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Hanna MARXEN
Born on 11 July 1994 in Wittlich (Germany)

ENGAGING CONSUMERS FOR FLEXIBILITY PROVISION IN RESIDENTIAL ELECTRIC VEHICLE SMART CHARGING AND HEATING

Dissertation defence committee

Dr Gilbert Fridgen, dissertation supervisor
Professor, Université du Luxembourg

Dr Maxime Cordy
Research Scientist, Université du Luxembourg

Dr Christian Fisch, Chairman
Professor, Université du Luxembourg

Dr Philipp Staudt
Professor, University of Oldenburg

Dr Michael Schöpf, Vice Chairman
Business Development Manager, Venios GmbH

"All things are difficult before they are easy."

Dr. Thomas Fuller (1654 – 1734)

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Abstract

The energy transition requires the integration of renewable energy sources (RES). However, since some RES are intermittent, energy supply does not always match demand. Demand response (DR) programmes encourage consumers to adjust their energy consumption to align with supply. One approach within DR is direct load control (DLC), where consumers allow a third party, such as an energy supplier, to control their energy-consuming appliances. DLC allows the supplier to provide energy to appliances during off-peak hours when the availability of RES is higher. By providing this flexibility, consumers help balance supply and demand.

DLC is particularly viable for high-consumption appliances such as electric vehicles (EVs) and heating systems, which are the focus of this thesis. Despite its benefits and minimal impact on consumer convenience, consumers are often reluctant to accept DLC because they fear losing control and comfort. Therefore, it is essential to understand the conditions under which consumers are willing to accept DLC and to explore strategies for encouraging their participation.

This cumulative thesis consists of an introductory part and six published conference and journal papers. It focuses on how personal characteristics such as energy literacy influence the provision of flexibility for residential EV charging and heating, and how to motivate users to provide such flexibility.

Furthermore, DLC for electrical appliances, such as charging EVs, requires data that EV users need to provide to the energy supplier. The more data that is available, the smarter and more efficient the control of the appliances can become. Therefore, I also analyse what types of data, with varying levels of sensitivity, consumers are willing to share, which factors—such as prior data-sharing habits—influence this willingness, and how much monetary compensation consumers request for sharing data of different sensitivity levels.

The results of this thesis provide researchers with insights into the consumer perspective on providing flexibility and an understanding of how consumers want the related data to be handled.

Declaration

I, Hanna Marxen, declare that I wrote this thesis by myself and that it has not been previously submitted for any other degree or professional qualification. For the jointly authored research papers, I have clearly distinguished my contributions from those of the other authors. I confirm that I have correctly referenced the work of others whenever I refer to it.

I used the AI tools DeepL, Grammarly, and ChatGPT to improve the language and clarity of parts of my work. However, I carefully reviewed the output from these tools to ensure understanding and accuracy, incorporating only selected suggestions.

I confirm that I have no financial interests to disclose in relation to this research. I commit to conducting my research with transparency, integrity, and adherence to ethical principles, ensuring the reliability of my work.

Hanna Marxen

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List of Acronyms

DLC direct load control

DR demand response

DSM demand side management

EV electric vehicle

HEMS home energy management system

RES renewable energy sources

RP research paper

SEM structural equation modelling

SM smart meter

SOC state of charge

SOC_{min} minimum state of charge

I Introduction

1 Motivation

In recent years, there has been a significant acceleration in the use of renewable energy sources (RES) as part of global efforts to drive forward the energy transition. However, integrating RES into the energy system is challenging as some RES, such as solar and wind, are intermittent (Lund et al., 2015). Since RES supply is weather-dependent, the feed-in of RES might lead to unreliable power supply. To address these reliability issues, energy storage solutions like batteries are considered (Schuitema et al., 2017). Yet, their high cost makes them a less feasible option at the moment (Amin et al., 2020).

Another approach to mitigate the unreliable power supply is to focus on the demand side and compensate for the other side of the equation ($supply = demand$). Those demand response (DR) programmes fall under demand-side flexibility measures and encourage consumers to provide flexibility in their energy usage behaviour. By doing so, consumers help, for instance, energy suppliers to balance their demand and supply (Schuitema et al., 2017).

We can differentiate DR programmes between indirect and direct control programmes, legally and technically also referred to as implicit and explicit respectively (Freire-Barceló et al., 2022). Indirect control programmes use price signals or incentives to encourage consumers to change their behaviour (Amin et al., 2020). However, these indirect control programmes assume that consumers know how to respond to price signals (Schuitema et al., 2017), which is often not the case. For instance, in a survey with 1393 people in Sweden, only 3.8-8.5% knew their tariff, understood its features and how their behaviour affected their costs (El Gohary et al., 2023). These results indicate that more than 90% of consumers do not know enough about their tariffs to respond to price signals.

Meanwhile, direct load control (DLC), part of direct control programmes, could be a more viable solution as it is automated and requires less consumer knowledge and involvement. With DLC, the consumer hands over control to an external party, such as the energy supplier, to control the load by rescheduling it or turning on or off devices (Yilmaz et al., 2021).

Although DLC involves different actors, this thesis focuses on energy suppliers as the example case. By accepting DLC, users provide flexibility to the energy supplier. This flexibility provision can occur at different levels: the energy supplier may have full control of all devices at all times, or may control certain devices only during specific periods. This thesis focuses on the latter case, where the energy supplier partially controls the devices.

One application of DLC is smart charging of electric vehicles (EVs). Smart charging means adapting the charging schedule of EVs to the conditions of the energy system and the requirements of the EV user (IRENA, 2019). EV users can specify a time window for charging and the desired battery percentage by the end of that time window.

However, despite the potential benefits, with DLC, some consumers fear losing control, leading to inconvenience (Delmonte et al., 2020; Schuitema et al., 2017). These concerns indicate that most consumers will not immediately adopt DLC. For instance, most participants in a smart charging trial of a charging study preferred manual control of EV charging over DLC for charging (Delmonte et al., 2020).

Research has started to better understand the factors that lead people to accept DLC and provide flexibility (Parrish et al., 2020; Srivastava et al., 2019; Will and Schuller, 2016). One investigated factor to explain flexibility provision is personal characteristics such as energy literacy, i.e. a basic understanding of energy use, its relationship to one's behaviour, and its practical application (DeWaters and Powers, 2013). The qualitative study by Walker and Hope (2020) finds a link between energy literacy and energy-shifting behaviour based on price-signals. However, there is a lack of quantitative confirmation. Other studies focus on how behavioural interventions encourage people to provide flexibility, for instance, using monetary incentives and nudges (Huber, Schaule, et al., 2019; Kacperski et al., 2022; Parrish et al., 2020). Nevertheless, there is no conclusion on which ones are particularly effective as those studies do not investigate the effect of multiple incentives and nudges within a single study. Therefore, this thesis addresses the following research questions:

RQ1: How are personal characteristics related to residential flexibility provision?

RQ2: Which behavioural interventions increase residential flexibility provision?

Nevertheless, to implement DLC programmes, energy suppliers and grid operators need data to predict better and plan energy consumption accordingly (Fernández et al., 2022; Marxen, Chemudupaty, Fridgen, et al., 2023; Negnevitsky et al., 2009). However, consumers are concerned about the privacy and security of their data (Balta-Ozkan et al., 2013; Li et al., 2021; Wilson et al., 2015). Concerns may relate to invasion of privacy, data falling into the wrong hands, or concerns that a third party may know about routines and occupancy (Balta-Ozkan et al., 2013). Because of these concerns, consumers may be reluctant to share their data for DLC programmes, even though energy suppliers need the data to make full use of flexibility. Studies have looked at factors such as privacy concerns or monetary benefits which can predict data sharing, for example with websites (Acquisti et al., 2013; Cichy et al., 2021; Hirschprung et al., 2016). However, these studies do not relate to data sharing for DR. This thesis therefore examines data sharing as a key factor in optimising DR, addressing the following research question:

RQ3: Which data types do consumers intend to share for smart charging and which factors influence their intention?

This thesis answers the three posed research questions and provides researchers and practitioners insights into the consumer perspective regarding flexibility provision and the associated handling of their data.

2 Thesis overview

This cumulative thesis consists of six chapters. After this introductory chapter I, chapter II discusses theories of decision-making, specifically rational choice theory and bounded rationality, which form the theoretical rationale of this thesis. To demonstrate the relationships examined in the research paper (RP)s included in this thesis, I developed an illustrative model that outlines them. Chapter III explains key concepts such as DLC and flexibility provision and how they relate to broader concepts as demand side management (DSM) and DR. As consumers respond differently to DLC, it is essential to understand the factors influencing these varied responses. I address the first and second research questions, focusing on personal characteristics like energy literacy and the effect of behavioural interventions on flexibility provision. This chapter III also includes an additional analysis of the monetary value of flexibility to energy suppliers. Table 1 summarises the RPs included in this thesis.

Chapter IV explores the transfer of consumer data for DR and consumers' privacy concerns. I then discuss the current state of research and contributions related to the third research question, which focuses on data sharing behaviour in DR.

In chapter V, I conclude and summarise the thesis, highlight my contributions, discuss limitations and suggest ideas for future research. Chapter VI acknowledges the collaborative nature of the research papers and the foundation of existing research they build upon. The appendix A consists of three parts: a list of relevant publications, a contribution statement for each publication, and the full text of all appended publications.

Table 1: Research overview of publications in this thesis.

RP[1]#	Title (and Outlet)	Length[2]	Reference	Role[3]
RP1	Are you flexible enough? The impact of energy literacy and environmental values on flexibility provision (EEM)	F	Andolfi, Marxen, et al. (2024)	E
RP2	Towards an evaluation of incentives and nudges for smart charging (ECIS)	S	Marxen, Chemudupaty, Graf-Drasch, et al. (2022)	L
RP3	Empirical evaluation of behavioural interventions to enhance flexibility provision in smart charging (Transportation Research: Part D)	F	Marxen, Ansarin, et al. (2023)	L
RP4	Impact of minimum energy requirement on electric vehicle charging costs on spot markets (Powertech)	F	Chemudupaty et al. (2023)	S
RP5	Maximizing smart charging of EVs: The impact of privacy and money on data sharing (ICIS)	F	Marxen, Chemudupaty, Fridgen, et al. (2023)	L
RP6	The role of gender in data sharing for smart charging of electric vehicles (AMCIS)	F	Frank et al. (2024)	E

[1] RP= research paper, [2] S = Short paper, F = Full paper; [3] L = Lead author, E = Equal author, S = Subordinate author.

II Decision-making theory streams and models

Even if DR programmes can have a high degree of automation, as in the case of DLC, the consumer could decide to drop out. To better understand consumers' decisions about flexibility provision, we can first examine theories and generalisable knowledge about human decision-making before studying their behaviour empirically. Specifically, rational choice theory and bounded rationality are main theories for understanding decision-making. They are outlined in section 1, as they relate to this thesis' research rationale. Section 2 then describes different psychological and sociological models, including the model of Kollmuss and Agyeman (2002), to place the empirical analysis of the RPs within a theoretical context. I selected and adapted the model by Kollmuss and Agyeman (2002) to represent the relationship between the variables studied in the RPs of this thesis.

1 Rational choice theory and bounded rationality

Researchers studied decision-making in various fields such as economics, mathematics, and psychology and developed different theories (Edwards, 1954). These theories aim to either describe or predict consumer behaviour and financial decisions (Liu, 2023). Theories can be categorised as descriptive (explain decision-making), normative (describe how people should make decisions), or prescriptive (offer strategies to improve decision-making) (Bell et al., 1988).

The first attempts to describe human behaviour came from economics and referred to rational choice theory, also known as expected utility theory (Carvajal, 2022). This theory, which continues to influence empirical research, posits that consumers conduct a cost-benefit analysis to determine which option provides the greatest utility (Browning et al., 1999; Edwards, 1954). Rational choice theory divides decision-making into three contexts: under certainty, risk, and uncertainty (Mousavi and Gigerenzer, 2014): Under certainty, all consequences of an action are predictable; under risk, the outcomes and their likelihood of occurrence are known; under uncertainty, the outcomes, but not their probabilities of occurrence, are known.

Savage's theorem (Savage (1972)) is one of the most prominent theories for rational decision-making under uncertainty (Steele and Stefánsson, 2020), building on Neumann and Morgenstern (1953)'s theorem for decision-making under risk. According to Neumann and Morgenstern (1953), rational decision-making is guided by four axioms (Steele and Stefánsson, 2020): completeness (the ability to compare and rank alternatives), transitivity (consistent preferences), continuity (small probability changes lead to small preference changes), and independence (choices between alternatives remain unaffected by other options). Savage's theorem extends these axioms to situations where objective probabilities are unknown, relying instead on subjective probabilities derived from personal experience (Savage, 1972). The idea is then that a person can make an optimal decision using these axioms.

