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Charging electric vehicles on long trips and the willingness to pay to reduce waiting for charging. Stated preference survey in Norway

Fredrik Solvi Hoen [a,*], María Díez-Gutiérrez [b], Sahar Babri [b], Stephane Hess [a,c], Trude Tørset [a]

[a] Department of Civil and Environmental Engineering, Norwegian University of Science and Technology, Høgskoleringen 7a, 7034 Trondheim, Norway
[b] SINTEF, Department of Mobility and Economics, S.P. Andersens veg 3, 7031 Trondheim, Norway
[c] Institute for Transport Studies, University of Leeds, Leeds LS29JT, United Kingdom

A R T I C L E I N F O

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A B S T R A C T

Technological developments in charging speed and battery capacity are leading to an increased use of electric vehicles (EV) for long trips, but the charging infrastructure network is too scarce to satisfy the growing energy needs. Few public charger stations are available outside urban areas, triggering long queues waiting for a vacant charger. A better understanding of charging behaviour on long trips is needed to optimise the provision and distribution of charging facilities. This research contributes to existing literature by estimating the willingness to pay for reducing waiting time for charging, as well as understanding the role of explanatory variables in influencing decisions about charging at public charging stations on long trips. Responses from a stated preference (SP) survey in Norway in 2021 were analysed with a mixed logit model. Results showed that price, waiting time, charging speed and facilities were significant variables for station characteristics, while for trip features, the distance to destination and remaining range, also play a significant role. Finally, if deciding to charge, respondents to charge the battery to a higher level rather than a small top-up. There is extensive heterogeneity in preferences across travellers.

1. Introduction

Electric vehicles (EVs) are an important component of plans to achieve decarbonization of the transport sector (Archsmith et al., 2015) and meet sustainable policy requirements (Xu et al., 2021), through reducing oil dependency, global and local emissions and noise exposure compared to traditional vehicles (Egbue and Long, 2012; Sovacool et al., 2017). The widespread adoption of EVs is still dependent on policy measures and incentives (Cherchi, 2017; Kester et al., 2018; Lebrouhi et al., 2021), combined with information campaigns (Kester et al., 2018). In Norway, several incentives became effective from 2000 (Figenbaum et al., 2014). Today, there are incentives lowering the price of buying, owning, and using the vehicles, as well as incentives that make it easier and more attractive to use and recharge the vehicles. Consequently, Norway has the highest market share of EVs internationally, and the market share is

* Corresponding author.
E-mail addresses: fredrik.s.hoen@ntnu.no (F. Solvi Hoen), maria.diez@sintef.no (M. Díez-Gutiérrez), sahar.babri@sintef.no (S. Babri), S.Hess@leeds.ac.uk (S. Hess), trude.torset@ntnu.no (T. Tørset).

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expected to increase more than 20% by 2030 (AT 4907, 2022). In the first half of 2021, 3 out of 4 new private vehicles sold in Norway were EVs, reaching a total of 12% of the total registered private cars (SSB, 2021).

Nevertheless, research emphasizes the importance of an adequate charging infrastructure for a large scale implementation of EVs (Gönül et al., 2021; Harrison and Thiel, 2017; Khalid et al., 2019; Osieczko et al., 2021; Schulz and Rode, 2022; Yang et al., 2021) as a reliable network of charging stations can increase the willingness to purchase an EV (Fang et al., 2020). EVs have a great flexibility for charging as charging facilities might be located: (1) at or near home; (2) at workplaces; (3) at publicly accessible locations, such as shopping malls or parking lots; or (4) along travel corridors. Some studies question the need for public charging infrastructure (Lin and Greene, 2011) and suggest that the majority of car drivers are unwilling to pay a basic fee for the possibility of using public charging infrastructure (Globisch et al., 2019). Research shows that public and corridor charging stations are the least used (Hardman et al., 2018), which could be explained by the historically short range of EVs and consequently the low probability to undertake long distance trips (Figenbaum and Kolbenstvedt, 2016). The rapid technology development in battery capacity, charging speed and charging infrastructure, followed by an increasing use of EVs on longer trips, may reinforce the significance of public charging infrastructure.

Due to high investment costs of developing fast charging infrastructure, researchers have tried to find out how many public chargers are needed to effectively support the spread of electric vehicles (Jochem et al., 2019), whilst becoming commercially viable (Morrissey et al., 2016). Determining the location and capacity of charging stations is a complex problem given the increasing EVs fleet, limited vehicle range and low number of current charging stations (Rahman et al., 2016). In establishing new charging stations, it is important to cover the increasing charging demand, whilst reducing the energy loss, ensuring an adequate coordination in relation to the power distribution to avoid overloading the charging network (Lebrouhi et al., 2021). Battery type, driving and charging behavior are the main factors affecting the charging load (Fotouhi et al., 2019). However, due to the limited number of studies on detailed charging behaviour, models aimed at analysing integrated EV use and power system assume predetermined charging behaviours rather than considering heterogeneity of the drivers for evaluating the efficiency of pricing and energy policies (Daina et al., 2017a).

This research contributes to the existing literature by estimating 1) explanatory variables for choosing to charge at public charging stations on long trips; and 2) willingness to pay for reducing waiting time for charging. In our study, the explanatory variables are limited to trip features such as the current state of charge and distance to the destination, and charging station characteristics including price, waiting time and facilities at the charging location. For this purpose, a stated preference (SP) survey was distributed in Norway in 2021, obtaining a sample of 465 respondents, with the resulting data analysed with a mixed logit model in order to understand under which conditions the EV drivers choose to charge or not. The findings are useful for policy makers, as well as public and private charging station suppliers as this research is a first step to develop recommendations regarding localisation and power of charging infrastructure as well as pricing of charging.

The article is structured as followed. A more thorough literature review is comprised in section 2. Section 3 describes the survey design, the data sample, and the method. Results are presented in section 4, followed by a discussion in section 5. Conclusion and policy implications are summarised in section 6.

2. Literature review

2.1. Charging infrastructure

There are two types of EV charging ports; alternative current (AC) chargers and direct current (DC) chargers, where DC chargers are the fastest. AC chargers are dependent on an on-board charger which converts the AC into direct current (DC). The charging speed of AC chargers is limited to 22 kw. DC chargers usually delivers 50 kw or 100 kw but may provide much more. The fastest chargers today deliver up to 350 kw, but at the moment very few EV models can utilise this charging speed.

In Norway, charging infrastructure is supplied by energy providers, petrol stations, restaurants, supermarkets, shopping malls. Each of them offers different charging options in terms of availability, power, and price, as well as the services nearby. The most extensive charging infrastructure, not only in Norway but internationally, is Tesla's. The charging stations are characterized by great availability for Tesla owners to avoid waiting times. Recently, Tesla has opened its charging infrastructure for all type of EVs, thus increasing the availability of charging possibilities for all EV users.

