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Empirical evaluation of behavioral interventions to enhance flexibility provision in smart charging

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ABSTRACT

The growing adoption of Electric vehicles (EVs) puts pressure on the power grid, and implementing smart solutions can ease this pressure. Smart charging at home is a solution where users offer flexibility in their charging schedule, which energy suppliers and/or other aggregators can exploit by charging during times of low demand and low market prices. However, giving charging control to the energy provider can concern EV users, particularly about driving range, and give a sense of loss of control. We conducted an experimental online survey with EV users (n = 289), examining the effect and perception of different behavioral interventions to improve flexibility provision. We found that all monetary incentives (high, low, credit points) resulted in higher flexibility, while environmental framing, feedback and badges, default-setting, and battery-related tips had no effect. The perception of all behavioral interventions did not correlate significantly with the flexibility offered for any of the interventions.

1. Introduction

Many countries worldwide tackle climate change by aiming to reduce their greenhouse gas emissions (IEA, 2022). One relevant goal is to electrify the transportation sector, where burning fossil fuels contributes a large portion of greenhouse gas emissions. Here, electric vehicles (EVs) have the potential to make a significant impact (IEA, 2022). EV uptake is accelerated by EV-friendly regulations and improved EV range, especially in industrialized countries. The International Energy Agency projects that by 2030, EVs will account for 30% of all vehicle sales globally (IEA, 2022).

This tremendous rise in EVs increases electricity demand. When EVs charge simultaneously, a significant strain is imposed on the power grid (Huber et al., 2019b). Smart charging can help alleviate this issue. Smart charging involves adapting the charging schedule of EVs to both the conditions of the power system and the needs of the EV users (IRENA, 2019). This can drastically reduce the need for expanding grid capacity at both distribution and transmission system levels. As two examples, studies focused on Germany (Schmidt and Busse, 2013) and the United Kingdom (Greenflux, 2020) have illustrated that using smart charging algorithms can move charging to low demand periods and thus mitigate demand peaks.

To make the charging process smart, the EV user must provide charging flexibility to the energy provider. In the case of home charging, which is our focus, this includes leaving the EV plugged in while it is parked, selecting a low power for charging, and a low final state of charge (SOC). The more flexibility the EV user offers, the more the energy provider can charge the EV during periods of no grid congestion. Additional relevant benefits could also exist, such as when charging during periods with low electricity market prices and high renewable energy sources (RES) generation. For the EV user to provide flexibility means relinquishing control over

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when exactly the EV is charged. This lack of control and/or the possibility of having insufficient battery charge for the next trip can concern EV users (Delmonte et al., 2020; Bailey and Axsen, 2015; Libertson, 2022) who may thus be hesitant to provide flexibility.

Encouraging EV users to embrace flexibility (Kubli, 2022), despite any potential risks or discomfort is important. Flexibility provision can be achieved through monetary incentives, nudges and tips (Schuitema et al., 2017; Huber et al., 2019b,a; Huber and Weinhardt, 2018). Incentives are monetary benefits from choosing the desired alternative. In contrast, nudges focus on non-economic benefits. They are "any aspect of the choice architecture that alters people's behavior predictably without forbidding any options or significantly changing their economic incentives" (Thaler and Sunstein, 2008, p.6). It is thus a way to influence people's behavior without issuing prohibitions (e.g., feedback messages on previous energy consumption are supposed to influence future consumption). By tips, we refer to rational advice based on which users can make an informed decision (e.g. tips on what battery percentage is optimal for charging the EV).

Many studies have looked at incentives and/or nudges for smart charging decisions (Will and Schuller, 2016; Huber et al., 2019a; Huber and Weinhardt, 2018; Huber et al., 2019b; Kacperski and Kutzner, 2020; Kramer and Petzoldt, 2022; Kacperski et al., 2022; Ensslen et al., 2018; Verbong et al., 2013; Wong et al., 2023). These studies use different study designs to investigate the effect of incentives and nudges. They often do not consider several incentives and nudges in their study designs, making it difficult to compare their effectiveness.

Moreover, previous studies on these interventions mainly assess either the perception or efficacy, but not both. Studies also did not explicitly *distinguish* between perception and effectiveness. In our study, "perception" refers to how positively or negatively people assess interventions. With "effectiveness", we refer to its effect on people's behavior, in this case, flexibility provision. Effectiveness is typically assessed through experimental designs or real-life observations (Huber et al., 2019a; Kacperski et al., 2022). Perception, in contrast, is commonly measured through qualitative studies or those that do not employ experimental designs (Huber et al., 2019b; Delmonte et al., 2020). As the measurement can influence the outcome, we distinguish between them.

The link between the perception and effectiveness of incentives, nudges, and tips is especially relevant in practice: If incentives, nudges, and tips are viewed favorably but have no actual effect, there is no point in deploying them. For water saving, Tijs et al. (2017) point to a difference: Although people perceived the monetary appeal as most attractive, the environmental appeal was more effective in water saving while showering. Few studies in the smart charging domain look at both perception and effectiveness. Thus, it is uncertain whether the effectiveness of incentives, nudges, and tips is directly related to a positive perception of them.

In an experimental survey design, we investigate the effect of different behavioral interventions, (i) monetary incentives, (ii) nudges, and (iii) tips on flexibility decisions in the context of charging. We aim to identify which incentives, nudges, and tips are most effective in fostering smart charging. These results are particularly interesting for practitioners who aim for (increased) flexibility provision via home smart charging. Also, we investigate for which incentives, nudges, and tips a positive perception is related to a higher flexibility provision. These findings are of particular methodological relevance for consumer researchers designing studies to evaluate the impact of these behavioral interventions. Our research questions are as follows:

RQ1: Which incentives, nudges, and tips lead to a higher flexibility provision in electric vehicle charging?

RQ2: Is a positive perception of incentives, nudges, and tips associated with increased flexibility provision?

In the subsequent section, we discuss the literature surrounding different incentives, nudges, and tips for smart charging and derive our hypotheses. In Section 3, we describe our survey design based on the results of focus groups and the recruitment procedure for participants. In the results Section 4, we analyze if incentives, nudges, and tips lead to a higher flexibility provision and whether this is linked to their perception. This Section also contains an exploratory analysis of smart charging literacy and the minimum required state of charge. Section 5 discusses the survey results, illustrates practical and theoretical implications, and points out limitations.

2. Theoretical background and hypothesis development

So far, academic literature and real-world mobile applications have mainly focused on monetary incentives for smart charging. However, an increasing amount of authors also point to the importance of factors such as the integration of renewables (Will and Schuller, 2016; Huber et al., 2019b). In the study by Will and Schuller (2016), the integration of renewables affected the acceptance of smart charging, while monetary incentives did not. Verbong et al. (2013) even went as far to say that "too much focus on [...] economic incentives can become a barrier". Tarroja and Hittinger (2021, p.1) argued that "non-monetary incentives may be needed to increase smart charging participation". These non-monetary incentives may refer to nudges or tips. This study focuses on the monetary incentives and environmental nudges, which have been identified as the primary motivators for smart charging (Will and Schuller, 2016; Huber et al., 2019b). Additionally, we look at smart charging as a default option, battery-related tips and how the character trait risk aversion influences charging flexibility.

