metropolitan area, which is the largest in the central part of Japan, whereas the Chubu region includes the Nagoya metropolitan area, one of the three largest cities, leading the nation in the automotive industry. The respondents only owned BEVs, and the manufacturers included Toyota Motor Corporation, Nissan Motor Corporation, Honda Motor Company, Mazda Motor Corporation, Mitsubishi Motors Corporation, Tesla, and other foreign manufacturers.

Table 2 presents the socioeconomic characteristics of the respondents, demonstrating the total percentage of the sample and the percentage according to the residential area. The dataset included a comparable percentage of male and female respondents, and in comparison, there were 51.6% females in the screening survey and 48.4% males. Overall, 32% of the respondents had an annual household income of JPY 4–8 million (approximately USD 29–58 thousand). In contrast to the screening survey, approximately 34% of the respondents had an average annual income of JPY 4–8 million, and only 15% of the total sample had an annual household income of JPY 8–20 million. Khan et al. [45] reported the average yearly income of Japanese households to be between JPY 5.5 and 6 million based on data from the National Livelihood Survey conducted by the Ministry of Health, Labour, and Welfare in 2017.

In our dataset, a significant association was observed between BEV ownership, income, and age. Japanese BEV users were older than 40 years in both residential regions, which also related to another study in which Norwegian BEV users were aged between 36 and 55 years [46]. However, in the screening survey, 52% of the respondents were aged between 40 and 59 years. The age distribution of BEV drivers can be attributed to the fact that EVs tend to be more appealing to middle-aged individuals. Middle-aged individuals typically exhibit greater openness to adopt new technologies and are often attracted to the innovative features and advancements offered by EVs. The descriptive statistics on income and BEV ownership highlight a contrast with the conventional assumption that higher-income households are more likely to adopt EVs. One possible explanation for this phenomenon is that lower operating costs and potential incentives make BEVs more attractive to low-income households. This finding suggests that affordability plays a significant role in influencing the vehicle preferences of lower-income households. Nevertheless, it is important to note that the demographic characteristics of survey respondents may not be representative of the broader Japanese population. However, the study sample provides insights into the demographics of the populations in the Chubu and Kanto regions, where cars remain in high demand. However, the descriptive statistical analysis alone did not provide conclusive findings. Insights derived from descriptive statistics should be considered in conjunction with the results of the model analysis to provide potential findings.

Table 2. General characteristics of the respondents (N = 441).

Socioeconomic Characteristics	Level	Total Sample Percentage (%)	Residential Area (%)	
			Chubu Region	Kanto Region
Sex	Male	58.5	57.0	70.0
	Female	41.5	43.0	29.0
Age (mean, 50); years	18–24	5.2	3.1	3.5
	25–39	20.2	22.3	14.9
	40–54	34.9	37.5	32.5
	55–60	39.7	37.1	49.1
Annual household income (JPY) (mean, 8.19 million)	<4 million	17.2	24.7	12.3
	4–8 million	32.2	40.2	36.0
	8–12 million	22.2	25.9	28.9
	12–20 million	7.5	7.1	13.2
	20 million or above	3.6	1.9	9.6
Employment status	Full time	60.5	63.7	61.4
	Part time	18.5	20.7	18.4
	Unemployed	20.8	15.5	20.2
Number of vehicles owned (mean, 1.4)	1	56.5	49.4	71.9
	2 or more	43.5	50.6	28.0
Vehicle frequency usage (mean, 5)	6–7 days per week	48.52	59.7	24.4
	4–5 days per week	36.05	31.0	50.4
	2–3 days per week	15.41	9.3	25.2

In our dataset, the sample included full-time, part-time, and unemployed individuals. The employment statistics of the total survey indicate that 55.3% of the respondents were engaged in the manufacturing, finance, civil services, medical and welfare, and construction industries. Of the 441 respondents, 60.5% worked full time in regular or regular offices and 18.5% worked part time. Through the screening questions, respondents who owned non-EVs were excluded, because this study aimed to understand the preferences of BEV owners for charging waiting times.