2.2. Charging behaviour

Charging duration, including waiting time, is the most important factor in overall assessment of a charging infrastructure (Alkhalidi et al., 2021; Globisch et al., 2019). Long waiting times at charging stations can be explained by supply–demand imbalance (Yang et al., 2021), which is translated into inconvenience and high social costs (Oda et al., 2018). Some solutions could be increasing the number of chargers (Poyrazoglu and Coban, 2021), installing chargers with larger batteries (Aziz et al., 2016), improving the communication between the EVs and the booking systems in charging stations (García-Magariño et al., 2018; Vanitha et al., 2021), or demand-responsive pricing schemes (Yang et al., 2021). As some of these solutions require high investment costs, greater knowledge on the user acceptance of waiting time is needed. Recent literature is putting more attention on the uncertain waiting time at charging stations (Keskin et al., 2021), which was previously disregarded (Poonthalir and Nadarajan, 2019). Philipsen et al. (2016) pointed out that users are more willing to make a detour than to accept waiting times for charging. Studying users' willingness to detour to a fast-charging stations shows that there are differences between private and commercial users and between working and non-working days (Sun et al., 2016), indicating variations among travel purposes.

Range anxiety is the second main concern among EV drivers (Metais et al., 2022), this refers to the risk of running out of battery before finishing the trip or reaching a charging station. This stressful situation could be reduced by keeping a buffer range of battery level (Franke et al., 2012), although it might lead to more frequent charging and longer charging time than strictly needed (Shao et al., 2009).

While charging behaviour of EV drivers differs depending on driver characteristics(Helmus et al., 2020) and heterogeneity among drivers (Franke and Krems, 2013), charging decisions are likely to be influenced substantially by the characteristics of charging stations, price, trip features, and vehicle properties. Table 1 depicts explanatory variables previously estimated in the literature to assess the charging behaviour.

The typical data collection method for gaining knowledge on the charging behaviour is based on SP surveys (Daina et al., 2017a), which gather data about the respondent's intentions in hypothetical settings. SP data collection gives us the opportunity to design hypothetical scenarios to gain a better insight into how EV drivers trade off changes between key variables (Pan et al., 2019). The impact of these variables on charging behaviour is normally estimated through discrete choice models based on random utility maximisation (Daina et al., 2017b; Jabeen et al., 2013; Latinopoulos et al., 2017; Sun et al., 2016, 2015; Wang et al., 2021; Xu et al., 2017; Yang et al., 2016; Zoepf et al., 2013), which assumes that a person chooses the option which gives them the greatest utility, where the utility is influenced by the attributes of the alternatives (Train, 2009). In our context, the utility could be influenced by several factors, such as price or charging time for example, and differ among alternatives or individuals. The trade-off between price and other factors can be used to derive the willingness to pay (WTP) for these factors (Breidert et al., 2006). Whilst existing research

Table 1
Variables for charging behaviour in previous research.

Charging station characteristics	
Charging power (kW) or type of charger (fast or slow)	(Chaudhari et al., 2019; Daina et al., 2017b; Dorcec et al., 2019; Ge et al., 2018; Lokesh and Hui Min, 2017; Pan et al., 2019; Wen et al., 2016)
Charging consumption	(Weldon et al., 2016)
Charging price	(Chaudhari et al., 2019; Daina et al., 2017b, 2013; Dorcec et al., 2019; Ge et al., 2018; Jabeen et al., 2013; Latinopoulos et al., 2017; Lokesh and Hui Min, 2017; Pan et al., 2019; Wang et al., 2021; Wen et al., 2016)
Charging time	(Chaudhari et al., 2019; Daina et al., 2017b, 2013; Jabeen et al., 2013; Kim et al., 2017; Pan et al., 2019; Sun et al., 2015; Weldon et al., 2016; Xu et al., 2017; Yang et al., 2016)
Waiting time	(Lokesh and Hui Min, 2017; Wang et al., 2021)
Location	(Jabeen et al., 2013; Lokesh and Hui Min, 2017; Pan et al., 2019; Sun et al., 2016)
Number of chargers	(Lokesh and Hui Min, 2017)
Parking price	(Pan et al., 2019)
Charging facilities satisfaction	(Lokesh and Hui Min, 2017; Wang et al., 2021)
Charging station loyalty	(Kim et al., 2017)
Trip characteristics	
Average speed	(Daina and Polak, 2016)
Travel time	(Weldon et al., 2016; Yang et al., 2016)
Travel distance	(Lokesh and Hui Min, 2017; Weldon et al., 2016)
Travel cost	(Yang et al., 2016)
Time of day and/or type of day	(Chaudhari et al., 2019; Daina et al., 2017b; Dorcec et al., 2019; Jabeen et al., 2013; Kim et al., 2017; Latinopoulos et al., 2017; Sun et al., 2015; Weldon et al., 2016; Xu et al., 2017; Yu and MacKenzie, 2016; Zoepf et al., 2013)
Weather conditions	(Kim et al., 2017)
Trip purpose	(Chaudhari et al., 2019; Daina and Polak, 2016; Latinopoulos et al., 2017)
State of charge (SoC)	(Chaudhari et al., 2019; Daina and Polak, 2016; Dorcec et al., 2019; Jabeen et al., 2013; Pan et al., 2019; Sun et al., 2015; Wang et al., 2021; Weldon et al., 2016; Wen et al., 2016; Xu et al., 2017, 2017; Yang et al., 2016; Yu and MacKenzie, 2016; Zoepf et al., 2013)
Remaining range	(Daina et al., 2013; Ge et al., 2018; Pan et al., 2019; Wang et al., 2021; Wen et al., 2016)
Distance to next destination	(Daina et al., 2017b, 2015; Daina and Polak, 2016; Ge et al., 2018; Jabeen et al., 2013; Pan et al., 2019; Wen et al., 2016; Yu and MacKenzie, 2016; Zoepf et al., 2013)
Distance to next charging opportunity	(Daina et al., 2015; Sun et al., 2016; Wen et al., 2016; Yang et al., 2016, 2016)
Last trip characteristics	
Last charging details (time, power charged)	(Lokesh and Hui Min, 2017)
Next trip characteristics	
Travel distance for the next day	(Sun et al., 2015; Xu et al., 2017)
Dwell time (time to next trip)	(Chaudhari et al., 2019; Ge et al., 2018; Jabeen et al., 2013; Pan et al., 2019; Sun et al., 2016; Wang et al., 2021; Wen et al., 2016; Xu et al., 2017; Yu and MacKenzie, 2016; Zoepf et al., 2013)
Personal characteristics	
Socioeconomics	(Daina et al., 2017b, 2015; Daina and Polak, 2016; Ge et al., 2018; Latinopoulos et al., 2017; Pan et al., 2019; Wang et al., 2021; Yang et al., 2016)
Driving experience	(Chaudhari et al., 2019; Latinopoulos et al., 2017; Wang et al., 2021)
Charging experience	(Kim et al., 2017; Latinopoulos et al., 2017; Sun et al., 2015; Xu et al., 2017)
Risk attitude / range anxiety	(Chaudhari et al., 2019; Daina and Polak, 2016; Latinopoulos et al., 2017; Pan et al., 2019; Wang et al., 2021)
Number of trips per day, travelled distance, and energy consumed	(Weldon et al., 2016)
Vehicle type (range)	(Chaudhari et al., 2019; Daina et al., 2015; Lokesh and Hui Min, 2017; Xu et al., 2017)
Charging regularity	(Kim et al., 2017)

has looked at the WTP for buying an EV, few studies have focussed on the WTP for charging (Dorcec et al., 2019), which is critical for investing in a sustainable and efficient charging station network (Hertel and Wiesent, 2013). Some of the previously observed factors that could influence the WTP for charging were: state of charge (Babic et al., 2017), electricity source (Nienhueser and Qiu, 2016); electricity price (Bashash and Fathy, 2014); charging speed (Babic et al., 2017); or time of the day (Daziano, 2022).