2.1. Monetary incentives

Literature has explored the effects of monetary incentives in various manners. These incentives refer to dynamic pricing schemes and discounts on the final energy bill (Will and Schuller, 2016). During peak periods, electricity prices are at their highest and vice versa during off-peak hours; thus, customers can reduce their electricity bills by shifting their load to off-peak times. The frequency of price variation is dependent on the particular dynamic tariff plan. In specific dynamic pricing systems, tariffs alter hourly or every few minutes to reflect the real-time energy market (e.g., real-time pricing) (Dutta and Mitra, 2017). While in other schemes, the different block rate tariffs are offered to consumers within a period (e.g., time of use, critical peak pricing) (Zhang et al., 2017;

Newsham and Bowker, 2010). A smart charging trial in the UK discovered that by utilizing dynamic tariffs, most of the EV users shifted their charging events to off-peak times (Greenflux, 2020). Another smart charging trial in Canada looked into the influence of dynamic pricing on the charging behavior of users (Goody et al., 2020). They found that, compared to a control group, the dynamic pricing group offered more flexibility and charged their EVs more often in the off-peak period around midnight. However, consumers might only be willing to accept dynamic tariffs if they perceive a significant difference in their final energy bills.

Incentives can also be given directly on the monthly energy bill. Will and Schuller (2016) conducted a survey asking EV users what the minimum discount would be on their electricity bill to participate in smart charging. Surprisingly, the anticipated discount had no notable influence on the willingness to participate in smart charging. Furthermore, in the interview study by Paetz et al. (2012a), EV smart charging was not motivated by cost savings but rather the desire to drive free of emissions.

In addition to reduced tariffs and cheaper electricity bills, incentives could be paid every time EV users allow smart charging, i.e., offer flexibility. Kramer and Petzoldt (2022) conducted an experimental survey where they examined the effect of cost saving on smart charging decisions: Cost savings had a statistically significant effect on the decision to select regular or smart charging for public charging (Kramer and Petzoldt, 2022).

EV users can also be rewarded with monetary incentives for participating in a smart charging program. Wong et al. (2023) conducted a survey and found that monetary incentives increased the interest to participate in a smart charging program for EV owners/lessees and EV interested buyers/lessees. Delmonte et al. (2020) conducted interviews with actual and potential EV users. Also, here, the EV users' willingness to participate in smart charging programs was related to reduced charging costs.

Overall, studies have differing results on the effectiveness of monetary incentives for smart charging. These discrepancies could be due to the different study designs and operationalizations of monetary incentives. However, as most studies state that monetary incentives lead individuals to participate in smart charging programs, we hypothesize:

H1: Monetary incentives lead to a higher flexibility provision.

The amount of monetary incentives may also affect the flexibility provision. Prior studies, for example Delmonte et al. (2020), mention that regular EV charging costs are already lower than refueling an internal combustion engine vehicle. With cheaper regular charging, motivating people to use smart charging further would require incentives significantly higher than those savings. Wong et al. (2023), who conducted a survey asking participants to join a smart charging program based on increasing monetary incentives, had similar results: Higher incentives were attributed to an increased interest in smart charging programs. To confirm this effect, we formulate the following hypothesis:

H2: High monetary incentives lead to a higher flexibility provision than low monetary incentives.

Monetary incentives can also be given in a fun and engaging manner on a digital interface using game elements. Game elements "vary widely in terms of the type of games, target, and features that might be appealing and motivating" (AlSkaif et al., 2018, p.101). Morganti et al. (2017) and AlSkaif et al. (2018) classified a rewarding system as a game element. These elements include credit points, which users can collect in an app through a desired behavior. The desired behavior would be smart charging in our study. These credit points have a monetary value and could be accumulated and utilized, for example, to charge EVs. With credit points, transparency (calculating and accumulating them) is important (Tamis et al., 2018). Credit points may function similarly to other monetary incentives because they have a monetary value. Therefore, we propose the following hypothesis:

H3: Credit points lead to a higher flexibility provision.

2.2. Nudges

Many studies have found that environmental values are essential for users of EVs. Eco-values, as well as ecological motives such as usage of RES while smart charging is considered highly relevant for the acceptance of smart charging (Frenzel et al., 2015; Geske, 2014; Huber et al., 2019b; Jochem et al., 2012; Paetz et al., 2012b; Schmalfuß et al., 2015; Tamis et al., 2018; Will and Schuller, 2016). In the following, we describe environmental nudges like framing, feedback, and badges, which might influence the charging choices of EV users.

First, framing "is the conscious formulation and description of the decision situation to encourage people to behave in a certain way" (Huber et al., 2019a, p.87). In the context of smart charging, framing can be using text messages to influence the EV users' decision-making so that they are more likely to provide high flexibility. Framing messages can be depicted in an application prior to the charging decision. Environmental frames make it clear to the EV user that smart charging contributes to environmental protection (Huber et al., 2019a). Huber et al. (2019a)'s study found that environmental frames did not affect the smart charging decision of participants. This result differs from results of studies in other adjacent research areas, such as energy-saving literature, where such frames were found to be effective (Schaule and Meinzer, 2020). In certain studies, environmental and monetary frames were both effective (Steinhorst and Klöckner, 2018), while in others, environmental frames were more effective (Asensio and Delmas, 2015). One possible explanation for the latter finding is that environmental frames enhance pro-environmental intrinsic motivation (Steinhorst and Klöckner, 2018). Steinhorst and Klöckner (2018) also hypothesized that environmental framing, contrary to monetary framing, influences long-term behavior change. However, they did not find any support in their study: The framing messages did not affect long-term self-reported energy-saving behavior and neither the yearly household electricity consumption. In a further experiment, Berger et al. (2022) tested the effectiveness of environmental framing when selecting programs for the washing machine and dishwasher. The use of environmental frames resulted in participants being more inclined to choose the eco-program over shorter alternatives. The effect of environmental frames was even more potent than default nudges. Based on these findings, we formulate the following hypothesis:

H4: Environmental framing leads to a higher flexibility provision.

Second, feedback allows users to be informed about their electricity consumption. It also assists them in interpreting their data and serves as a catalyst for behavioral change (Verbong et al., 2013). Environmental feedback could be provided on the corresponding carbon footprint, i.e., the amount of carbon emissions saved by smart charging when compared to regular charging (Huber and Weinhardt, 2018). Schmalfuß et al. (2015, p.9) indicate that EV users might use smart charging as they are "motivated by the feeling of doing something good". Seeing positive environmental consequences could be a motivator to use smart charging further. With reference to the energy-saving literature, Tiefenbeck et al. (2019, p.1) found environmental feedback to be specifically effective: Hotel guests who "received real-time feedback on their energy consumption while showering consumed 11.4% (0.21 kWh) less energy than guests in a control group", even without receiving any monetary incentives. Thus, we also hypothesize for smart charging:

H5: Environmental feedback leads to a higher flexibility provision.

Third, badges are a gamification element (AlSkaif et al., 2018) and should have their typical functions: to appeal, motivate, and include users (Morganti et al., 2017). This engagement is necessary as Lagomarsino et al. (2022, p.11) have pointed out that "a mere automatization of smart charging choices without user integration is likely to fail, and decrease[s] the acceptance of the technology". Badges can be considered as a 'nice-to-have functionality,' a feature that enhances the enjoyment of an application (Tamis et al., 2018) and displays the user's achievement level (Beck et al., 2019). In practice, some smart charging applications already use environmental badges. For example, the US-American application Fleetcarma awards badges to users for achieving minimum emission savings (FleetCarma, 2018). To the best of our knowledge, there is a lack of research on the impact of badges on smart charging behavior or similar behaviors such as energy-saving behavior. In the longitudinal study by Cominola et al. (2021), participants earned points, badges, and rewards and received recommendations for conserving water in a 6-month period. Two years later, 47% of households had reduced their consumption by 8% compared to before the project. Although the effect of all behavioral interventions was measured, it is possible that the badges may have contributed to this outcome. Based on this, we propose the following hypothesis:

H6: Environmental badges lead to a higher flexibility provision.

