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Do I need to charge right now? Tailored choice architecture design can increase preferences for electric vehicle smart charging

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ABSTRACT

The increasing diffusion of electric vehicles (EVs) can challenge the stability of distribution grids. Smart charging systems can reduce the stress of EV charging on the grid, but the potential of the technology depends on EV drivers' participation in smart charging schemes. To investigate this potential, we conducted an online randomised-controlled experiment with two waves (baseline and experimental phase, $N = 222$), in which we examined drivers' preferences for smart charging and tested a behavioral intervention to increase the number of smart charging choices. We translated state-of-charge (SoC) information from percentage of battery level into *miles* corresponding to the battery level and *tailored* information, i.e., the number of driving days covered by the actual SoC based on participants' personal driving profiles. Participants preferred to use smart charging systems to decrease costs and to increase renewable energy use. However, they tended to overestimate the importance of the battery SoC when setting charging preferences. This overestimation was especially evident for participants who only drive short distances and may be lead to inefficient use of smart charging technology. Translating battery SoC into *tailored* information corrected for this bias and increased the number of smart charging choices. Our findings illustrate how behavioral interventions can be leveraged to attain energy transition goals.

1. Introduction

Electric vehicles (EVs) are expected to play an important role in the transition to low-carbon transportation (IEA, 2020a; Rietmann et al., 2020; Wood Mackenzie, 2020). Many governmental energy strategies on CO_2 emission reduction put EVs in the foreground, including supply-side policies (e.g. stimulating R&D investments) and demand-side policies (e.g. financial incentives for EV purchases) (IEA, 2020a). At the same time, public interest in EVs increases as these cars are progressively recognised as environmentally-friendly, viable and price-competitive (Rietmann et al., 2020).

The increasing adoption of EVs will lead to significant changes not only for the transportation market but also for the operation of power systems. Most importantly, the diffusion of EVs will increase electricity demand, which may lead to severe congestion on existing distribution grids (Deb et al., 2018; Fan et al., 2013; Gupta et al., 2021; Hahnel et al., 2013; Heuberger et al., 2020; Sehar et al., 2017). With conventional (i.e., uncoordinated) charging systems, which are the most used technology nowadays, the charging process starts at maximum power as soon as the cars are plugged in. Such charging systems do not consider any relevant information about the power system, which can be problematic as EVs are often charged during electricity demand peaks, such as in the early evening (Beaufils and Pineau, 2019; Langbroek et al., 2017; Wolbertus et al., 2018). This additional load causes stress on the electricity grid as existing demand peaks become intensified.

Technical studies suggest *EV smart charging* as a promising solution to secure grid stability and increase renewable energy use (Hossain et al., 2016; Jian et al., 2018; Kara et al., 2015; Pudjianto et al., 2013). Smart charging refers to coordinated charging systems that manage the charging process in order to optimise for collective needs (e.g., maintaining grid stability) and/or individual preferences of EV owners (e.g., charging when electricity prices are low). The basic principle behind the technology is that, instead of charging the EV at full power immediately after it has been plugged in, the EV is charged at a variable power to meet the aforementioned goals (Hahnel et al., 2013; Hossain et al., 2016; Jian et al., 2018; Kara et al., 2015). As a result, smart charging usually

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takes longer than conventional charging. By charging EVs at reduced and variable power, smart charging can alleviate the stress on the grid caused by charging a high number of EVs at the same time. In addition, smart charging can postpone EV charging to times with high renewable energy production, thereby transforming EVs into a flexible electricity demand. This flexibility enables better integration of large shares of intermittent renewable energy sources such as wind energy and photovoltaic (PV) solar energy.

Although a variety of smart charging systems exists with different degrees of user involvement (Bailey and Axsen, 2015; Sintov and Schultz, 2015; Wang et al., 2016), in most cases, the potential of smart charging is intertwined with individuals' acceptance and use of the technology (i.e., their charging preferences and strategies). If drivers do not endorse and use smart charging schemes, their envisioned benefits will not be realised sufficiently. Therefore, a better understanding of drivers' decision-making preferences and strategies towards smart charging choices is needed to ensure that the potential of the technology for the energy transition is fully exploited. Accordingly, our research questions are the following: what are the main factors that influence drivers' decisions to opt for smart charging? And how does range information provided at the point of decision-making influence such decisions?

We first empirically investigated drivers' preferences towards smart charging systems and the underlying determinants of their charging decisions, i.e., the baseline phase (Wave 1). Specifically, we investigated whether UK drivers prefer to charge their vehicle right away (immediate charging) or enable the smart charging option to modulate EV charging to reduce charging costs, the demand load of the power system, and increase renewable energy use. Furthermore, we hypothesised and found that, when making a charging decision, drivers give high importance to battery state of charge (SoC) information (H1). We moreover tested a behavioural intervention to increase the amount of smart charging choices, i.e., the experimental phase (Wave 2). Following the literature on choice architecture (Beaufils and Pineau, 2019; Huber et al., 2019; Kara et al., 2015; Momsen and Stoerk, 2014; Pichert and Katsikopoulos, 2008), we investigated how translating provided information on battery SoC into more comprehensible and meaningful units for the decision-maker affects their charging choices. Based on the literature indicating that drivers tend to underestimate the amount of available battery range at the point of decision-making (Bailey and Axsen, 2015; Das et al., 2020; Huber et al., 2019; Sintov and Schultz, 2015), we translated battery SoC information from percentages into the number of personal driving days that can be covered by the battery level. In line with our hypotheses, translating SoC information increased the likelihood that participants chose smart charging over conventional charging (H2). We finally assumed that the intervention would affect more strongly drivers for whom smart charging is actually most suitable. In accordance, respondents with short daily driving distances allocated less importance to the SoC information when they were provided with tailored range information (i.e., battery SoC) (H3).

Our results unravel drivers' charging decision-making strategies and offer behavioural insights on how to optimise the use of smart charging in the future. We provide practical recommendations on how to present charging-related information to increase smart charging processes, insights from which policymakers, grid operators, and users can benefit.

2. Theoretical background

2.1. Smart charging decisions: behavioural insights

Smart charging refers to flexible systems that allow fulfilling a variety of goals (Das et al., 2020). From a technical and economic point of view, smart charging systems can contribute, for example, to curtailing peak demand (van der Kam and van Sark, 2015), minimising distribution loss (Veldman and Verzijlbergh, 2015), reducing costs to generate and purchase electricity (Gonzalez Vaya and Andersson, 2012), and maximising the use of renewable energies (Hossain et al., 2016). From the point of view of EV owners, the use of smart charging systems can similarly result in economic benefits as well as further benefits such as environmental ones (Gangale et al., 2013; Huber et al., 2019).

Benefiting from the aforementioned advantages of smart charging, however, comes at a cost for the user (Hahnel et al., 2013; Huber et al., 2019; Sintov and Schultz, 2015; Will and Schuller, 2016). Under smart charging, the charging process is usually extended or shifted so that the charging system can optimise the charging process for a specific goal (e.g., reduce costs; increase the amount of renewable energy). Therefore, drivers lose driving flexibility as the extended charging time may conflict with individual mobility needs. For example, the charging process might not have been finished or even started when the driver wants to make an urgent and/or spontaneous trip (Hahnel et al., 2013); in this case, the battery may not be charged enough to enable the trip.

As smart charging systems only exploit their full potential (e.g., increasing grid stability) when drivers opt for smart charging as often as possible, it is crucial to attaining behavioural insights into the decision-making strategies drivers pursue when using the charging systems. More specifically, it is important to examine how often drivers would opt for smart charging as well as to unravel the underlying processes shaping these decisions. A growing body of literature has investigated how drivers evaluate the costs and benefits of smart charging, i.e., whether or not they accept this technology in the first place (Gangale et al., 2013; Honebein et al., 2011). However, only a few studies compared different types of intervention, such as incentives, to increase the use of smart charging (Friis and Christensen, 2016; Huber et al., 2019; Kacperski and Kutzner, 2018). For example, Friis and Christensen (2016) studied shifting EV charging manually (by physically plugging in the EV) under static time-of-use tariffs in a field trial. However, insights into decision preferences and strategies for using EV smart charging technology are still scarce. We contribute to filling this gap by revealing the most important factors underlying drivers' charging decision preferences and identifying a behavioural intervention to increase smart charging choices.