3. Methodology

3.1. Sample recruitment

The web-based questionnaire, coded in Surveyengine (SurveyEngine, 2021), was conducted in Norway from June to October 2021. The target population were current owners of EVs, as they have experience with charging stations. There is no readily available panel of respondents that are current EV users, nor are there statistics relating to the socioeconomic characteristics of EV users, and how they differ from the general population. This also changes over time, though in Norway at least, the share of EV owners, especially amongst new vehicles, is so high as to reduce any detrimental impact of our sampling approach in this context.

The questionnaire was distributed using online social media (LinkedIn, and Facebook), as well as via internal posting in three Norwegian institutions (with approximately 18,000 employees in total), the Norwegian University of Science and Technology (NTNU), SINTEF, and the Norwegian Public Roads Administration. In addition, flyers were put on the windows of EVs when these were parked at public spaces in the Trondheim area. The questionnaire had a completion time of approximately 10 min, and a prize draw (€100) was used as an incentive for participating.

A total of 856 respondents were recruited, where, after filtering out incompletes and respondents with missing information on several important variables, a final sample of 465 respondents was retained. Of this sample, 84 were Tesla owners which were included in the descriptive analysis but not in the choice model, as their access to Tesla's own network of charging stations makes the choice tasks irrelevant for this group.

3.2. Survey design

The questionnaire consisted of a number of sections where the focus in this paper is on the stated choice (SC) experiments where each respondent was presented with 6 different choice tasks. In addition, data was gathered on current EV features and socioeconomic information. The questionnaire, including the choice tasks and the descriptions of the scenarios, was tested in a pilot survey to detect potential misunderstandings or lack of important information.

Respondents were presented with a hypothetical situation describing a long distance trip done in the summer (Fig. 1). It is conceivable that the timing, context and distance of a trip influence charging decisions, and as such, presenting each respondent with the same context allowed us to cancel out the influence of this effect. Of course, the actual impact of these external factors on charging decisions remains an interesting avenue for further research.

The respondents were grouped according to characteristics of their electric vehicle. This allowed more customized alternatives,

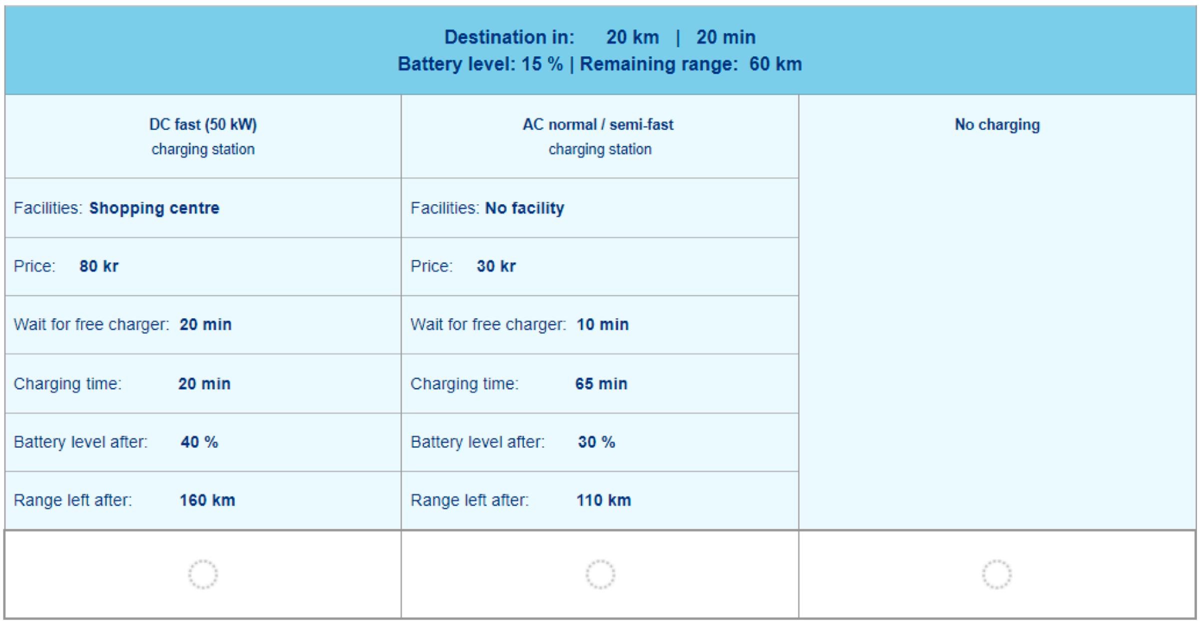

Fig. 1. Scenario definition (SP choice task).

attributes, and levels; as for example, some EVs cannot use fast chargers, affecting possible charging speed. The features of the registered EVs in Norway were observed and divided into five groups depending on range and available charging options (Table 2). The values for the battery capacity, on-board charger, and the maximum charging power accepted by the EV in DC were average values within each group. Table 2 also presents the share of respondents belonging to each group, excluding the Tesla owners.

Three alternatives were available in each scenario, with the choice between two charging stations and the decision of not to charging the EV.

A total of 8 attributes were used for the experimental designed that developed the scenarios, as shown in Table 3. Two of the attributes were scenario based (distance to destination, and state of charge, or battery level), while the other six (charger type, facilities, fee for charging, waiting time, charging time and range after) related to the charging options. Three levels were defined for the charger types, AC normal/semi-fast charging station or DC fast charging station supplying 50 or 100 kW. Longer distances were shown for cars with greater batter capacity, while the type of possible charger also varied across car groups. Finally, charging time was also different depending on the type of charger.

To make the scenarios more customized, realistic and easier to interpret, additional variables were created based on transformations of these attributes and presented to the respondents. An example on how the scenarios were presented to the respondents is depicted in Fig. 1.

In particular, and dividing the attributes into those relating to the scenario and those relating to the two charging alternatives, we have the following:

Scenario variables:

- T*ime to destination* was shown alongside distance, where time was estimated based on the *distance to destination* assuming an average speed of around 60 km/h.
- *State of charge (SoC) was shown to respondents as battery level (in %), which is easier to understand than the more technical term.*
- *Remaining range* was shown alongside the SoC, and was calculated as a function of the *SoC before charging*.

