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Research Article

Improving Electric Vehicle Charging Station Efficiency through Pricing

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Recent studies show that charging stations are operated in an inefficient way. Due to the fact that electric vehicle (EV) drivers charge while they park, they tend to keep the charging station occupied while not charging. This prevents others from having access. This study is the first to investigate the effect of a pricing strategy to increase the efficient use of electric vehicle charging stations. We used a stated preference survey among EV drivers to investigate the effect of a time-based fee to reduce idle time at a charging station. We tested the effect of such a fee under different scenarios and we modelled the heterogeneity among respondents using a latent class discrete choice model. We find that a fee can be very effective in increasing the efficiency at a charging station but the response to the fee varies among EV drivers depending on their current behaviour and the level of parking pressure they experience near their home. From these findings we draw implications for policy makers and charging point operators who aim to optimize the use of electric vehicle charging stations.

1. Introduction

The transport sector in Europe, which accounts for a quarter of greenhouse gas emissions, is the only main sector that has not been able to reduce emissions over the past 25 years [1]. Electric vehicles (EVs) show great promise to meet CO_2 reduction targets in the transport domain and to reduce local air pollution [2]. Adoption of these vehicles is starting to take off [3] as the main barriers, being the purchase price and the limited range due to high battery costs [4], are overcome by the introduction of more affordable, long range EVs into the market. One of the opportunities EVs offer in comparison to other Alternative Fuel Vehicles (AFVs) [5] is the possibility of charging the car while being parked. This reduces the need for fast refuelling stations. Cars are parked 90-95% of the time [6], which provides the opportunity to overcome problems of limited range and long recharging times even with currently available short range vehicles. This requires instalment of

(public) charging infrastructure at places where users park their cars such as at home, at work, or at public facilities such as shopping centres [7].

Investments in the necessary charging infrastructure have been trailing due to chicken-and-egg related problems. In order to solve this, governments stepped in to facilitate basic public charging infrastructure. Efficient use of the limited available charging stations is important in early adoption phases to ensure a positive experience for early adopters and to reduce resistance among nonadopters [8]. Effective usage triggers high throughput which in turn creates a positive business case for charging point operators [9]. Descriptive statistics in the scientific literature [10, 11] and experiences in the field [12], however, show that efficiency at both slow and fast charging stations is not optimal. At slow (level 2) public charging stations (up to 11 kW) only 20 to 40% of the time connected to the charging station is actually used for charging. At fast charging stations these rates are better,

but idle times are more costly because charging speeds are higher.

Currently, many charging point operators use a business model that is based upon the sales of the energy transferred, not providing an incentive for the driver to move the vehicle once fully charged. Charging point operators are seeking ways to improve the efficiency of their operations without interfering with the user experience. Learning from parking studies (e.g., [13, 14]), the introduction of time-based fees could help to increase the efficiency of charging station capacities. Although it is known that fees influence the decision to charge [15], there is little knowledge about how fees influence the decision to move the vehicle once fully charged. Straightforward implementation of a time-based fee could prove not to be the optimal solution, because it could interfere with a 'parking is charging' regime; the advantage EVs have over other AFVs. Moreover there are large differences in the way EV drivers use public charging infrastructure. This depends among others on the location (e.g., home or work) and the time of day [16]. Besides such circumstantial differences, there is a diversity among drivers in their parking and charging patterns [17, 18]. Such differences could also influence the way time-based fees are influencing the behaviour of EV drivers. For a successful implementation of a time-based pricing structure, heterogeneity among EV drivers in their parking and charging behaviour is important to understand and take into account.

This paper aims to add to the understanding of the effect of time-based fee structures on charging behaviour and the underlying factors that drive heterogeneity of EV drivers' responses to a new pricing scheme. The effect of a time-based fee during different situations is estimated using a stated choice survey in which respondents are asked whether or not they would move their EV once fully charged. Heterogeneity is addressed using sociodemographic characteristics of respondents. In addition, since all respondents were actual EV drivers, their regular charging behaviour and vehicle characteristics were also used as underlying explanatory variables. By using a latent class discrete choice model, different user types are identified across which the effect of a time-based fee differs.

In Section 2 a literature overview is presented, which is followed by an outline of the structure of this paper. In Section 3 the methodology of the stated preference choice experiment is further explained, followed by the data collection process in Section 4. Results of the model estimations are shown in Section 5, followed by an interpretation of the results and their meaning in the policy context in Section 6.