The literature indicates that individuals are motivated to pursue different goals when using smart charging (Huber et al., 2019; Will and Schuller, 2016). Accordingly, environmental concerns and the reduction of electricity costs seem to be strong motivational factors in adopting and using smart technologies (Friis and Christensen, 2016; Gangale et al., 2013; Will and Schuller, 2016). In contrast, drivers are also concerned about fulfilling their individual mobility needs, such as the aspiration for freedom (Hahnel et al., 2014; Herberz et al., 2020) and safety (Franke et al., 2012b; Huber et al., 2019). Thus, to what extent users prioritise the different, partially conflicting goals at stake when making charging decisions remains an open question.

Literature on bounded rationality illustrates that individuals often apply decision shortcuts, *heuristics*, that simplify complex judgments and decisions such as described charging decisions with conflicting goals (Kahneman, 2003; Simon, 2000). For example, individuals tend to grant past choices as indicators of optimal options and stick with options that do not require any change, i.e., *default options* (Alós-Ferrer et al., 2016; Kahneman, 2003; Simon, 2000). Moreover, people tend to base their decision on the most salient goal they have at the point of decision-making (Hille et al., 2019; Mertens et al., 2020). Goals have the function of driving attention towards goal-relevant information, which in turn receives stronger weight in the decision-making process (Locke and Latham, 2002).

In the context of smart charging, it can be assumed that drivers' most salient intrinsic goal at the point of decision-making is to ensure that the battery will be recharged (Huber et al., 2019). This objective is not only inherent to the charging process itself but also corresponds to drivers' habits (Brook Lyndhurst Ltd, 2015; Delmonte et al., 2020). Drivers are used to refuelling or charging their (conventional) car right away, meaning that immediate charging can be considered the default charging option.

Moreover, the literature on range concerns offers supporting evidence on the high importance that individuals allocate to EV driving range. Previous research highlights that range concern is a major barrier to EV adoption and use (Bailey and Axsen, 2015; Das et al., 2020; Sintov and Schultz, 2015; van der Kam et al., 2019). Individuals may refrain from buying EVs because they are worried about being restricted in their freedom (Hahnel et al., 2014). Moreover, drivers have been shown to apply a substantial safety buffer in their range utilisation (Huber et al., 2019).

We draw the following inferences from this review of the literature: information about the remaining energy in the battery, i.e., the battery state of charge (SoC) at the time of decision-making is likely to be a highly salient attribute when drivers decide between smart vs immediate charging. As a consequence, environmental and financial goals are likely to have less priority in the decision process, and thus information related to these goals has less weight for the charging decision. Thus, we hypothesise that:

H1. When deciding to charge immediately or smartly, individuals allocate higher importance to the battery state of charge (SoC) than other factors such as electricity price, electricity mix, and grid stability.

2.2. Choice architecture intervention: tailoring battery state of charge (SoC) attribute information

If charging decisions are predominantly shaped by battery SoC information, it is important that drivers understand and use this information accurately. Any misperception of battery SoC information could lead to suboptimal decision-making. This concern is of particular relevance in light of research illustrating that individuals are particularly prone to misperceptions and decision biases in the energy domain (e.g., Attari, 2018). Misperceptions are, to some extent, driven by the fact that most laypersons have rather fuzzy concepts of energy systems and energy consumption (Burgess and Nye, 2008; Hahnel et al., 2020; Hargreavesn et al., 2010; Herberz et al., 2020) and little experience with units of energy, such as kWh (Herberz et al., 2020; Mertens et al., 2020). This circumstance increases the likelihood that individuals rely on cognitive shortcuts and heuristics instead of comprehensively processing the provided information (Kahneman, 2003; Simon, 2000). Whereas decision heuristics can be effective in helping individuals to make decisions with relatively little cognitive effort, the energy domain provides various examples where the use of heuristics may lead to systematic errors, misperceptions and energy inefficient choices (Cowen and Gatersleben, 2017; Herberz et al., 2020; Marghetis et al., 2019; Mertens et al., 2020; Pichert and Katsikopoulos, 2008; Schley and DeKay, 2015).

Regarding charging choices, when drivers do not accurately understand provided range information (i.e., battery SoC) the resulting decisions may be biased. For instance, when the SoC of an EV battery is presented in percentage of energy remaining in the battery, this information requires drivers to (1) translate the percentage information into available range based on the total battery capacity and then to (2) mentally compare this range value with their own driving demand. Given the high complexity of this mental task, drivers may be prone to rely uniquely on percentage quantities to make their decisions, especially if they are not familiar with the battery capacity. In the literature, this phenomenon is associated with the *numerosity heuristic*. It occurs when individuals focus exclusively on the numerical value instead of considering as well the units in which the information is expressed (Burson et al., 2009; Herberz et al., 2020; Pandelaere et al., 2011; Pelham et al., 1994). This heuristic may guide drivers to assume low battery percentage levels as insufficient, independent of the actual remaining driving range of the EV. Misperceptions of percentage values, in turn, may prevent individuals from using smart over immediate charging. This aspect is particularly problematic when considering that a significant majority of individuals drive less than 6 miles (≈10 km) a day, meaning that even a low battery SoC would exceed by far daily driving ranges (Pasaoglu et al., 2012). In other words, for the majority of drivers, there is no reason to prefer immediate charging over smart charging in most occasions (Beaufils and Pineau, 2019; Pearre et al., 2011).

Behavioural insights on cognitive misperceptions and biases associated with suboptimal information provision can provide the foundation of novel evidence-based behavioural interventions. This notion is supported by a growing body of literature on the concept of choice architecture design, illustrating that theory-guided changes in the decision context can result in more personally and societally beneficial decision outcomes (Beaufils and Pineau, 2019; Huber et al., 2019; Kara et al., 2015; Momsen and Stoerk, 2014; Pichert and Katsikopoulos, 2008). Most relevant for our research, the concept of *attribute translation* refers to the notion that expressing the same information in an alternative way by emphasising highly correlated, but still different aspects of the decision attribute, facilitates the correct use and integration of this piece of information, resulting in more desirable decisions (Herberz et al., 2020; Mertens et al., 2020; Ungemach et al., 2018). For example, translating information on the electricity consumption of household appliances from kWh into an energy consumption rating increased attention towards energy-efficient options as well as energy-efficient choices (Mertens et al., 2020).

Inspired by the concept of *attribute translation,* in our study, we examine the impact of changes in battery SoC information on smart charging choices. Specifically, we controlled for the effect of an alternative way of battery SoC information presentation already applied in practice (*Miles* condition) and tested the effect of a novel tailored way to present battery SoC information (*Tailored* condition). First, we translated battery SoC information from a percentage into the remaining driving range in miles (*Miles* condition). We expected that providing the SoC in miles (*Miles* condition) increases evaluability of the information compared to percentage information, and, therefore, the extent to which the information is accurately integrated into the decision-making process. Drivers are familiar with miles as it is the default unit for distance in the UK, where our study took place. Higher familiarity with an attribute unit has been associated with higher evaluability (Herberz et al., 2020; Lembregts and Pandelaere, 2013). Thus, we hypothesise that:

H2a. Providing information on EV battery SoC in miles that can be covered by the battery SoC (*Miles* condition) increases the likelihood that participants choose smart charging compared to the *Control* condition.