Variables relating to charging alternatives:

- *Charger type and facilities were presented directly using the attributes from the experimental design.*
- *Fees* for charging EVs in Norway use three different structures, where these depend on the charging time, the used electricity, or both. For simplicity, we use the first type, including an average price among the power supplies for each charging station type, and using three levels, pivoting the average price with 50% decrease and increase. These three levels (0.5, 1, 1.5) were used in the design and applied to the charging fee, which is of course in Kr/kWh. In the survey, the actual calculation was made for the respondent such that what was shown was the actual total *price* for reaching the specific state of charge shown for that alternative.
- *Charging time* was used directly from the design.
- *Battery level after charging* was calculated from the range after charging and the total range of the car. The value was rounded to the closest 5% before being shown to the respondent.
- *Range after* charging was used directly from the design, with constraints such that the values correspond to the SoC before charging, the type of charger and the charging time.

The different scenarios were designed to cover three different situations where 1) the remaining range was equal to the distance to the destination (zero margin), 2) the range was larger than the remaining distance (positive margin), and 3) the range was shorter than the remaining distance (negative margin). Moreover, as the battery size and the state of charge influences the charging speed, it was assumed that the use of charging stations would provide a maximum of 80% of battery level, as above that level, the charging speed decreases.

The experimental design for the SC scenarios was generated using the software Ngene (ChoiceMetrics, 2014). A D-efficient design (Rose and Bliemer, 2014) was developed, using 3 blocks of 6 choice tasks, with each respondent allocated to one block. The design process included constraints to ensure realistic attribute combinations while at the same time also aiming to achieve good attribute level balance. Small priors that focus on the expected sign (rather than magnitude) of the parameters were used. The design was optimised for a Multinomial Logit (MNL) model which is standard practice – this does not affect the consistency of estimates when later estimating a Mixed Logit model and relies on fewer assumptions.

Table 2
Main features of the registered EV models in Norway.

GROUP	Range (km)	# EV models	Battery capacity (kWh)	On-board charger (kW)	Max. DC charging power (kW)	Sample% (n = 381)
A	Less than 200 km	4	25	3.6	–	4% (14)
B	Less than 200 km	13	25	3.6	50	22% (82)
C	210—300 km	15	38	6.6	50	25% (97)
D	310—400 km	18	65	7.4	125	23% (89)
E	more than 410	9	80	11	150	26% (99)

3.3. Model

A mixed logit model was developed to estimate the role of explanatory variables in the charging decisions.

The model was developed under the assumptions of Random Utility Theory (McFadden and Train, 2000), where an individual (n) associates a utility (U) with each alternative (i) in the choice task (t), and is expected to choose the alternative with the highest utility. The utility expression is shown in equation (1)

$$U_{nit} = V(\beta, X_{nit}) + \varepsilon_{nit} \tag{1}$$

where the deterministic part of the utility (V) is expressed as a linear in attributes function of observable characteristics (X) and a set of β-parameters to be estimated. The error term (ε) is assumed to be distributed following a Gumbel distribution.

The mixed logit model (McFadden and Train, 2000) is an extension of the multinominal logit (MNL) model, allowing for random coefficients to capture individual taste variations and error components to capture correlation between alternatives (Train, 2009). The probability for an individual (n) to choose alternative i is defined as the integral of the MNL probabilities over an assumed distribution of the taste parameters (β). With repeated choice, we instead calculate the probability of the sequence of choices for each individual (with $ni^{*}t$ used to refer to the alternative chosen by individual n in task t):

$$P_n = \int_{\beta} \prod_{t=1}^{T} \left[\frac{e^{V(\beta,\ X_{ni^{*}t})}}{\sum_{j=1}^{J(n)} e^{V(\beta,\ X_{njt})}} \right] f(\beta) d\beta \tag{2}$$

In the survey, the respondents had to choose between tree alternatives; two different charging options, and one option of not charging. The utility for the no charging option was used as the base, i.e. set to zero, while the following specification was used for the first two alternatives:

$$\begin{aligned} V_{nit} &= \delta_{n,i} \\ &+ \beta_{margin\ before,n} * x_{margin\ before,nt} \\ &+ \beta_{shift\ margin\ befre \le 0} * \left(x_{margin\ before,nt} \le 0\right) \\ &+ \beta_{charging\ speed,n} * x_{charging\ speed,nit} \\ &+ \beta_{margin\ after} * x_{margin\ after,nit} \\ &+ \beta_{distance,n} * x_{distance,nt} \\ &+ \beta_{waiting\ time,n} * x_{waiting\ time,nit} \\ &+ \beta_{fee,n} * x_{fee,nit} \\ &+ \beta_{cafe} * x_{cafe,nit} * \left[\frac{x_{distance,nt}}{mean(x_{distance})}\right]^{\lambda} \\ &+ \beta_{shopping} * x_{shopping,nit}, \\ & i = 1, 2 \end{aligned}$$

We look at the different components of this specification in turn:

- **Alternative specific constants (ASC, defined as δ)** were included for the first two alternatives, capturing a baseline preference (or dislike) for the charging options vs no charging, along with order effects between the two charging options. Along with estimating the mean of these two constants, we included a shared random term that captures heterogeneity across individual respondents in their utility for charging vs not charging, thus allowing also for correlation between the utility for the two charging options. The two ASCs thus follow a normal distribution, with different means but the same standard deviation.
- We hypothesise that respondents are more likely to choose a charging option when the **margin before charging** (km), which is the difference between the remaining range and the distance to destination, becomes smaller. The impact of remaining margin on the utility for charging should consequentially be negative, and we used a negative lognormal distribution to allow for heterogeneity across respondents, with coefficient $\beta_{marginbefore,n}$. We also included a term in the utility for charging that captured any additional impact of a **zero or negative margin**, i.e. whether respondents are more likely to charge if and when the remaining range is no longer sufficient to reach their destination with spare capacity. This was included as a non-random parameter in the model, with

Table 3
Attributes and levels in the choice tasks.

		Group A	Group B	Group C	Group D	Group E
Distance to destination (km)		(10, 60)		(15, 90)	(20, 120)	(25, 150)
State of charge (SoC) (%)		(5, 15, 30)				
Charger type		(AC)	(AC, DC_50)		(AC, DC_50, DC_100)	
Facilities		(No facilities, coffee shop, shopping centre)				
Pivot on Kr/kWh fee		(0.5, 1, 1.5)				
Waiting time for free charger (min)		(0, 5, 10, 20, 30, 45)				
Charging time (min)	AC charger	(85,145)	(85,155)	(50, 105)	65	50
	DC_50 charger	Not applicable	(15,20)	(15,20)	20	20
	DC_100 charger	Not applicable	Not applicable	Not applicable	10	10
Range after (km)		(50, 70, 100)	(50, 70, 100, 105, 155)	(60, 90, 110, 135, 140, 185)	(70, 110, 120, 160, 170, 220)	(85, 130, 135, 180, 205, 255)

coefficient $\beta_{shiftmarginbefre\leq 0}$. We tested a specification with a separate continuous effect for negative margins, but the simple offset term above led to better performance, possibly due to the low number of negative levels used.