Meanwhile, empirical research in economics and related disciplines has demonstrated that people often violate rationality assumptions (Keys and Schwartz, 2007; Shafir and LeBoeuf, 2002). For example, the Allais paradox demonstrated by Allais (1979) reveals that people's decisions deviate from the predictions of the rational choice theory. Here, people especially violate the independence axiom in quick decision-making scenarios. Furthermore, numerous cognitive biases have been identified to explain why decisions sometimes fall short of rationality (Haselton et al., 2015). One such bias is the framing effect, where the way options are presented can significantly influence the choices people make (Kahneman, 2013).

To address the limitations of rational choice theory, Herbert Simon first introduced the concept of bounded rationality, which refers to behaviour that deviates from at least one of the assumptions of absolute rationality (Simon, 1990). Bounded rationality belongs to the discipline of behavioural economics. Behavioural economics attempts to combine economic theories with insights from psychology (Camerer and Loewenstein, 2004).

Prospect theory, a theory from behavioural economics, builds on the idea of bounded rationality. It suggests that people evaluate potential gains and losses relative to a reference point rather than seeing them in absolute terms (Kahneman and Tversky, 2013). It also states that people are risk-averse when making gains and risk-seeking when avoiding losses (Camerer and Loewenstein, 2004). However, like rational choice theory, prospect theory assumes that individuals do not differ in their utility function (Camerer and Loewenstein, 2004).

Bounded rationality also include the concept of nudging. This approach is based on the assumption that people make bad decisions because they are not always paying full attention, do not always control themselves and have limited cognitive abilities (Camerer and Loewenstein, 2004). According to Camerer and Loewenstein (2004), nudges can help to guide people toward better decisions by altering the choice architecture without changing economic incentives or eliminating options. A nudge might be setting the preferred option as the default. People may be likelier to stick with the suggested option as they would otherwise need to opt out. For example, setting a preferred option as the default choice can nudge people toward it, as they would need to actively opt out otherwise (Parrish et al., 2020).

Nevertheless, theories of bounded rationality have several limitations that prevent them from being predominant. First, they are descriptive rather than normative, which limits their use in empirical testing and making concrete economic recommendations. For example, researchers identified a list of biases indicating that people do not act rationally (Haselton et al., 2015). However, lists do not offer specific strategies for addressing these biases. Second and resulting from the first limitation, due to this lack of normative guidance, bounded rationality theories are of little importance for the practical work of economists but to some extent for other disciplines, such as for business economists, e.g. in marketing.

Psychological and sociological models offer valuable frameworks for understanding how individuals make decisions (Carvajal, 2022), providing insights into the factors that influence these choices. These models can be empirically tested to evaluate their validity and applicability. In this context, it is important to note that the concepts of rationality and bounded rationality are not mutually exclusive. Instead, they can coexist with decision-making processes encompassing both rational elements and elements of bounded rationality, such as behavioural nudges.

The empirically tested models seem to follow a more rational approach and include some elements of behavioural economics. The RPs in this thesis mostly assume rationality but include some aspects of bounded rationality. The following sub-chapter briefly overviews some common psychological and sociological models.

2 Psychological and sociological models of decision-making

Researchers across different disciplines have modelled behaviour and the factors that lead to certain types of behaviour. Many of those models include the components attitudes, behavioural intentions and behaviour (Kollmuss and Agyeman, 2002). One of the oldest and best-known theories is the theory of reasoned action by Fishbein and Ajzen (1977). According to it, attitudes towards behaviour influence behavioural intentions, which influence actual behaviour.

Several models have been developed to address the value-action and attitude-behaviour gap, where individuals' actions often do not align with their values and attitudes. This discrepancy is particularly noticeable in pro-environmental behaviour, where people's actions towards environmental protection may not always align with their environmental values and attitudes (Steg et al., 2015). These gaps highlight that other factors may influence behaviour beyond the attitudes and behaviour intentions.

One such model by Fietkau and Kessel (1981), states that pro-environmental behaviour is influenced by several key factors: opportunities to act pro-environmentally, incentives to act pro-environmentally, perceived consequences of behaviour, and environmental attitudes and values, the latter influenced by environmental knowledge. A variety of models exist with some explanatory power for specific contexts.

One of the models best adaptable to flexibility prevision is the one by Kollmuss and Agyeman (2002) on pro-environmental behaviour. Kollmuss and Agyeman (2002) summarised the factors that lead to pro-environmental behaviour in their model, acknowledging that it is not easy to fit all theories into a comprehensive framework. Their model identifies internal factors, such as personality traits and value systems and external factors, including infrastructure, political, social, cultural, and economic conditions, as determinants of pro-environmental behaviour. Additionally, the model recognises barriers to pro-environmental behaviour, such as old behaviour patterns or a lack of internal or external incentives.

The model by Kollmuss and Agyeman (2002) provides a framework to contextualise this thesis' RPs, i.e. those addressing research questions one and two. Most RPs of this thesis (RP1, RP2, RP3, RP5, RP6) can be integrated into this model. The exception is RP4, which analyses the effect of flexibility provision on the resulting monetary benefits and does therefore not fit into the model. Figure 1 depicts the model, adapted for this thesis, to reflect the analysed variables. The research to answer research question one and two (RP1, RP2, RP3) is depicted in blue and research to address research question three in green (RP5, RP6). I renamed internal factors to personal characteristics and external factors to behavioural interventions to provide clarity and adapt it further to the context of this thesis.

RP1 examined how environmental values (a personal characteristic linked to value systems, as described by Kollmuss and Agyeman (2002)) and energy literacy (a personal characteristic linked to knowledge) affect flexibility provision. Meanwhile, RP2 and RP3 explored the influence of risk aversion (a personal characteristic linked to personality trait) and monetary incentives, nudges and tips (behavioural interventions) on flexibility provision. Flexibility provision might be considered pro-environmental behaviour as it can facilitate the integration of more RES into the grid.

RP5 investigated various factors influencing data sharing intentions, including privacy awareness (a personal characteristic linked to attitudes), trust in the energy supplier (a personal characteristic linked to attitudes), perceived privacy risks with a smart home application, perceived benefits of the application, previous location-sharing habits (old behaviour), desired automation of the application (a personal characteristic linked to attitudes) and monetary incentives (behavioural intervention).

RP6 examined the association between gender (personal characteristic), perceived privacy risks with the smart home application and data sharing intentions. It can be argued that data sharing behaviour also constitutes pro-environmental behaviour, as the data collected can optimise smart charging algorithms, potentially increasing the use of RES.

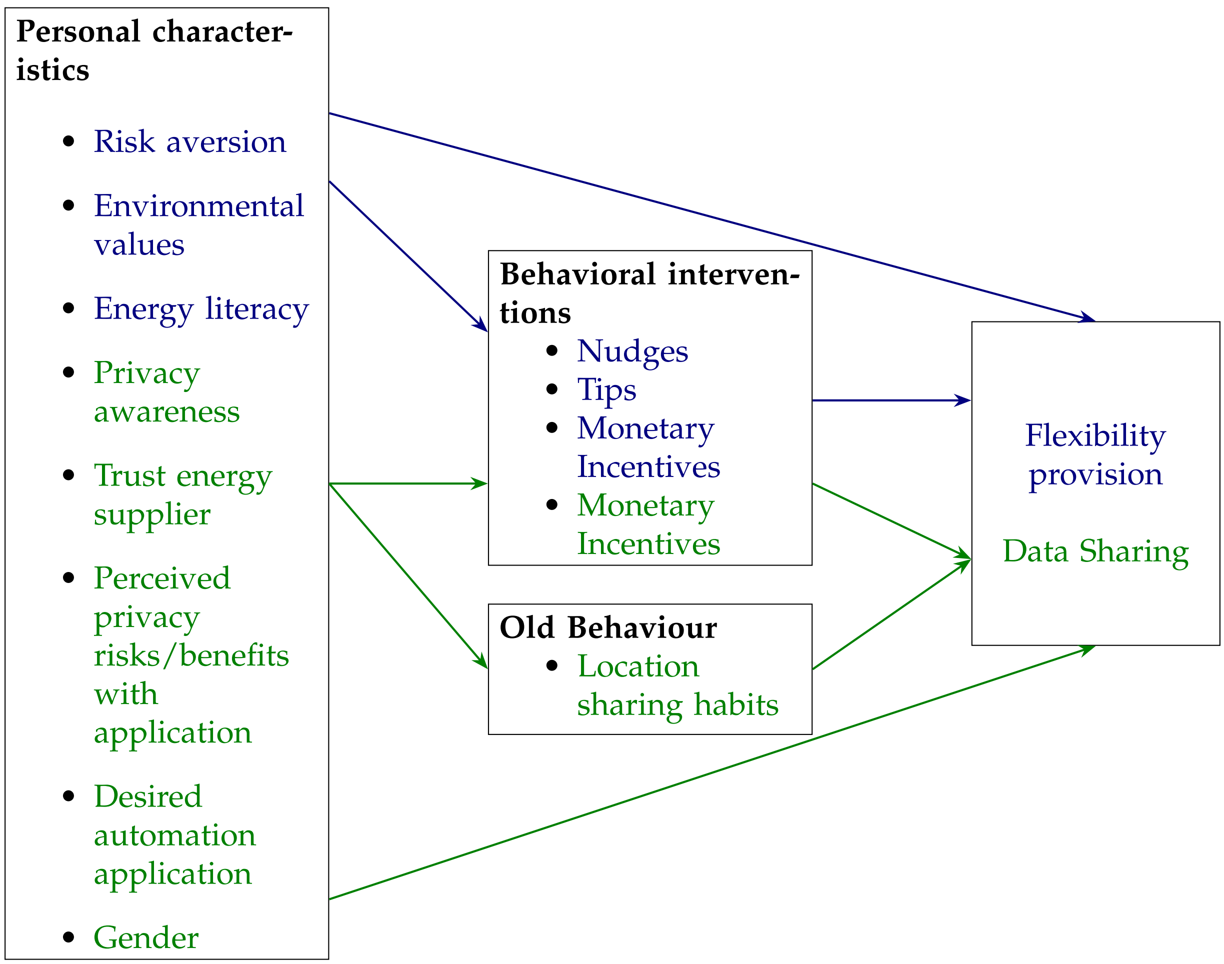

Figure 1: Adapted model by Kollmuss and Agyeman (2002) to represent main variables of RPs, blue: RP1-3, green: RP5,6.

III | Demand response

In this thesis, consumer acceptance of DLC, i.e. providing flexibility for the energy supplier, is a core concept. Section 1 describes DLC and its broader concepts DSM, and DR. Section 2 examines how different consumer types respond to DLC and highlights the need for further research to understand flexibility provision. Sections 3 and 4 address this by outlining personal characteristics associated with flexibility provision and reviewing the current state of research on behavioural interventions. These sections also explain how the first and second research questions are answered and how this related research adds to existing knowledge. Finally, section 5 presents an additional analysis of the flexibility component minimum state of charge (SOC_{min}) and its monetary benefits for the energy supplier.

1 Classification of demand response programmes

DR is a subset of DSM. DSM was introduced in the 1970s and refers to the planning and executing activities to influence consumers' electricity use (Gellings, 2017). The primary goal of DSM is to reduce peak demand over the long term by eliminating electricity usage or shifting it to non-peak times (Newsham and Bowker, 2010). DSM can involve either demand reduction or DR (Parrish et al., 2020).

Demand reduction refers to a permanent decrease in electricity consumption, achieved through behaviour changes or the adoption of more efficient technologies (Parrish et al., 2020). In contrast, DR involves a temporary shift in electricity consumption, encouraging consumers to reduce or increase their consumption at specific times (Parrish et al., 2020). The European Union views DR as crucial for enhancing energy efficiency and maintaining grid stability (Bertoldi et al., 2016). For instance, the Energy Directive provides the legal framework for the development of DR across Europe (Bertoldi et al., 2016).

As the introduction chapter outlines, DR can be categorised into indirect and direct control programmes. Indirect control programmes rely on price signals (Amin et al., 2020), incentivising consumers to adapt their behaviour to electricity supply. These programmes offer lower prices under favourable conditions and can take various forms (Parrish et al., 2020): With critical peak pricing, consumers pay higher rates during peak periods. With time of use plus critical peak pricing, rates vary depending on the time of day, with even higher rates at peak times. With dynamic time of use pricing, rates change daily based on market or system conditions and can fluctuate rapidly. With real time pricing, rates adjust hourly or more frequently depending on market prices.