Fourth, we describe studies on the nudge smart charging as a default. Setting high charging flexibility as the default option for smart charging is a way to nudge users to choose this option. Users would have the option to opt-out for another choice, but the default option would encourage them to choose high flexibility. For example, when selecting an energy contract, energy providers often offer green energy contracts as the default option, where energy is generated using RES. In the study by Momsen and Stoerk (2014), by setting a contract with energy from RES as the default, the proportion of individuals who chose this contract increased by 44.6%. Vetter and Kutzner (2016) had similar results, which were independent of individuals' environmental attitudes. Similarly, default nudges can significantly increase participation in smart grids (Toft et al., 2014).

Smart charging as a default is recommended by the UK Energy Task Force (Force, 2019) and Delmonte et al. (2020). Currently, the standard practice is to charge EVs immediately, similar to how people are used to fully refueling their conventional cars (Lagomarsino et al., 2022). However, setting smart charging as the default option could reduce the number of decisions and cognitive effort required for the user and decrease interaction with the smart charging system (Delmonte et al., 2020). Based on this, we propose the following hypothesis:

H7: The default setting leads to a higher flexibility provision.

2.3. Battery-related tips

Battery-related tips can also be considered as gamification elements (AlSkaif et al., 2018). Strictly speaking, they are not nudges, as they provide the user with information that allows them to make a rational decision about charging. For some batteries, charging to a low battery percentage is better for the battery life (Tan et al., 2016) and offers more flexibility to the energy provider (Huber et al., 2019b). In focus groups conducted by Huber et al. (2019b), experts identified low battery degradation as one of the benefits of smart charging. Preserving the battery should also interest EV users.

Nevertheless, they must first be aware of the benefits of not fully charging the battery to make informed decisions. This information can be provided through battery-related tips. Therefore, we propose the following hypothesis:

H8: Battery-related tips lead to a higher flexibility provision.

2.4. Risk aversion and smart charging

Range anxiety, defined as "the worry that one will run out of battery before reaching the destination" (Herberz et al., 2022, p.2), is a frequently discussed topic. Range anxiety is related to risk aversion, a character trait in which people prefer low-risk alternatives to high-risk alternatives, even if the average outcome is equal or higher (Werner, 2008). As EV users become more risk-averse, they become more concerned about their remaining battery capacity, tend to charge more frequently, and draw more energy when charging (Xing et al., 2021). The counterparts of risk-averse individuals are risk-seeking ones. Risk-seeking people consider variables such as battery percentage, prices, and charging location when charging. In contrast, risk-averse people primarily focus on ensuring enough charge for the next trip (Pan et al., 2019). In the experiment by Huber et al. (2019a, p.11), "participants who consider[ed] themselves more willing to take risks [were] slightly more flexible" and selected a lower state of charge. Thus, we hypothesize:

H9: The lower the personal risk aversion, the higher the flexibility provision.[1]

[1] H9 was slightly adapted after the preregistration. Previous version: A high personal risk assessment negatively moderates the relationship between the nudge/incentive group and the flexibility provided.

2.5. Perception versus the effectiveness of incentives, nudges, and tips

The above-described studies differ in various characteristics, such as whether they use quantitative or qualitative analysis, whether they measure the effectiveness or perception of incentives or nudges, or how they operationalize the dependent variable flexibility or smart charging acceptance. Hence, it is difficult for these studies to compare the effectiveness of all the incentives and nudges. Also, most studies measure the perception or effectiveness of incentives and/or nudges. However, Tijs et al. (2017) demonstrate that the perception and effect of incentives and nudges do not always align for water-saving. In the flexibility field, we have not found any study investigating the perception and effectiveness of incentives, nudges, and tips. For this reason, in addition to examining the effect of these behavioral interventions, we aim to investigate how these perceptions relate to their effectiveness.

3. Methods

3.1. Focus groups and survey development

Before conducting the survey, we sought to gain a preliminary understanding of user preferences for different incentives, nudges, and tips in the context of EV smart charging and the factors driving these preferences. To do this, we conducted three focus groups ($n_1 = 4, n_2 = 4, n_3 = 5$) with 13 EV users in Luxembourg (2 women, 11 men). We took the help of one of our industry partner Enovos Luxembourg SA, who started a call for our focus groups. From the pool of participants, we selected all EV users who had been driving their EV for several months or more. The focus groups were recorded and transcribed and were conducted onsite with a predetermined agenda. Further information and results of the focus groups can be found in Appendix A and more detailed information in the paper by Marxen et al. (2022).

The results of the focus groups helped us design the survey but did not provide a clear indication of user preferences for different incentives, nudges, and tips. Therefore, the survey included all incentives, nudges, and tips. We also wanted to measure different motivations for EV usage (environmental, financial, technological, and social) in the survey, as the focus group results indicated that those are related to preferences for incentives, nudges, and tips.

We designed the survey material, and then discussed a first draft with five energy researchers/experts and three non-experts to ensure comprehensibility. Subsequently, we conducted the adapted survey in a pre-test with 25 participants, who left comments on various aspects of the survey. We simplified the content, including the definition of smart charging, and then preregistered our survey at Aspredicted.[2]

3.2. Recruitment, procedure for participants and measures

The questionnaire was available online from February 22, 2022, to June 29, 2022. The whole survey can be found in the supplementary material. Participants could answer the survey in English, German, or French. The primary goal was to obtain a sample of EV users from Luxembourg, Germany, Belgium, and France, all of whom speak French and/or German. So, we primarily shared the survey on German-and French-speaking platforms. However, we did not restrict participation from individuals residing in other countries. We shared the survey across various online platforms, such as Facebook groups, LinkedIn, Twitter, email distributions, and EV and university forums.

For the participants, the survey consisted of an experiment and a part in which they replied to items of questionnaires and further questions. Fig. 1 gives an overview of the experimental part of the survey. Before the experiment, participants indicated their familiarity with smart charging on a scale from 1 ("not familiar at all") to 7 ("extremely familiar"). They read an explanation of the concept of smart charging (Appendix A) and answered an attention question to confirm their understanding. Afterward, we measured their willingness to allow their energy provider to control the charging process with one item: "I would have the charging process of my EV controlled by my energy supplier". They indicated their agreement on a 7-point Likert scale ("strongly disagree" to "strongly agree").

Participants then read a scenario in which they imagined the following smart charging situation: *You come home at 18:00 with your electric vehicle (EV). Your battery percentage is 15%. The next day, you have to leave at 8:00 and drive 200 km (round trip). You have told your smart charging app that you have to drive 200 km the next day*. We used the term "battery percentage" instead of "SOC" for a better understanding. For the scenario, EV users would need a SOC of 40%

In our study, flexibility relates to the charging flexibility of the energy provider. This charging flexibility is higher if the user requests a lower $SOC_{Departure}$ for a charging session. Within our paper, we use the term $SOC_{Departure}$ whenever users request a SOC for the end of the charging session. To simplify our study design, we set a $SOC_{Departure}$ of 65% as an anchor point to differentiate between high and low flexibility. Therefore, in our study, high flexibility entails that users select a $SOC_{Departure}$ of up to 65% and above and vice versa for low flexibility (Fig. 2). We intentionally have set the beneficial $SOC_{Departure}$ (anchor point) at an acceptable level. For example, if the beneficial $SOC_{Departure}$ is 90%, the small margin of 10% would greatly impact the effect size and make it difficult to test the effect of incentives, nudges, and tips with a suitable sample size and statistical power.