- Some of the variables used to describe the alternatives are inter-related, and this affected the specification to use. We already discussed how charger type, charging time, battery level after charging and range after charging are correlated and their impacts cannot be separately estimated. Our modelling work could have used various combinations of these attributes. After a number of different specifications were tested, the best performing approach was one that used two variables created from the above, namely **charging speed** (km increase in range per minute of charging), and the **margin after charging** (calculated as the difference between the range after charging and the remaining distance, in km). Both of these effects were initially specified using positive lognormal distributions, but no heterogeneity was found for the latter, leading to a random coefficient for charging speed, given by $\beta_{chargingspeed,n}$, and non-random coefficient for margin after charging, given by $\beta_{marginafter}$.
- We further hypothesise that all else being equal, i.e. after accounting for margin and charging speed, respondents with longer **remaining distance** (km) are more likely to charge. We included the impact of this term with a positive lognormally distributed coefficient, given by $\beta_{distance,n}$.
- **Waiting time** (min) was included using a negative lognormally distributed coefficient, given by $\beta_{waitingtime,n}$.
- **Fee** (kr) was included using a negative lognormally distributed coefficient, given by $\beta_{fee,n}$, where this related to the total fee for charging.
- For facilities, **café** and **shopping centre** were included, with the reference being "no facilities". These parameters were included as non-random terms, given by β_{cafe} and $\beta_{shopping}$ but with an interaction between cafe-facilities and the distance to destination, where an elasticity parameter, λ, was estimated. No such interactions were found for shopping centres.

4. Results

4.1. Data statistics

Respondents from all over the country were represented in the sample, although most of respondents were living in Trondheim. The socioeconomic characteristics of the respondents are presented in Table 4.

The most popular EV among respondents was the Nissan Leaf, followed by Volkswagen e-Golf, Tesla model 3, and Audi e-tron. Fig. 2 shows the market share of the most popular EVs models from the sample compared to the EVs registered in Norway. Tesla model 3 and Polestar 2 are slightly overrepresented in the sample. The share of other EVs (not among the most popular shown in Fig. 2) is 32% in the sample. Among EVs registered in Norway, this share is 44%.

In our sample, 23% of the respondents had owned the EV for less than 1 year, whilst 24% had owned it for 4 years or more. The range of the EVs was evenly distributed for ranges between 210 and 400 km, although 35% of the respondents had an EV with a range larger than 410 km, as shown in Table 5.

Almost 30% of respondents use public charging stations weekly or more often, even though 91% have access to home charging. Most of the respondents used their EV for long trips monthly or less.

4.2. Model

4.2.1. Specification and estimation

The models were estimated using Apollo (Hess and Palma, 2019) and R (R Core Team, 2022). A detailed specification search was carried out to capture the role of explanatory variables as well as deterministic and random heterogeneity in preferences.

We made attempts to capture the role of socio-demographic variables in explaining heterogeneity in preferences. This included interacting the price sensitivity with income, gender with price, waiting time and range, as well as the choice between the charging and non-charging alternatives. These efforts were not successful, nor where attempts to include an impact of the age of the EV. The initial idea was for this latter variable to serve as a proxy for years of EV ownership and thus experience with EVs, but the lack of effect suggests that future studies should also capture data on years of EV ownership aside from the age of the current vehicle alone. This lack of deterministic heterogeneity, in contrast with the random heterogeneity we uncovered, suggests that differences in sensitivities in the context of EV charging decisions are idiosyncratic to individuals and not necessarily linked to observable characteristics.

In addition to socio-demographics, attitudes and perceptions are important behavioural determinants in many areas of human behaviour, but we left the role of risk averseness to future work.

In our study of charging choices, the focus is instead on a selection of attributes and characteristics of the charging stations and some trip-specific features. Among the attributes of the charging station, price, charging speed and facilities were included, together with waiting time for a vacant charger as a mean of addressing capacity issues.

The facilities included in our survey were café and shopping mall, serving as proxies for the possibility to eat and to do some errands while waiting for the car to charge, as well as for bathroom breaks.

There are several aspects that may be important for charging choices that could have been, but were not, included in the survey. Information about the charging options at the destination may clearly impact the charging choices. For example, possibilities to charge for free overnight, or if charging at the destination must be done on a public charging station similar to the charging options along the road. Other factors that may influence choices are the distance already travelled, the purpose of the trip and whether people are travelling alone or with others.

Trip planning is also an important issue. Because of the scarce availability of chargers outside of the biggest cities and their closest surrounding areas, it is common among EV-drivers to plan their trips with respect to charging, especially for longer trips where charging is needed. The planning of charging stops may include the planning of driving length and travel route, the length of breaks, and activities during the trip. All these factors may influence what people experience as the important determinants for their charging choices.

It's also worth noting that how EV drivers emphasize margin for the decision to charge may be somewhat influenced by the distance to destination. We tested an interaction between margin and distance to destination, which pointed in the direction that as the distance increases, the less important the margin is for the charging decision. However, this effect was no longer significant when a random term was introduced for margin.

Finally, while there is a certain geographical distribution of respondents, most are in Trondheim, and the sample size is too small to analyse differences in choice preferences between geographical regions or between urban and more rural areas.

4.2.2. Results

The results of the estimated model are shown in Table 6.

In the following section, the results from the choice model presented in Table 6 are summarized and commented upon.

The two means for the alternative specific constants for charging are positive, showing that, all else being equal, respondents have a preference for the charging options. The estimate for the second charging option is more positive, and we can reject the null hypothesis of equal means at high levels of confidence, indicating the presence of some order effects, and justifying the inclusions of two separate means. In addition, the estimate for the standard deviation, $\sigma_{\delta_{1,2}}$ shows the presence of heterogeneity across individuals in the baseline utility for charging, and hence correlation between the utilities for the two charging alternatives.

The margin before charging is the difference between remaining range before charging and the distance to destination. A negative margin means that charging is necessary to reach the destination, while a positive margin means that the destination can be reached without charging. The β-coefficient for the margin before charging (when included in the utility for the charging alternatives) was found to be negative in earlier MNL models, meaning that in our model the probability of charging decreases as the margin increases,

Table 4
Socioeconomic characteristics of the sample.

Socioeconomic variables (N = 465)	#	%
Gender		
Female	154	33%
Male	288	62%
Other	3	1%
Age		
18–24 years old	7	2%
25–34 years old	55	12%
35–44 years old	127	27%
45–54 years old	137	29%
55–64 years old	94	20%
65–74 years old	23	5%
75 years old or more	3	1%
Yearly income (household)		
Under 40.000 €	5	1%
40.000—–79.000 €	66	14%
80.000—–119.000 €	126	27%
120.000—–159.000 €	141	30%
160.000—–199.000 €	56	12%
Over 200.000 €	21	5%