4. Waiting Time Behaviors of EV Users

In this section, we examined the charging behaviors and waiting time experiences of EV users for both fast and normal charging at various locations. This study utilized a combination of the RP and SP methods to gather information on waiting time behaviors, consumer characteristics, and actual and preferred waiting times at charging stations for EVs. The average and maximum waiting times experienced by respondents may vary across drivers owing to their different attributes and preferences. Hence, respondents were presented with specific questions to determine their average and maximum waiting times at different locations to gain insight into their tolerance and preference regarding waiting times at charging stations. The survey focused on the average and maximum waiting times experienced and consumer preferences to tolerate acceptable waiting time behaviors at charging stations.

4.1. User Experiences of the Average Waiting Time for Charging EVs

EV users show flexibility in their charging behaviors, as the charging facilities may be located at workplaces, shopping malls, and parking lots at or near their home [22], and may have to queue at charging stations, especially during peak times. They may not choose charging stations with EVs in a queue. Therefore, we asked respondents about the average waiting time they experienced at different charging locations with charging facilities, either normal or fast.

Figure 1 shows the distribution of the average waiting times at each charging location based on the real-life experiences of the respondents. Typically, the EV users charge their vehicles at publicly accessible locations such as large commercial facilities, convenience stores, and car dealerships. Approximately 40% of the respondents did not encounter any waiting time for both fast and normal charging at car dealerships, commercial facilities, and convenience stores, and almost 15–30% of the respondents experienced 5 min to less than 30 min of average waiting times at these locations. Most respondents did not experience any waiting time at home because the charging facilities at home eliminated the need to wait, as respondents could conveniently charge their EVs whenever needed. However, only a few respondents owned fast chargers at home. Approximately 25% of the respondents did not experience any waiting time at highway service areas/parking areas (SAs/PAs) or workplaces for fast and normal charging; in the same manner, only a few respondents (approximately 30%) experienced 5 min to less than 30 min of average waiting times on highway SAs/PAs. The EV users experienced a longer average waiting time for fast charging at commercial facilities, convenience stores, car dealerships, highway SAs/PAs, and the workplace. It appears that the respondents prefer fast charging to normal charging in publicly accessible locations.

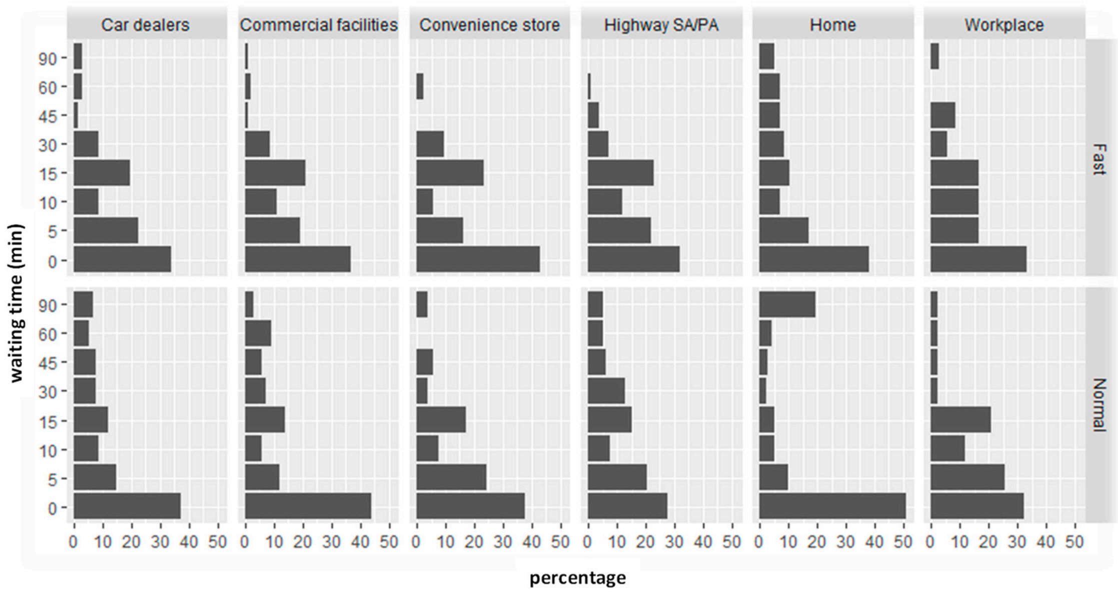

Figure 1. Distribution of average waiting times at various charging locations.