2. Literature

This literature review addresses two topics, first the heterogeneity in charging behaviour and the factors that drive the decisions to charge and second literature on the influence of pricing on charging behaviour. The relevant knowledge gaps are identified and the last paragraph describes how these gaps are filled with this contribution.

2.1. Heterogeneity in Charging Behaviour. The field of charging behaviour has been found to be under increasing interest of scholars. The number of studies that model charging behaviour based upon assumptions or criteria (e.g., [19–21]) or driving data from conventional cars (e.g., [22–24]) for infrastructure planning is increasing. More recently, attention has shifted towards analysing differences in charging patterns from actual EV drivers. Studies that discuss heterogeneity in charging behaviour fall into two categories, those that discuss heterogeneity in charging patterns (e.g., home, workplace and public charging) and those that study heterogeneity in the factors that drive charging decisions (e.g., pricing and routine behaviour).

The number of studies that investigate heterogeneity in charging patterns using actual driving- or charging data from EVs is small due to the limited number of vehicles on the road. However, with the growing number of EVs on the road, it can be observed that the number of such studies also begins to increase. A number of studies such as by Azadfar, Sreeram, and Harries [25], Robinson, Blythe, Bell, Hübner, and Hill [26], and Morrissey et al. [7] describe charging behaviour and try to derive general conclusions from this. They identify patterns often corresponding to home and workplace charging, the two most dominant modes currently used. Heterogeneity among charging profiles was more systematically addressed by several studies such as Robinson et al. [26] and Desai et al. [10] which both used cluster analysis to identify several charging profiles. Helmus and Van den Hoed [16] identified 6 different user types based on charging data in the city of Amsterdam. Franke and Krems [17, 18] identified two different user battery interaction styles among EV drivers in a trail in Germany; some users preferred to interact with the battery level of the vehicle, while others displayed more opportunity driven recharge styles. Sadeghianpourhamami, Refa, Strobbe, and Develder [27] make use of charging data to determine different user types to assess their flexibility in charging behaviour and therefore their suitability for load shifting purposes. They identify three different user groups using k-means clustering: home, workplace, and park-to-charge charging. The results are largely in line with Robinson et al. [26].

In studies that investigate the factors that drive charging decisions, heterogeneity among EV drivers is often modelled by using random parameter logit models [28–32]. These studies find differences in how EV drivers interpret, e.g., distances to charging stations and different charging speeds. Latent class analysis is used to investigate heterogeneity among the determining factors of charging decisions by Wen, Mackenzie, and Keith [15]. Although they identified three different user groups, these were not linked to actual recharge patterns found in studies based on actual charging behaviour such as in Robinson et al. [26], Van den Hoed and Helmus [16], and Sadeghianpourhamami et al. [27] but on sociodemographic and vehicle characteristics. The only study that does make such a link is by Kim, Yang, Rasouli, and Timmermans [33] who used a latent class hazard duration model to identify differences in user groups in intercharging session duration. The predefined two groups were based upon charging (ir)regularity. Latent class analysis showed that

charging behaviour and vehicle characteristics can predict whether users are (ir)regular chargers.

The overview shows that random parameter models are mostly used to capture heterogeneity in decision rules in charging decisions. Descriptive studies, however, more focus on clustering users based on their behaviour. Linkage between these methodologies is mostly missing with the exception of Kim et al. [33].

2.2. Price Incentives for Charging Behaviour. The effect of pricing strategies to steer charging behaviour has mainly been studied in the context of so-called smart charging [34]. Smart charging is the concept in which pricing is used to prevent peaks in grid loads, to let charging coincide with renewable energy production or to feed back into the grid during high energy demand. An overview of the various modes of smart charging is given by García-villalobos et al. [35] and Tamis, van den Hoed, and Thorsdottir [36]. Price setting usually happens in a centralized manner by so-called aggregators as individual users do not have enough volume to trade on energy markets. Setting the price is done dynamically based on current energy prices or using more static time-of-use prices in which differences are made between, e.g., day and night [34]. Generally in studies based on stated choice experiments, a significant positive effect of price on the decision to postpone or to leave control to an aggregator is found [37]. There are, however, studies indicating that too complex pricing strategies have a negative effect on reaching set goals [38].

Besides the influence of price incentives for "smart charging" a few studies have looked into the influence of pricing on more general charging behaviour. Latinopoulos, Sivakumar, and Polak [39] looked into price setting in relation to charging decisions combined with parking reservations. They find that EV drivers are willing to pay more to ensure charging station availability. Wen, MacKenzie, and Keith [15] model the choice to start charging with mixed and latent class models, in which they include the price of the charging session based upon a stated preference survey among EV drivers. In the latent classes they do find differences on price sensitivity between respondents.