On the other hand, direct control programmes allow a third party to directly control the load and adjust it according to system needs (Amin et al., 2020). In this context, direct control means that the energy supplier has the authority to modify the load based on supply requirements. Direct control can manifest as load shedding or DLC (Amin et al., 2020). Load shedding means the system operator reduces or cuts off the electric power in certain areas when demand exceeds supply (Amin et al., 2020). In DLC programmes, consumers grant a third party the right to control the electricity consumption of specific appliances based on the needs of the electricity system (Eid et al., 2016; Parrish et al., 2020). In the case examined in this thesis, the energy supplier acts as the third party. In the most rigid form of DLC, consumers provide the energy supplier with unrestricted access to control their devices, offering the highest degree of flexibility. In a lighter form, the energy supplier has restricted access to the user's devices, which is the focus in this thesis.

2 Classification of energy consumer types

Researchers have classified consumers into different types based on their use of energy technologies (Osman et al., 2024). These classifications could also apply to varying behaviours in flexibility provision for DLC.

According to Strengers (2014), developers of smart energy technologies often design them for a specific type of consumer, also called *Resource Man*. *Resource Man* is portrayed as a rational, male energy consumer focused on optimising energy use and actively participating in the energy transition (Strengers, 2014). He responds to price signals, makes informed decisions, understands his consumption data, and wants to change his energy habits (Strengers, 2014).

However, this representation does not reflect the majority of consumers (Strengers, 2014). The concept of the *Resource Man* misinterprets the aspirations and realities of most people, as smart energy technologies often fail to consider important social dynamics and the complexities of energy use (Goulden et al., 2018; Strengers, 2014). In contrast, Goulden et al. (2018) identify a consumer type that is the opposite of the *Resource Man*, the *indifferent consumer*. This consumer is "disengaged, lazy, irrational, ignorant" (p.180) (Goulden et al., 2018) and is referred to as the "ghost of the grid", uninterested in energy matters.

Resource Man and the *indifferent consumer* might be extreme ends of the spectrum, but more consumer types are necessary to capture the full range of behaviours. In a study by Renström (2019), participants were asked about the role they wanted to play in the energy transition. The responses revealed a wide range of attitudes: some consumers wanted to make their own decisions and receive guidance that fore; others were resistant to change, while some were willing to alter their behaviour; and opinions varied on whether individual behaviour would make a difference, while others thought that their behaviour did not matter in the broader energy landscape.

Different groups of consumers may provide varying levels of flexibility. Therefore, research could explore how and why different consumer types differ in their flexibility provision and response to DLC. This understanding could then inform decision-makers in developing tailored approaches or policies to engage and reach various types of consumers (Strengers, 2014).

3 The influence of personal characteristics on flexibility provision

One reason people differ in their responses to DLC might be due to personal characteristics, such as energy literacy, environmental values, and demographics. In RP1 and RP3, we aimed to explore the role of those personal characteristics in flexibility provision, addressing the first research question (*RQ1: How are personal characteristics related to residential flexibility provision?*).

The first personal characteristic of energy literacy can be categorised into four types (Van den Broek, 2019): device energy literacy, action energy literacy, financial energy literacy, and multifaceted energy literacy. Device energy literacy involves understanding the energy consumption of a specific device, action energy literacy focuses on awareness of energy-saving actions. Financial energy literacy refers to the ability to assess the economic consequences of energy use, and multidimensional energy literacy encompasses the capacity to evaluate the socio-economic and environmental impacts of energy consumption.

Researchers argue that higher levels of energy literacy can contribute to greater flexibility provision (Andolfi, Akkouch, et al., 2023). A qualitative study has found a link between energy literacy and flexibility provision in DR programmes (Walker and Hope, 2020). However, to our knowledge, no quantitative research has examined this relationship. To fill this gap, RP1 investigated the relationship between energy literacy and flexibility provision for smart EV charging and heating using a survey with 472 residents in Luxembourg. Smart EV charging in RP1 refers to giving the energy supplier control over charging during specific evening hours, ensuring the desired state of charge (SOC) is reached by morning. Similarly, smart heating allows the energy supplier to control the heating for certain hours of the day, while maintaining the user's requested temperature, which is possible due to a water storage system.

Due to the lack of an established scale for the measurement of energy literacy, we developed an energy literacy scale in several iterations within RP1, based on DeWaters and Powers (2013) and Van den Broek (2019). After creating the first version of the energy literacy scale, we conducted a pretest, made adjustments and then used it in the main survey of RP1. We find that higher energy literacy is associated with a greater intention to provide flexibility for residential EV charging and heating. The results indicate that promoting energy literacy could enhance flexibility provision, highlighting the potential role of energy literacy programmes in achieving this goal.

The personal characteristics of environmental values might significantly influence flexibility provision, as consumers know that one goal of flexibility provision is to increase the use of RES. In related fields, environmental values are drivers for engaging in environmental behaviour (Bouman et al., 2020). For example, in the context of smart EV charging, environmental values are positively associated with the acceptance of these technologies (Schmalfuß et al., 2015; Will and Schuller, 2016). In RP1, we also found a positive relationship between environmental values and the intention to provide flexibility for both EV charging and heating. This result suggests that energy suppliers could increase flexibility provision by promoting environmental values.

Risk aversion, another personal characteristic, also affects flexibility provision. People with higher risk aversion, meaning those who tend to avoid risks, are generally less likely to provide flexibility for EV charging (Huber, Jung, et al., 2019). In RP3, risk aversion was found to explain additional variance in flexibility provision for EV charging beyond what was explained by monetary incentives alone. This highlights the importance of considering personal characteristics like risk aversion, which can play a crucial role beyond just monetary incentives.

Demographic variables also influence flexibility provision. For instance, Srivastava et al. (2019) find that age is negatively related to flexibility provision, with younger individuals being more likely to provide flexibility. We observed the same trend for smart heating flexibility provision in RP1. Additionally, we found that higher education levels are positively related to smart heating flexibility provision. Ownership of specific technologies also plays a role; owning an EV was positively related to EV charging flexibility provision, and owning a heat pump was positively associated with heating flexibility provision.

4 Behavioural interventions for consumers' flexibility provision

In addition to personal characteristics, studies indicate that behavioural interventions like incentives, nudges, or tips can encourage consumers to provide flexibility (Huber, Schaule, et al., 2019; Kacperski et al., 2022; Parrish et al., 2020). Incentives refer to monetary benefits of choosing the desired option (Marxen, Ansarin, et al., 2023). Nudges involve changing the environment in which people make decisions (choice architecture) to influence their behaviour without forbidding options or changing monetary incentives (Thaler and Sunstein, 2008). These nudges can highlight economic, environmental, or social benefits (Huber, Jung, et al., 2019). For example, economic nudges emphasise the economic advantages of flexibility provision, environmental nudges highlight environmental benefits, and social nudges stress benefits to society.

Monetary incentives and environmental nudges are crucial drivers of flexibility provision (Parrish et al., 2020) and smart EV charging acceptance (Huber, Schaule, et al., 2019). However, for smart EV charging, there was limited research on which incentives and nudges are most effective, and some have not yet been tested in this context. We therefore aimed to answer the second research question within RP2 and RP3 (*RQ2: Which behavioural interventions increase residential flexibility provision?*).

In RP2, we first conducted an integrative literature review across various disciplines to get an overview of possible incentives and nudges for flexibility provision in smart EV charging. This review identified several behavioural interventions, including monetary incentives, framing, feedback, setting smart EV charging as the default, and gamification.

Framing involves using words for description or texts to change the context of a decision situation, e.g. whether to use smart EV charging or not (Huber, Jung, et al., 2019). Feedback provides information on behaviour outcomes, like CO_2 savings or financial benefits associated with smart EV charging (Huber, Jung, et al., 2019). Default nudges make the desired option the standard, requiring people to opt out if they do not want to participate (Parrish et al., 2020). Gamification introduces game elements, such as points or challenges, into non-game contexts (Deterding et al., 2011) to engage and motivate consumers (Morganti et al., 2017) and can include credit points or tips (AlSkaif et al., 2018). Credit points are also a type of monetary incentive, and tips offer behavioural advice.

To gain initial insights into how current EV users perceive different incentives, nudges and tips, we conducted three focus groups (n= 13) as part of RP2. The findings indicated that most participants found monetary incentives and smart EV charging as the default most attractive. However, these results should be interpreted with caution due to the small sample size.

While some studies have explored the effect of incentives and nudges to encourage flexibility provision (e.g. Huber, Jung, et al. (2019) or Wong et al. (2023)), studies rarely assess multiple incentives and nudges in a single study. As a result, it remains unclear which incentives or nudges are the most effective. In addition, some studies have measured perceptions and others their effect, yet both types of studies often interpret results as if they were measuring effects. For instance, in Tijs et al. (2017), different results were observed when comparing the perception of monetary and environmental appeals of water conservation to their effectiveness.

In RP3, we measured and compared both the effect and perception of several monetary incentives and nudges and tested whether the perception correlates with their effect. We conducted an experimental survey with 289 EV users, focusing on the identified incentives, nudges and tips from RP2: high and low monetary incentives, an environmental framing message, environmental feedback, smart charging as default, credit points and tips messages on EV charging flexibility provision.

The survey results in RP3 revealed that only monetary incentives led to flexibility provision. Both high and low monetary incentives, as well as credit points, had an effect, whereas the nudges and the tip did not. Interestingly, the impact of high monetary incentives was similar to that of low ones. This aligns with the conclusion of Lagomarsino et al. (2022) that the magnitude of the incentive is less crucial than the fact that people receive an incentive at all.

A pilot study by Bailey et al. (2023) also tested the effects of monetary incentives and a nudge highlighting the societal grid benefits of load shifting on EV charging behaviour and found that only monetary incentives had a significant impact. The authors noted that the incentive amount was relatively small. A study published after RP3 further confirms these findings, indicating that incentives and not nudges affect EV user behaviour (Bailey et al., 2023). They additionally conducted a longitudinal study and found that once the rewards were removed, EVcharging behaviour approached that of those who never received incentives. This result indicates that small, ongoing incentives may be necessary to sustain flexibility provision.

Moreover, RP3 found no correlation between the perception and effect of any incentive or nudge. This finding underscores the importance of testing the effects of incentives and nudges in experimental contexts rather than relying on measuring their perception in qualitative studies.

5 Monetary value of EV charging flexibility for energy supplierss

When EV users provide their energy suppliers with flexibility, the energy supplier can adjust EV charging patterns to optimise costs by charging the vehicles during periods of lower electricity prices. This can result in cost savings.

However, the actual flexibility ultimately available to the energy supplier depends on factors such as parking duration and user preferences. These preferences might include departure time, the required SOC by departure, and SOC_{min}. SOC_{min} refers to the battery percentage to which the EV is immediately charged at full power (Fridgen, Häfner, et al., 2016). The lower the SOC_{min}, the more flexibility the energy supplier has in managing the EV's charging, making it advantageous for the supplier if the user selects a lower SOC_{min}.

In their paper, Ensslen et al. (2018) introduced SOC_{min} to address range anxiety and to give users a feeling of security by ensuring that their EV is sufficiently charged for immediate use, such as in emergencies. At the same time, SOC_{min} was intended to increase flexibility for energy suppliers by discouraging users from charging immediately (i.e., setting a 100% SOC_{min}). The difference between the SOC_{min} and the requested SOC by departure represents the flexibility energy suppliers can use to optimise charging. The time window that EV users allow for charging also contributes to this flexibility.

Ensslen et al. (2018) looked at the impact of SOC_{min} on energy procurement costs and found that when users set a SOC_{min} value, the energy suppliers' costs decrease compared to immediate full charging. However, their analysis only considered the case where users set a SOC_{min}, without exploring how different SOC_{min} values affect costs. In this notion, in RP4, we analysed the effects of specific SOC_{min} values (0, 20, 40, 60, 80, 85, 95, and 100%) on energy procurement costs for energy suppliers. The objective was to identify a SOC_{min} threshold that maintains EV user comfort but at the same time brings financial benefits to the energy supplier.

To achieve this, we utilised a synthetic German mobility dataset comprising 1000 EVs, which reflected typical mobility behaviour. We evaluated the monetary value of the flexibility using a two-stage scenario-based stochastic optimisation model designed to minimise energy procurement costs while participating in both day-ahead and intraday markets. Energy procurement for charging the EVs was calculated over the month of January 2020. The boundary conditions assumed that EVs would charge at home, be plugged in whenever parked at home, and charge up to 100% SOC or as much as possible during the available parking time. Figure 2 illustrates the results of these simulations.