4.2. User Experiences of the Maximum Waiting Time for Charging EVs

Respondents were asked about the maximum waiting time they experienced at different charging stations with fast and normal charging facilities. This information provides a realistic perspective on the challenges and limitations faced by EV owners while charging their vehicles.

Figure 2 illustrates the distribution of the maximum waiting times reported by the respondents. The EV users reported longer waiting times for fast-charging facilities at car dealerships, commercial facilities, convenience stores, and highway SAs/PAs. Conversely, regarding workplace charging, the respondents indicated minimal waiting times, ranging from 5–15 min for fast charging. This can be attributed to the fact that at their workplace, EV users typically plug in their vehicles and leave them to charge while performing their work duties.

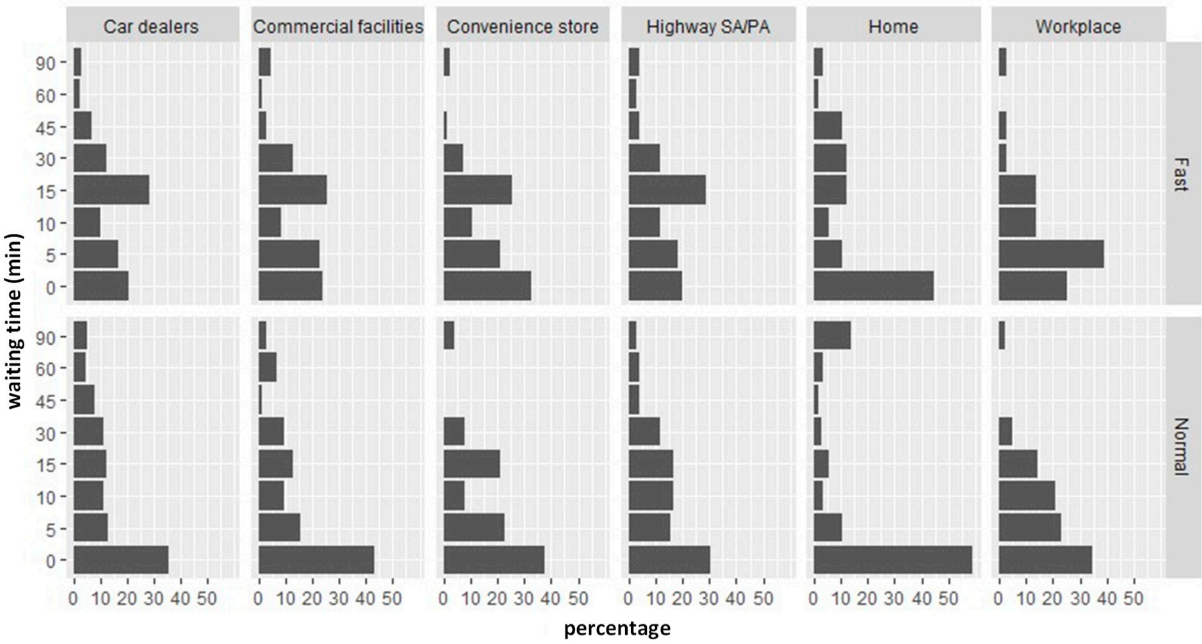

Figure 2. Distribution of maximum waiting times.

Notably, nearly 40% of the respondents did not experience waiting times for either fast or normal charging at car dealerships, commercial facilities, convenience stores, or highway SAs/PAs. This observation aligns with the behaviors observed in the average waiting times reported by the respondents, except for highway SAs/PAs. However, in contrast to the waiting time for normal charging, the respondents reported experiencing a longer maximum waiting time at fast-charging stations across all locations. It is possible that EV owners are more attracted to fast charging speeds, resulting in a higher demand and potential waiting times. Approximately more than 50% of the respondents did not report a maximum waiting time for normal charging at home. However, a few respondents reported a maximum waiting time of 90 min or more at each charging location.

Notably, the maximum waiting times for fast charging on highways (SA/PA) and at commercial facilities and convenience stores generally approach the average waiting time. Although waiting times can occasionally be longer in public locations, they are generally manageable and within acceptable limits. However, it is essential to pay attention to ensure efficient and reliable fast-charging facilities at these sites to maintain a positive charging experience for users. However, the workplace charging infrastructure requires more attention, as the average waiting time that respondents have experienced exceeds the maximum waiting time. This indicates that there are cases in which individuals encounter waiting times that surpass the predefined maximum waiting times.