In studies that make use of charging data Sun, Yamamoto, and Morikawa [40] find that EV drivers in Japan are willing to make longer detours for free charging stations from their route than for paid chargers. Motoaki and Shirk [41] find that installing a flat fee at fast charging stations resulted in longer charging sessions and less energy transfer per minute connected. Users wanted to get the most out of the money they paid. Consequently, users also fill their car beyond 80% after which charging becomes less efficient. Such inefficient use of the time connected to a charging station with flat fees or other nontime based fees was found to be even worse at slower (level 2) charging stations in Netherlands. Wolbertus and van den Hoed [11] found that only 20% of the time connected to a charging station was actually used for charging. Charging behaviour at "lower" power outlets is more related to parking behaviour in which vehicles stay in the same place for much longer times than is needed to recharge the car. Also on level 2 charging stations in the

United States, Francfort [42] found that installing time-based fees reduced charging times. The report however does not quantify the precise reduction the fee caused after charging was first free.

To summarize, there are various indications that pricing strategies can have an influence on charging behaviour. The studies indicate the location, timing, duration, and the willingness to give up control over the charging process can be influenced. The charging station choice could also be influenced if prices vary enough. However, a quantification of the effect of pricing strategies is missing, especially for time-based strategies.

2.3. Knowledge Gaps and Contributions. In sum, this overview has shown that a growing body of literature is investigating charging behaviour of EV drivers using revealed preference data. Descriptive studies and random parameter models show that heterogeneity is present in charging patterns and in the determining factors which drive the decisions regarding where, how long, and how much to charge. Understanding this heterogeneity is crucial to correctly predict charging demand. Links between descriptive studies which often show clear habitual patterns and studies that model heterogeneity in charging decision rules are sparse. Furthermore, the literature on determining factors focusses on the decision to charge (or not) and not on the duration of the charging session.

The effect of price on the charging sessions is mainly studied in the context of "smart charging" in which the user is asked to hand over a certain amount of control over the charging process for a lower price. Information about price sensitivity mostly comes from stated preference studies or studies that investigate the difference between paid- and free chargers. These studies often find significant effects of such price changes. Literature from other domains, such as parking [43, 44], suggests that behaviour could be well steered by setting the price level and pricing mechanism.

This study contributes by shedding more light on the effect of pricing mechanisms on charging behaviour while taking the heterogeneity of EV drivers in their charging behaviour into account. It does so by looking more at current charging patterns described in the literature. Using a stated preference study on the decision to end a charging session once completely charged, given a certain price per hour, it is investigated how such a pricing strategy can lead to more efficient charging station use. Actual charging patterns are used to simulate scenarios about the timing, location, and parking pressure of charging sessions under which the effect of a time-based fee is tested. Moreover, the participants, all EV owners, are asked about their recharging patterns. This information is used in a discrete choice latent class model to determine if these charging patterns lead to a different evaluation of the proposed pricing mechanism.

3. Methodology

A stated choice study was performed among EV drivers, in which they were asked to imagine that they were charging their electric vehicle at a level 2 public charging station. They

TABLE 1: Overview of variables used in stated choice experiment.

Variable	Levels
Fee (€)	€0,25/hour
	€1/hour
	€1,75/hour
Time to move car	5min
	10min
	15min
Time until next drive	2 hours
	5 hours
	8 hours
Time of day and location	9:00 at work
	14:00 at home
	17:00 at home

TABLE 2: Exemplary choice set.

Situation 2	
Location	Home
Time of arrival	17:00
Time finished charging	19:00
Expected departure	9:00 next morning
Time required to move car into different parking sport	10 minutes
Fee if car Is not moved 1 hour after charging	€1,00/hour

If you do not move your car between 19:00 and 20:00 you will pay an additional fee of €4,00.

2. Would you move your car between 19:00 and 20:00

☐ Yes

☐ No

were presented with the scenario in which the EV was fully charged two hours after having started the charging session. The two hours is the average time needed to recharge [11]. The driver is asked to make the choice to move his vehicle away from the charging station within the next hour. If the driver does not comply, he will be faced with an additional time-based fee. Such a fee was not applicable between 23:00 and 8:00 hours as this would hamper overnight charging sessions and would only create empty charging spots due to the fact that during these hours demand for charging is generally very low.