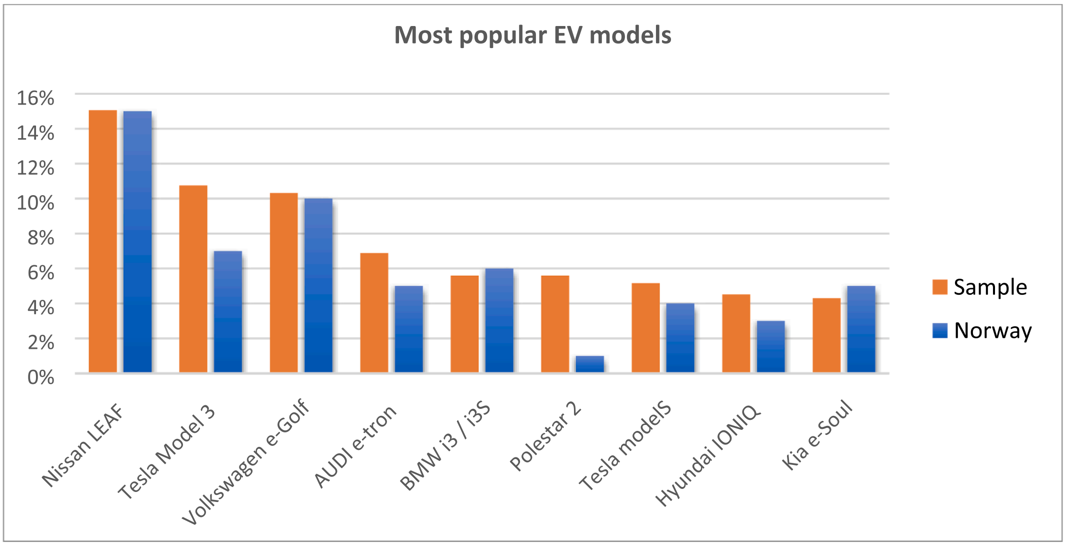

Fig. 2. Distribution of the most popular EV models in the sample and registered in Norway by December 2021 (()).
Source: Elbilstatistikk, 2021

Table 5
Range of EVs from the sample.

Range (N = 465)	#	%
Less than 200 km	89	19%
210——300 km	104	22%
310——400 km	110	24%
More than 410 km	162	35%

while with a reduced and especially negative margin, the probability would increase. We specified a negative lognormal distribution for this coefficient, where the estimates then relate to the mean and standard deviation of $\log(-\beta)$. We see clear evidence of heterogeneity across individuals in their sensitivity to margin before charging. An additional shift for negative or zero margin was included in the model to capture an additional increase in the likelihood of charging with negative or zero margins. The estimate for this was positive, but only different from zero at lower levels of confidence (p-value for one-sided test $p = 0.118$).

The next two attributes are charging speed and margin after charging, both of which were found to have positive impacts on utility. For the former, this means that respondents prefer charging stations with faster chargers, while, for the latter, it means that respondents prefer charging their cars to a higher battery level as opposed to the minimum top-up that would be required to reach their destination. For the charging speed attribute, we found clear evidence of heterogeneity in sensitivities.

Aside from the above, remaining distance to destination also has an impact on the decision to charge, where we found higher probability of charging when further from the destination. We again used a positive lognormal distribution, with evidence of heterogeneity across respondents.

Waiting time for a charger and fee for charging have negative impacts on the utility of charging at a specific station, leading us to use negative lognormal distributions, with again evidence of heterogeneity in sensitivities for both attributes.

Finally, respondents have a positive utility for charging stations that have café or shopping facilities (compared to no facilities). There is also an interaction effect between café-facilities and the remaining distance. The positive λ-coefficient means that the farther away from the destination, the more important is the presence of a café at the charging station, in line with intuition.

5. Analysis of results

5.1. Explanatory variables for choosing to charge at public charging stations on long trips

We can use the model to predict the probability that someone choses to charge under given conditions. We do this by looking at marginal effects, i.e., predicting the impact of changing one attribute at a time.

5.1.1. Trip features

As expected, the margin before charging has an important impact on the decision whether to charge or not. The relationship between the margin and the probability of charging is illustrated in Fig. 3. When the margin is negative, almost everyone would choose

Table 6
Model results.

	Coefficient		Rob S.E.	Rob t-value
ASC charging option 1	0.8311		0.9901	0.8395
ASC charging option 2	1.1114		0.9963	1.1156
Sigma (correlation between 1 and 2)	−3.2524		0.4797	−6.7807
ASC no charging				
Margin before charging– mean (mu)	−0.3200	(-1.9065[a])	0.2411	−7.9070
Margin before charging – sd (sig)	0.6104	(-1.2387[a])	0.2962	−4.1813
Shift for margin <= 0	1.1418		0.9616	1.1874
Charging speed – mean (mu)	0.3004	(-2.3071[b])	0.3997	−5.7720
Charging speed – sd (sig)	0.8553	(-1.4862[b])	0.2498	−5.9496
Margin after charging	0.0295		0.0060	4.9293
Distance to destination – mean (mu)	0.0395	(-4.3429[b])	0.5134	−8.4599
Distance to destination – sd (sig)	0.1134	(1.4911[b])	0.1994	7.4772
Waiting time – mean (mu)	−0.0572	(-2.9979[a])	0.0991	−30.2633
Waiting time – sd (sig)	0.0322	(-0.5241[a])	0.1588	−3.3000
Fee – mean (mu)	−0.0190	(-4.2160[a])	0.1656	−25.4622
Fee – sd (sig)	0.0154	(-0.7114[a])	0.0818	−8.6980
Facilities: cafe	0.5776		0.1271	4.5428
Lambda (λ) (Café – Distance interaction)	0.5962		0.1660	3.5910
Facilities: Shopping	0.4598		0.1099	4.1834
Model Summary				
Sample Size	381			
Number of parameters	18			
Final log likelihood	−1559.56			
AIC	3155.11			
Adjusted Rho-squared	0.3657			
Number of draws for random terms	5000			

[a] The coefficients for margin before, waiting time and fee were specified to follow negative lognormal distributions, meaning that the estimated mean (μ) and standard deviation (σ) parameters relate to the normally distributed logarithm of the coefficients. The mean and standard deviations for the lognormally distributed coefficients are then calculated as follows:.$E[e^{\beta}] = -e^{\mu+(\frac{\sigma^2}{2})} sd[e^{\beta}] = \sqrt{e^{2\mu+\sigma^2}(e^{\sigma^2}-1)}$.

[b] The coefficients for charging speed and distance to destination were specified as being positively lognormally distributed. The mean and standard deviation are then calculated as above, except the minus-sign before the mean.