4.3. Acceptable Waiting Time Preferences of EV Consumers

To model the acceptable waiting times, it is essential to understand consumer preferences regarding their willingness to tolerate waiting times at charging stations. This entails gathering data on consumer attitudes and perceptions regarding the acceptable waiting time that they are willing to endure. Therefore, the respondents were asked to answer the questionnaire with the SC experiment on the acceptable waiting time when the charging facility was busy. Figure 3 shows the distribution of allowable waiting times reported by the respondents to determine their expectations and preferences regarding waiting times. The graph reveals that the majority of respondents prefer to have no waiting time at each location for both normal and fast charging. Following no waiting time, the respondents showed a preference for a tolerable waiting time of 5 min at each location. As the waiting time increased beyond 5 min, the number of respondents willing to tolerate the waiting time increased. The graph clearly illustrates that the respondents had a limited tolerance for waiting times at charging stations.

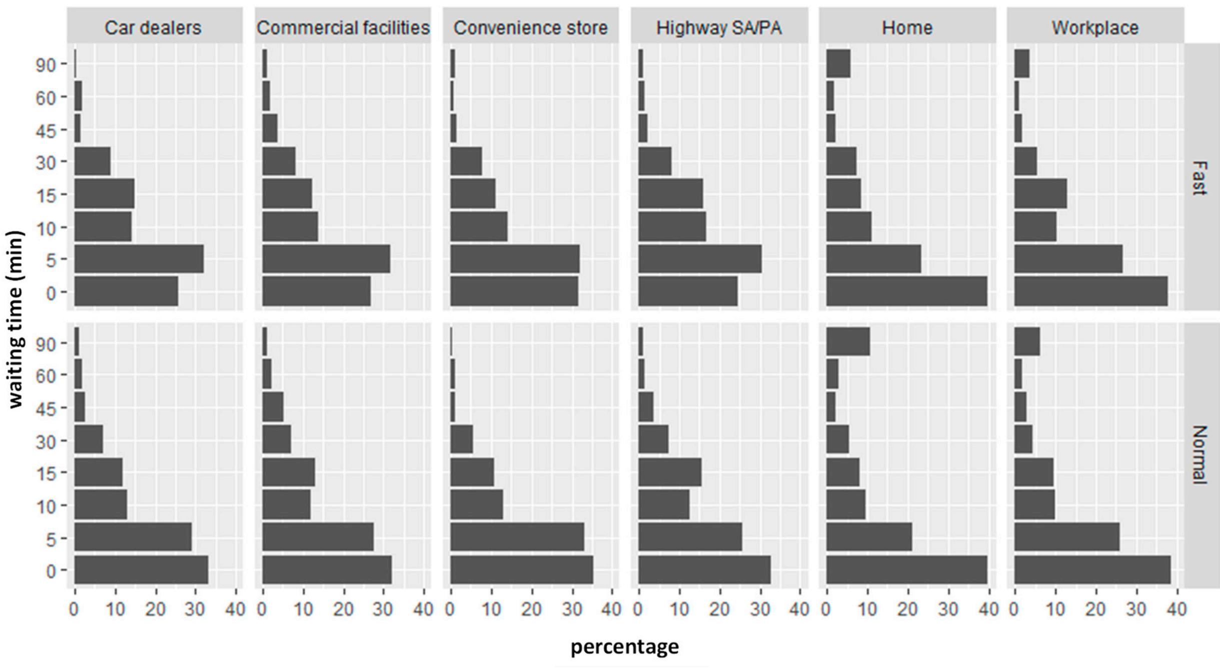

Figure 3. Distribution of allowable waiting times at various charging locations.

When comparing the average and maximum waiting time scenarios with the SP scenario of an acceptable waiting time, the respondents indicated a reluctance to tolerate longer waiting times at public charging stations. In the SP scenario, in which the respondents were asked about the acceptable waiting time, they expressed a preference for shorter waiting times. This implies that EV users have a low tolerance for prolonged waiting periods at public charging stations. These findings emphasize the importance of focusing on fast-charging facilities in the public charging infrastructure.