After reading the scenario, the participants were randomly assigned to either the control group or one of the eight experimental groups. In the control group, the participants saw a neutral message. An incentive, nudge, or tip message was given in the

[2] https://aspredicted.org/9ji4w.pdf.

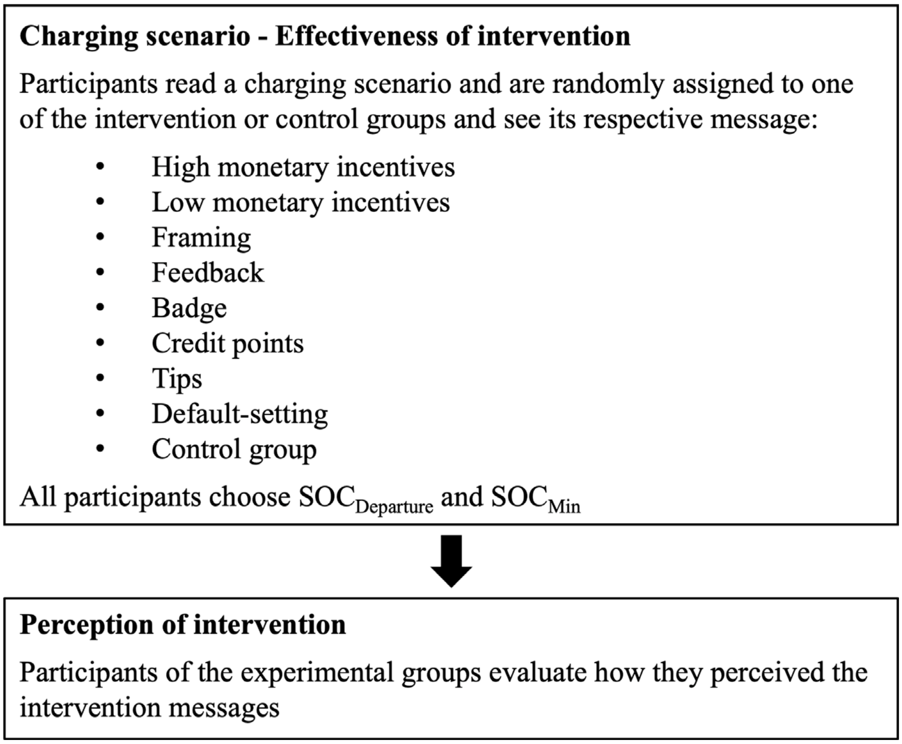

Fig. 1. Overview of the experimental survey design.

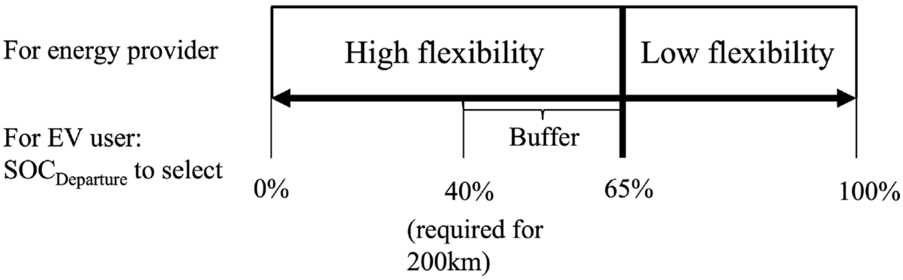

Fig. 2. Illustration of the simplified flexibility definition for the experimental design.

experimental groups regarding participants charging their EV only up to a $SOC_{Departure}$ of 65%. Fig. 3 depicts the messages for the high monetary incentives group, and other messages are in Appendix B (Fig. B.5). Regarding the high, low monetary incentives and credit points messages, we assumed a baseline electricity tariff of 25 ct/kWh. We established this baseline tariff after considering the electricity prices in Luxembourg and Germany during the years 2021–2022, which ranged roughly from 20–30 ct/kWh (Eurostat, 2022; Economy, 2022). In the high incentives group, participants got a reduction of 40% (15 ct/kWh) if they chose a $SOC_{Departure}$ up to 65%, and in the low incentives group, a reduction of 20% (20 ct/kWh). The participants also read the exact amounts they would save.

On the following page, participants in the experimental groups saw the message again, this time on a smartphone mock-up with an option to select the $SOC_{Departure}$ for the next day. We decided to repeat this message to ensure that all participants saw it; in the pretest survey, two participants missed it when it was only displayed once with further information. In addition to the smartphone mock-up, they saw an information table on how far they could travel with different SOC levels. Fig. 4 depicts this for the high incentives group. In the other groups, participants saw the exact mock-up and information table, respectively, with their group's message.

Then, all participants selected a $SOC_{Departure}$ (0%–100%) and a desired minimum SOC (SOC_{Min}) (0%–100%). $SOC_{Departure}$ is the desired battery percentage for the following day. SOC_{Min} is the battery percentage up to which the EV will be charged in an uncontrolled manner at full power right after it is connected to the charger (Fridgen et al., 2016).

Participants in the experimental groups then answered an attention question on the content of the message and questions on how they perceived the message. To measure the perception of the intervention message, we used the satisfaction sub-scale from Van

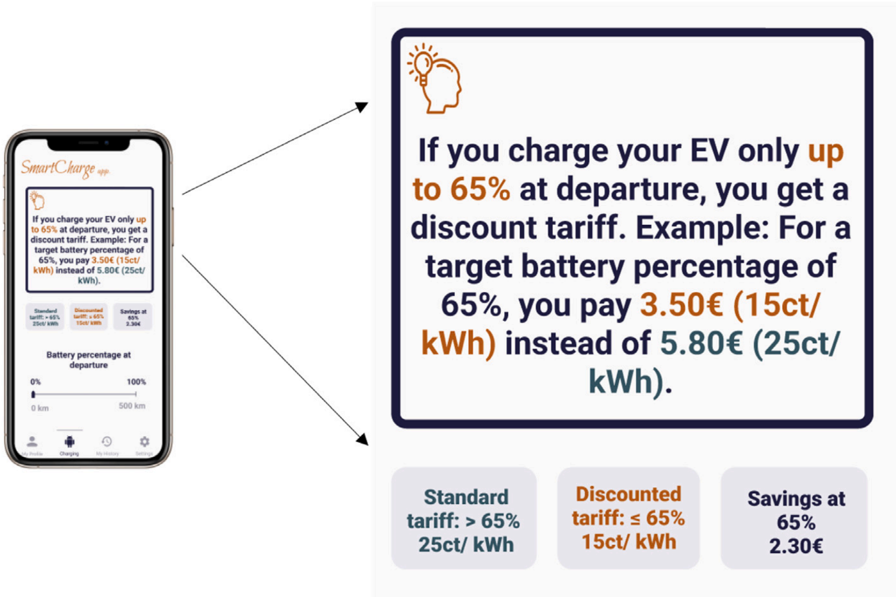

Fig. 3. Example of message for the high monetary incentives group.