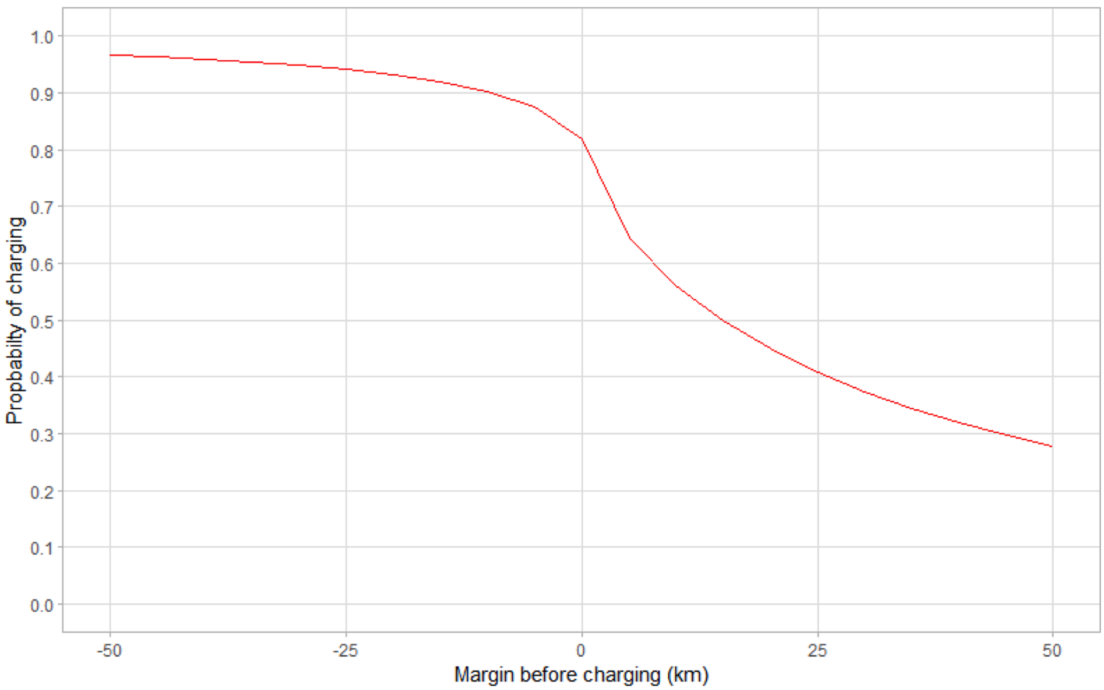

Fig. 3. The probability of charging decreases as the margin increases.

to charge.

The slope descends gently as the margin approaches zero. This makes sense, as its likely that the range anxiety levels off as the margin increases. More experienced drivers also show less range anxiety (Chaudhari et al., 2019), and may adjust their driving, e.g., drive slower, to save energy instead of charging. Also, as the margin increases, more people are probably willing to take the risk that they reach the destination without charging. As the margin becomes positive, the slope descends rapidly. Still, even at margins as large as 50 km, almost 30% are expected to charge. Most drivers prefer to keep their battery level above a certain threshold and these results are in line with previous studies (Franke et al., 2012). Even with sufficient range to reach the destination, charging may be desirable to keep battery level above this threshold. While we did not find a clear relationship between the preferred battery levels and charging choices, charging, and keeping a buffer range, provides both increased security and flexibility for the remaining part of the trip (and until next charging opportunity).

5.1.2. Characteristics of the charging stations

Characteristics of the charging stations, such as the price for charging, the speed of the chargers available, availability in terms of waiting time in queue before charging, and facilities such as a café or shopping centre in conjunction with the charging station, are also important when deciding whether to charge or not.

Fig. 4 shows the almost linear relationship between the probability of charging and the price, as the price changes from a 50% decrease to a 100% increase. The price elasticity of –0.108 is very low, indicating that even if the drivers prefer the cheaper charging alternative, they are less sensitive to changes in price when deciding to charge or not.

Several studies pinpoint the importance of charging time and waiting time on the assessment of public chargers (Alkhalidi et al., 2021; Globisch et al., 2019). The charging time is obviously dependent on charging speed. In our model, faster charging options are clearly preferred.

As battery sizes increases, the time it takes to fully charge the batteries also increases, but fewer charging stops are needed as the initial ranges are longer. On the other hand, larger batteries and accompanying longer driving range, may increase the number of long trips conducted by EVs and consequently increase the time there are EVs charging at charging stations.

The charging time is often predictable. The time it takes to charge to a given battery level is for the most part a function of the charging speed and the state of charge of the EV before charging, both factors that may be estimated in advance when planning the trip. The charging speed may still vary with the demand, as most fast chargers split the effect between the EVs they are charging simultaneously, resulting in slower charging speed. This means that if two EVs are charging at a 100-kW charger, the EVs get 50 kW each.

Waiting time on the other hand, is much more unpredictable and less flexible than the charging time since it is dependent on the other people who are already charging. While long queues may put a mild social pressure on the people who are occupying the chargers to finish sooner, long queues also indicate a waiting time for charging, and may serve as a visual cue and incitement to keep driving instead of stopping to charge.

Facilities at the charging stations are important for charging decisions. First, facilities may increase the comfort during charging,

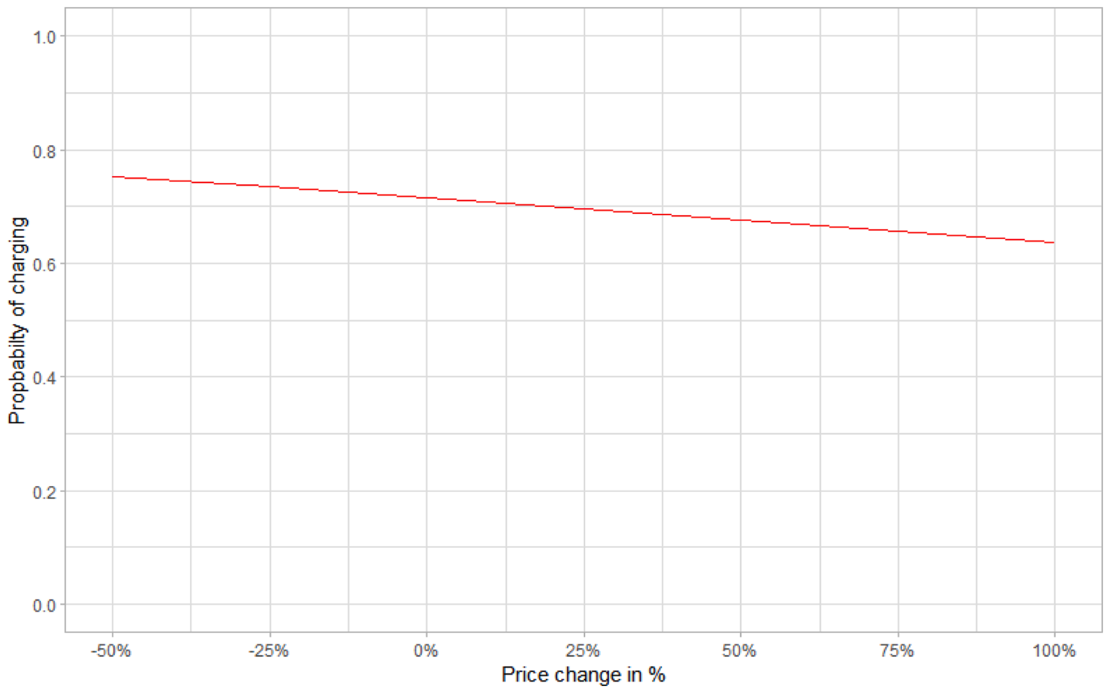

Fig. 4. The probability of charging decreases as price increases.

and provide the opportunity to utilize the time while charging to do other activities like eating, resting, shopping etc. Second, the facilities may also be the main reason to stop, e.g., a much-needed break, time to eat, or to do grocery shopping. The option of charging, even if not strictly necessary, are convenient, and may also reduce the need for additional stops, or reduce the time spent at next charging station.

As an example of use of the model, we can look at a potential trip between Trondheim and Bergen, where the shortest route is about 600 km (Table 7).

First, we can look at a scenario close to the situation today (October 2022). Given a pool of EVs with a range between 400 and 600 km, uniformly distributed (as of October 2022, new long-range EVs have up to 600 km of range) we can estimate the share of EVs that choose to charge along the route.