Different charging scenarios were constructed including the most important factors. These factors were determined by a literature review and interviews with policy makers and EV drivers. Three factors were identified as most relevant in the decision to move the vehicle once the charging session was finished: first, the timing of the charging session in the day, which often coincides with location due to habitual patterns of drivers such as charging at home or work; second, the time until the next drive was relevant; drivers indicated that they would not likely move their car if the parking period after a finished charging session was very short. Last, drivers also indicated that parking pressure or the ability to park somewhere close without too much hassle was relevant. An overview of the variables and their levels is shown in Table 1.

As input to establish the right levels to represent the timing of the charging session, evidence from charging patterns in literature was taken. Jabeen et al. [29] and Hoed, Helmus, Vries, and Bardok [45] showed that significant differences exist between home and workplace charging, the two most dominant modes of charging. These are represented in the survey as 9:00 at work and 17:00 at home. During weekends different patterns arise, in which charging peaks are observed during the afternoon, represented by the 14:00 at home level in the experiment.

The times until the next drive variable levels are based upon typical charging patterns observed in Netherlands [46]. Three levels are chosen based upon a review of the data: removal of the vehicle within 2 hours, 5 hours, and 8 hours after a finished charging session. The two-hour level resembles short sessions mainly observed during the morning and

afternoon, the five-hour level resembles morning sessions ending in the afternoon, and the 8-hour level represents sessions of more than 10 hours, often overnight.

During interviews with policy makers and EV drivers about a potential fee, an often mentioned comment was that EV drivers were willing to move the vehicle once fully charged, but they did not have the opportunity to park elsewhere without cruising for a parking spot for a considerable amount of time. Parking pressure in the surroundings of the charging station is resembled by the *time to move the car* variable. The variable represents the time cruising for a parking spot and the additional walking time to reach the destination. The variable is set with a 5 minute interval with a maximum of 15 minutes as it was expected that drivers would not remove their car if cruising time would be longer.

Finally we resemble an hourly fee for using the charging station without actually charging with a variable that was set on three levels from *low* (€0.25/hour) to *medium* (€1.00/hour; similar as the regular charging costs) and *high* (€1.75/hour). Levels are still below average parking costs. Total fee costs, based upon the fee level multiplied with the remaining number of hours of parking and with exceptions between 23:00 and 8:00, are precalculated. An exemplary choice set (translated from Dutch) is showed in Table 2.

The experimental design was based upon Taguchi's [47] orthogonal arrays. The design uses 3^4 dimensions, resulting into nine different choice sets. Each respondent was faced with each of these nine choices. In the second part of the survey respondents were asked about their social demographic characteristics. Additional information about their electric vehicle (type), reason of purchase, and their recharging behaviour on public charging stations was asked at the end of the survey.

To analyse the data both a binary logit and a latent class discrete choice model were estimated. The time and location, time until next drive, and the time to move the car variables were effect coded. For each of the categorical variables the first value was chosen as a reference point. This reference level is indicated in the results. In effect coding the sum of all the coefficients equals zero. This implies that the coefficient for

the reference category can be calculated as the negative sum of the coefficients [48]. Z-values and p-values are not derived for these reference levels. The continuous fee variable was calculated with the shown fee multiplied with the time until the next drive variable in order to capture the total cost of not moving the car. Nonlinear versions of the fee variable were tested but did not provide a better model fit. The logit model was estimated using BIOGEME [49].

To capture the heterogeneity among the EV drivers a latent class discrete choice model was estimated. Latent class choice models are particularly useful in this case, since they divide behaviour into groups of different EV drivers. As seen in the analyses by Jabeen et al. [29] and Helmus and Van den Hoed [16] based upon real charging data, defining different user types is very well possible. Other models, such as mixed logit models, assume a continuous distribution of the taste parameters, making it impossible to link the heterogeneity to the discretely defined user groups. Latent class models are therefore the most suited in this case and can provide the most insight for policy makers as such a discrete distribution into classes provides a richer and often more understandable interpretation of the heterogeneity among EV drivers.

For the latent class model, predictor variables for class membership were entered as covariates in the model. The model is estimated using Latent GOLD 4.0 [50]. The number of classes was determined using ρ^2 and Bayesian Information Criterion (BIC) values.