5. Analysis

The study first analyzed the basic information regarding the respondents, such as socioeconomic characteristics, demographics, and waiting time experiences, using descriptive statistics. Table 3 lists the sociodemographic and EV usage–related variables used in our model for the estimation.

Table 3. Explanatory variables.

Variables	Definition	Percentage (%)
Male	1 if male; 0 otherwise	58
	Age	
Youth	1 if the age of the respondent is 18 to 24 years; 0 otherwise	5.2
Young	1 if the age of the respondent is 25 to 39 years; 0 otherwise	20.2
Senior	1 if the age of the respondent is 40 to 54 years; 0 otherwise	34.9
Elderly (base)	1 if the age of the respondent is 55 to 80 years; 0 otherwise	39.7

Table 3. *Cont.*

Variables	Definition	Percentage (%)
	Household Income	
Low-income household	1 if household annual income is lower than JPY 4 million; 0 otherwise	20.8
Lower-middle-income household (base)	1 if household annual income is JPY 4–8 million; 0 otherwise	38.9
Middle-income household	1 if household annual income is JPY 8–12 million; 0 otherwise	26.8
Upper-middle-income household	1 if household annual income is JPY 12–20 million; 0 otherwise	9.0
High-income household	1 if household annual income is JPY 20 million or more; 0 otherwise	4.4
	Employment Status	
Full-time worker	1 if civil servant, management office worker, technical worker, or office worker; 0 otherwise	60.5
Part-time worker	1 if self-employed, freelancer, or part-time job; 0 otherwise	18.5
Unemployed (base)	1 if full-time housewife, student, other, or unemployed; 0 otherwise	20.8
	Residential Area	
Residential area	1 if Chubu region; 0 otherwise	69.2
	Vehicle Ownership	
One vehicle owned (base)	1 if a respondent has one vehicle; 0 otherwise	56.5
Two vehicles owned	1 if a respondent has two vehicles; 0 otherwise	43.5
	Vehicle Frequency Usage	
Vehicle frequency usage (6–7 days a week)	1 if respondent is using vehicle 6–7 days a week; 0 otherwise	48.52
Vehicle frequency usage (4–5 days a week)	1 if respondent is using vehicle 4–5 days a week; 0 otherwise	36.05
Vehicle frequency usage (2–3 days a week) (base)	1 if respondent chooses fast charging at each location; 0 otherwise	15.41
	Fast Charging	
Fast charging	1 if fast charging; 0 otherwise	-

5.1. Gologit Model

The alternatives presented in Table 1 were merged into four categories: no waiting time, 5 to less than 15 min, 15 to less than 60 min, and 60 to 90 min, presented in Table 4. Next, in the model, the ordinal categories were denoted as no, short, medium, and long allowable waiting times. When handling dependent variables that have an ordinal nature [47], researchers commonly employ logistic regression methods to predict the probabilities of discrete outcomes for different alternatives, given a set of candidate explanatory variables. When the response variable consists of ordered categories, it is essential to account for ordering in the regression method. Ordered logit models, also known as proportional odds models [48], are specifically designed to analyze ordinal response variables within a logistic regression framework [49]. The ordered logit model estimates the cumulative probability of each logit, with the regression coefficients assumed to be constant across the response categories.

Gologit [35] is utilized to consider the unobserved heterogeneity across individuals and allow for varying thresholds. The gologit model extends the ordered logit model by allowing thresholds to vary randomly among the individuals. This accounts for individual-specific preferences or characteristics that influence the response variables. In this study, we employed the gologit model to explore the possible relationships between the acceptable waiting time preferences and individual characteristics. This model estimates the extent to which each factor might influence an individual's behavior by considering the ordered nature of the response variable and accounting for the potential unobserved heterogeneity. Using the gologit model, we can capture the nuanced relationships between the explanatory and ordinal response variables while considering individual-level variations and random effects in the threshold estimation.

Table 4. Aggregation of the choice set.