Furthermore, we translated the percentage of battery level into how many working days individuals could drive without charging the EV based on their personal driving profile (*Tailored* condition). We expected that providing personal information on covered working days facilitates accurate decision-making further, as this information provides a direct comparison of battery SoC information with drivers' personal demand. This translation does not only provide highly evaluable information about the remaining EV range, but also indicates whether this range is sufficient to cover one's individual demand for the upcoming trips. Additional support for the effectiveness of this translation can be found in the literature from the health domain in which tailored interventions are defined as customised information, for instance, provided in communication material (see Noar et al., 2007, for a review). First results suggest that tailored information is also an effective means to promote pro-environmental behaviour (Abrahamse et al., 2007; Ahmed et al., 2020; Wang and Sun, 2018). Thus, we formalise the following hypothesis:

H2b. Providing information on EV battery SoC in working days that can be covered based on drivers' personal driving profile (*Tailored* condition) increases the likelihood that participants choose smart charging compared to the *Miles* and *Control* condition.

We further aimed to investigate the mechanisms underlying

intervention effects. We expected individuals' driving profile to moderate the effect of translations on charging decisions. The more an individual uses the car, the more battery SoC information should play a determining role in their charging decisions (Will and Schuller, 2016). Individuals who drive many miles a day need to make sure that postponing the charging process will not lead to insufficient battery levels. On the contrary, for individuals who drive only a few miles a day, battery SoC information should play a minor role in the charging decision, as the possibility to run out of battery is very low (Beaufils and Pineau, 2019; Brook Lyndhurst Ltd, 2015; Pasaoglu et al., 2012; Pearre et al., 2011). We expected the battery SoC translations provided here to assist drivers in making more accurate judgments in line with their actual driving profile. Specifically, the translations should affect the weight participants assign to the battery SoC as a function of their actual driving demand. These assumptions lead to the following hypothesis:

H3. The presence of translations of the battery SoC information (*Miles*, *Tailored*) affects the importance allocated to the battery SoC information based on individuals' actual driving profile. The fewer individuals drive, the more the translations decrease the importance allocated to the battery SoC information – especially in the *Tailored* information condition.

The UK was selected as the target country to test our hypotheses, as it is a country with a relatively high uptake of EVs and charging infrastructure (IEA, 2021; Wills, 2020). Furthermore, the UK government has the explicit ambition to incorporate smart charging based on user preferences in the build-up of charging infrastructure to be able to handle the charging demand of the projected 15 million EVs on the road in 2030 (ofgem, 2021), making our policy recommendations directly relevant to UK.

3. Methodology

The online study was based on a 2 (study wave: baseline/experimental) X 3 (condition: *Control, Miles,* and *Tailored*) mixed experimental design (see Fig. 1). In both study waves (baseline/experimental phase), respondents completed a charging choice task in which they decided whether they would choose immediate or smart EV charging in a series of charging scenarios. In the choice task, participants made a total of 21 charging choices (immediate vs smart charging) based on a full-profile conjoint analysis. In Wave 1 (baseline), the information provided was identical for all participants. In Wave 2 (experimental phase), the information provided on the battery SoC was experimentally manipulated (battery SoC information condition: *Control, Miles,* and *Tailored*). The *Control* condition was identical to Wave 1. In the *Miles* and *Tailored* conditions, we added a translation of battery SoC information into miles and working days covered by the battery SoC, respectively (see Section 3.4 for more details).

3.1. Participants

We recruited participants on Prolific Academia (online survey platform) with a minimum approval rate of 90%. Participants received 2£ in total (Wave 1, 7–10 min: 80p; Wave 2, 7–10 min: 80p; Bonus for completing the entire study: 40p). A power analysis for a repeated measures ANOVA (3 x 2 mixed design), with a within-between factor interaction (effect size Cohens's $d = 0.1$, $\alpha = 0.05$, and power = 0.80) suggested a sample size of 246 respondents. Based on the research design including two waves and 21 choice measurements for each wave, the actual power is supposed to be higher than 0.80 reported above. To define the sample size at Wave 1, we accounted for a 25% dropout rate as estimated by the participants' recruiting platform (i.e., Prolific), as well as for our defined exclusion criteria, namely a) people who are not interested in smart charging, and b) people who indicate to drive 0 miles per day. We thus recruited 400 respondents at Wave 1.

Respondents were required to have a driving license (215 respondents) or to be in the process of obtaining it (7 respondents) as prescreening criteria. Selecting potential drivers provides first insights into overall preferences for smart charging in a population that will be most likely to have the opportunity to use the technology in the future.

Four hundred and eight respondents completed Wave 1, which was launched and ended on August 6, 2020. We excluded 23 respondents that failed more than one out of four attention checks and respondents who reported difficulties in completing the charging decision task. Attention checks were added after the provision of information on smart charging before the charging task (see Section 3.2) to ensure that participants understood the basic principles of smart charging (e.g., "Based on what you just read, which charging strategy does usually use higher % of renewable energy?"). Moreover, to increase ecological validity of the study, only respondents that used their car regularly were examined. Overall, 81 respondents reported driving 0 miles on a working day and were thus excluded. Finally, only individuals who were interested in smart charging systems completed the charging decision task at Wave 1 and 2. Respondents who answered, "No, I'd not be interested in a smart charging system and I CANNOT think of any circumstances that might change my mind" (n = 23), were automatically excluded from the choice tasks (Wave 1 and 2).

Of the 271 eligible respondents, 206 completed Wave 2 between October 14 and October 25, 2020. In Wave 2, we discarded six participants that failed more than one attention check and one participant that reported and confirmed to drive 5000 miles a day. The final sample size of participants was N = 222 (138 female). For the analyses of the full-profile conjoint results, the sample size was N = 199, as 23 respondents were not interested in smart charging systems (Fig. 1).

Demographics. Participants' mean age was 37.6 and ranged from 18 to 76 years. Fourteen participants were students, 142 worked full-time, 36 worked part-time, 1 was a caregiver, 9 were homemakers, and 11

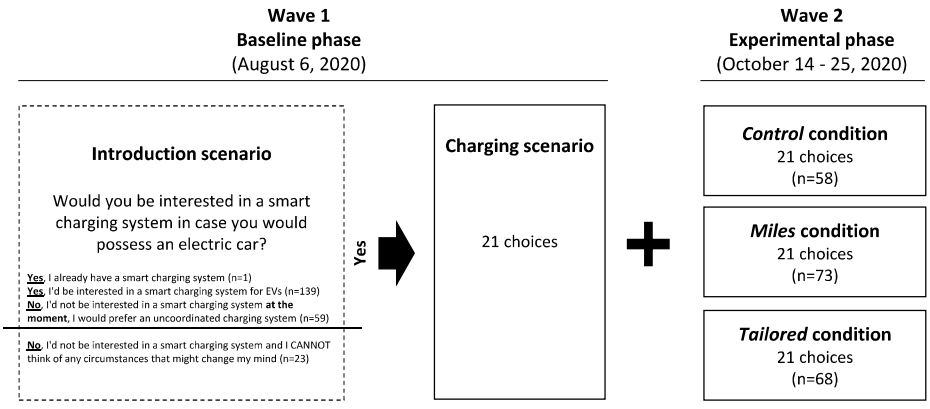

Fig. 1. Schematic design of the online two-wave choice experiment. Information on the subsamples (n) is based on the final sample size.

were unemployed. On average, participants' yearly household income was 40,000£ to 45,000£ (SD = 15,000£; 12 participants preferred not to answer). Also, 33% of participants had no college degree. The rest of the participants had an associate, bachelor, master, doctoral or professional degree (see the Supplementary Material for detailed demographic information). Following the same classification of political orientation as Lammers and Baldwin (2018) (2 items; Cronbach's alpha, α = 0.826), 49.3% of participants were self-identified liberals (combined political orientation score lower than the midpoint), 15.8% were centrist (at the midpoint), and 34.9% were conservative (above midpoint). Seven participants preferred not to answer any of the two questions on political orientation. Moreover, no differences in demographic variables between experimental conditions were observed (see the Supplementary Material, Table SM6-SM7 for descriptive statistics and Table SM8 for the corresponding ANOVA results). However, we could observe differences between our sample and the population of UK drivers (see Supplementary Material, Table SM5 for the comparison details).