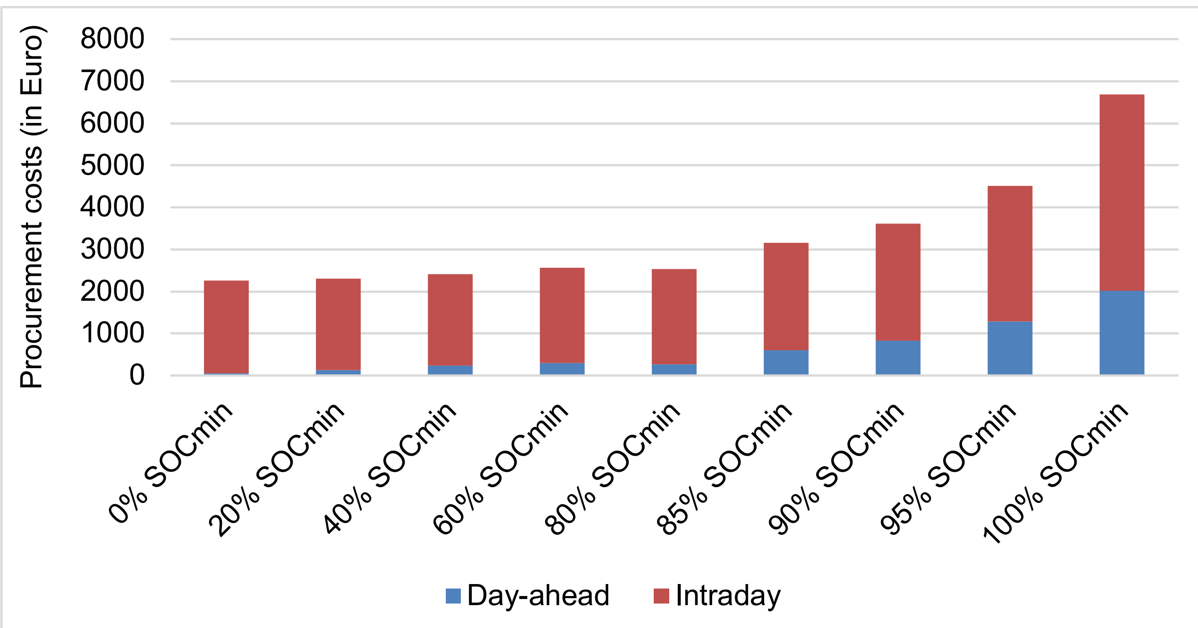

Figure 2: Energy procurement costs dependent on different minimum state of charge values.

The graphics indicate energy procurement costs increase as the SOC_{min} value rises. However, this increase is not linear. Costs remain relatively stable for SOC_{min} values between 0-80% but increase sharply beyond SOC_{min} 80%. Specifically, when EV users select a SOC_{min} value of 80%, the costs are 50% lower than when they choose a SOC_{min} value of 100%. An SOC_{min} of 80% means little loss of comfort for the user as it is sufficient for most daily trips (El Gohary et al., 2023). Moreover, if needed, the EV can still be fully charged over a longer period that suits the energy supplier's schedule.

The SOC_{min} value of 80% seems to be a critical threshold that balances user convenience with financial benefits for energy suppliers. Therefore, in RP4, we concluded that energy suppliers should encourage users to choose SOC_{min} values below 80%. Energy suppliers could then use the money earned from flexibility provision to fund incentives for users. An effective incentive scheme might decrease incentives as SOC_{min} values increase, with no incentives provided once SOC_{min} reaches 80%. This strategy could effectively balance the needs of both EV users and energy suppliers.

IV Data sharing for direct load control

Detailed consumption data allows energy suppliers to forecast demand better, which helps to plan actions on load balancing, ensuring grid stability and reducing the risk of power outages. In addition, consumption data helps to develop DR programmes as DLC tailored to specific consumer groups. For instance, based on historical charging data, energy suppliers can determine the best times to charge EVs, considering consumer requirements.

This chapter focuses on how consumption data is used for DLC. Section 1 details how smart meters (SMs) measure and transfer consumption data for DLC. Given consumers' privacy concerns and their potential reluctance to share detailed consumption information, section 2 and 3 outline the current research status on consumers' privacy concerns and willingness to share data relevant to DR, as well as the factors influencing this decision. This section addresses research related to the third research question.

1 Consumer data transfer for direct load control

SMs measure household's energy consumption by gathering information on energy flow, power levels and voltage (Pitì et al., 2017). They can measure electricity, water and gas consumption (Dileep, 2020), but the focus of this thesis is on the measurement function for electricity. SMs record the energy consumption in intervals ranging from every 15 minutes to once a day, depending on the SM model and its specifications (Erlinghagen et al., 2015). Generally, a SM consists of a measuring device and a gateway, representing a communication unit that transmits the consumption data (Telegärtner, 2024). Ideally, this consumption data is transmitted to the energy supplier in real time.

The main aim of meters, and therefore also of SMs, is to measure consumption (Erlinghagen et al., 2015). However, the term 'smart' in SM indicates that it's not just a data-measure device and transmitter but a two-way communicator (Erlinghagen et al., 2015), capable of transmitting and receiving information. For instance, it can send measured consumption data to the energy supplier while receiving information from the supplier, and forward DR signals, such as pricing updates, to the consumer. (Dileep, 2020). Consumers can then receive real time information on their consumption, displayed in applications on in-home devices or other screens connected to the SM gateway (Erlinghagen et al., 2015).

To make use of DLC in households, SMs need to be integrated into a home home energy management system (HEMS). The HEMS can forecast energy demand, access market prices, and decide when to schedule different electrical devices (Pitì et al., 2017). It also takes the consumers' requirements into account. Consumers specify their flexibility potential via a platform such as a smartphone application, which is forwarded to the HEMS (AlSkaif et al., 2018). For instance, depending on electricity prices or consumer constraints, the HEMS automatically selects when devices are used, considering consumer requirements and the most beneficial conditions for demand flexibility. The HEMS then automatically selects when the device is used, considering the consumer requirements and most beneficial conditions for demand flexibility. The HEMS can also remotely switch strategically high-consumption devices on and off or reduce their performance at certain times; these devices can also be categorised and prioritised for use (Munoz et al., 2022). For instance, for smart charging, the HEMS can stop the charging of EVs during peak load periods and resume charging in times of lower demand. Specifically for smart charging, in addition to the SM, a wall box is installed to measure the EV's consumption separately from other electrical devices in the house.

If consumers want the functions of the HEMS, they must purchase and install the necessary devices. The HEMS can either be hardware at the household or virtually hosted at the distribution system operator (AlSkaif et al., 2018). It is connected to the SM as part of the home area network (a computer network that enables communication between electrical devices at home).

The SM communication architecture can take various forms, one of the most common of which is communication via a data concentrator (Chren et al., 2016). A data concentrator collects consumption data from several SMs, stores it, and then, upon request, sends it to the energy supplier (Chren et al., 2016). However, the specific SM communication architecture is country-dependent.

The parties that have access to the SM consumption data include grid operators who use it to help ensure grid stability; energy suppliers, for example, to implement DR programmes and for billing purposes; consumers who can see their consumption data on connected devices, and possibly data analytics companies; data security companies that manage encryption.

2 Privacy concerns of consumers

As many parties have access to consumer data, consumers might have privacy concerns and are reluctant to give access to their data for automated solutions (Aloise-Young et al., 2021; Cichy et al., 2021). They fear losing control of their data and other negative consequences, such as illegal disclosure of data and misuse by hackers (Cichy et al., 2021). Additionally, with an increasing number of smart device sensors, the perceived level of intrusion increases (Cichy et al., 2021). For SMs, Quinn (2009) categorise customers' concerns into four groups: individuated patterns, real time surveillance, information detritus and physical invasion. The individuated patterns concern relates to individuals' worries that third parties can infer from their current behaviour based on patterns of future behaviour, such as when someone is at home and making dinner. Real time monitoring extends this concern to monitoring different behaviours in real time. Information detritus concerns that third parties could have access to consumption data. Physical invasion concerns involve fears that real time data could be misused, such as determining whether someone is at home and then breaking in.

3 Data sharing behaviour of consumers

Smart home technologies such as smart charging require data to function. With consumer data, energy suppliers can predict and plan energy usage behaviour (Fernández et al., 2022; Marxen, Chemudupaty, Fridgen, et al., 2023). For instance, smart charging of EVs relies on data to forecast future charging patterns. This foresight empowers energy suppliers to proactively allocate energy and power, make more financially sound decisions, and purchase more favourably. The details of how consumers share data for smart charging and the factors influencing their decisions are still poorly understood. Hence RP5 and RP6, explore consumers' data sharing intentions for smart charging and address research question three (*RQ3: Which data do consumers share for DR and which factors influence this decision?*).

Historical charging data are sufficient to realise DLC. However, the more sensitive the data, the more information it reveals about a person's movement patterns and the more valuable it might be to optimise and automate smart EV charging. Consumers' data then enables more accurate predictions of energy use. In RP5 and RP6, we investigate which data types consumers are willing to share for smart EV charging. We focus on three types of data, each with a different level of sensitivity: charging data, location data, and calendar data. The focus on those three data types does not imply that this is the data the energy supplier needs. Rather, the aim was to explore which data of varying sensitivity levels, consumers would be willing to share. To investigate this, we conducted a survey with 479 participants.

Sharing data also benefits the consumer, as it allows the smart charging application to be automated, so consumers do not have to make that many settings. In this respect, data sharing represents a trade-off between monetary gains, comfort and potential privacy loss for the consumer. As there has been little research on data sharing for smart charging, the data consumers are most likely to share for smart charging still needs to be clarified.

The results of RP5 indicate that the majority of consumers are willing to share historical charging data, are ambivalent about sharing location data, but do not agree to share calendar data. RP5 also explores the factors influencing the intention to share this data, testing an adapted version of Barth and Jong (2017)'s rational decision-making model with structural equation modelling (SEM). The SEM was calculated three times, respectively, with charging data, location data, and calendar data as the dependent variable. Figure 3 illustrates the results of these SEMs. Perceived risks with the application are associated with sharing charging, location, and calendar data; perceived benefits with the application are linked to sharing charging and location data; and prior location-sharing habits to sharing location data.

In economics, numerous studies examine the willingness to pay for data sharing or the required compensation to accept sharing data (Acquisti et al., 2013; Hirschprung et al.,

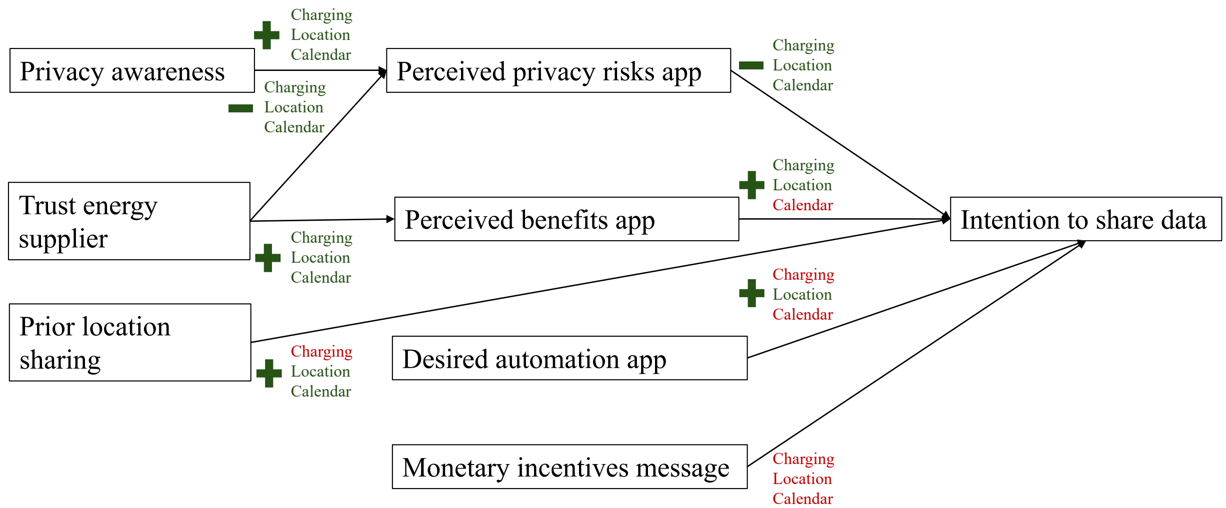

Figure 3: SEM Results of RP5: Influencing factors of the intention to share calendar, location and calendar data, +: positive statistically significant effect, -: negative statistically significant effect, red: no statistically significant effect, green: statistically significant effect.

2016). However, these studies typically focus on data sharing for websites rather than for DR, especially not for smart charging. The aim of RP5 was also to test whether people would share their data for money and how much money they request to share charging, location and calendar data.