Choice Set	Aggregation
I cannot tolerate any waiting time	No waiting time
Less than 5 min 5 min or more and less than 10 min 10 min or more and less than 15 min	Are merged as 5 to less than 15 min
15 min or more and less than 30 min 30 min or more and less than 45 min 45 min or more and less than 60 min	Are merged as 15 to less than 60 min
60 min or more but less than 90 min 90 min or more	Are merged as 60 to 90 min (used as a base in the model)

The four ordinal alternatives for an acceptable waiting time behavior are as follows: (1) no allowable waiting time (I cannot tolerate any waiting time), (2) short allowable waiting time, (3) medium allowable waiting time, and (4) long allowable waiting time. Owing to the ordinal nature of the four allowable waiting time alternatives, the gologit model was applied [50], where j is the ordinal dependent variable category. The probability of choosing j categories for the gologit model is calculated as follows:

$$\mathrm{Prob}(\mathrm{y}_i > j) = \mathrm{F}(\alpha_j + \beta_j' x_i) = \frac{exp\left(\alpha_j + \beta_j' x_i\right)}{1 + \left[exp\left(\alpha_j + \beta_j' x_i\right)\right]}, j = 0, 1, \ldots\ldots, J-1 \quad (1)$$

where the dependent ordinal outcome variables, which represent the different categories of an outcome, are divided into $J-1$ logit equations (Equation (2)). $\mathrm{Prob}(\mathrm{y}_i > j)$ represents the probability of the outcome being in a higher category than j. $F\left(\alpha_j + \beta_j' x_i\right)$ is the cumulative distribution function and denotes the linear combination of α_j and x_i by their respective coefficient β_j, where α_j and β_j are the parameters associated with category j, where α_j represents the intercepts and captures the baseline thresholds at which the response category transitions occur, and β_j represents the coefficients associated with the predictor variable x_i, and x_i is the vector of independent variables. $exp\left(\alpha_j + \beta_j' x_i\right)$ represents the exponentiated linear combination of that particular category's parameters and independent variables. $1 + \left[exp\left(\alpha_j + \beta_j' x_i\right)\right]$ ensures that the probabilities sum up to 1 across all possible categories. Therefore, our model includes four levels of outcome variables, the implications of which are as follows [51]:

$$\begin{gathered}\mathrm{Prob}(\mathrm{y}_i = 0|x_i) = 1 - F(\alpha_0 + \beta_0' x_i),\\ \mathrm{Prob}(\mathrm{y}_i = 1|x_i) = F(\alpha_0 + \beta_0' x_i) - F(\alpha_1 + \beta_1' x_i),\\ \mathrm{Prob}(\mathrm{y}_i = 2|x_i) = F(\alpha_1 + \beta_1' x_i) - F(\alpha_2 + \beta_2' x_i),\\ \mathrm{Prob}(\mathrm{y}_i = 3|x_i) = F(\alpha_2 + \beta_2' x_i).\end{gathered} \quad (2)$$

In the gologit model, the coefficients vary across ordinal categories, meaning that the relationships between the predictor variables and utility differ for each category. Thus, in this manner, the gologit model captures the heterogeneity of the effects of the predictor variables on the utility. This allows for a more flexible and nuanced modeling of the decision-making process compared with the ordered logit model, where the coefficients are the same across categories [51].

5.2. Estimated Model Results

This study used the gologit model that explicitly considers the utility across each category. Table 5 presents the estimation results for the socioeconomic characteristics and charging locations with the allowable waiting time preferences. We presumed that the indications for all the estimated coefficients follow our expectations.

Table 5. Estimation model results.

Log-likelihood			−5019.7
AIC			10,159.30
Sample size			4380
Variable	Alternative 1: no allowable waiting time	Alternative 2: short allowable waiting time	Alternative 3: medium allowable waiting time
	Coefficient	Coefficient	Coefficient
Intercept	2.16 ***	1.74 ***	1.24 **
Male	−0.48 *	−0.37	−0.43 *
Youth	−1.80 ***	0.68.	-
Young	-	0.87 ***	0.67 *
Senior	-	-	-
Low-income household	−0.45 *	−0.94 ***	−0.68 ***
Middle-income household	-	-	-
Upper-middle-income household	0.59.	-	0.65 *
High-income household	-	-	-
Full-time workers	−1.15 ***	−0.73 **	−0.74 **
Part-time workers	-	-	-
Two vehicles owned	-	-	-
Vehicle frequency usage (6–7 days a week)	0.46.	-	-
Vehicle frequency usage (4–5 days a week)	−0.27	−0.51 *	−0.51 *
Fast charging	-	0.50 ***	0.47 **
Charge at the workplace	0.47 *	0.63 **	0.64 **
Charge at a convenience store	1.68 ***	2.26 ***	2.01 ***
Charge at a commercial facility	0.86 ***	1.51 ***	1.66 ***
Charge at car dealerships	0.95 ***	1.67 ***	1.63 ***
Charge on highways	1.17 ***	1.86 ***	2.02 ***
Alternative 4 (long allowable waiting time) is the base			