4. Data Collection

Respondents were recruited via email using the database from the Dutch association for electric drivers (Vereniging Elektrische Rijders). In total 559 people were contacted of whom 128 (23%) responded. Additional EV drivers were recruited via an online EV driver platform and through a message by Dutch charging station organisation "ELaadNL" on social medium platform Twitter. In total 168 respondents completed the online survey. After filtering out incomplete surveys and unrealistic responses, 119 responses were useful. Each respondent was asked to fill in 9 different choice sets, resulting in 1058 choices in total which were used for the model estimation.

The respondents were mainly male (92%) and the income level was distributed upwards in comparison the Dutch average (CBS, 2015). This profile is consistent with the average Dutch EV owner [51]. Table 3 presents the sample distributions of sociodemographic and background characteristics. In contrast to the average Dutch EV owner, the respondents mostly consisted of Full Electric Vehicle (FEV) owners [52]. Nearly 90% of Dutch EV owners have a plug-in hybrid electric vehicle (PHEV), while in the sample this is only 32.2%. Moreover they were more likely to own the car instead of leasing it, which is also inconsistent with the current population of EV owners. The majority of the respondents indicated to have a private charging point at home instead of relying on on-street parking and public charging overnight.

TABLE 3: Sociodemographic figures of respondents to the survey.

Gender	
Male	92.2%
Female	7.8%
Age	
0-30	2.1%
30-60	79.2%
60+	16.6%
Unknown	2.1%
Annual income	
<€50.000	18.7%
€50.000 - €75.000	23.3%
€75.000 - €100.000	14.5%
€100.000 - €125.000	24.9%
>€125.000	18.5%
Type of EV	
FEV	67.8%
PHEV	32.2%
Car ownership	
Privately owned	67.3%
(Company) Leased	32.7%
Private charging point	
Private at home	77.2%
Public at home	22.8%

5. Results

5.1. The Logit Model. First, a standard logit model is estimated to assess the overall effects of the attributes on the choice to move the EV from the charging station to another parking spot (once fully charged). Table 4 shows the results of this analysis and the estimated coefficients for the standard model.

The results show that, as expected, a fee increases respondents' utility and thus increases the probability to move the car. For the *time of day* variable we find that users are more willing to move their vehicle during the evening hours than at the middle of the day. An explanation might be that drivers are not going elsewhere after 19:00 hours and are willing to move their car for neighbours. The interpretation of the *time to move* variable is not straightforward as only the "10 minutes" value has a positive and significant effect. It is unclear why the "15 minute" value is not significantly different from zero. A similar effect can be seen in the time until the next drive variable, where a longer parking time gives a higher utility for the "5 hour" value, but no significant effect is found for the "8 hour" value. A possible explanation is that the fee is relatively high when there are 8 hours until the next drive regardless of the hourly based fee. The effect of the 8 hour variable would then be partially captured by the fee variable.

In general, the model yields plausible results, but nonlinear effects in the time to move the car and time until next drive variables are hard to interpret. The effect of implementing a fee is significant and has the highest relative contribution of the variables in the model. The model provides a reasonable

Table 4: Results of binary logit model estimation.

Attribute	Coefficient	z-value
Constant	-0.413**	-3.172
Fee	0.297**	8.521
Time to move car		
5 min (ref. cat.)	-0.208	
10 min	0.299**	2.266
15 min	-0.090	-0.868
Time until next drive		
2 hours (ref. cat.)	-0.521	
5 hours	0.500**	3.950
8 hours	0.021	0.135
Time of day and location		
9:00 at work (ref. cat.)	0.080	
14:00 at home	-0.479**	-3.900
17:00 at home	0.399**	3.054
Model fit		
Null log likelihood	- 699.033	
Final log likelihood	- 547.409	
ρ^2	0.217	

∗∗Significant at the 0.05 level.
∗Significant at the 0.10 level.

fit to the data; the ρ^2 value of 0.217 indicates a substantial reduction of the Final LL compared to the Null LL.

5.2. The Latent Class Discrete Choice Model. To assess heterogeneity in the responses of respondents to the pricing scheme, a latent class choice model was estimated. In this model it is assumed that there exist latent (unobserved) segments in the population, which have different sets of parameters along which the population in these segments asses the choice attributes. For example, there may be a group which is very price-sensitive (high parameter value for the "fee" variable), while another group is very sensitive to parking pressure (high parameter value for the "time to move" variable). The latent classes are inferred from the distributions of the choice parameters emerging from the observed choices using the maximum likelihood principle.

A benefit of using a latent class choice model to reveal heterogeneity in the parameters is that additional explanatory variables can be included in the model to explain latent class membership. For example, it may be plausible to assume that a lease driver who does not have to pay the price of charging (or staying connected) himself is less likely to belong to a "price-sensitive" class/segment. A systematic overview of the model is shown in Figure 1.