The results of the SEM analysis in RP5 indicated that monetary incentives did not significantly affect the intention to share any of the data types. There was no statistically significant difference regarding the intention to share data between the participants who received monetary incentives and those who did not, comparing a control and experimental group. Participants in the experimental group were additionally asked how much money they would want to receive to share each data type. For the sake of simplicity, participants received the information that their monthly bill was €100 and were asked how much of this they would like to receive back in exchange for sharing their data. They also had the option to indicate that they did not want to share their data. Figure 4 illustrates the results on the of amount of monetary compensation requested by participants for sharing different types of data, in euros. Notably, around 40% of participants wanted 10-100% or more than 100% of their charging costs reimbursed to share their location and calendar data.

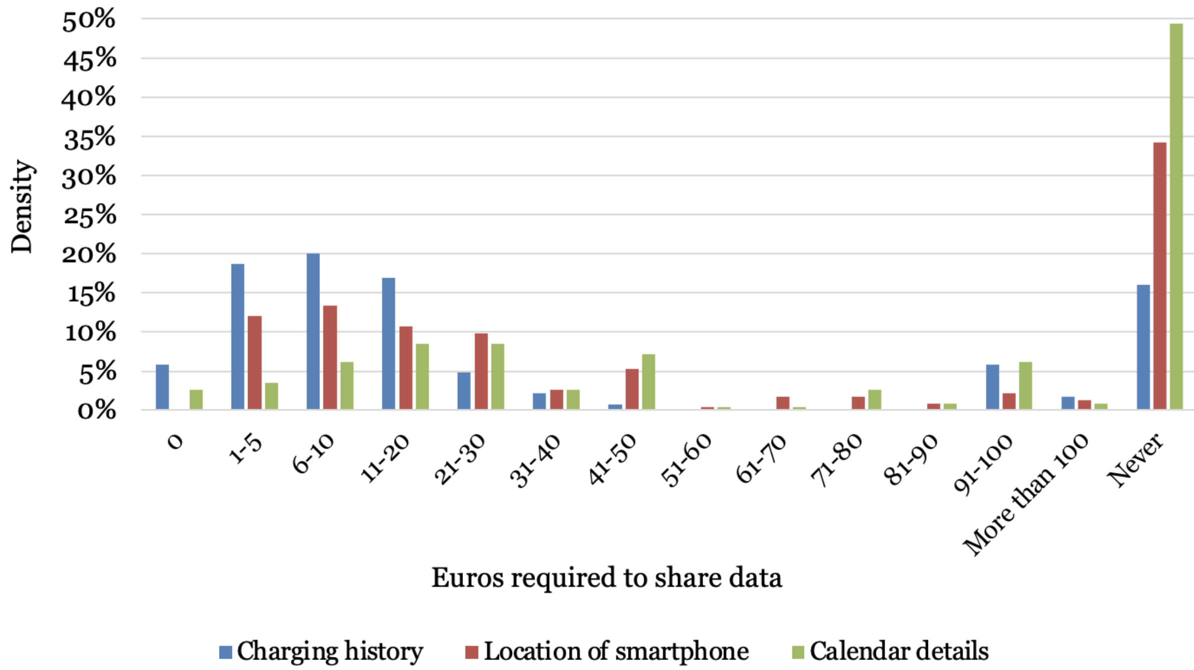

Figure 4: Amount of monetary compensation requested by participants for sharing their data.

For all types of data, most participants in the experimental group indicated a willingness to share their data for money—the more sensitive the data, the higher the amounts participants requested. Our research indicates that the majority's willingness to share data in exchange for money presents promising opportunities for energy suppliers and network operators. However, the financial viability of this data sharing for energy stakeholders is crucial. The requested sums seem unrealistically high, particularly for location and calendar data.

As an extension of RP5, in RP6, we analysed a subset of the data of RP5, focusing on the Europeans in the sample (n= 383) and examining gender differences. The motivation for this analysis comes from previous studies that identified gender differences in the electric mobility field concerning attitudes, privacy values, and data sharing behaviour (Sovacool, Kester, Noel, and De Rubens, 2018; Sovacool, Kester, Noel, and Zarazua De Rubens, 2019). Similar research in related fields, such as data sharing on social network sites, has also examined gender differences (Lin and Wang, 2020). Since there seemed to be a lack of empirical studies on data sharing for DR, our goal was to gain a deeper understanding of why people differ in their intentions to share data with energy suppliers.

The results of RP6 indicate that gender influences decisions regarding data sharing. Specifically, men had a higher intention to share location data than women, while there was no statistically significant difference regarding charging and calendar data. One possible explanation for this difference is that men may be less concerned about the potential secondary use of their data, which could reduce their hesitation in sharing location data compared to women. In RP6, the perceived risks of the smart charging application, i.e. the fear of secondary use of data mediated the relationship between gender and the intention to share data for all three data types.

Additionally, RP6 explored whether there were gender differences in the amount of financial compensation participants expected in exchange for sharing their data. Interestingly, only for location data did women expect statistically significantly higher compensation than men. There was no statistically significant gender difference for charging and calendar data. This heightened sensitivity to location data among women may be because they perceive it as more sensitive than calendar data, as it could allow third parties to track their movements in real time. This concern may be linked to women's greater fear of harassment, leading to a higher demand for financial compensation for sharing location data.

V Conclusion

Consumers play a significant role in demand-side flexibility since they decide whether and how to respond to signals that encourage adjustments in energy consumption to better align with supply. Therefore, it is essential to understand the factors related to flexibility provision and data sharing, including personal characteristics and behavioural interventions that foster it. This thesis, including six publications, contributes to a deeper understanding of the consumer's role in flexibility provision and data sharing in the context of DLC. Section 1 discusses how this thesis extends existing knowledge in these areas.

1 Synthesis and contributions

RP1 and RP3 addressed the first research question (*RQ1: How are personal characteristics related to the provision of residential flexibility?*). RP1 examined the relationship between the personal characteristics of energy literacy, environmental values and the provision of flexibility for smart EV charging and heating. Since no established measure existed, we developed a questionnaire for this study. To our knowledge, this study is the first to quantitatively assess the relationship between energy literacy and flexibility provision. The findings indicate that higher levels of energy literacy and stronger environmental values are associated with increased flexibility provision for smart EV charging and heating. These results indicate that energy literacy programmes, such as those through smartphone applications, could positively influence flexibility provision. Additionally, the relationship between environmental values and flexibility provision for smart EV charging and heating implies that environmental awareness could enhance flexibility provision.

Beyond personal characteristics, the academic literature discusses monetary incentives and nudges in promoting flexibility provision. However, there was no clear consensus on which incentives, nudges or tips are most effective for encouraging flexibility provision in smart charging. Moreover, some potential incentives or nudges for smart charging had yet to be tested, and most studies did not compare multiple incentives and nudges within a single study. To address this gap, as a first step within RP2, we first conducted an integrative literature review on potential incentives and nudges for smart EV charging. This was followed by discussions with EV users in focus groups. The literature review identified several strategies to increase flexibility provision: monetary incentives, framing, feedback, smart charging as a default, tips, and gamification. The focus group participants tended to prefer monetary incentives and smart charging as a default, but the small sample size limits the ability to draw broader conclusions.

To further investigate the effect of the incentives, nudges and tips identified in the literature review, we tested their effect in an experimental survey within RP3. This study also aimed to address the second research question (*RQ2: Which behavioural interventions increase residential flexibility provision?*).

Recognising that some previous studies often measured perceptions rather than actual effects but interpreted results as if they had measured them, we also investigated the relationship between perception and the effect of incentives, nudges, and tips. The results revealed that all forms of monetary incentives (high, low, credit points) statistically significantly increased flexibility provision. In contrast, nudges and tips did not have a statistically significant effect. Moreover, the perception of monetary incentives, nudges and tips did not correlate with their impact. Interestingly, we found no statistically significant difference in the effectiveness of high versus low monetary incentives in promoting flexibility in smart charging.

RP3 provides insights into how energy suppliers can motivate consumers to offer flexibility in their energy usage. The study indicates that if energy suppliers want to encourage consumers to provide flexibility, they should focus on offering monetary incentives. Interestingly, the amount of the incentive does not seem to be the most critical factor; instead, it is the presence of an incentive itself that matters. Additionally, the findings from RP3 provide suggestions for researchers who want to investigate the effect of behavioural interventions further. These investigations should be conducted in experimental settings rather than relying on qualitative methods to assess the effects accurately.

High consumer flexibility is highly beneficial for energy suppliers in terms of cost savings. However, the financial viability of flexibility provision depends on the extent to which the consumer provides flexibility. In RP4, we simulated how different SOC_{min} values, affect EV charging costs for energy suppliers. The simulation results indicate that if consumers set their SOC_{min} between 0-80%, the energy supplier's costs are significantly reduced compared to settings above 80%. Importantly, consumers experience minimal loss of comfort with an SOC_{min} of 80%, as SOC_{min} only represents the battery percentage at which the battery is charged at full power immediately. Therefore, energy suppliers could use the savings generated from increased flexibility to fund the incentives offered to consumers, creating a mutually beneficial situation.

In addition, the effective implementation of smart charging for EVs or heating systems requires detailed data on consumer requirements. The need for extensive data collection increases as these processes become more automated. The more sensitive the data is, the more helpful it is for the energy supplier to predict energy procurement. However, studies were scarce on what data consumers would share with energy suppliers for DR. RP5, and RP6 therefore investigated the third research question (*RQ3: Which data types do consumers intend to share for smart charging and which factors influence their intention?*).

RP5 explored the types of data with varying sensitivity levels—such as charging, location, and calendar data—that consumers might be willing to share for smart charging purposes. The study found that most participants were willing to share their charging data, showed ambivalence toward sharing location data, and were generally unwilling to share calendar data. Data sharing intentions were influenced by perceived privacy risks and benefits, prior location-sharing habits, the desired level of automation, and indirectly by privacy awareness and trust in the energy supplier. When monetary incentives were introduced, most participants indicated a willingness to share charging, location, and calendar data. These results indicate that most people are willing to sell their data. For the energy supplier, however, the question is whether the data is worth the high amounts mentioned by respondents.

In RP6, the study further revealed gender differences in data sharing preferences. Specifically, it found that men are significantly more willing than women to share location data for smart EV charging. Moreover, men require less monetary incentive than women to agree to share their location data. To the best of our knowledge, this is the first research to identify gender differences in data sharing behaviours for DR, thereby contributing to a better understanding of how demographics, such as gender, influence data sharing decisions in this context.

2 Limitations and outlook

The RPs of this thesis have several limitations that need to be acknowledged. First, it is important to recognise that flexibility is a complex, multidimensional concept. However, for the purposes of study design, the research in this thesis has necessarily simplified the concept. All studies within this thesis assume DLC as a prerequisite for flexibility provision, meaning that the energy supplier or another external entity has direct control over the energy consumption of an energy-consuming device. For instance, in RP1 DLC is equated with flexibility provision, while in RP3, it is linked to the requested SOC. The definition in RP3 is that flexibility for the energy supplier increases as the desired battery percentage decreases. However, other factors, such as parking time or the SOC_{min} value, influence flexibility and could be included in the calculation. A future study could test these aspects, further exploring the complexity of flexibility.

Second, our survey samples might lack generalisability since the surveys for this thesis, in RP2, RP5 and RP6, were conducted in the French-German language area. This cultural specificity might limit the applicability of the findings to other regions or populations. Therefore, future studies could aim to validate these results in different cultural or geographical contexts to enhance their broader relevance and applicability.

Third, while RP1, RP2, RP3 have focused on the behavioural aspects of flexibility provision and its economic effects in RP4, there is still much to explore. Future studies could focus more on the technical, financial, and political dimensions of flexibility provision. For example, a further step could be to analyse which policies are necessary for flexibility provision, opening up new avenues for research and potential solutions.

Fourth, RP3 only analysed the effects of incentives, nudges and tips in providing flexibility for smart charging. However, further research could extend this analysis by examining the combined impact of incentives and non-monetary factors (Christensen et al., 2020) on flexibility provision across various devices and contexts. The effect of other nudges, especially social ones, could also be investigated. Social norms, for instance, are informal rules accepted within a group or society (Bicchieri et al., 2011), which describe a group's behaviour and can influence individual actions. An example is OPOWER, a company that provides households with feedback on their energy consumption by comparing it with their neighbours' usage (Allcott, 2011). Allcott (2011) estimates the impact of this program, based on data from 600.000 participants, led to a 2% reduction in energy consumption.

Fifth, the consumer insights provided in the RPs of this thesis are based on surveys that measured either behavioural intention or behaviour in controlled experiments. However, future pilot studies could test these research questions in real-world settings. For example, RP5 and RP6 measured the intention to share data, but not the actual data sharing behaviour. The privacy paradox, where users express concern for their privacy but do little to protect their data, highlights the gap between stated intentions and actual behaviour (Barth and Jong, 2017). Investigating what data consumers would share in real-life scenarios and under what conditions would be valuable.