Driving-related information. On average, participants have been driving for eight years (SD = 3.25). Twelve participants had no conventional car, 175 had one car, and 35 had two cars or more. Seven participants had a hybrid (no plug-in) car, two had a plug-in hybrid car, and two had a full electric car that they drove for a year or less.

As we collected our data during the COVID-19 pandemic and mobility has been dramatically affected by the crisis (IEA, 2020b), we accounted for pandemic effects on mobility by measuring self-reported driving behaviour at three different points in time; past (before COVID-19), present, and future driving behaviour (as suggested by Fell et al., 2020; see Supplementary Material for the questions formulation and detailed results). Participants reported the value in miles. For computation of the tailored SoC information (i.e., days covered by SoC based on personal driving profile), we used participants' reported future driving behaviour at Wave 2, i.e., expected driving behaviour in one year after data collection (18.88 miles, SD = 18.70).

3.2. Charging scenario

In Wave 1, we first measured a series of driving-related questions (see Supplementary Material, Table SM1 for the questions and corresponding results). Then, we provided general information on smart charging systems and subsequently asked respondents to report their interest in such a system as well as the main goals they would aim to pursue with smart charging (Huber et al., 2019; Schmalfuß et al., 2015; Will and Schuller, 2016). Specifically, we measured to what extent it was important for respondents to use smart charging for a) maximising the share of renewable energy in the battery, b) minimising the costs of charging, and c) reducing the stress on the grid by charging at off-peak times on a 7-point scale ranging from 1 = "Not important at all" to 7 = "Extremely important" (see Supplementary Material for related results).

After reporting smart charging goals, we asked respondents to envisage having purchased an EV as well as a smart charging system, and we explained that the upcoming decision task (full-profile conjoint analysis) was meant to configure their smart charging system (see Huber et al., 2019 for a similar approach) (Fig. 1). The configuration involved the decision of charging an EV in an uncoordinated way (immediate charging) or by means of smart charging (i.e., cost/energy/grid optimised) under various conditions (see Fig. 2 for an example). Prior to the task, each attribute provided in the charging scenario was described in detail.

In Wave 2, we tested a behavioural intervention to increase the number of smart charging choices (see Section 3.4). In Wave 2, the study structure was identical to Wave 1, but respondents were randomly assigned to one of the three experimental conditions (see Fig. 1 and Section 3.4 for more information).

3.3. Charging attributes

We used a conjoint analysis with a traditional full-profile design to test our hypotheses. We programmed the study on Sawtooth Software Lighthouse Studio 9.8.1. To balance statistical and informant efficiency (Orme, 2010), respondents made 21 choices (charging scenarios) in randomised order (see Fig. 2 for an example of Wave 1 and the *Control* condition of Wave 2). The charging scenario was determined by a randomised combination of the attribute levels. Specifically, we selected five attributes and the corresponding attribute levels based on the

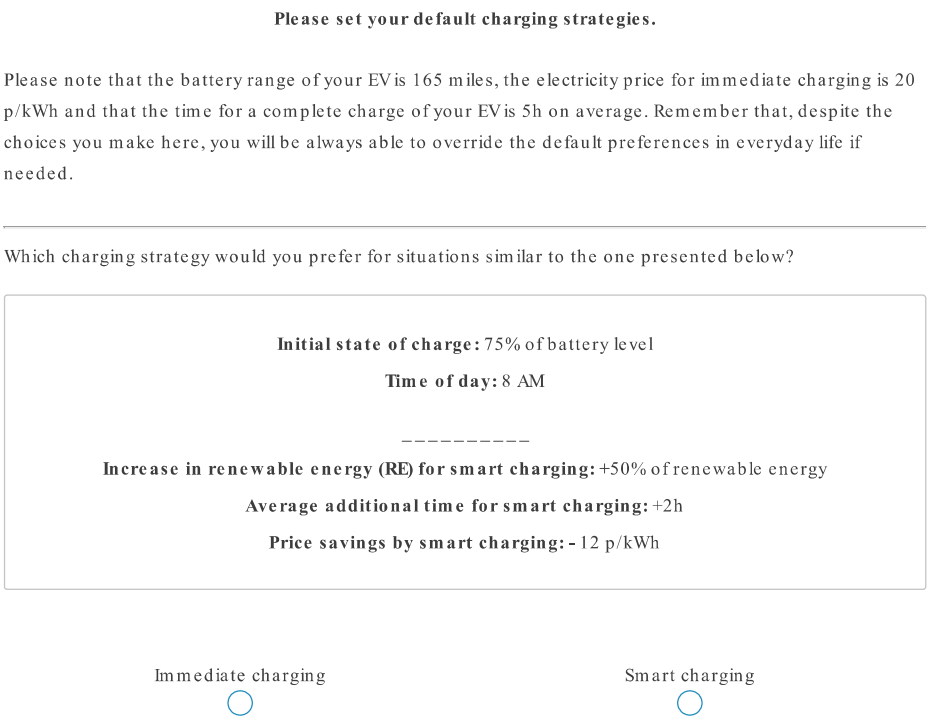

Fig. 2. Example of the charging choice task (Wave 1 and Wave 2 *Control* condition).

information observed in practice and provided by the literature (Bailey and Axsen, 2015; Delmonte et al., 2020; Jian et al., 2018; Kara et al., 2015; Wang et al., 2016). Table 1 depicts the five attributes and the corresponding attribute levels used in the charging decision task. Specifically, two attributes were referring to the given decision situation: battery SoC of the EV and the time of day. Moreover, three attributes were providing information on how smart charging would impact the charging process: increase of charging duration, increase of the amount of renewable energy, and decrease of charging costs due to smart charging.

3.4. Translations of battery SoC information

In Wave 2, we tested the effect of two translations of battery SoC information (*Miles* and *Tailored*) on charging decisions i.e., the amount of chosen smart charging choices. In the *Miles* condition, we provided information on the remaining driving range in miles in addition to information on battery SoC in percentage, based on average EV performance. We specified that the battery range of the EV was 165 miles, thus we computed the corresponding available miles for the three percentages of battery SoC selected (see Table 1).

In the *Tailored* condition, we provided personalised information on the battery SoC by indicating how many working days participants could drive with the remaining driving range. We used individually self-reported information on the daily driving distances to provide each participant with a tailored value based on their driving profile, i.e., remaining driving range in battery divided by individual average daily driving distance (see Table 1).

3.5. Analyses

Determinants of drivers' charging decisions. To test H1, we analysed stated preferences towards smart charging in Wave 1. The full-profile conjoint results allowed estimating how the different attributes affected the decisions in the choice (i.e., attribute utilities and attribute importance). Whereas utilities refer to the impact of the levels of a given attribute on choices, relative attribute importance refers to the weight of a given attribute in the decision process, considering the entire set of attributes. For the estimation of utilities, a Hierarchical Bayesian estimation was applied. Part-worth utilities reveal, for each attribute, the extent to which participants preferred one attribute level over others (Orme, 2010). The utilities are zero-centered, such that "the total sum of the differences in utility between the worst and best levels of each attribute across attributes is equal to the number of attributes times 100" (Sawtooth Software, 2007, p. n.a.). Moreover, the least preferred level is used as a reference level, which always has negative utility. For the relative importance estimation, the range of part-worth utilities for each attribute was divided by the total utility range for all attributes and multiplied by 100 (Moser et al., 2015). We tested whether the importance assigned to the five attributes in the charging task was significantly different. Moreover, we tested for differences in attribute levels within attributes using extracted utility values.