In the present application, the following four variables are entered into the model as predictors of class membership: having a full electric (FEV) or plug-in hybrid electric vehicle (PHEV), whether the car was owned or leased, if the participant already moved their car away from the charging station once fully charged, and if the participant experienced high parking pressure in the neighbourhood near their home.

Sociodemographic variables were also included as predictors of class membership, but these turned out to be insignificant. In line with Kim et al. [33] we therefore focused on the vehicle and charging characteristics. Overall, predictors were found to vary across the different classes in a meaningful way.

To estimate the optimal number of classes, consecutive Latent class models (LCMs) were estimated with the number of classes ranging from 1 to 5. Table 5 shows the various model fit indicators for each of the estimated models. The Bayesian Information Criterion (BIC) indicator points to a 3 or 4 class model. To determine the optimal number of classes the predictors in the 3 and 4 class models were assessed. The parameter estimates in the 4 class model could not be meaningfully interpreted, especially as the class sizes became too small. Therefore the 3-class model was chosen as the best fit.

The results of the latent class model estimation are shown in Table 6. In general the LCM provides a substantial improvement in model fit (ρ^2 =0.483 versus 0.217). The classes have clear different meanings when we look at how they interpret the coefficients.

Class 1: members of class 1 do seem sensitive to all four variables. A time-based fee increases the chance of moving the car for respondents in the first class. For the members of the first class the *time to move the car* variable only has a significant negative parameter for the 15-minute level. This shows that severe parking pressure can be of influence on the decision to move the car. This effect was already captured in the membership model for class 3. The *time until the next drive* variable has an expected effect for the 2 and 5 hour levels but surprisingly has no significant effect for the 8 hour level in class 1. As predicted, the longer the duration of the remaining parking time is, the more likely drivers are willing to move their car. The insignificance of the 8 hour parameter could be explained by the effect of the duration and could be partly captured by the fee. The *time of day* and *location* variables are in line with the binary logit model, in which we see that drivers are more likely to move their car in the evening at home than during the afternoon.

Classes 2 and 3: they are relatively insensitive to most of the variables as we see that none of the variables is significant. This is especially relevant for the time-based fee and can be explained by the fact they either nearly always move (class 2) or nearly always stay (class 3). The intercepts (although not significant for classes 2 and 3) play a dominant role in the observed probabilities for members in these two latter classes. Implementing a time-based fee for the latter groups would thus not be as effective. The latter can be related back to the membership model where the same respondents stated that they experienced high parking pressure near their homes and therefore might not see opportunities to park their car elsewhere once fully charged.

The class membership model is displayed in Table 7. For the predictors of class membership the *currently moving* and *parking pressure at home* variables were found to have a significant effect on class membership.

(i) **Class 1:** members did not have a specific profile according to the covariates in the model. Class 1

TABLE 5: Model fit estimators for different number of latent classes.

