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Smart charging of EVs: Would you share your data for money?

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Abstract

Many governments worldwide aim to eventually replace most combustion engines on the roads with electric vehicles (EVs). But this change causes an additional load on the electrical grid, especially if many EVs are charged simultaneously at peak times. Smart charging is a solution to better distribute the load throughout the day or night, while considering consumer preferences. For home charging, the idea is for EV users to always plug in their EVs when they are at home, and for the energy supplier to then decide when to charge which EV. By using (sensitive) consumer data, such as charging history, location of the smartphone and calendar information, the energy supplier can plan and optimize the charging of the EVs even better. In a survey, we seek to understand which of these data consumers are willing to share for smart charging, and what factors, such as privacy concerns and data sharing habits, influence this decision. Furthermore, in an experiment within the survey, we investigate whether consumers are more willing to share data if they receive monetary incentives. Our research design is based on the theoretical framework of Barth and de Jong (2017). 20 participants took part in the pretest, after which we adjusted the survey. We then shared the survey through various channels.

Smart charging, consumer data, data sharing, privacy concerns, monetary incentives

Extended abstract

Governments around the world want to dramatically increase the share of electric vehicles (EVs) on the roads and incentivize EV adoption. “In 2021, there were about 5.5 million electric cars on European roads – more than three-times the stock of 2019 before the Covid-19 outbreak“ (p.17, IEA, 2022). This huge uptake of EVs leads to a rise in electricity demand. The situation is even worse when EVs are charged simultaneously, causing significant tension in the electricity grid (Huber et al., 2019). One of the technical solutions is smart charging. Smart charging means adapting the charging cycle of EVs to both the conditions of the power system and the needs of vehicle users (IRENA, 2019).

To optimize EV charging and make it smarter, data on when and where the EV is available for charging is necessary. This data, which is often personal, helps energy suppliers predict charging patterns and procure energy and balancing services at a lower cost. Different types of data can be used to understand charging patterns: Historical charging behavior and smartphone location data will help predict future charging behavior, while data linked to a person's actual plans (e.g., via a calendar) can be even more accurate and helpful for optimizing smart charging. Additionally, by predicting charging patterns accurately, the energy supplier can provide better service to the EV user. As the charging patterns become more understood, the smart charging application can be more automated, requiring less interaction from the EV user. However, revealing personal data necessary to predict charging patterns may raise privacy concerns and be perceived as intrusive. Research has shown that many people have concerns about sharing their data for privacy reasons (Barth et al., 2019; Smith, 2008; Smith et al., 2011), such as the illegal disclosure or misuse of their data by hackers (Cichy et al., 2021).

There is a significant amount of research on privacy and data sharing with (digital) technologies in multiple disciplines as information systems (IS) (Buckman et al., 2019; Cichy et al., 2021; Kim et al., 2019; Wu et al., 2020). However, these results cannot simply be transferred to smart charging as it differs from other technologies: In addition to the virtual space, here the physical space is touched (Cichy et al., 2021). If the physical space is concerned, it can be inferred, for example, which places someone visits and how much time they spend there (Cichy et al., 2021). Little research is available on data sharing with similar technologies such as smart charging. Therefore, we want to focus on this topic and investigate through an online survey which data consumers would be willing to share with their energy supplier for the purpose of smart charging. We also want to find out which factors influence data sharing. For our theoretical framework, we adapted the framework of Barth and de Jong (2017) to the context of smart charging (Figure 1).

In their paper, Barth and de Jong (2017) summarize existing theories relevant to why individuals disclose private information with mobile apps. They differentiate between rational and biased decision-making theories when risk is involved and present these ideas in two theoretical frameworks. We apply their framework of rational decision-making to smart charging. The reason for choosing the rational framework is as follows: As smart charging is a new technology; most people have not yet experienced it. In our study, we explain smart charging to the participants, including its advantages and disadvantages so that they can make informed decisions when answering our survey. We want to find out which data they would be willing to share with the energy supplier without introducing additional biases, which normally play into real world decisions.

The framework of Barth and de Jong (2017) is a comprehensive summary of key theories, and we measure its main constructs: attitudes towards information disclosure, context, perceived risks, and perceived benefits. However, we do not capture the actual information disclosure. In regard to attitudes towards information disclosure, we assess privacy awareness, trust in the energy supplier, and previous experience with location sharing. Additionally, we measure perceived privacy risks and benefits of the app, as well as contextual factors such as the desired level of app automation and the influence of a monetary incentive message. Using this adapted model, we formulate the following research question and hypotheses:

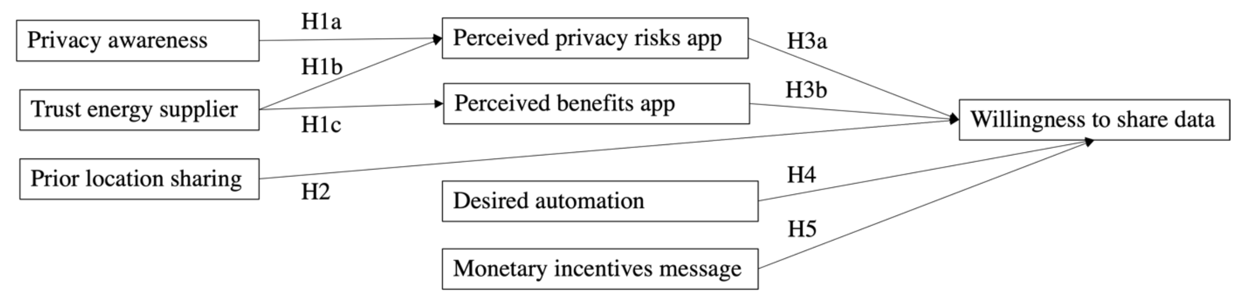

Figure 1. Research Model

RQ1: Which factors impact individuals' willingness to share data with their smart charging application?