Sixth, RP5 and RP6 explored the data sharing preferences for smart charging, but they did not address other energy technologies. Future studies could investigate how consumer behaviour differs when sharing data for other technologies, such as smart heating systems. The risks associated with smart charging and smart heating are distinct, which could influence consumer behaviour differently. For example, the primary concern with smart charging might be that the EV is not charged by the desired time. In contrast, the risk might involve privacy concerns with smart heating, such as the energy supplier or other stakeholders gaining insights into when devices are used and potentially misusing that information. Understanding these differences could help tailor strategies for encouraging data sharing across different energy technologies.

Seventh, while this thesis has primarily focused on demand-side flexibility, future research could also explore supply-side flexibility provision, which is expected to become increasingly important (Schuitema et al., 2017). As consumers transition into prosumers—individuals who both consume and produce energy—they will have the potential not only to provide flexibility but also to sell excess power back to the grid or consume it directly (Schuitema et al., 2017).

Finally, this thesis focused on residential smart EV charging and heating. Future research could explore how consumers' flexibility and data-sharing behaviour differ in the context of public charging. Specifically, behaviour at public charging locations—such as public parking lots, supermarkets, or workplaces—could be examined.

VI Recognition of previous and related work

The RPs in this thesis emerged in collaborations with other researchers in the FINATRAX Research group and with the University of Hohenheim/Forschungszentrum für Informationsmanagement. Idea exchanges and discussions led to the development of research ideas and made the research output possible. In the following, I would like to mention the most important papers of these institutions that have contributed to the development of the ideas of the thesis.

For RP1, we used the literature review on energy literacy by Andolfi, Akkouch, et al. (2023) as a base to build upon and develop the idea for the survey study.

The paper by Graf et al. (2020) was instrumental in providing a first understanding of the use of behavioural interventions and gamification for sustainable decision making. This knowledge benefited the development of the ideas for RP2 and RP3. Also, the paper by Gimpel et al. (2020) on factors affecting smart energy technology adoption, along with the study by Geske and Schumann (2018) on what influences vehicle-to-grid participation, contributed to shaping ideas for developing behavioural interventions for smart EV charging, which were further explored in RP2 and RP3.

In their study, Fridgen, Häfner, et al. (2015) discussed the value of flexibility in electricity demand, which influenced the development of RP4. RP4 aimed to measure the monetary value of flexibility provision for energy suppliers, building on their insights.

Fridgen, Thimmel, et al. (2021) explored the types of data consumers need to share for smart charging, evaluating the value of this exchange. Their research helped us understand which data types are essential for smart charging. This was a key influence in shaping our privacy and data sharing survey, which we used in RP5 to explore how willing people are to share their data for smart charging.

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A | Appendix

A1 Relevant publications

Included publications

- Andolfi, L., Marxen, H., Frank., M. (2024). Are You Flexible Enough? The impact of energy literacy and environmental values on flexibility provision. Proceedings of the 20th International Conference on the European Energy Market.
- Marxen, H., Chemudupaty, R., Graf-Drasch, V., Schöpf, M., Fridgen, G. (2022). Towards an evaluation of incentives and nudges for smart charging. Proceedings of the 30th European Conference on Information Systems.
- Marxen, H., Ansarin, M., Chemudupaty, R., Fridgen, G. (2022). Empirical evaluation of behavioural interventions to enhance flexibility provision in smart charging. Transportation Research: Part D.
- Chemudupaty, R., Ansarin M., Bahmani R., Fridgen G., Marxen H., Pavić I (2023). Impact of minimum energy requirement on electric vehicle charging costs on spot markets. Proceedings of 2023 IEEE Belgrade PowerTech.
- Marxen, H., Chemudupaty, R., Fridgen, G., Roth, T. (2023). Maximising smart charging of EVs: The impact of privacy and money on data sharing. Proceedings of the 44th International Conference on Information Systems.
- Frank, M., Marxen, H., Fridgen, G. (2024). The role of gender in data sharing for smart charging of electric vehicles. Proceedings of the 30th Americas Conference on Information Systems.

Excluded publications

- Weigl, L., Amard, A., Marxen, H., Roth, T., and Zavolokina, L. (2022). User-centricity and Public Values in eGovernment: Friend or Foe?. Proceedings of the 30th European Conference on Information Systems.
- Marxen, H., & Ansarin, M. (2023). Smart charging of EVs: Would you share your data for money? Proceedings of the 43rd International Conference on Information Systems.
- Chemudupaty, R., Bahmani, R., Fridgen, G., Marxen, H., Pavic, I. (2024). Uncertain electric vehicle charging flexibility, its value on spot markets, and the impact of user behaviour. Applied Energy. (under review)

A2 Contribution statements

The following section outlines each author's contribution to the papers included in this thesis. I then elaborate in detail on how I contributed to the respective papers.

RP3 - Are you flexible enough? The impact of energy literacy and environmental values on flexibility provision

Contribution statement: Laura Andolfi: Investigation, Methodology, Conceptualisation, Data curation, Formal analysis, Software, Validation, Visualisation, Writing – original draft, Writing – review & editing. Hanna Marxen: Investigation, Methodology, Conceptualisation, Data curation, Formal analysis, Software, Validation, Visualisation, Writing – original draft, Writing – review & editing. Muriel-Larissa Frank: Writing – original draft, Writing – review & editing, Supervision.

As an equal author, I contributed by generating ideas for the paper, analysing parts of the data, writing parts of the manuscript, and thoroughly revising the entire text.

RP3 - Towards an evaluation of incentives and nudges for smart charging

Contribution statement: Hanna Marxen: Investigation, Methodology, Conceptualisation, Data curation, Formal analysis, Validation, Visualisation, Writing – original draft, Writing – review & editing. Raviteja Chemudupaty: Conceptualisation, Writing – original draft, Writing – review & editing. Valerie Graf-Drasch: Conceptualisation, Writing – original draft, Writing – review & editing, Supervision. Gilbert Fridgen: Writing – review & editing, Supervision, Funding acquisition. Michael Schöpf: Conceptualisation, Writing – review & editing, Supervision.

As the lead author, I was responsible for the majority of the work. I contributed to developing the idea and conducted the entire literature review. In collaboration with my co-authors, I organised and conducted the focus groups. I also took the lead in analysing the data and wrote the majority of the manuscript.

RP2 - Empirical evaluation of behavioural interventions to enhance flexibility provision in smart charging

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

As the lead author, I did most of the work for this paper. I helped develop the idea, did the literature research, designed the survey in discussion with my co-authors, and ensured its dissemination. I also analysed the data on my own, but in discussion with my co-authors, and wrote most of the manuscript.

RP6 - Impact of minimum energy requirement on electric vehicle charging costs on spot markets

Contribution statement: Raviteja Chemudupaty: Conceptualisation, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualisation. Mohammad Ansarin: Supervision. Ramin Bahmani: Conceptualisation, Methodology, Writing – original draft, Writing – review & editing. Gilbert Fridgen: Writing – review & editing, Supervision, Funding acquisition. Hanna Marxen: Conceptualisation, Writing – original draft, Writing – review & editing. Ivan Pavić: Conceptualisation, Validation, Writing – review & editing, Supervision.

As a subordinate author, I collaborated with the lead author in discussing the initial idea, wrote specific paragraphs for the paper, and provided feedback on the entire manuscript.

RP4 - Maximising Smart Charging of EVs: The Impact of Privacy and Money on Data Sharing

Contribution statement: Hanna Marxen: Investigation, Methodology, Conceptualisation, Data curation, Formal analysis, Software, Validation, Visualisation, Writing – original draft, Writing – review & editing. Raviteja Chemudupaty: Conceptualisation, Writing – original draft, Writing – review & editing. Tamara Roth: Writing – original draft, Writing – review & editing, Supervision. Gilbert Fridgen: Writing – review & editing, Supervision, Funding acquisition.

As the lead author, I did most of the work for this paper. I helped develop the idea, did the literature research, designed the survey in discussion with my co-authors, and ensured its dissemination. I also analysed the data alone, but in discussion with my co-authors, and wrote most of the text.

RP5 - The role of gender in data sharing for smart charging of electric vehicle

Contribution statement: Muriel-Larissa Frank: Investigation, Methodology, Conceptualisation, Writing – original draft, Writing – review & editing, Supervision. Hanna Marxen: Investigation, Methodology, Conceptualisation, Data curation, Formal analysis, Software, Validation, Visualisation, Writing – original draft, Writing – review & editing. Gilbert Fridgen: Writing – review & editing, Supervision, Funding acquisition.

As an equal author, I contributed to idea development through brainstorming, conducted the data analysis, and participated in writing and revising sections of the manuscript.

A3 Appended research publications

A3.1 Research Paper 1 - Are you flexible enough? The impact of energy literacy and environmental values on flexibility provision

Are You Flexible Enough? The Impact of Energy Literacy and Environmental Values on Flexibility Provision

Laura Andolfi[1], Hanna Marxen [2], Muriel Frank[3]
University of Luxembourg (SnT), L-1359, Luxembourg, Luxembourg[1,2,3]
laura.andolfi@uni.lu[1], hanna.marxen@uni.lu[2], muriel.frank@uni.lu[3]

***Abstract*— The residential sector plays a crucial role in the sustainable energy transition. By accepting direct load control, households can provide flexibility and contribute to stable energy systems where supply and demand are in balance. First studies indicate that when residential consumers are energy-literate, i.e., when they have a basic understanding of the use of energy and how it relates to their daily use of energy-related technologies, their willingness to provide flexibility increases. However, empirical confirmation is still scarce. Therefore, our study surveyed residential consumers in a European country (*n* = 442) to examine their understanding of energy use and their motivations for providing flexibility for heating and charging of electric vehicles (EVs). Results reveal that energy literacy and environmental values are key predictors for flexibility.**

***Index Terms*— Electric Vehicle Charging, Energy Literacy, Environmental Values, Flexibility Provision, Heating.**

I. Introduction

Global strategies to combat climate change and reduce carbon emissions are manifold. One approach is to invest heavily in increasing the share of renewable energy. Another is to electrify certain sectors, such as mobility and heating [1]. However, these developments, especially increasing the share of renewable energy, present a major challenge to the power system [2]. This is because renewable energy sources (RES), such as wind and solar, are intermittent and less flexible at peak times [3].

To integrate RES and maintain grid balance, demand side management (DSM) can be applied. DSM refers to measures aimed to reduce consumers' energy use or shift it away from peak periods [4]. This encompasses demand response (DR) measures, which encourage consumers to change their energy consumption [5] based on grid conditions [6]. However, many DR programs require consumers to actively respond to price signals. Studies find that a large majority, more than 90% in Gohary's [7] study, lack an understanding of the impact of their behaviour on energy consumption. This means that most people lack the prerequisite knowledge to respond to DR price signals. Direct load control (DLC), which also falls under DR programs [6] might offer a more viable solution. With DLC, consumers authorize a third party (i.e., energy supplier, network operator) to remotely control specific household devices [8]. By giving control to a third party, consumers do not have to actively engage with energy price signals. Nevertheless, consumer preferences, such as when and at what percentage the electric vehicle (EV) should be charged, are considered by the third party. For example, DLC for EV charging means that consumers would give the energy supplier control over when to charge the EV, while still respecting charging preferences.

So far people are reluctant to accept DLC since they are afraid of losing control and comfort [5], [9]. Recent studies have begun to unravel the factors that motivate household consumers to provide flexibility. A first qualitative study suggests that energy literacy, or the lack of it, has a significant impact on consumption behaviours [10]. Energy literacy typically includes financial and energy knowledge as well as a general awareness of energy-related decisions and their impact on energy consumption and energy systems [11]. Other studies suggest that environmental considerations, such as maximizing the use of green energy, impact individuals' willingness to change their consumption habits [1], [12], [13]. What is still lacking, however, is a quantitative validation of energy literacy and environmental values in the context of flexible use of heating and charging. Thus, our research question is formulated as follows:

RQ: How do energy literacy and environmental values influence the intention to provide flexibility for heating and charging?

Combining the insights of previous qualitative studies, e.g., by Walker and Hope [10] as well as Martins et al. [11], we empirically examine the relationship between the provision of flexibility through the acceptance of DLC and energy literacy and environmental values. Our focus is on EV charging and heating, as they have the greatest potential for household flexibility [14]. Analysing survey data from 442 customers of a medium-sized European distribution system operator (DSO), our results indicate that the provision of flexibility varies across technologies. We find that environmental values and energy

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literacy are driving forces behind the intention to provide flexibility for charging and heating. Our study is one of the first quantitative confirmations that residential consumers need some basic understanding of how power systems work to make the best energy-related decisions.