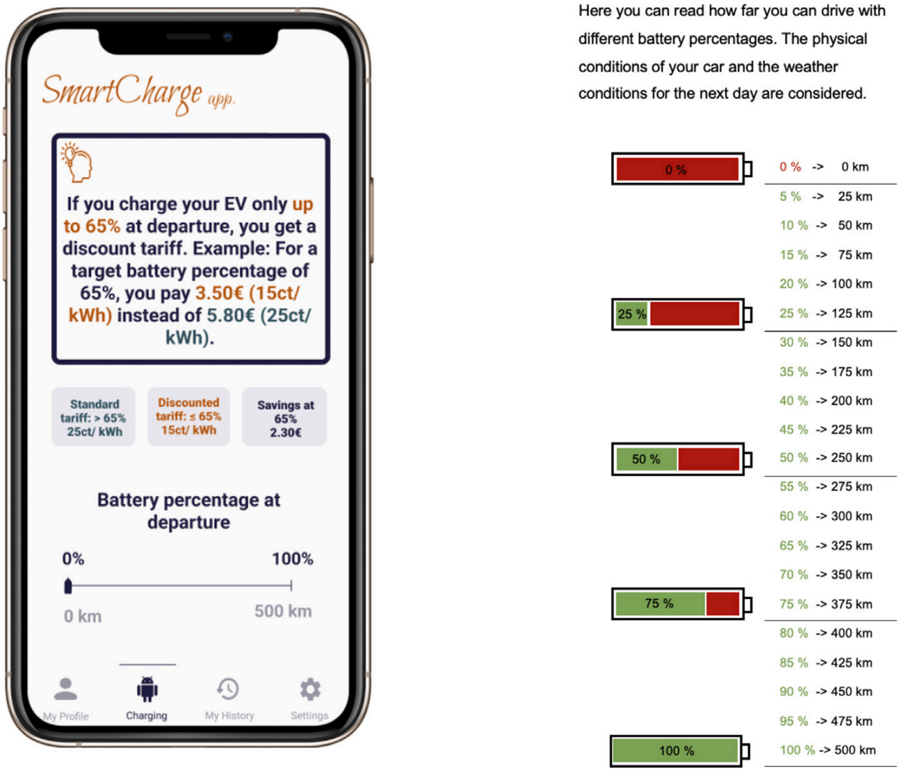

Fig. 4. Example mock-up and information sheet for the high monetary incentives group.

Der Laan et al. (1997). On a scale from 1 to 7, participants evaluated the message based on four pairs of adjectives (e.g., “1 unpleasant – 7 pleasant”). The scale had satisfactory internal consistencies in the different experimental groups of our survey, with Cronbach’s alphas above the threshold of $\alpha = .70$ (Hair et al., 2021): Perception of high incentives ($\alpha = .75$), low incentives ($\alpha = .83$), framing

Table 1
Distribution of participants in experimental and control groups.

Groups	Frequency	Percentage
High monetary incentives	24	8.30
Low monetary incentives	34	11.76
Framing	32	11.07
Feedback	30	10.38
Badges	31	10.73
Credit coins	37	12.80
Battery tips	28	9.69
Smart charging as default	39	13.49
Control group	34	11.76

(α = .90), feedback (α = .95), badge (α = .92), credit points (α = .96), battery tips (α = .87), and smart charging as a default (α = .92).

After the experiment, participants answered questions about their mobility behavior and vehicle and EV usage. These questions were about the most used transportation means, EV usage, number of vehicles, number of household members with a driving license, and daily kilometers driven. Participants additionally answered questions about their vehicle's range and battery capacity, the average distance they drive it, the time it spends at home on weekdays and weekends, and their usual charging location. They then answered questions about their motivations to drive an EV. These questions were presented on a 7-point Likert scale (ranging from "strongly disagree" to "strongly agree"). To measure technological motivation, we adapted four items from Kacperski and Kutzner (2020) (in our survey Cronbach's α = .77, example item: "I drive an electric vehicle because it is comfortable to drive due to its silent motor".). For environmental EV usage motivation, we adapted three items from Kacperski and Kutzner (2020) (in our survey α = .88, example item "…I can be part of the sustainability movement".). To measure financial EV usage motivation, we adapted three items by He et al. (2018) (in our survey α = .66, example item "…it helps me spend less on fuel".) and for social EV usage motivation four items from Wang et al. (2021) (in our survey α = .89, example item: "…I am judged favorably by others".). All participants then answered questions about their environmental concerns and risk aversion level. To measure environmental concern, we used the brief ecological paradigm scale (López-Bonilla and López-Bonilla, 2016), a short version of the new environmental paradigm (in our survey α = .80, example item: "Humans are severely abusing the environment".). To measure risk aversion, we used the general risk aversion scale by Mandrik and Bao (2005) (in our survey α = .83, example item: "I feel comfortable improvising in new situations"). Finally, participants answered demographic questions about their gender, age, nationality, highest level of education, occupation, industry, monthly income, and country of residence. In the end, participants were allowed to read about the background and research goals of the study. They could also provide feedback on the study and enter a raffle to win a voucher.

3.3. Sample

To determine the sample size for a multiple logistic regression a priori, we followed the method by Hsieh et al. (1998), which delivers accurate results for sample sizes of n > 200 (HHU, 2021). Using Python, we simulated all possible combinations of the following ranges: *OR* (2.0, 2.5 and 3.0) as similar studies used *OR* = 2.5 (Kramer and Petzoldt, 2022), Pr(Y = 1/X = 1) H0 (0.15, 0.2, 0.25), the proportion of the sample size experimental/control group (0.4, 0.45, 0.5, 0.55, 0.60), R^2 between the variables (0.01–0.2 in 0.01 steps). We aim for a sample size that covers at least 75% of the simulated cases. The simulations indicated we need a minimum sample of n = 282.

A total of n = 306 EV users completed the survey. We considered only participants who indicated that an EV was associated with their household. We also eliminated n = 17 participants for the following reasons: Participants answered both attention questions incorrectly (n = 12), were multivariate outliers according to the Mahalanobis statistic measure (n = 2) or said they did not understand the messages (n = 3). The final sample size was n = 289. The number of participants was similar across the different groups (Table 1).

Most of the participants are from Germany, Luxembourg, or France and reside in these countries (see Table C.5). The sample is predominantly male and highly educated, with an average age of 43.03. Our sample can be considered representative for EV users, as research from both Europe and the United States has found that EV users are typically male, middle-aged, well-educated, and have high incomes (Sovacool et al., 2018b; Shin et al., 2019; Plötz et al., 2014). The International Energy Agency also reports that EV users generally have high socio-economic status (IEA, 2022).

3.4. Analysis

We calculated a multiple logistic regression to answer research question 1 (*Which incentives, nudges, and tips are effective for individuals' flexibility provision in electric vehicle charging?*) and H1 and H3–H8. The aim was to ascertain the effects of seeing an incentive or nudge message on the likelihood of choosing a $SOC_{Departure}$ up to 65% (offering high flexibility) versus over 65% (offering low flexibility). To do this, we transformed the dependent variable $SOC_{Departure}$ into a categorical variable, with 1 representing a $SOC_{Departure}$ up to 65% and 0 representing a $SOC_{Departure}$ of 66%–100%. We created a dummy variable for each of the eight experimental groups, with the control group receiving a value of 0 for each dummy variable. We then compare the effect of each

Table 2
Results of multiple logistic regression testing the effect of incentives, nudges and tips on flexibility provision (Model 1) and with risk aversion (Model 2).