*, **, and *** show statistical significances at 10%, 5%, and 1% levels, respectively; -: parameters are not statistically significant.

The intercept terms were included for the first three alternatives, capturing a baseline preference and cutoff points for the no, short, and medium allowable waiting times, and were significantly positive. This indicates that, all else being equal, the respondents prefer allowable waiting times. In our model, the coefficients for sex were significantly negative, indicating that male respondents are unwilling to wait at charging stations. Age categories were statistically significant for the allowable waiting time preferences, with a negative effect on no allowable waiting time and a positive effect on a short allowable waiting time. This shows that younger individuals are more willing to accept short allowable waiting times at charging stations, which appears to make them more inclined to accept shorter waiting times instead of opting for no waiting time. However, young people demonstrated a positive effect on the allowable waiting times, showing strong intentions towards short and medium acceptable waiting time preferences compared with longer allowable waiting times. However, the allowable waiting time preferences of the senior age group were not statistically significant. This may be attributed to some biases in the survey; however, Zhuge et al. [52] found that older BEV drivers were not willing to queue for a long time at charging stations. It is possible that seniors may prioritize convenience and efficiency in their daily activities, and they may have a higher demand for services that can be accessed quickly without significant waiting times.

The household income was also identified as a statistically significant variable. For example, low-income households showed a negative effect on the allowable waiting time preferences, indicating that low-income households show lower intentions for no, short, and medium allowable waiting times. However upper- and middle-income households showed a positive effect on no allowable waiting time and medium allowable waiting times. This may be because low-income households have stricter time constraints and upper- and middle-income households have fewer time constraints, enabling them to prefer all allowable waiting times. Zhuge et al. [52] showed that people with higher individual incomes did not want to wait longer to charge their vehicles, whereas those with higher-income households had the opposite tendency. However, for middle- and high-income households, the allowable waiting time preferences were not statistically significant in our model.

The full-time parameters showed a negative effect on the allowable waiting time preferences, demonstrating a lower likelihood for all allowable waiting time intervals. These individuals may have strict schedules and time commitments owing to their employment [53]. The residential area (Chubu region) was not statistically significant and was thus removed from the estimation model to improve its log likelihood and Akaike Information Criterion (AIC) values. This may be because the sample size was insufficient, and it was difficult to capture the allowable waiting time preferences for the region.

The EV usage behavior is an important factor in allowable waiting time preferences. We used driving experience in terms of vehicle usage per week as an independent variable, which was determined to be a significant variable for the preferences of allowable waiting times and improved the model log likelihood and AIC values. The respondents who used their vehicles more regularly (approximately 6–7 days a week) showed significant positive effects on no allowable waiting time, whereas EV users who used their vehicles 4–5 days a week showed negative effects on short and medium allowable waiting times. This finding suggests that EV users who drive more regularly may be more adept at strategically planning their routes to minimize waiting times. However, the respondents who used their EVs 4–5 days a week exhibited a lower likelihood of preferring short and medium allowable waiting times, indicating a relationship between the vehicle usage frequency and allowable waiting time preferences. Vehicle ownership (respondents owning more than one vehicle) was not statistically significant.