H1: (H1a) Privacy awareness is positively related to perceived risks and (H1b) trust towards the energy supplier is negatively related to perceived risks. (H1c) Trust in the energy supplier is positively related to perceived benefits.

H2: Prior location sharing habits are positively related to the willingness to share data.

H3: (H3a) Perceived risks are negatively and (H3b) perceived benefits are positively related to the willingness to share data.

Users do not want to constantly interact with their smart home applications (Marxen et al., 2022; Schomakers et al., 2021). Schomakers et al. (2021) indicate that users prefer semi-automated applications for smart home technology. However, this automation requires user data. If users are aware of this, those who want a more automated app should also be willing to share more data. Therefore, we formulate the following hypothesis:

H4: The desired app automation is positively related to the willingness to share data.

With regard to monetary incentives, we know that privacy has a price (Hirschprung et al., 2016), which means that most people would assign a monetary value to their data. Through an experimental setting within the survey, we want to find out whether participants are more likely to share their data if they receive monetary incentives for it, and whether incentives impact the willingness to share the four data types differently. Our hypothesis and research questions are as follows:

H5: Participants who receive monetary incentives have a higher willingness to share data than participants who do not.

RQ2: Which data types are individuals willing to share and which role do monetary incentives play?

RQ3: How much does the monetary incentive need to be for individuals to share different data types?

We want to address these hypotheses and the research questions with data collected by an online survey. One participation requirement is to be a smartphone user. The survey is available in English or German and should not take more than 10-15 minutes. It consists of a brief questionnaire and an experiment.

In the questionnaire, the concept of smart charging is explained. Then, participants answer questions on data sharing habits with applications, privacy awareness (Barth et al., 2019), trust in the energy supplier (Döbelt et al., 2015), environmental concerns (López-Bonilla & López-Bonilla, 2016), political orientations (Curtice & Bryson, 2012), EV usage and demographics. We use 7-point Likert scales ("strongly disagree" – "strongly agree") for most of the measures. In the experiment, participants are asked to imagine coming home with an EV, plugging it in for charging and using a smart charging app. They see the smart charging app mockup and the information the app requires from them. To measure the desired app automation, they are asked how often they would like to enter this information manually ("once when installing the app/mostly automated"-"before every trip/settings manually"). Afterwards, they are randomly assigned to a control or experimental group. Participants of the experimental group read that they can get a portion of their electricity costs back if they share their data with the app. Participants in the control group do not receive this information. All participants are then asked which data (smartphone location, charging times and preferences, limited and full details of the calendar) they would be willing to share with the application. In the experimental group, participants are additionally asked to imagine to be a frequent driver and to spend 100 euros per month on charging. They should indicate how much of the cost they need to recover to share each of the four data types. It is also possible to indicate not to want to share any data type for money. At the end of the survey, participants read about the background and aim of the study, can participate in a lottery, and give feedback on the survey.

To answer H1-H5 and to test our model, we plan to calculate a structural equation model (SEM). To a priori determine the necessary sample size, we used a SEM sample size calculator (Soper, 2022) based on Cohen (2013) and Westland (2010). To calculate our model and to detect an effect, we need at least a sample of $n = 314$ (considering a medium effect and power of 0.8). For the dependent variable willingness to share data, we take the average of the four data sharing items and calculate a standardized composite score. To answer RQ2, we calculate a MANOVA. Here, we compare the effect of how the experimental and control groups (two independent variables) differ regarding which data types they share (four dependent variables). For the MANOVA and follow-up univariate ANOVAs, a sample size of $n = 280$ is required (considering a medium effect and power of 0.95) according to G*Power (Faul et al., 2007). To answer RQ3, we analyze the results descriptively. We additionally plan to calculate exploratory multiple regressions with the data sharing types as dependent variables. We conducted a pretest of the survey with 20 participants. Each page of the survey included a comment field for participants to provide feedback. Most of the comments related to the comprehensibility of the wording. As a team of researchers, we discussed the comments and made necessary adjustments to the survey. After receiving approval from the ethics committee of the university, we started to disseminate the survey on social media and EV user forums.

The results of the survey will have both theoretical and practical implication. In terms of theoretical implications, we will test the adapted theoretical framework of Barth and de Jong (2017) in the context of smart charging, providing a foundation for future research in this field. In terms of practical implications, the information consumers are willing to share will help energy suppliers plan the optimization of smart charging. They will also get an idea on roughly how expensive it will be to get certain types of data from their customers.

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