Attribute translations and charging decisions. To test H2a-b, we examined the extent to which attribute translations influenced charging choices. To this end, we ran a multilevel logistic regression model that estimated the probability of choosing smart charging in the absence and presence of attribute translations. In the model, wave and attribute translation served as factors and charging choice as the dependent variable. To account for the repeated measures design of the charging task (21 decisions) and individual differences in charging preferences, we specified in the model a random effect for the task (i.e., the specific attribute combination of each charging scenario) and subject, respectively. In follow-up models, we added self-reported charging goals, demographics (i.e., age, gender, income, and political orientation), and driving-related information (i.e., driving experience in years and expected driving behaviour) as covariates to the model.

The effect of attribute translations on attribute importance. To test H3, we investigated the moderating role of personal driving behaviour (individual daily driving distance in a working day) on the effect of attribute translations on the importance allocated to the battery SoC attribute. To this end, we ran a linear regression analysis with the importance of the battery SoC attribute at Wave 2 as the dependent variable and attribute translation, driving behaviours, and their interactions as predictors. To isolate the effect of attribute translations, we further controlled for the importance of the battery SoC attribute at Wave1 by adding the variable to the model. We tested for simple effects for the significant interaction between *Tailored* translation and driving behaviour. We reported the effect at two focal values, i.e., the 25th and 75th percentiles, of driving behaviour (Spiller et al., 2018).

4. Results

4.1. Determinants of drivers' charging decisions

We inferred participants' preferences for smart charging based on the choices they made in the charging decision task in Wave 1 (baseline without attribute translations). Participants' choices reflected a positive attitude toward smart charging. On average, participants decided to use smart charging 67.28% of the time. Fig. 3 displays the frequencies of choosing smart charging over immediate charging across the 21 decisions in the full-profile conjoint task in Wave 1.

Analyses of attribute importance (cf., Table 1 for attributes) revealed

Table 1
Full-profile conjoint analysis attributes specification and translations.

Attribute	Attribute levels		
Initial state of charge Wave 1 and Wave 2: *Control*	25% of battery level	50% of battery level	75% of battery level
Translation (Wave 2): Miles	25% of battery level = covering **41 miles without charging**	50% of battery level = covering **82 miles without charging**	75% of battery level = covering **124 miles without charging**
Translation (Wave 2): Tailored	25% of battery level = covering [41 miles/(daily driving distances)] **working days without charging** (based on your driving profile)	50% of battery level = covering [82 miles/(daily driving distances)] **working days without charging** (based on your driving profile)	75% of battery level = covering [124 miles/(daily driving distances)] **working days without charging** (based on your driving profile)
Time of day:	8 a.m.	6 p.m.	12 a.m.
Increase in renewable energy (RE) for smart charging:	+0% of renewable energy	+25% of renewable energy	+50% of renewable energy
Average additional time for smart charging:	+2h	+4h	
Price savings by smart charging:	−0 p/kWh	−6 p/kWh	−12 p/kWh

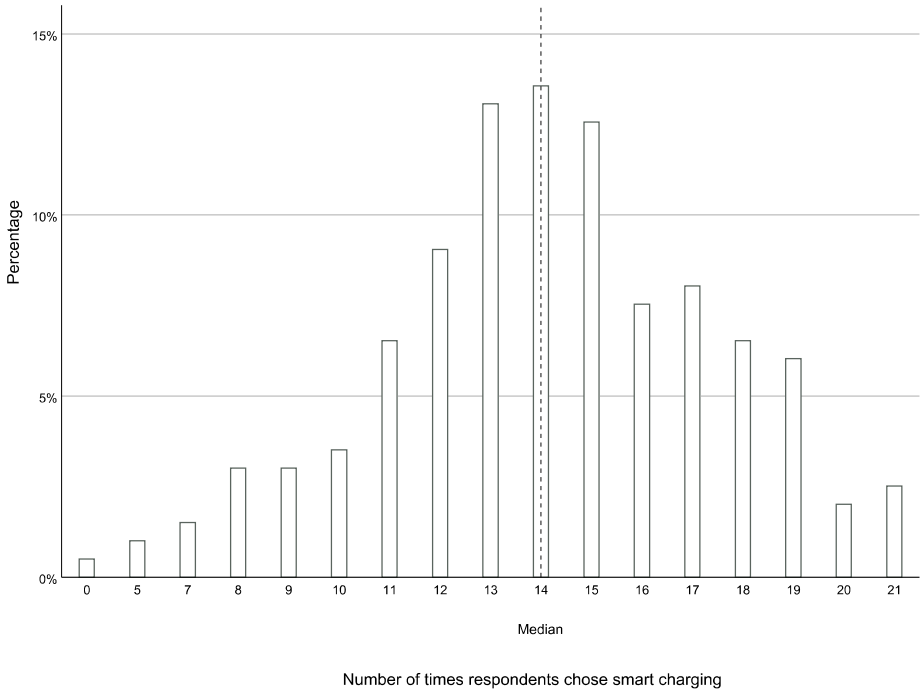

Fig. 3. Frequency distribution of the number of smart charging choices in Wave 1 (percentage). The maximum value is 21 choices.

Table 2
Average relative importance of attributes in the charging decision task and their standard deviation at Wave 1.

Attribute	Importance	Standard deviation
Time of day	27.73%	19.47*
Price savings by smart charging	25.15%	17.81*
Initial state of charge	24.01%	15.42*
Increase in renewable energy (RE) for smart charging	15.71%	11.03
Average additional time for smart charging	7.40%	5.83
Total	100.00%	

*Notably, these three attributes have a high standard deviation, meaning that the importance attributed to these attributes varied greatly among participants.

that the time of the day, price concerns and the initial SoC were the most important attributes (see Table 2); paired-samples tests showed no statistically significant differences between these attributes. The importance of the initial SoC was not significantly different to price ($t(198) = -.58$, $p = .564$) and time of the day ($t(198) = -1.83$, $p = .069$). In line with H1, the amount of renewable energy guaranteed by smart charging and the average additional time needed for smart charging played a significantly smaller role in participants' charging choices than battery SoC information (i.e., $t(198) = 5.84$, $p < .001$; and $t(198) = 13.98$, $p < .001$ respectively, see Table 2).

We then looked at part-worth utilities for each attribute level. Fig. 4 illustrates the results of the part-worth utilities for each attribute across respondents (see Supplementary Material for the results of independent t-tests comparing attributes levels). Variation in *battery SoC* significantly impacted charging choices. Compared to the reference level (i.e., the least preferred attribute level) of 25% SoC, participants preferred smart charging to immediate charging significantly more at 75% SoC, and 50% SoC. Moreover, participants preferred smart charging to immediate charging significantly more at 75% SoC compared to 50% SoC. Moreover, variation in *time of the day* significantly impacted charging choices: compared to the reference level of 8AM, participants preferred smart charging to immediate charging significantly more at 6PM, and at 12AM. Moreover, participants preferred smart charging to immediate charging significantly more at 6PM than at 12PM. Furthermore, variation in the *increase in renewable energy* significantly impacted choices: compared to the reference level of 0% increase in renewable energy (RE) for smart charging, participants preferred smart charging over immediate charging significantly more for 25% increase in RE, and 50% increase in RE. However, there was no difference in charging choices between 25% and 50% increase in RE. Moreover, variation in the *additional time* needed for smart charging, however, did not impact choices: participants opted for smart charging over immediate charging similarly when the estimated additional time for smart charging was 2 h and 4 h. Finally, variation in *price savings* for smart charging impacted choices: compared to the reference level of 0p/kWh savings for smart charging, participants preferred smart charging over immediate charging significantly more when they could save 6p/kWh and 12 p/kWh. However, there was no statistical difference in charging choices between 6 and 12 p/kWh savings.