Dummy variable	Model 1 (H1, H3-8)				Model 2 (H9)			
	z	*p*	*OR*	*95% CI*	*z*	*p*	*OR*	*95% CI*
High monetary vs. Control	2.89	.004	5.42	[1.72; 17.02]	2.91	.004	5.57	[1.75; 17.72]
Low monetary vs. Control	2.44	.015	3.66	[1.29; 10.34]	2.60	.009	4.06	[1.41; 11.64]
Framing vs. Control	1.72	.085	2.53	[0.88; 7.27]	1.86	.064	2.75	[0.94; 8.03]
Feedback vs. Control	0.87	.386	1.63	[0.54; 4.87]	0.95	.343	1.71	[0.57; 5.18]
Badge vs. Control	−0.74	.458	0.63	[0.18; 2.17]	−0.72	.473	0.63	[0.18; 2.21]
Credit Coins vs. Control	2.37	.018	3.43	[1.24; 9.53]	2.49	.013	3.74	[1.33; 10.55]
Battery tips vs. Control	−0.20	.844	0.89	[0.27; 2.95]	−0.12	.901	0.93	[0.28; 3.11]
Default vs. Control	0.69	.490	1.44	[0.51; 4.10]	0.84	.399	1.58	[0.55; 4.53]
Constant	−2.92	.004	0.31		−0.10	.920	0.76	
Risk aversion					−2.30	.021	0.94	[0.60; 0.96]
Nagelkerke (Pseudo R^2)			.122				.146	

experimental group with the control group using logistic regression. We used the following multiple logistic regression formula as illustrated in Eq. (1) below[3]:

$$L = \ ln(p/1-p) = b_0 + \sum_{i=1}^{8} b_i x_i + e \tag{1}$$

In this context, L represents the log odds of p, which is the probability of choosing a $\text{SOC}_{Departure}$ up to 65%. b_0 indicates the (predicted) $\text{SOC}_{Departure}$ value of the control group. In contrast, b_i indicates the difference between the respective experimental and control groups concerning the selected $\text{SOC}_{Departure}$.

To test H9, we added risk aversion to the same logistic regression model to see if it increases the exploratory power. To test H2, we calculated a Chi-square test to compare the high and low monetary incentive groups concerning the chosen $\text{SOC}_{Departure}$.

To answer our second research question (*Is a positive perception of incentives, nudges, and tips associated with increased flexibility provision?*), we calculated Spearman's correlations (r_{Sp}) between the categorical variable $\text{SOC}_{Departure}$ and the perception of the respective intervention messages. We also conducted Independent-Sample Kruskal–Wallis Tests to determine whether the perception of the intervention message differed for the different types of intervention messages. This non-parametric test was used because the perception of the intervention message was not normally distributed for all eight groups.

As an exploratory analysis, we also calculated Pearson correlations (r) between SOC_{Min} and further variables as SOC_{Min} is part of the flexibility concept but less studied. Additionally, we calculated correlations between income, risk aversion, and further variables. If income was correlated with the main variables ($\text{SOC}_{Departure}$, risk aversion), we controlled for its influence in our analysis.

4. Results

We calculated a logistic regression to test H1, H3-H8 if seeing incentive, nudge, or tip messages leads to higher odds of choosing a $\text{SOC}_{Departure}$ up to 65% (offering high flexibility) versus over 65% (offering low flexibility). This is the Model 1, which was significant, X^2 (8, n = 289) = 27.13, p <.001 and explained 12.20% (Nagelkerke R^2) of the variance in the choice of $\text{SOC}_{Departure}$. Seeing the high monetary (*OR* = 5.42, *95% CI* [1.72, 17.02]), low monetary (*OR* = 3.66, *95% CI* [1.29, 10.34]), or credit point message (*OR* = 3.43, *95% CI* [1.24, 9.53]) increased the odds of offering high flexibility in comparison to the control group. Seeing the framing, feedback, badge, battery tips or default message did not increase likelihood to choose a high flexibility in comparison to the control group (Model 1, Table 2).

To test H9 (*The lower the personal risk aversion, the higher the flexibility provided*), we added risk aversion to the model (Model 2, Table 2). Adding the continuous predictor risk aversion to our logistic regression requires checking if the preconditions of logistic regression are observed: 1. No extreme outliers, 2. linearity of the logit, and 3. no multicollinearity. First, Cook's influence statistics were below 1.0, indicating no extreme outliers. Second, the Box-Tidwell test was non-significant, indicating the logit's linearity. Third, Variance Inflation Factor values are around 1, and tolerance values above 0.2, indicating no multicollinearity between the independent variables. By adding risk aversion, Model 2 was statistically significant, X^2 (9, n = 289) = 32.62, p <.001 and explained 14.60% (Nagelkerke R^2) of the variance in the choice of $\text{SOC}_{Departure}$. The change in comparison to Model 1 was statistically significant, X^2(1, n = 286) = 5.49, p = .019. High monetary incentives (*OR* = 5.57, *95% CI* [1.75, 17.72]), low monetary incentives (*OR* = 4.06, *95% CI* [1.41, 11.64]), credit points (*OR* = 3.74, *95% CI* [1.33, 10.55]), and lower risk aversion (*OR* = 0.76, *95% CI* [0.60, .96]) increased the odds of choosing high flexibility in comparison to the control group, whereas the framing, feedback, badge, battery tips, or default message did not.

[3] x_1: 1 if high monetary group, 0 otherwise, x_2: 1 if low monetary group, 0 otherwise, x_3: 1 if framing group, 0 otherwise, x_4: 1 if feedback group, 0 otherwise, x_5: 1 if badge group, 0 otherwise, x_6: 1 if credit points group, 0 otherwise, x_7: 1 if tips group, 0 otherwise, x_8: 1 if default group, 0 otherwise, e: random error.

Table 3
Overview on hypotheses related to RQ1: Which incentives, nudges, and tips lead to a higher flexibility provision in electric vehicle charging?

Hypotheses	Confirmed or rejected
H1: Monetary incentives lead to a higher flexibility provision.	Confirmed
H2: High monetary incentives lead to a higher flexibility provision than low monetary incentives.	Rejected
H3: Credit points lead to a higher flexibility provision.	Confirmed
H4: Environmental framing leads to a higher flexibility provision.	Rejected
H5: Environmental feedback leads to a higher flexibility provision.	Rejected
H6: Environmental badges lead to a higher flexibility provision.	Rejected
H7: The default setting leads to a higher flexibility provision.	Rejected
H8: Battery-related tips lead to a higher flexibility provision.	Rejected
H9: The lower the personal risk aversion, the higher the flexibility provision.	Confirmed

Table 4
Spearman correlations between perception of incentive, nudge or tips message and selected $SOC_{Departure}$.

Perception of message	$SOC_{Departure}$	
	Spearman's r	p-value
High monetary incentives	−.03	.908
Low monetary incentives	.21	.237
Environmental framing	.22	.236
Environmental feedback	.24	.198
Environmental badges	.23	.221
Credit coins	−.02	.917
Battery tips	.26	.182
Smart charging as default	−.03	.857

To test H2 (*High monetary incentives lead to a higher flexibility provision than low monetary incentives.*), the results of the Chi-squared association test indicate that subjects who saw the high monetary incentive message were not more likely to choose a high $SOC_{Departure}$ than subjects who saw the low monetary incentive message, $X^2(1, n = 67) = 0.15$, $p = .703$. Table 3 presents an overview on whether the hypotheses 1–9 were confirmed or rejected.

Concerning RQ2 (*Is a positive perception of incentives, nudges and tips associated with increased flexibility provision?*), the Spearman's correlations between $SOC_{Departure}$ and the perception of the respective stimulus messages were not significant for any of the stimulus messages (Table 4). Thus, the perception of the stimulus messages was not related to offering flexibility.

As an additional analysis, we conducted a Kruskal–Wallis test to identify if the perception of the message differed between participants of the different experimental groups. The test demonstrated that the perception of the stimulus messages did not differ based on the content EV users saw, H(7) = 7.51, $p = .378$. Thus, participants evaluated the eight messages equally well.