II. Theoretical background

Households' reluctance to participate in demand response programs can be attributed to a variety of factors. Research suggests that while incentives and tariffs can drive short-term changes in energy consumption, long-term behavioural change may also be influenced by personal characteristics such as energy literacy and environmental values [15]. As flexibility is a measure contributing to the decarbonisation of energy systems [16], individuals with strong environmental values should be motivated to engage in flexibility provision by shifting their consumption or accepting DLC. In parallel, such behavioural change may require awareness of energy use and an understanding of its implications [17]. This is also supported by Barido et al. [18], who suggest that improved access to energy information is associated with reduced energy consumption and increased participation in peak-shaving flexible demand events. Our study focuses on energy literacy and environmental values as potential influencers of flexibility intentions, and lays the theoretical groundwork in the following subsections.

A. Energy literacy and flexibility

Although energy literacy has attracted the interest of researchers from various disciplines, such as economics, psychology and education over the last decade, there is still no consensus on its definition [11]. One of the prominent definitions by Dewaters and Powers [19] encompasses three energy literacy dimensions: cognitive, behavioural, and affective. This means that energy literate people understand how energy is commonly used and produced. They are aware of the impact of energy decisions and the need to conserve energy. Finally, they put this knowledge into practice by taking appropriate action and committing themselves to the efficient use of resources.

On the other hand, van den Broek [20] identifies four dimensions: device, action, financial, and multifaceted energy literacy. Device energy literacy is about knowing how many kilowatt hours of energy (kWh) different devices consume. Action energy literacy extends the first dimension to include the awareness of which actions can save energy in the home and the impact of those actions. Financial energy literacy also incorporates the device and action aspects, but with an economic perspective; households with these skills can assess the financial consequences of their energy-related decisions. Finally, multifaceted energy literacy encompasses all the above, addressing socio-economic and environmental impacts.

A recent study indicates that energy literacy can influence various energy-related behaviours of a household, such as inspiring them to reduce their energy consumption or fostering investments in energy efficiency, such as retrofitting the house [21]. The authors also posit a positive relationship between energy literacy and flexibility provision. Other studies on this topic support these findings: they find that households with higher levels of energy literacy are more likely to shift their consumption in response to grid signals, as they are better able to estimate the energy use of daily tasks [10], [22]. Additionally, familiarity with the smart grid positively impacts household flexibility, encouraging behaviours such as delaying appliance use and temporarily disabling heating or air conditioning [23]. Finally, Chadwick et al. [12] identified energy literacy as a human factor that facilitates the adoption of energy technologies, including flexibility-enabling devices like smart meters or storage batteries. It can also relate to the acceptance of dynamic tariffs and third-party direct load control. Indeed, energy literacy may help overcome scepticism and risk aversion related to these relatively new products [24], [25]. All the studies mentioned in this section assess the link between energy literacy and changes in household activities, the adoption of energy technologies, or dynamic tariffs. However, none of them focuses on the relation between energy literacy and the acceptance of DLC for heating and charging. As the concepts are related, we expect energy literacy to play a role in encouraging households to provide flexibility by accepting DLC. We therefore formulate the following hypotheses:

H1: Energy literacy is positively related to the intention to provide flexibility for heating (H1.1) or charging (H1.2).

B. Environmental values and flexibility

Environmental or biospheric values refer to an individual's concern for the environment [26]. These values can influence their beliefs and behaviours [27] and serve as a main driver for engaging in environmental protection [28]. Environmental values have been identified as a predictor for concepts related to flexibility such as energy conservation behaviour [29].

With regards to flexibility provision, several authors find environmental values or related concepts influential for flexibility provision [1], [13], [30]. Environmental values or motivations have been identified as an important factor influencing consumer participation in flexibility programs [13] as well as environmental self-identity, i.e. the extent to which individuals regard themselves as environmentally friendly [1]. These environmental motivations stem from the understanding that providing flexibility helps to reduce greenhouse gas emissions and maximize the use of green energy [30], ultimately leading to a reduction in an individual's carbon footprint.

For EV charging, authors argue that environmental values as well as motives such as the integration of renewables, are crucial for people to accept smart charging [31], [32], [33]. In a pilot study, Schmalfuß et al. [32] examined the motivation of ten participants to try EV smart charging for five months. Their results indicate that ecological motives and the desire to improve society's well-being are key motivators for the use of smart charging. Will and Schuller [33] also find that integrating RES is positively related to accepting smart charging.

For heating systems, current research lacks insights into the relationship between environmental motivations and flexibility provision. One study has investigated factors influencing support for curtailments in heating during peak times in the workplace [34]. The authors find that environmental motivations predicted acceptance of such curtailments. In our study, consumers would not lose comfort, but rather relinquish control to a third party, enabling more usage of RES outside peak times. Knowing this could motivate people with strong environmental motivations to provide flexibility. Similarly, for EV charging, allowing a third party to charge at off-peak times wouldn't compromise convenience, but could increase the use of RES. Consequently, our second set of hypotheses is as follows:

H2: Environmental values are positively related to the intention to provide flexibility for heating (H2.1) or charging (H2.2).

III. RESEARCH METHOD

In this section, we present the data collection procedure and research approach. To examine the influence of energy literacy, and environmental values on flexibility provision, we conducted a survey among more than 540 customers of a medium-sized DSO in Europe.

A. Survey design and measures

To assess the level of energy literacy among our participants, their environmental values, and their intention to provide flexibility, we developed a survey (see Appendix). Since respondents were native speakers of either English, German, or French, we translated the survey into these languages, following a team-based approach [35], meaning that multilingual researchers independently translated the questionnaire into the target languages. The team then reviewed, discussed, and adjusted the versions until a harmonized and equivalent version was reached. To ensure that the survey is easy to understand, and the survey tool is working, we conducted a pre-test with 30 non-energy experts. Based on their feedback, we slightly adjusted the wording for the main study. To minimize common method bias [36] and to guarantee high quality of the data [37], we included attention checks.

To capture respondents' **intention to provide flexibility**, we asked whether they would allow remote control of their heat pump (HP) or charging of their EV during the peak loads from 17h to 20h. The scale ranged from 1 (=strongly disagree) to 7 (=strongly agree). To assess participants **environmental values**, we used the biospheric subscale of the Environmental Portrait Value Questionnaire [26], capturing an individual's concerns for the environment. Respondents indicated their agreement with each statement on a Likert scale, ranging from 1 (=totally not like you) to 7 (=totally like you). Cronbach's Alpha for this measure was $\alpha = 0.9$. To assess the level of **energy literacy**, we developed a test with multiple-choice questions. After an extensive literature review, we included several questions from one of the most widely used energy literacy surveys in schools [19] and questions related to the four dimensions [20]. We chose the most relevant questions to flexibility topics and further adapted them to the context. Questions, for example, assessed individual's knowledge of power demand of household appliances. To validate and improve the instrument, we ran a pre-test with 44 participants and used their feedback to tailor the difficulty level of the questionnaire and to reduce the number of questions. With the results of the pre-test and another round of expert interviews, we were able to reduce the number of questions from 33 to 13. Cronbach's Alpha for this measure was $\alpha = 0.61$. As **control variables**, we included standard questions regarding age, gender, education, and some more specific questions about flexibility, such as work schedule, and house ownership. We also asked about the appliances respondents had in their homes, what type of heating they used, and whether they owned or planned to own an EV or a photovoltaic installation (PV).

B. Data collection and demographics

We distributed the online survey through three different channels: a large-scale email campaign to customers who requested an upgrade of their power connection to a European DSO, social media, and the personal networks of the employees of the DSO. The email campaign addressed customers (n = 3959) who recently applied for a larger network connection related to the installation of an EV charger or PVs at their residence. Those who responded to the email campaign and answered the attention checks correctly received a €20 voucher for local shops. To further expand the sample, we ran a social media campaign, promoting the survey on X and LinkedIn. This time, no incentives were offered. The DSO also invited its employees and their families to participate in the survey. A total of 544 respondents completed the survey (n = 472 from the email campaign, n = 57 from the social media campaign, n = 14 from the DSO internal campaign). To minimize response bias, participants were assured that their answers and test scores would remain anonymous [36].

In the data cleaning phase, we filtered out participants (n = 44) who completed the survey in less than 11 minutes (10^{th} percentile of total survey time), those with incorrect attention check responses (n = 53), and incomplete responses (n = 5). Hence, we kept 442 observations for the analysis. Our sample consists of 80.21% men, while one fifth of the sample is female. Participants are on average 49 years old, have a high level of education (more than 40% with a master's degree) and an average household net income of more than 5000 Euros per month (70%). 49.89% of the participants own an EV, 50.80% PV systems, and 23.91% a HP.

C. Empirical analysis

To answer our research question, we run two multiple ordinary least squares (OLS) regressions: one for the intention to provide flexibility in EV charging, and the other for heating flexibility. Our models include energy literacy, environmental values, demographic variables, PV installation, HP ownership (for heating flexibility) or EV ownership (for charging flexibility). We used Stata for our analysis.

Prior to the analyses, we checked whether our data met the assumptions of multiple regression [38]. While no multicollinearity was found, the assumption of normality of the residuals was not met for either set of models. Homogeneity of residuals was only met for the model related to flexibility provision for EV charging, not for heating. We therefore also performed the analyses using ordered probit regression, known for its robustness with ordered categorical data [39]. Since the OLS coefficients are in the same direction and with the same statistical significance levels as the ordered probit regressions, we are confident about their robustness, and we present them in the following section. In addition, we used a Kruskal-Wallis test to assess potential differences in the distributions of dependent and independent variables across the samples [40], given the data collection took place through three different channels. The results indicate that the distributions of some variables vary significantly. Hence, we included a campaign control variable in our regression to account for these differences.

IV. RESULTS

Corresponding to hypotheses H1 and H2, we find that energy literacy and environmental values have a statistically significant positive effect on heating and charging flexibility: Individuals who are more energy literate and have higher environmental values, are more likely to provide flexibility (see Table 1).

TABLE I OLS MULTIPLE REGRESSION RESULTS

	Heating system	***Electric vehicle***
Energy Literacy	0.10* (0.04)	0.10* (0.05)
Environmental values	0.43*** (0.11)	0.50*** (0.12)
Age	-0.02** (0.01)	0.00 (0.01)
Education	0.21** (0.08)	0.12 (0.08)
Gender	-0.18 (0.25)	-0.06 (0.27)
Work schedule	0.37 (0.23)	0.22 (0.24)
HP owner	0.50* (0.23)	
EV owner		0.60* (0.27)
EV future owner		0.69* (0.29)
PV with battery	-0.97* (0.39)	-1.03* (0.41)
PV without battery	-0.27 (0.21)	-0.03 (0.21)
House owner	0.46 (0.43)	0.13 (0.46)
Social media campaign control	1.04** (0.34)	0.74* (0.36)
DSO campaign control	-0.09 (0.55)	0.03 (0.58)
Constant	0.88 (0.98)	-0.13 (1.03)
N	442	422
Adj. R^2	0.113	0.092

*Standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

Respectively, owning a HP or EV have a positive effect on heating and charging flexibility. Owning a PV installation with battery has a negative effect on flexibility in both cases. Older individuals are less likely to provide heating flexibility, while a higher level of education increases the likelihood of providing heating flexibility.

Since we analyse the intention to provide flexibility in two different contexts, we explored potential differences in flexibility provision. In an exploratory analysis, we compared the non-normally distributed dependent variables using a Wilcoxon signed-rank test. The test indicates a statistically significantly higher intention to provide charging flexibility ($Md = 6$, $n = 442$), compared to heating flexibility ($Md = 5$, $n = 442$), $z = 4.937$, $p < .001$.

V. DISCUSSION

This study explored how energy literacy and environmental values impact individuals' intention to provide flexibility by accepting DLC. Our results indicate a positive influence on flexibility provision for EV charging and heating. This study not only provides new insights on personal characteristics of flexibility, but also introduces a new energy literacy measurement for future research. In the following, we will discuss our findings, their theoretical and practical implications, and acknowledge limitations that provide avenues for future research.

A. Theoretical contributions and practical implications

To the best of our knowledge, very few studies have empirically measured the impact of personal characteristics on the intention to provide flexibility (e.g., [12], [10]). Thus, our work is the first to quantify the influence of two personal characteristics – energy literacy and environmental values – on the provision of flexibility for charging and heating.

Our findings indicate that individuals who are more energy literate are also more likely to accept DLC and therefore provide flexibility, which is in line with previous findings [21]. More importantly, this influence seems to be consistent across contexts (here: charging and heating), opening the possibility of including energy literacy in future studies to improve the predictive value of energy-related behavioural models. Another takeaway from our research is that individuals valuing the environment are more inclined to provide heating and charging flexibility, aligning with previous studies [41], [42]. Similarly, Schmalfuß et al. [32] find that ecological motives are a motivator for the use of smart charging. One explanation is that people understand that caring for the environment and supporting the growth of renewables requires a change in behaviour, such as accepting DLC.