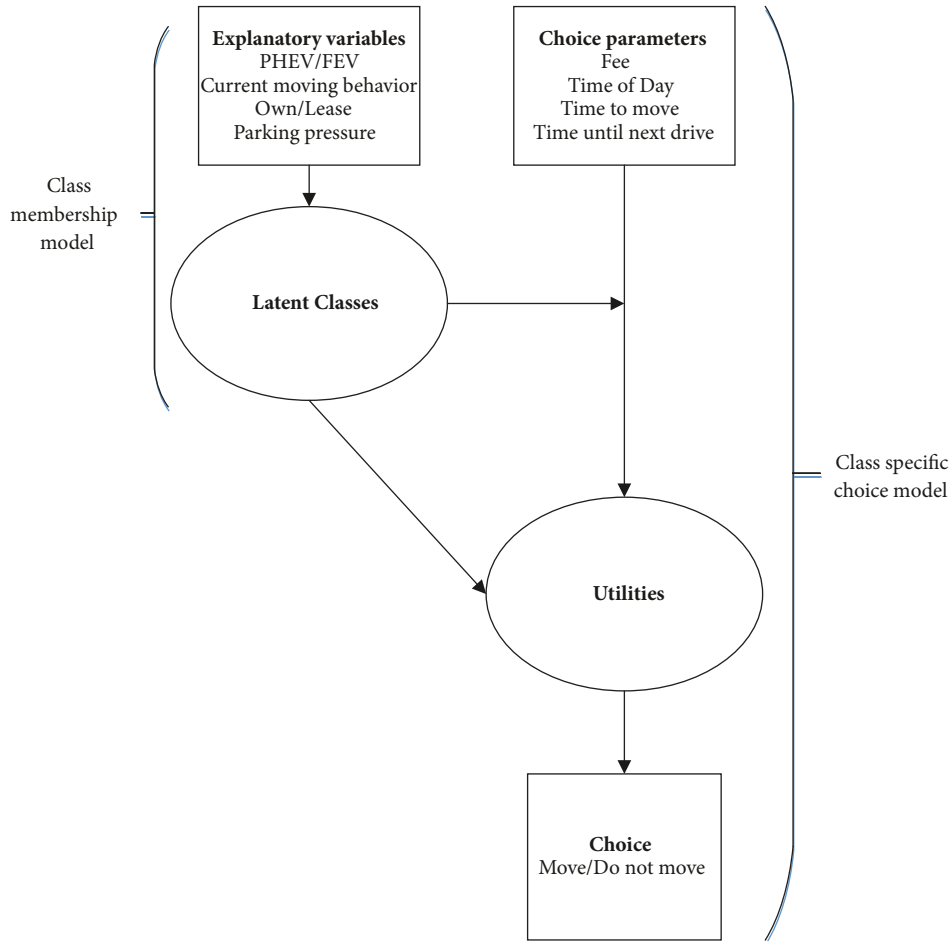| Number of classes	Number of parameters	Log Likelihood	BIC (LL)	ρ^2
1	11	-547.409	1133.051	0.2169
2	30	-429.102	958.565	0.3861
3	45	-361.750	885.912	0.4825
4	60	-330.085	884.789	0.5277
5	75	-310.849	908.446	0.5553

FIGURE 1: Visual representation of the latent class choice model, reproduced from [53].

represents the largest group of respondents (60%) and they are the most responsive to the hourly fee.

(ii) **Class 2:** members nearly always indicated to remove the car from the charging station during the experiment also indicated that this was their current behaviour. They also did not perceive parking pressure at home in comparison to members of the other classes.

(iii) **Class 3:** members experience more parking pressure near their homes. This could be one of the main drivers why they almost never choose to move the EV from the charging point.

6. Conclusion

This paper has examined the influence of a time-based fee on the decision to remove an EV from a charging station once fully charged. Results from a stated choice survey that have been analysed in a binary logit model show that such a fee can be effective and can result in more efficient use of charging stations. Other factors influencing the choice, such as parking pressure, time until next drive, and the time of day were also found to be relevant, although straightforward interpretation was not always possible.

To assess the heterogeneity among EV drivers regarding the time-based fee, a discrete choice latent class model was estimated. Additional variables about the type of EV and charging behaviour of the respondents were added to

TABLE 6: Results of latent class model estimation.

	Class 1		Class 2		Class 3	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Intercept	-2.333**	-5.836	1.503	1.683	-2.998	-1.294
Predictors						
Fee (€)	0.813**	5.268	0.854	1.128	0.003	0.006
Time to move car						
5min (ref. cat.)	1.175		1.774		1.223	
10min	0.215	0.796	-0.598	-0.460	0.182	0.161
15min	-1.390*	-1.947	-1.177	-0.152	-1.406	-0.931
Time until next drive						
2 hours (ref. cat.)	-1.244		0.590		1.767	
5 hours	1.860**	3.280	0.383	0.050	-1.704	-0.880
8 hours	-0.617	-0.898	-0.973	-0.124	-0.063	-0.110
Time of day and location						
9:00 at work (ref. cat.)	0.456		-1.688		-0.398	
14:00 at home	-1.779**	-3.400	0.756	0.098	-1.320	-0.947
17:00 at home	1.323**	1.989	0.932	0.120	1.718	1.261
Model fit						
Log Likelihood	-361.751					
ρ^2	0.483					

*Significant at the 0.10 level.
**Significant at the 0.05 level.

TABLE 7: Class membership model for 3-class model.