4.1. Exploratory analysis

In our exploratory analysis, we calculated correlations between 1. SOC_{Min}, 2. risk aversion, and 3. income with further variables. The higher the selected SOC_{Min} value, the more participants tended to be risk averse ($r = .13$, $p = .029$). Risk-averse participants tended to be generally older ($r = -.17$, $p = .005$).

Participants indicating a higher SOC_{Min} also tended to be less familiar with smart charging at the beginning of the survey, i.e., had a lower smart charging literacy, ($r = -.14$, $p = .014$) and were less willing to give their energy provider control on their charging process ($r = -.28$, $p < .001$). The selected $SOC_{Departure}$, however, was not related to familiarity with smart charging ($r_{Sp} = .05$, $p = .435$) and the willingness to give the energy supplier control on the charging process ($r_{Sp} = .09$, $p = .133$).

Those selecting higher SOC_{Min} values also tended to 1. provide a $SOC_{Departure}$ of above 65% ($r = -.25$, $p < .001$), to 2. have less environmental motivations to drive an EV ($r = -.15$, $p = .012$), and to 3. be less educated ($r = -.19$, $p = .001$).

Income was not correlated with $SOC_{Departure}$ ($r_{Sp} = -.05$, $p = .408$), SOC_{Min} ($r = -.03$, $p = .628$), or with risk aversion ($r = .01$, $p = .821$).

5. Discussion

Concerning the first research question (*RQ1: Which incentives, nudges, and tips are effective for individuals' flexibility provision in electric vehicle charging?*), H1 and H3 were confirmed. All monetary incentives, namely high incentives, low incentives, and credit points, led to a higher flexibility provision (choice of a $SOC_{Departure}$ of 65% vs. a $SOC_{Departure}$ of 66%–100%). H4-H8 were rejected: The nudges and battery-related tips did not lead to a higher flexibility provision. Nevertheless, they did not have a negative effect either. These results are in line with those of Bailey and Axsen (2015): For EV users, monetary incentives (reduced electricity bill) were more effective than environmental nudges. It appears that monetary incentives are generally more attractive to (mainstream) EV users than environmental or social nudges (Delmonte et al., 2020). Our study also demonstrated that this applies to various monetary incentives (low, high, and credit points).

Another question relates to whether a higher monetary incentive leads to better flexibility provision. In our study, H2 was rejected: There was no significant difference between groups given high and low monetary incentives regarding flexibility provision, i.e. low incentives were as effective as high incentives. This result is also supported by other academic studies (Kacperski and Kutzner, 2020; Kacperski et al., 2022). EV users seem to expect financial compensation for their flexibility, although this magnitude does not play a major role in whether or not they choose to provide this flexibility (Lagomarsino et al., 2022).

About the second research question (*RQ2: Is a positive perception of incentives, nudges, and tips associated with increased flexibility provision?*), perception of the incentives, nudges, and tips was not correlated with flexibility provision. This finding applied to all individual monetary incentives, nudges, and tips. The results align with Tijs et al. (2017), who also did not find a link between perception and effectiveness of nudges in a similar setting (water-saving while showering). This result implies that perceptions regarding these interventions might not play a crucial role for developing and designing behavioral interventions for smart charging as they might not be related to their actual effect.

The results confirmed H9, i.e. low risk aversion was related to high flexibility provision and explained additional variance. This finding aligns with the study by Huber et al. (2019a): People who consider themselves more willing to take risks are more likely to offer high flexibility.

Our exploratory analysis found that people who report lower $SOC_{Departure}$ values also report lower SOC_{Min} values and that SOC_{Min} correlates with risk aversion. These results suggest that factors associated with $SOC_{Departure}$, such as risk aversion, are also related to SOC_{Min}. Little research exists on SOC_{Min} in the behavioral context, although it is said that SOC_{Min} values increase the acceptance of smart charging (Will and Schuller, 2016; Ensslen et al., 2018; Geske and Schumann, 2018).

Another result of the exploratory correlation analysis was that participants with higher education levels and those more familiar with smart charging tended to choose a lower SOC_{Min}. Familiarity with smart charging is a form of smart charging literacy. Studies demonstrate that energy literacy is related to a higher flexibility provision (Reis et al., 2021). Our study further confirms that for smart charging. The correlation between SOC_{Min} and familiarity with smart charging indicates that people with higher smart charging literacy tend to provide higher flexibility. Our study is one of the first to demonstrate a relationship between smart charging literacy and the flexibility component SOC_{Min}. Another study by Baumgartner et al. (2022) examined the relationship between user experience and desired SOC_{Min} values. Surprisingly, the authors discovered no relationship between user experience and SOC_{Min} values. However, it is essential to note that in their study, user experience referred to the level of familiarity with EVs rather than knowledge specifically about smart charging.

5.1. Theoretical implications and directions for future research

Our results indicate that monetary incentives are most important to motivate EV users to provide charging flexibility.[4] Further research should focus on using monetary incentives for smart charging rather than on nudges and/or tips. In particular, research could be conducted to determine the minimum monetary incentive energy providers should offer to get charging flexibility. It would be further interesting to investigate how combining monetary incentives and environmental nudges impacts flexibility provision as explored by Kacperski et al. (2022) and to determine whether this combined approach is more effective than monetary incentives alone.

Our results also highlight the importance of appropriate experimental design for answering research questions. Although our results show the *effectiveness* of some behavioral interventions, we find no correlation between the *perception* of incentives, nudges, and tips and their effectiveness in improving flexibility provision. When the goal is to evaluate the effectiveness of such behavioral interventions, experimental approaches are highly valuable. Conducting a pilot study can also be beneficial. On the other hand, if the goal is to understand how incentives, nudges, and tips are perceived, focus groups or surveys without an experimental design might be a good choice. Measuring perception can be important in contexts where it is crucial for EV users to be engaged and to like the smart charging app.

Our study found a correlation between familiarity with smart charging and SOC_{Min}. Further research should be conducted to investigate this relationship in more depth. Instead of measuring familiarity with smart charging with a single item, it would be helpful to measure smart charging and energy literacy in more detail and investigate their relationship with flexibility provision. Smart charging literacy programs could also be explored to understand their impact on flexibility provision. It would be essential to determine the content and implementation of such programs, for example, by explaining to EV users how far they can travel with different $SOC_{Departure}$ values and how this relates to their specific profile. It is worth noting that participants who only drive short distances tend to overestimate the importance of SOC (Lagomarsino et al., 2022). Also Franke et al. (2017) did not find a significant correlation between daily travel distances and lower range satisfaction.

Regarding the link of risk aversion with flexibility provision, risk-averse people may particularly benefit from improved education and information. Additionally, it may be helpful to consider how this information is presented to users. As Lagomarsino et al. (2022) note, laypeople may need help understanding energy information presented in units like kWh or battery percentage (e.g., for how many kilometers which SOC would be sufficient). Therefore, future research should examine effective methods of transmitting information to EV users and the potential for educational programs to improve understanding. Studies can also be conducted on how information can be best transmitted to EV users about smart charging and related educational programs.

[4] Note however power limitations, discussed further below in the Limitations subsection.

5.2. Practical implications for energy providers

The results of the survey have several practical implications. For energy providers, our results indicate that offering monetary incentives can encourage users to provide higher levels of flexibility. The amount of the incentives does not appear to be as substantial as the fact that they are offered.