Prior waiting time experiences with BEVs affect the preferences for allowable waiting times at charging locations. In our model, we included six charging locations, each with normal and fast charging facilities, to determine the preference for acceptable waiting times. The fast charging variable was significantly positive, suggesting that respondents show a higher tendency to wait for short and medium acceptable waiting time intervals at each charging location, which is similar [19] to prior findings that people select the route choice for fast charging. However, fast charging is more expensive than slower charging, but with a higher income and higher education, individuals show a greater tendency for fast charging. Furthermore, Philipsen et al. [40] identified motorway service stations and shopping facilities as potential fast-charging station locations. Charging locations, including workplaces and public venues, exhibited positive and statistically significant coefficients across all allowable waiting time preferences. However, differences in the magnitudes of allowable waiting time preferences were observed. First, concerning workplace charging, the coefficient for the medium allowable waiting time was the highest at 0.64, strengthening the appeal of workplace charging owing to its convenience for employees to charge their vehicles during working hours. Second, the magnitude coefficients were more pronounced at convenience stores between short and medium allowable waiting times, with coefficients of 2.26 and 2.01, respectively. Similarly, for large commercial facilities, the coefficient for the medium allowable waiting time was 1.66, indicating the flexibility of charging while running errands at these locations. Third, the respondents were more inclined to wait for short and medium allowable waiting times at car dealerships and highway locations. This may be because individuals at these locations may engage in other activities, such as vehicle maintenance at car dealerships or taking a break while traveling on the highway, in line with the previous findings [1].

6. Conclusions, Policy Implications, and Limitations

The growing number of EVs highlights the importance of strategically designed charging infrastructures to promote their extensive adoption. This study concentrated on comprehending consumer preferences regarding acceptable waiting times at different charging locations equipped with charging facilities (normal or fast) and examined the nuanced impact of crucial attributes such as sex, age, household income, residential area, employment status, car ownership, and vehicle frequency. Beyond its practical implications, our research findings are consistent with those of the prevailing academic literature that underscores the significance of optimizing charging infrastructure planning. Oda et al. [33] reported that consumers did not want to wait longer to charge their vehicles, and they were willing to pay a substantial amount for that [32]. Furthermore, respondents placed a higher value on reducing waiting time than on reducing charging time. Notably, the outcomes of this study can be valuable inputs for optimizing charging station models, thereby enhancing the efficiency and strategic planning of charging stations. Our estimation using the gologit model revealed positive parameter estimates for various locations, signaling that respondents are more open to accepting zero to medium allowable waiting times.

The policy implications of this study inform stakeholders and transport policymakers, aiding the expansion of the public charging infrastructure. The study identified that male drivers are less willing to wait at charging stations, and age-wise differences were observed in the allowable waiting time preferences, with the youth and young people being more open to accepting medium waiting times than the elderly. Slow or fast chargers can be installed in public locations, such as convenience stores and commercial facilities, while prioritizing the elderly or senior members. The study also found that respondents from low-income households were less willing to wait for their vehicles to be charged, which could be attributed to their professional work commitments. Therefore, the time-constraint phenomenon of charging vehicles could be further investigated. In terms of income levels, upper- and middle-income individuals had more time to charge vehicles, while the lower-income group faced barriers outside of their professional working time. Intuitively, policy measures can be used to subsidize home charging facilities for low-income households. Employers can offer workplace charging options or incentives to employees to charge their vehicles during off-peak hours, thereby reducing congestion and waiting times during peak periods. In addition, stakeholders may consider providing charging facilities at the workplace with appropriate regulations and incentives.

The driving behavior, in terms of weekly usage, affects the preferences for allowable waiting times. Households with higher usage frequencies (e.g., 6–7 days a week) were more likely to charge their vehicles frequently. Policies could consider providing preferential access or priority charging to drivers with a higher usage frequency. Policymakers can prioritize the installation of charging infrastructure at these high-demand locations to reduce the allowable waiting times. For example, policymakers could explore partnerships with private stakeholders, such as convenience store chains or commercial property owners, to jointly fund and install charging infrastructure at their facilities. This collaboration can help expand charging networks more rapidly and efficiently. In addition, policy efforts should focus on expanding and improving charging facilities in other areas and service stations along highways.

Although this study has achieved noteworthy accomplishments in terms of discerning the allowable waiting time behaviors of EV drivers, there is still room for further exploration. First, a study analyzing the demand and infrastructure investment required to manage and optimize the charging locations for BEVs is needed, which could pave the way forward by exploring the range of EVs, trip conditions, and weather conditions. Future studies can also consider different geographical locations, as the placement of the charging infrastructure may also be affected by land utilization patterns. Second, additional studies are required to understand the characteristics of the charging infrastructure at charging stations. Third, the relationship between the battery type and charging duration could be further explored.

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