In this example, we assume that all the EVs are fully charged at the beginning of the trip. When reaching the charging station located half-way between Trondheim and Bergen, the EVs will then have different remaining range. The price for charging is set to an average of 7 kr/kwh, and the EVs are assumed to charge to 80% of battery capacity. The average waiting time is 5 min. All the chargers are 50 kw DC chargers (approximately 5 km increase in range per minute) and the stations have a cafe present. Given these conditions, a total of 98% choses to charge.

We can also alter some of the parameters to see how this influences the share that choose to charge, e.g., to predict possible consequences of rapidly increasing electricity prices, or a future increase in the range of EVs.

In September 2022, the average spot price of electricity in southern parts of Norway was about 4.5 kr/kwh on average. If this price increases further, we may expect charging prices to increase as well. Assuming a charging price at 12 kr/kwh the share who chooses to charge drops to 93%.

If on the other hand, nothing drastically happens with the electricity prices (keeping a price of 7 kr/kwh), but the range of EVs increases to 600 to 800 km, the share that chooses to charge is 58%.

5.2. *Marginal rates of substitution*

We finally look at some marginal rates of substitution (Table 8), i.e. the relative impact on utilities of two attributes, given by the ratios of partial derivatives of the utility function given our linear in attributes specification.

We first look at the relative impact of waiting time and fees, giving us the willingness to pay (WTP) for reduced waiting time. In the mixed logit model, both the price and waiting time coefficients are heterogeneously distributed across the individuals following a negative lognormal distribution. To obtain an estimate of the willingness to pay for reduced waiting time, we simulate the ratio of two lognormals. Based on our model, the estimated willingness to pay for reduced waiting time is about 300 kr per hour, or roughly €30 at the time of writing this paper. This value is relatively close to, but somewhat higher, than the value of travel time for car drivers in Norway, which is 223 kr per hour in general, and 187 kr per hour for leisure trips specifically (Flügel et al., 2018). There are two intuitive reasons for the higher valuations we obtain. First, EV users would in general be expected to have above average income, leading to a higher value of time than at the population average. Second, our finding relates to the value of waiting time rather than travel time, and our result is thus also consistent with the findings that drivers are more willing to accept a detour than they are to accept waiting time for charging (Philipsen et al., 2016). Having an estimate of the value of waiting time may be beneficial when planning the layout of a charging network, and when evaluating trade-off between increasing charging capacity at one location or establishing charging stations at nearby locations which might require some of the EV drivers to detour.

We also look at two other marginal rate of substitution calculations (Table 8). The first gives us the trade-off between charging speed and waiting time, showing that respondents would on average be willing to wait an additional 6.9 min for a charger that increases output by 1 km/min. Going from the slowest (1 km/min) to the fastest (10 km/min) charger would mean a gain in charging output of 9 km per minute, which would thus imply a willingness to wait an additional 62 min. As long as charging the battery would increase range by more than 69 km, the faster charger would then have a higher utility.

Finally, we look at the relative impact on utility of margin before charging and after charging. These two components have opposite

Table 7
Summary of scenario predictions.

Conditions common for all scenarios			
Distance Trondheim – Bergen	600 km		
SoC at start	100 %		
Remaining distance at charger	300 km		
Waiting time at charger	5 min		
Charger type /speed	DC 50 kw / 5 km increased range per min charging (300 km/h)		
Facilities	Café		
SoC after charging	80 %		
Scenario specific conditions	**Scenario 1 (today)**	**Scenario 2 (High price)**	**Scenario 3 (Long range)**
EV range at start	400 km – 600 km	400 km – 600 km	600 km – 800 km
Remaining range (at charger)	100 km – 300 km	100 km – 300 km	300 km – 500 km
SoC before charging	25% – 50%	25% – 50%	50% – 62.5%
EV range after charging	320 km – 480 km	320 km – 480 km	480 km – 640 km
Fee	7 kr/kwh	12 kr/kwh	7 kr/kwh
Share of drivers choosing to charge	**98 %**	**93 %**	**58 %**

Table 8
Marginal rates of substitution.

	Mean	Standard deviation
Waiting time vs fee (kr/hr)	299.57	326.12
Charging speed vs waiting time (mins for each additional km/min)	6.92	23.69
Margin before vs margin after	−10.84	20.54

signs for their impact on utility, reflected in the negative ratio. We see that the impact of margin before charging is substantially larger in absolute terms than the margin after charging. This is not unexpected as all charging options always led to a sufficient increase in battery level to reach the destination.

6. Conclusions

In Norway, the policy goal is that by 2025 all new personal vehicles should be zero-emission vehicles. For all practical purposes this means electric vehicles, as the share of hydrogen powered vehicles is almost negligible. As of August 2022, about 70% of the new cars are electric. Both as a mean of reaching this policy goal, and as a necessity to facilitate the growing population of electric vehicles, charging infrastructure is important.

The most important factor for the decision to charge or not is whether it is possible to reach the destination without charging. This means that if we want people to use EVs on long trips that exceeds the range of the car, there need to be reasonably fast charging options along the route.

Waiting time is an important measure of the availability of chargers and the capacity at charging stations. Our finding of a willingness to pay of 300 kr per hour for reduced waiting time may indicate a demand for more chargers.

With an increase in EV car ownership, it is also likely that more people have EVs as their primary or only car, something that will influence how EVs are used on an aggregate level. This will likely lead to more long-distance driving, and an increased demand for charging along travel corridors. The low price elasticity shows that pricing alone is not suitable to balance the charging demand directly. Pricing might still affect the demand by causing a reduction of long trips with EVs in favour of other transport modes on travel routes where alternatives are available. In addition, the increasing range of new EVs may have a dampening effect on the demand for fast charging along the road, as shown in the forecast scenarios (Table 7). At the same time, the demand for charging options at the destination may increase.

Further development may be to integrate this EV charging behavioural model with other models, for example on route choice, energy demand and supply, grid capacity to simulate an optimal spatial and temporal capacity allocation for a potential charging network.

Further research that may improve on this model, may be to look at destination charging, and consider the issue of trip planning, as well as capturing the role of risk averseness. The use of EVs in less predictable situations, and in winter conditions are also interesting aspects not covered in this study. With the increase in use of EVs, more data on observed charging behaviour may become available, and revealed preference studies can complement and expand on our results. A better understanding of attitudes and perceptions of EV drivers may also contribute to explain more of the heterogeneity in charging behaviour. Finally, the sample used in our study was largely convenience-based, and in the absence of clear statistics on the socioeconomic composition of the population of EV users, it is difficult to establish the representativeness of our sample, and generalisability of our results. This is a further avenue for future work, though the lack of clear findings for socioeconomic drivers of preferences should reduce any bias of our findings.

CRediT authorship contribution statement

Fredrik Solvi Hoen: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **María Díez-Gutiérrez:** Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Sahar Babri:** Conceptualization, Methodology, Investigation, Writing – original draft, Project administration. **Stephane Hess:** Writing – review & editing, Supervision. **Trude Tørset:** Conceptualization, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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