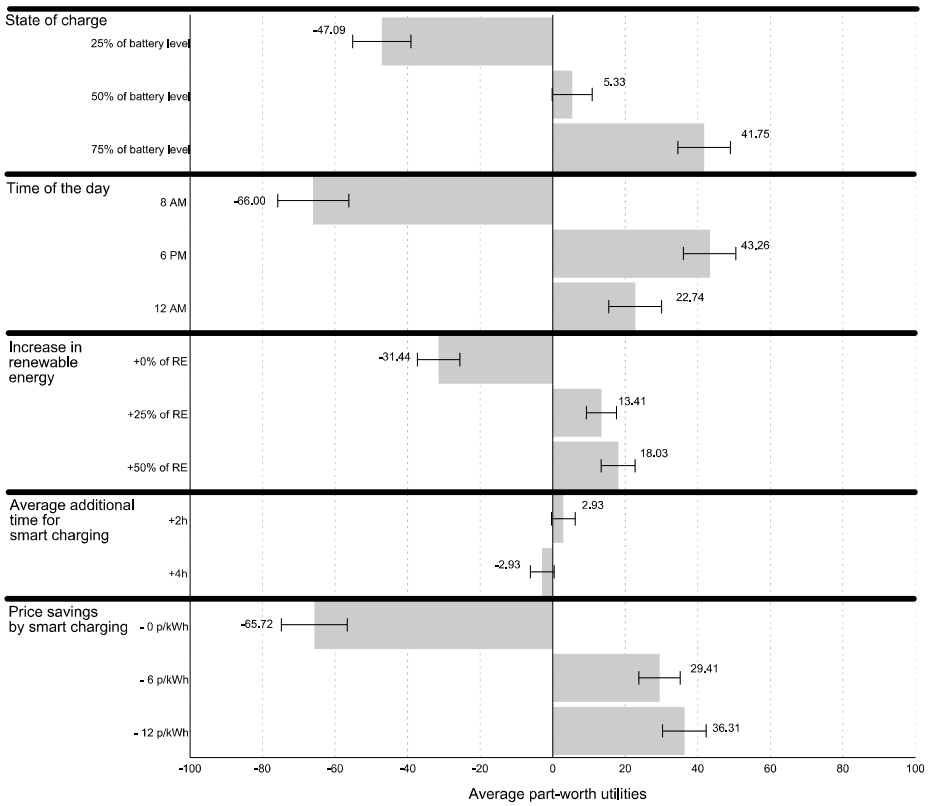

Fig. 4. Average part-worth utilities for all attributes and attribute levels at Wave 1. The part-worth utilities within an attribute sum to 0 (zero-centered). The least preferred levels served as reference with negative utilities. Error bars depict 95% confidence intervals.

4.2. Translations of SoC information and charging decisions

Next, we tested whether translations of battery SoC information increased smart charging choices (H2a-b). Across conditions, the proportion of choices to use smart charging increased from 67.28% at Wave 1 to an average of 71.05% at Wave 2. However, as illustrated in Fig. 5, there was a significant interaction of wave and attribute translation on smart charging choices ($\chi 2 = 9.38$, $p = .009$ (ANOVA Type 2), see Supplementary Material, Table SM9: Model 1) indicating that the changes across waves were subject to the experimental conditions in Wave 2. In the *Control* condition, participants' choices were consistent across Wave 1 and Wave 2 (OR = 0.98, 95% *CI* [0.80–1.20], $Z = -0.19$, $p = .848$). In the *Miles* condition, however, respondents chose significantly more often smart charging at Wave 2 compared to the baseline at Wave 1 ($OR_{Miles} = 1.34$, 95% *CI* [1.11, 1.61], $Z = 3.06$, $p = .002$), thus supporting H2a. In the *Tailored* condition, respondents chose, as well, significantly more often smart charging at Wave 2 compared to the baseline at Wave 1 ($OR_{Tailored} = 1.49$, 95% *CI* [1.23, 1.80], $Z = 4.16$, $p < .001$), thus supporting H2b. Specifically, in the experimental phase compared to the baseline phase (battery SoC in percentage) the likelihood that a participant chose smart charging over immediate charging was 1.34 times more likely in the *Miles* condition and 1.49 times more likely in the *Tailored* condition. In the *Control* condition, there was no difference in smart charging choices between the baseline and experimental phase (i.e., OR close to 1).

We then added self-reported smart charging goals (cf., Supplementary Material Table SM9: Model 2), demographics, and driving behaviours (Table SM9: Model 3) as covariates to the model. Results showed a significant effect of the goal to increase the amount of renewable energy on smart charging choice (see Supplementary Material, Table SM9: Model 2; $OR_{Goal:+RE} = 1.23$, 95% *CI* [1.11, 1.37], $Z = 3.88$, $p < .001$). The more participants aimed to increase the amount of renewable energy used for driving, the more they chose smart charging compared to immediate charging. The remaining goals did not significantly affect smart charging choices. When controlling for charging goals, demographics and driving behaviours, the interactions between wave and *Miles* and *Tailored* conditions remained significant (see Supplementary Material, Table SM9: Model 3: $OR_{Miles} = 1.36$, 95% *CI* [1.03, 1.81], $Z = 2.14$, $p = .032$; $OR_{Tailored} = 1.53$, 95% *CI* [1.15, 2.04], $Z = 2.94$, $p = .003$).

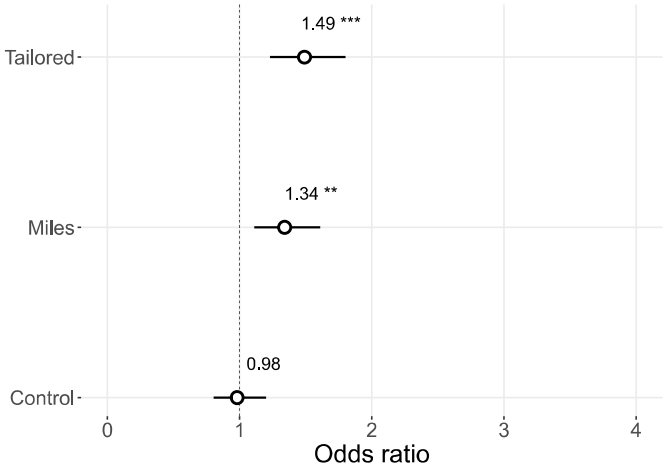

Fig. 5. Effect of attribute translations on smart charging choice. Odds ratios reflect changes in smart charging choices between Wave 1 and Wave 2 as a function of experimental condition. Error bars depict 95% confidence intervals, ** p< 0.01, *** p< 0.001.

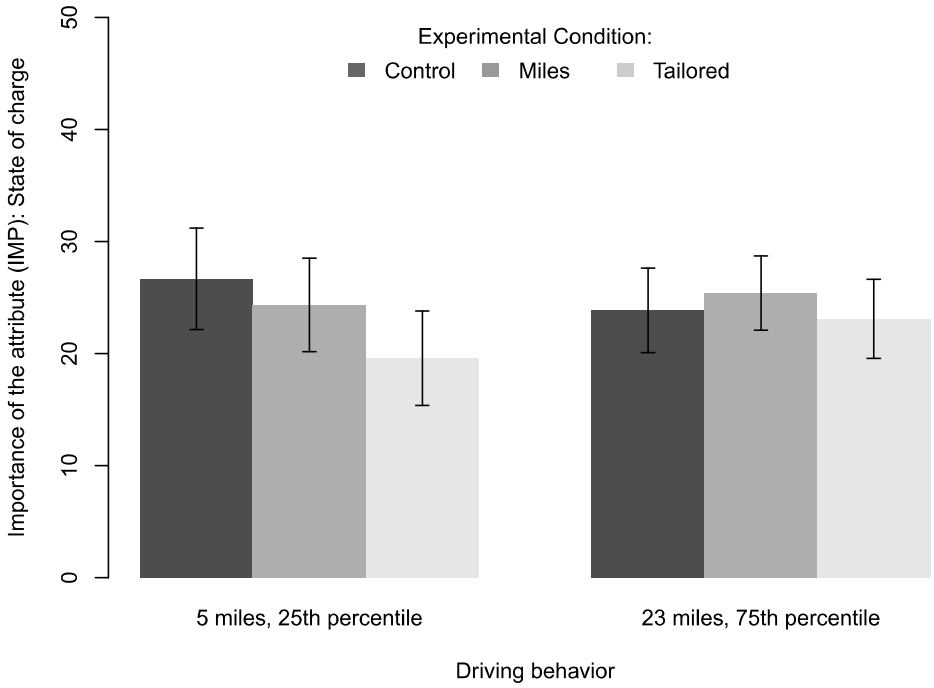

Fig. 6. Moderating effect of individual driving behaviour ("How many miles do you expect to drive on a typical working day in a year from now?") on the effect of battery SoC information the on importance allocated to the *state of charge* attribute at Wave 2. Error bars depict 95% confidence intervals.