Class membership model	Class 1		Class 2		Class 3	
Class size	60.0%		30.9%		9.1%	
% Choice to move (observed)	53.8%		93.6%		13.2%	
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Intercept	0.981	2.430	0.303	0.683	-1.284	-2.066
Attributes						
Full Electric	0.165	0.437	-0.186	-0.431	0.021	0.038
Lease	0.395	0.950	-0.425	-0.886	0.031	0.050
Currently moving	-0.397	-1.041	1.232**	2.937	-0.835	-1.391
Parking pressure at home	-0.690	-1.544	-0.978*	-1.777	1.668**	2.728

**Significant at the 0.05 level.
*Significant at the 0.10 level.

the model as predictor of class membership. Results show that three types of users could be distinguished: those that responded to the fee, users that always moved their car once fully charged, and those that refused to move, regardless of the set fee level. Membership variables showed that members of the second class indicated that indeed this behaviour belonged to their normal charging behaviour. Members of the third class were more likely to experience parking pressure when parking at home. Users in the third class might not see the opportunity to park their car elsewhere once fully charged. Such distinctions are important for policy makers because those that experience parking pressure are mostly drivers who rely on curb side charging and parking because they make use of public charging infrastructure on a daily basis. Although in some countries the majority of EV drivers

have charging facilities at home; the needs of future drivers, which might be more dependent on on-street parking and charging facilities, have to be taken into account by policy makers. This is especially relevant in more dense urban areas. Municipal policy makers can make distinctions between inhabitants and visitors, possibly relieving the impact of a time-based fee for those that experience parking pressure in the city they live in.

The results show that taking into account the heterogeneity among respondents can be very relevant. Using a discrete choice latent class approach has the benefit that results are easier to interpret for policy makers, as users are divided into clear groups. This allows for assessing biases among respondents groups. In this case early adopters can display distinct different charging behaviour

regarding on- and off-street charging at home, which resulted in a different acceptance of the proposed pricing scheme.

7. Discussion

This research is limited by the fact that the respondents are not completely representative for the population of Dutch EV drivers. The research was aimed solely at EV drivers as it was believed that non-EV drivers did not have the experience to correctly predict what their response would be to the scenarios in the choice experiment. This limited our search to members of the Dutch association for EV drivers. The respondents drove more full instead of plug-in hybrid electric vehicles and were less likely to be company lease drivers compared to the population of Dutch EV drivers. From practical experience it is known that company lease drivers very often do not have to pay for charging costs themselves. They are therefore less aware of the costs and they could therefore be more reluctant moving the vehicle once fully charged even when presented with a time-based fee. Although no effect was found for having company lease car in the latent class membership model, future research could look more into differences between private owners and company lease drivers.

For charging point operators the results of this study show that implementing a time-based fee could result in a higher efficiency in charging station usage. The results show that even with a modest fee, to not frustrate EV drivers, a substantial improvement could be reached. In the final design of the fee, the charging point operators would have to take into account the segment of drivers that experience severe parking pressure and are therefore not willing or able to move their vehicle away from the charging station once fully charged. The design of the fee could focus on only preventing very long charging sessions (e.g., >24 hours) as suggested by Wolbertus and Van den Hoed [46]. This would also prevent misuse by EV drivers, who could set the charging speed at a very low rate to prevent them from completing the charging session. Another important factor that has to be taken into account when considering an implementation of a time-based fee is the precondition that the policy is only effective when the fee is communicated clearly. This requires all costs related to the time-based fee to be at least specified in the transaction data and the bill and preferably beforehand at the charging location.

This study builds on various studies that investigate the effects of pricing strategies to influence charging behaviour. The results are in line with previous studies [39–41] which also find that pricing strategy can be an effective strategy to steer charging behaviour. This study has been the first to quantify this effect for a time-based fee. Moreover, in addition to previous studies, this study added the influence of charging behaviour (as a variable in the model). Finally, it has provided a segmentation of EV drivers using characteristics of their car, their current behaviour, and the effect of parking pressure. This segmentation has proved to be useful, as the time-based fee was assessed differently by the three different segments found in this study. Doing so this paper has given additional insight into the motivations of charging behaviour in an urban context.

As the literature review showed, many applications can benefit from dynamic price signals in the context of smart charging, charging station efficiency, or station reservation. Such price signals make sense from the perspective of the problem owner, the grid operator, the charging point operator, or the parking manager, respectively. However as electric vehicle charging is a combination of these different areas, it is evident that implementation of each of these pricing strategies is not in the interest of the EV driver. Dynamic price setting should be considered carefully for each application separately.

Future research could also look at heterogeneity among more charging decisions such as charging station choice. Understanding differences in user groups can be important for policy makers for the spatial planning of a charging infrastructure. Further understanding of pricing effects can also be important in being able to steer charging behaviour to goals of stakeholders. This research and others have shown that clustering users based upon their charging behaviour and vehicle characteristics is useful to capture heterogeneity in charging decision rules.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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