In this study, we only tested two realistically payable incentives by energy providers, so it cannot be ruled out that much higher incentives may lead to even higher levels of flexibility. The energy providers could design an incentive scheme for flexibility provision. Within this incentive scheme, energy providers can motivate EV users based on the monetary benefits the providers achieve while trading this flexibility in electricity markets.

Also, energy providers should provide their users with smart charging literacy programs, including a clear and easy-to-understand introduction to smart charging, perhaps through a smart charging application. These programs could include information about the risks and benefits of using smart charging and explanations of $\mathrm{SOC}_{Departure}$ and SOC_{Min} data.

5.3. Limitations

There are several limitations to our study design. First, a simplification of the concept of flexibility was necessary to facilitate our experimental design. Flexibility is a continuous variable that includes factors other than $\mathrm{SOC}_{Departure}$, such as SOC_{Min} and parking duration. Therefore, our study's categorical representation of flexibility gives an approximation of the reality of flexibility with EV smart charging.

Gamification elements must be analyzed engagingly within a dynamic setting; whereas our study allowed for gamification elements in a static and non-interactive setting. Since gamification elements are all about engagement, the best way to understand how they work is through direct interaction with an app. In our study, we only used a smart charging app interface, but participants did not have the opportunity to interact with the app and click through it. To more accurately assess the effectiveness of gamification elements, they should be tested in a more interactive experimental design.

Our sample size (n = 289) is relatively small. According to a posthoc power analysis in G Power (Faul et al., 2007) for the multiple logistic regression, only for the effect of the high monetary incentives group, a sufficient power of above 0.80 was reached. This value fell short of low monetary incentives and credit points (0.65, 0.64). The reasons for this are *a priori* unexpectedly high correlations between the independent variables. However, the results of the high monetary incentives are substantive. Since the slightly underpowered variables, low monetary incentives, and credit points are related in content with high monetary incentives; it can be assumed that monetary incentives generally work.

Even though our sample can be considered representative of current EV users, it might suffer from non-response errors. For this reason, individuals who voluntarily participated in the study might differ from those who decided not to do so (Sovacool et al., 2018a). EV users interested in our topic may have reacted differently to behavioral interventions than those who did not show this interest.

Furthermore, our study includes a sample of EV users from various countries, primarily Luxembourg and Germany, and other German- and French-speaking European countries. As a result, our sample predominantly represents EV users in Luxembourg and its border region. Samples per country are too small to perform a country comparison analysis with sufficient power.

The external validity of our study is also limited by the experimental design. The scenario-based nature of the experiment impacts the results (Lagomarsino et al., 2022). A field study (e.g., a pilot study) should be conducted to increase external validity.

Moreover, our study is a snapshot of a single decision, while users have to make multiple smart charging decisions over time. For smart charging to reach its full potential, it must be used regularly. Therefore, it is important to investigate how frequently EV users choose to use smart charging and what factors influence this decision (Lagomarsino et al., 2022).

6. Conclusion

In an experimental survey, we assessed whether various behavioral interventions, i.e. monetary incentives (low, high, credit points), framing, feedback, badge, smart charging as a default, and battery-related tips, lead to a high flexibility provision for smart home charging. We also explored whether the perceived effectiveness of these interventions is linked to their overall effectiveness.

Out of all the behavioral interventions, only the monetary incentives (low incentives, high incentives, and credit points) affected increased flexibility provision. At the same time, nudges and tips had neither a positive nor negative effect. Low and high monetary incentives were equally effective. The results indicate that energy providers should incentivize EV users for their flexibility, while the incentive amount does not appear to play a decisive role.

A positive perception of the behavioral intervention was not correlated with their effectiveness for any of the interventions. This result has theoretical and methodological implications for future research. If the effect of behavioral interventions is to be determined, experiments should be employed rather than relying on perceptions of hypothetical behavioral interventions.

In our exploratory correlation analysis, we found that participants with higher smart charging literacy and higher education level indicate lower SOC_{Min} values, i.e. higher flexibility provision. This result indicates that smart charging literacy programs could help to achieve higher charging flexibility.

Fig. B.5. Intervention messages and control group messages. 1. High monetary, 2. Low monetary, 3. Framing, 4. Feedback, 5. Badge, 6. Credit points, 7. Tips, 8. Default-setting, 9. Control group.

CRediT authorship contribution statement

Hanna Marxen: Investigation, Methodology, Conceptualization, Data curation, Formal analysis, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Mohammad Ansarin:** Writing – review & editing, Supervision. **Raviteja Chemudupaty:** Conceptualization, Writing – review & editing. **Gilbert Fridgen:** Writing – review & editing, Supervision, Funding acquisition.

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. Focus groups

Our focus groups followed a predefined agenda of 120 min. The focus was to discuss the incentives, nudges and tips. After the discussion, we asked the participants to rank those according to their perceived attractiveness using a short survey. Five participants

Table C.5
Description of the sample - EV users.

	Frequency	Percentage
Gender		
Male	235	81.31
Female	48	16.61
Transgender female	1	0.35
Gender variant/Non-conforming	2	0.69
Prefer not to disclose	1	0.69
Others	2	0.35
Highest degree of education		
Some high school	6	2.08
Highschool/GED	24	8.30
Some college	27	9.34
Associates' degree	53	18.34
Bachelor's degree	64	22.15
Master's degree	103	35.64
Doctoral degree'	12	4.15
Occupation		
Student	16	5.54
Working (full-time)	220	76.12
Working (part-time)	25	8.65
Housewife/househusband	18	6.23
Pensioner	7	2.42
Unemployed	3	1.04
Income (net)		
less than 1000 €	10	3.46
1000–2999 €	76	26.30
3000–4999 €	100	34.60
5000–6999 €	42	14.53
7000–8999 €	16	5.54
≥9000 €	12	4.15
No indication	33	11.42
Nationality		
German	165	57.09
Luxembourgish	46	15.92
French	17	5.88
US-American	12	4.15
Swiss	7	2.42
Austrian	6	2.08
Others	36	11.07
Residence country		
Luxembourg	158	54.67
Germany	69	23.88
France	17	5.88
US	13	4.50
Austria	9	3.11
Switzerland	5	1.73
Belgium	3	1.04
Others	18	6.23

indicated monetary incentives as most attractive, five participants smart charging as default, one participant framing, no one feedback and gamification, and one participant did not do the ranking. Looking at the next ranks, there was no clear ranking of the incentives, nudges and tips participants found most attractive. This was different for the ranking of the gamification elements. Here, six participants ranked tips first, five credit points, one energy communities, and no-one badges. These results were consistent with the next ranks. With regard to gamification, participants also mentioned the point that younger people might like it more. Furthermore, we investigate whether motivations for purchasing electric vehicles and incentives preferences are related. For this, we transcribed the focus group recordings and analyzed them using qualitative content analysis, a method that combines the deductive and inductive coding approach (Cho and Lee, 2014). We first deductively defined categories (e.g., different incentives, nudges, motivations) and coded them in the transcripts. Second, we inductively coded additional constructs, such as further motivations. Then we looked at the overlaps of different codes. In our analysis, the environmental and economic motivations to purchase an EV seemed to be related to the preference for incentives and nudges. Participants with environmental EV purchase motivation were mainly interested in nudges indicating their contribution to environmental protection (e.g., feedback, framing). Participants with economic motivation owned their EV mainly because their companies covered most of their purchase and charging costs. They had a higher preference for monetary incentives.

Appendix B. Survey material

See Fig. B.5.

Appendix C. Description of the sample

See Table C.5.

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.trd.2023.103897.

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