4.3. The effect of SoC information translations on attribute importance

Finally, we tested whether attribute translations affected the importance of decision attributes in addition to actual choices and whether this effect was moderated by participants' driving behaviour (H3) (cf., Supplementary Material, Table SM10: Model 4). The main effect of *Tailored* condition was significant ($b = -8.84$, $p = .015$, 95% *CI* [−15.93, −1.75]) in that individuals in the *Tailored* condition overall allocated significantly less importance to the battery SoC information than respondents in the *Control* condition when making the charging choice.

In line with H3, this effect was qualified by a significant interaction between the *Tailored* condition and driving behaviour ($b = 0.35$, $p = .011$, 95% *CI* [0.08, 0.62]), indicating that tailored information only decreased the importance of battery SoC information for drivers covering short driving distances. Fig. 6 illustrates the average importance of the initial state of charge attribute at 25th and 75th percentiles of covered driving distance for each condition. Analysis of simple effects shows that when participants only covered short distances (25th percentile, average daily driving = 5 miles), the *Tailored* translation significantly decreased the importance allocated to battery SoC information compared to the *Control* condition ($b = -7.08$, $p = .026$, 95% *CI* [−13.29, -.87]). That is, in the *Tailored* condition, drivers who covered only short distances assigned relatively little weight to battery SoC information, in line with their restricted driving behaviour. In the *Control* condition, however, those drivers did not adapt the weight assigned to the battery SoC information to their driving behaviour. Instead, when participants covered relatively long distances (75th percentile, average daily driving = 23 miles) there was no significant difference between the *Tailored* condition and the *Control* condition ($b = -0.75$, $p = .777$, 95% *CI* [−5.94, 4.34]). That is, when drivers covered long distances, the weight they assigned to battery SoC information in the decision process was relatively high, independent of the experimental condition. Under this condition, assigning high relevance to battery SoC information is in line with individuals' intensive driving behaviour and the associated need to assure high battery SoC.

Moreover, there was no main effect of the *Miles* condition ($b = -3.40$, $p = .332$, 95% *CI* [−10.30, 3.50]) nor an interaction effect of the *Miles* condition and driving behaviour on choices ($b = 0.22$, $p = .092$, 95% *CI* [−0.04, – 0.47]). Additionally, the main effect of driving behaviour was not significant ($b = -.16$, $p = .096$, 95% *CI* [−0.34, −0.03]) indicating that, in the absence of *Tailored* information, participants assigned similar importance to battery SoC information independent of their actual driving behaviour. Finally, the main effect of the covariate battery SoC attribute importance at Wave 1 was significant ($b = 0.31$, $p < .001$, 95% *CI* [0.18, 0.44]), meaning that the more respondents allocated importance to the battery SoC information at Wave 1, the more they did at Wave 2.

5. Discussion

Smart charging is a promising technology to reduce costs and CO_2 emissions associated with EV charging as well as to reduce stress for the grid resulting from intensified electricity demand (Hossain et al., 2016; Jian et al., 2018). To tap the full potential associated with smart charging, however, future users should engage in smart charging schemes. In a randomised-controlled online experiment with two waves (baseline and experimental phase), we examined drivers' charging decisions and the underlying processes in the context of EV smart charging. Our analysis shows that participants chose smart charging over immediate charging in 67.28% of choices in the baseline phase. However, given the relatively short daily driving distances it is indicated that using smart would have been a viable option in most occasions (~100% of the times). Moreover, respondents assigned high importance to battery SoC information when making charging decisions, independent of their actual driving behaviour (H1). That is, even drivers covering short daily distances based their decisions to a large extent on the battery SoC at the point of decision-making, even though the available range would be sufficient to cover their actual demand.

Our findings corroborate previous research demonstrating that laypersons tend to misjudge energy information as it is often presented in units about which they have limited knowledge (e.g., kWh, percentages of battery level). As a consequence, laypersons are likely to refer to simplified information and cognitive shortcuts in their decision-making

(Cowen and Gatersleben, 2017; Herberz et al., 2020; Marghetis et al., 2019; Mertens et al., 2020; Pichert and Katsikopoulos, 2008; Schley and DeKay, 2015). The high importance assigned to battery SoC is moreover in line with previous research highlighting the role of range concerns in EV-related decisions and the potential decision biases derived from these concerns (Charilaos et al., 2017; Franke et al., 2012a). In agreement with the previous literature, we observed that respondents' decisions were primarily driven by the goal of having the car fully charged as fast as possible (Delmonte et al., 2020; Huber et al., 2019). As a consequence, most drivers overestimated the importance of battery SoC information, which resulted in inefficient charging decisions for them and the overall power system.

We assumed that battery SoC information expressed in percentage contributed to this misalignment between actual driving behaviour and the relatively high relevance assigned to battery SoC information. In line with the choice architecture literature (Beaufils and Pineau, 2019; Huber et al., 2019; Kara et al., 2015; Momsen and Stoerk, 2014; Pichert and Katsikopoulos, 2008), providing more evaluable information in miles (H2a), and especially tailored information on the individual working days covered by the battery SoC (H2b), supported respondents to make decision that are more in line with their actual demand, resulting in a higher amount of smart charging choices. According to our Hypothesis 3, the effect of this tailored battery SoC information was particularly pronounced for drivers who drive short distances in their everyday life (H3). That is, the behavioural intervention specifically addressed the target group of drivers that should be less concerned by the battery SoC due to their restricted driving behaviour. However, a better understanding of the SoC information did not increase the selection of smart charging choice for individuals who instead drive long distances regularly, as smart charging may indeed be incompatible with their mobility needs.

Our intervention seem to facilitate two cognitive steps that are required to transform battery SoC information in percentage into evaluable information in the decision process. In the first step, percentage information needs to be translated into available range, which needs, in the second step, to be compared with one's actual demand. In line with our hypotheses, we observed that facilitating both steps by means of range and tailored information could increase smart charging choices, with stronger effects in the *Tailored* condition. Whereas range information is already displayed in various existing EVs, tailored battery SoC information could be likewise implemented with little effort in practice. Data on daily driving patterns could be accessed and communicated to the smart charging system, which then translates battery SoC information into tailored information. Whereas the effect size of our intervention may appear relatively small and the increase in smart charging decisions between the intervention phase (Wave 2) and the baseline (Wave 1) were only slightly higher in the *Tailored* condition as compared to the range (*Miles*) condition, scaling up this low-cost intervention to the general population could result in significant positive impacts on energy costs, renewable energy usage, and grid stability.

Our research also has limitations that can point to new avenues for future research. First, we did not limit our study to EV users but targeted a broad spectrum of drivers, as we aimed to provide first insights on overall preferences for smart charging in the population and thus on the potential of this technology on a large scale. However, due to this choice we were not able to analyse how actual EV experience influences the charging decision. For example, it could be expected that the observed strong assigned importance to battery SoC information as observed here decreases with EV experience (Franke et al., 2012b; Krems et al., 2010). Even though the large importance assigned to battery SoC may dilute with experience, the found overreliance on associated information can nevertheless be considered relevant for the success of smart charging, as charging habits are most likely to be formed in the early stages after technology adoption (Alós-Ferrer et al., 2016).

Second, we are aware that the external validity of our results is influenced by the scenario-based setup of our study. However, as the current number of EV drivers and especially the number of available smart charging systems is still limited, an analysis of drivers' decisions in the field with actual EV drivers and smart charging systems was not possible at this stage. We think that our results can nevertheless provide an empirical basis for future research on choice architecture design and smart charging based on field trials.

Third, we acknowledge that the way we presented the charging scenarios may have affected participants' choices. By highlighting how smart charging performs in comparison to immediate charging, it is possible that we draw attention toward the smart charging option and thus increased the subjective value of this option. As a result, it is conceivable that smart charging choices would even be lower under conditions where benefits of this option are less salient. We think it would be an interesting research avenue to investigate more systematically whether and how the framing of EV charging attributes influences drivers' charging decisions.

Fourth, the long-term consequences of the COVID-19 crisis on mobility behaviour are uncertain, and changes in mobility behaviour might influence the potential for EV smart charging. A decrease in car (or EV) trips due to, for example, an ongoing popularity of home-working could increase the attractiveness of smart charging, as drivers would have to worry less about the battery charging level. However, a low demand for charging would also lead to little flexibility offered by EVs, unless the charging infrastructure also allows the discharging of EV batteries to deliver energy management services, known as vehicle-to-grid. In contrast, an increase in car trips due to ongoing concerns that public transportation may increase the risk of infection, could decrease the attractiveness of smart charging. This scenario would increase the importance for grid operators to avoid large peaks in charging demand, for instance in the early evening when people return from work. Finally, changes in commuting patterns will also determine the extent to which flexibility could be offered during office hours in work areas and residential areas, respectively. Smart charging could play an important role in all these scenarios, but user preferences could significantly differ depending on the evolution of mobility behaviour in the coming months and years.

6. Conclusion and policy implications

EVs play an important role in energy transition strategies worldwide (IEA, 2020a; Rietmann et al., 2020). Uptake of EVs, however, needs to be coupled with optimised usage of renewable energies for charging and a grid-friendly integration of the technology (Hossain et al., 2016; Jian et al., 2018; Kara et al., 2015). Smart charging systems can contribute to these objectives but require the participation of the end-user to exploit its full potential. For policymakers, this means that the mere adoption of smart charging systems will not be sufficient to ensure that the technology will contribute to an ecological, economic, and grid-friendly integration of EVs.

In line with the literature on choice architecture (Beaufils and Pineau, 2019; Huber et al., 2019; Kara et al., 2015; Momsen and Stoerk, 2014; Pichert and Katsikopoulos, 2008) and tailored interventions (Abrahamse et al., 2007; Ahmed et al., 2020; Wang and Sun, 2018), our research illustrates that low-cost and low-invasive behavioural interventions have the potential to increase smart charging usage and thus could serve as an important instrument to support the effective implementation of the technology. Specifically, policy makers could develop guidelines not only on what information should be displayed to EV smart charging users but also on how this information should be presented. Similar to common practice with electricity appliances in many countries, governments could require car manufacturers and charging point operators to provide users with transparent and user-friendly information. For example, the UK government already highlighted its intention to "coordinate with the Electric Vehicle Energy Taskforce and industry to make sure that users have access to the right information and advice to choose the right goods or services for their needs, and to get products

set up in line with their preferences" (ofgem, 2021, p. 32). Our results can inform the development of such recommendations by illustrating how providing tailored information can increase the usage of smart charging options.

Overall, our results illustrate that individuals are inclined to use smart charging but they seem to have difficulties to understand and integrate the various pieces of information relevant for smart charging decisions; information that may satisfy various conflicting goals. Contrary to assumptions made by the information deficit model (for a discussion, see Suldovsky, 2017), providing users with relevant information alone does not seem to be sufficient to guarantee that they will successfully translate knowledge into behaviour (Owens, 2016). It is essential as well to ensure that users understand the provided information and integrate it into their decision-making process. Choice architecture interventions, and attribute translations in particular, can support users by making pertinent information salient at the point of decision-making and by signalling choice options that best aligns with their personal goals and demands. As supported by our findings, providing tailored information about battery SoC may not only decrease drivers' range anxiety, but also boost users' willingness to provide more temporal flexibility in the charging process, especially for those users who can provide flexibility based on their driving profile. The effect of this intervention is beneficial for securing grid stability, but may also strengthen drivers' confidence towards EV and smart charging systems. Taking these benefits together, leveraging behavioural insights as presented here to increase technological impact and user satisfaction should be of great interest for car manufacturers, policymakers and charging point operators.

The behavioural intervention we proposed could be coupled with classic policy instruments such as financial incentives. In accordance, our decision analysis revealed that cost reduction was among the most important decision attributes. A more in-depth analysis of part-worth utilities, however, showed that a cost reduction from 0 to 6 Cents strongly affected charging decisions, whereas an additional cost reduction from 6 to 12 Cents did not significantly affect choices. In line with previous research, this neglect of the magnitude of benefits indicates that individuals tend to rely more strongly on subjective affect rather than on cognitive calculation-based processes (Hsee and Rottenstreich, 2004). It seems that drivers rather expect some financial benefit of any magnitude to be willing to restrict their freedom by opting for smart charging but are relatively insensitive to gradual price changes. We could observe the same decision pattern for the increase in renewable energy due to smart charging as changes from 0% to 25% strongly affected drivers' decisions. In contrast, changes in the share of renewable energy from 25% to 50% were almost ineffective. This information is highly relevant for the design of smart charging incentive structures. For example, rather than aiming to provide linearly increasing monetary benefits, incentives could be calibrated to the threshold at which users perceive the savings as a significant benefit.

We would moreover like to stress that user engagement in smart charging schemes, as examined here, should be seen as an opportunity to raise awareness, inform, and increase citizen participation in the energy transition rather than as a mere instrument to secure grid stability and increase renewable energy use. In this perspective, a mere automatisation of smart charging choices without user integration is likely to fail and decrease the acceptance of the technology. In accordance, the literature illustrates that people strive to have control over their charging processes and assign high relevance to their individual mobility freedom (Huber et al., 2019; Sintov and Schultz, 2015; Will and Schuller, 2016). Our design thereby may point to a practical and efficient solution in which users configure the systems by setting decision defaults that then become implemented into the charging schedule by the system. In the medium and long term, intelligent algorithms using artificial intelligence could suggest changes in choice patterns, for instance, when set defaults unnecessarily privilege immediate over smart charging.

Future research could also test the effect of setting smart charging as the default option. Although this intervention may be an effective strategy to increase the use of smart charging, our intervention has the added value of making the information more accessible and easier to be understood, while relying on the status quo does not imply any learning effect and builds on a cognitive bias (i.e., status quo bias) rather than increasing competencies of the decision maker (Hertwig and Grüne-Yanoff, 2017). In accordance, the tailored intervention was especially effective for car drivers with short daily driving distances, and thus targeted drivers for which smart charging is most feasible. In contrast, setting smart charging as the default option might overall nudge drivers to use smart charging and in turn could even be risky for drivers who drive long distances and have to rely on high battery SoC.

Overall, our research illustrates how behavioural insights can be leveraged to ensure more effective implementation of technological innovations to push the energy transition forward. Specifically, our findings can help to design smart charging interfaces, develop more effective incentives structures, and point to opportunities to couple behavioural insights with classic policy instruments. Finally, our research illustrates that a successful energy transition needs EV policy design that goes beyond mere investments in technology.

7. Data availability

Data have been deposited in the Open Science Framework (https://osf.io/ajcpy/?view_only=26c03fc31a7941e2941c1fdc8093140e).

CRediT authorship contribution statement

Maria Lagomarsino: Conceptualization, Methodology, Data curation, Formal analysis, Investigation, Writing – original draft, Visualization. **Mart van der Kam:** Conceptualization, Writing – review & editing. **David Parra:** Conceptualization, Funding acquisition, Writing – review & editing. **Ulf J.J. Hahnel:** Conceptualization, Methodology, Supervision, Validation, Funding acquisition, Writing – review & editing.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enpol.2022.112818.

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