The third contribution is a new instrument for measuring energy literacy, comprising 13 questions with varying levels of difficulty. We suggest that it can contribute to a better understanding of energy literacy. Consequently, we hope to encourage scholars to draw on our measurement instrument when investigating the impact of energy literacy in different use cases. However, as this is the first empirical study using this instrument, further validation is needed.

The exploratory analysis revealed a statistically significant difference in flexibility intentions for charging and heating. Residential consumers are more open to charging flexibility, but hesitant about providing heating flexibility. This contrasts with findings from Hansen and Hauge [43] and Yilmaz et al. [8], which indicate higher acceptance for HPs than EVs. A possible explanation for our findings could be the composition of our sample, with 50% EV and 24% HP owners. This is in line with a recent study showing that familiarity with technology is linked to flexibility in charging [44]. In addition, the timing of the data collection, after the energy crisis of 2021, may have shifted priorities, with households preferring to keep control over their heating systems.

Our study also provides some valuable insights regarding the effect of controls. Age negatively affected heating flexibility provision, which is in line with Globisch et al. [45].

Education, HP ownership, and EV ownership predict acceptance of DLC. The negative effect of PV with battery may be due to the desire of these households to have full control over their consumption.

Our findings also offer several implications for practice. First, our work highlights the role of energy literacy as a determinant of flexibility, even without financial incentives. In short, our results indicate that the more energy literate people are, the higher their willingness to provide heating and charging flexibility. To enhance energy literacy, governments, energy suppliers, and companies could employ accessible smart home apps, explanatory videos, TV programs, or workshops to educate the public on energy usage and flexibility.

A similar discourse can be applied to environmental values, which in our sample are positively associated with the intention to provide flexibility both for heating and charging. Stressing the environmental impacts of DR programs, like DLC, may increase customers' willingness to participate. Previous studies, such as Gyamfi and Krumdieck [46], find that consumers change their behaviour when provided with information about their emissions. More recently, Lashmar et al. [47] state that it is essential for residential consumers to learn about the link between flexibility and renewable energy integration.

B. *Limitations and future research*

Our study has limitations, many of which provide opportunities for future investigations. First, the selection of participants from customers who requested an upgrade of their power connection to a European DSO resulted in a biased sample, with a predominance of males, EV users and those with high incomes. This could lead to over-representation of certain groups [48] and be the reason why some demographic variables did not have an impact on flexibility provision [49]. A future study could aim for a more representative sample, including more women and lower income households. On the other hand, EV users are currently more likely to be male and have higher incomes [50]. Furthermore, despite not being representative of the country of study, our sample has some characteristics which makes it unique for our research questions. Our participants are more advanced in the use of smart technologies as reflected in a higher percentage of EV, HP, and PV ownership, compared to the average of the study country. Considering the characteristics of our sample, our results may help to understand how consumers will respond to DLC in a future with a greater diffusion of these devices and what factors will influence their choices. In general, however, it would be valuable to expand our current research and repeat the survey with a representative sample and study the differences between heating and charging flexibility.

Second, the use of intentions as a dependent variable always raises the question of whether intentions correspond to actual behaviour. However, following Fishbein and Azjen [55], we argue that measuring intentions is a feasible approach because they are a sufficiently good representation of actual behaviour. Nevertheless, in a future study, one could conduct a field or experimental study and observe actual behaviour.

Our study may not have covered all the factors that influence the provision of flexibility. Variables like trust in the technology or in the third party [6], range anxiety for charging flexibility or fear of freezing for heating flexibility, might also play a role. Further research could explore these additional variables. In addition, our study focuses exclusively on personal characteristics and does not examine the potential influence of monetary incentives, although previous research suggests their impact on flexibility provision [56], [57]. Future research could therefore investigate the effect of both personal characteristics and monetary incentives on flexibility provision.

VI. CONCLUSIONS

In light of efforts to combat climate change and integrate more renewable energy into the grid, energy stakeholders and governments are well-advised to understand what motivates residential consumers to contribute to these goals, for example, by providing flexibility. This work is the first to quantitatively examine the relationship between energy literacy, environmental values, and the provision of flexibility for heating and charging. Our results indicate a positive impact of energy literacy and environmental values. Overall, our research highlights that literacy is a key variable to focus on in future studies and suggests that energy stakeholders, rather than relying solely on monetary incentives, may want to offer energy literacy and environmental awareness programs to increase their customers' flexibility.

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APPENDIX

TABLE II SURVEY QUESTIONS

Heating flexibility
I would allow the energy supplier to adapt my heating system during the peak time (17h – 20h) if needed. (This does not affect your comfort since you have sufficient hot water storage and insulation to keep your preferred temperature throughout the day)
Charging flexibility
I would allow my energy supplier to slow down the charging of my electric vehicle during the peak time (17h – 20h) if needed. (Your electric vehicle will have the desired battery charge when you need it the morning after)
Energy literacy
In general, from a household perspective, which period marks the time where the electricity consumption is the highest? (peak consumption hours) 1. from 23:00 to 03:00, 2. from 14:00 to 17:00, 3. From 17:00 to 20:00, 4. I do not know, 5. I don't understand the question
What is the impact if you largely increase your consumption during peak consumption hours (e.g., by charging your electric vehicle)? You can select maximum of 3 choices 1. There is no impact, 2. Increased stress on the electricity grid, 3. Provoking the necessity for electricity expansion works in the electricity grid, 4. A shorter battery lifetime as batteries of smartphones, laptops or electric vehicles heat up more if charged during peak consumption hours, 5. I don't know, 6. I don't understand the question
What are the benefits of shifting your consumption from peak hours to a time of day where the consumption is lower? You can select maximum of 3 choices 1. Charging an electric vehicle, smartphone or laptop is faster, 2. To have a lower electricity bill due to lower grid expansion costs, 3. There is no benefit for the household consumer, 4. Generally lower CO_2 emissions because fewer gas power plants need to be deployed, 5. I don't know, 6. I don't understand the question
Assuming there are a lot of Photovoltaic - PV (solar) installations in your neighbourhood. Are there any benefits of shifting your consumption from peak hours to a sunny time of day? 1. Yes, it is important to consume the electricity when and where it is produced to prevent grid congestions, 2. Yes, otherwise the electricity is lost as soon as it enters the grid, 3. No, we can easily store all excess energy in summer and use it in winter, 4. No, the electricity can easily be transported over long distances, so it can be consumed elsewhere, 5. No, there is not a lot of electricity production during sunny weather, 6. I don't know, 7. I don't understand the question
Do you know how to delay the start of your dishwasher? 1. Yes, 2. Not, 3. It does not have this function, 4. I don't have a dishwasher, 5. I don't understand the question
Do you know how to delay the start of your Electric Vehicle charging? 1. Yes, 2. No, 3. It does not have this function, 4. I don't have an Electric Vehicle, 5. I don't understand the question
What challenges does the switch to 100% renewable electricity generation entail? *You can select maximum of 4 choices* 1. Renewable energy generation is highly volatile (changes constantly), 2. Renewable energy generation is decentralized (a lot of small production plants instead of few large ones), 3. Difficult to store renewable energy, 4. Difficult to align generation and consumption, 5. I don't know, 6. I don't understand the question
On average, when a device works for one hour, rank them from the highest (up) consumption to the lowest (below) consumption 1. Dishwasher / laundry, 2. Tumble dryer, 3. light bulbs, each at 10 W, 4. Electric Vehicle, 5. TV and music player, 6. Heat pump
How much electricity does it take to fully charge an electric vehicle? 1. 0.3 - 1 kWh, 2. 1 - 30 kWh, 3. 30 - 100 kWh, 4. 100 - 300 kWh, 5. 300 - 1000 kWh, 6. I don't know 7. I don't understand the question
Do you know the amount of your monthly electricity bill? NB: Please indicate your best guess without checking your bill! 1. No, 2. Yes, I pay approximatively: Enter your bill amount €/month
Which heating system would you prefer for your home, considering both have a 15-year lifespan? 1. Model A with a retail price of €3750 and a monthly bill of €100, 2. Model B with a retail price of €5000 and a lower monthly bill of €80, 3. I have no preference, both models are equally adequate, 4. I don't know, 5. I don't understand the question
Which of these household appliances uses the most electric energy during one day? 1. fridge/freezer, 2. stove/oven, 3. I don't know, 4. I don't understand the question
Which of these household appliances generates the highest peak power demand? 1. fridge/freezer, 2. stove/oven, 3. I don't know, 4. I don't understand the question
Environmental values – Biospheric subscale (Bouman et al., 2018)
It is important to [him or her] to prevent environmental pollution. It is important to [him or her] to protect the environment. It is important to [him or her] to respect nature. It is important to [him or her] to be in unity with nature.

A3.2 Research Paper 2 - Towards an evaluation of incentives and nudges for smart charging

Towards an evaluation of incentives and nudges for smart charging

Hanna Marxen
University of Luxembourg, hanna.marxen@uni.lu

Raviteja Chemudupaty
University of Luxembourg, raviteja.chemudupaty@uni.lu

Valerie Graf-Drasch
Project Group Business & Information Systems Engineering of the Fraunhofer FIT, valerie.graf-drasch@fim-rc.de

Gilbert Fridgen
University of Luxembourg, gilbert.fridgen@uni.lu

Michael Schoepf
University of Luxembourg, michael.schoepf@fit.fraunhofer.de

TOWARDS AN EVALUATION OF INCENTIVES AND NUDGES FOR SMART CHARGING

Research in Progress

Hanna Marxen, University of Luxembourg, Luxembourg, Luxembourg, hanna.marxen@uni.lu

Raviteja Chemudupaty, University of Luxembourg, Luxembourg, Luxembourg, raviteja.chemudupaty@uni.lu

Valerie Graf-Drasch, Chair of Digital Management, University of Hohenheim, and FIM Research Center, Project Group Business & Information Systems Engineering of the Fraunhofer FIT, Stuttgart, Germany, valerie.graf-drasch@uni-hohenheim.de

Michael Schöpf, University of Luxembourg, Luxembourg, Luxembourg, michael.schoepf@uni.lu

Gilbert Fridgen, University of Luxembourg, Luxembourg, Luxembourg, gilbert.fridgen@uni.lu

Abstract

Electric vehicles (EVs) are an important cornerstone to achieve transport decarbonization. Still, simultaneous charging of EVs when home charging increases peak demand, especially during evenings. Smart charging allows optimal distribution of load, thus preventing peak loads. Nevertheless, this incorporates certain risks for the EV user, e.g., unavailability of EVs for unplanned events. This might lead to a lack of user acceptance. This paper focuses on specific incentives and nudges, motivating users to adopt smart charging. We conducted an integrative literature review, bringing together literature from different areas. Possible incentives and nudges are monetary incentives, feedback, gamification, or smart charging as a default-setting. We conducted three focus groups with 13 EV users in Luxembourg to get first insights into which of those incentives and nudges they prefer. Preliminary results indicate that incentives and nudges should be individualized. In the future, we would use these first insights to develop a large-scale survey.

Keywords: Smart charging, incentives, nudges, user behaviour.

1 Introduction

A central step towards mitigating climate change includes the transformation of society towards carbon neutrality. Thereby, particularly the decarbonization of the transport sector is paramount, as this sector accounts for a quarter of the EU's total greenhouse gas emissions (European Environment Agency, 2021). Out of the many solutions to reduce the emissions associated with the transport sector, replacing the internal combustion engine with an electric drivetrain seems to be the most viable one (Wentland, 2016): When charged with renewable energy, the emissions of electric vehicle (EV) usage are almost negligible. Thus, electric vehicles (EVs) represent a key lever for putting the brakes on carbon emissions (Huber et al., 2019a). In that notion, favorable conditions such as EV-friendly policies, efficient drivetrains, or reduction in battery costs have rapidly increased the EV market penetration. This development is expected to accelerate in the forthcoming years (International Energy Agency, 2020).

Still, even if EVs address aspects of the climate crisis, the rapid electrification of the transport sector causes a rise in electricity demand. The situation further exacerbates when EVs charge simultaneously, thus causing a significant strain on the power grid (Huber et al., 2019b). This caveat could be tackled either from the supply side or the demand side: First, solutions associated with the supply side imply an increase in conventional generation capacity to meet the rising peak demand due to EV charging. This is quite expensive and incompatible with the renewable energy expansion goals (Amin et al., 2020). Second, solutions associated with the demand side refer to the control of EV charging by using demand response programs (Ireshika et al., 2019). Within such demand response programs, the EV load is controlled using indirect and direct load control strategies. In an indirect load control strategy, various dynamic pricing schemes are designed that positively correlate with peak demand, and users adapt their charging schedules to minimize their total cost (Amin et al., 2020). In a direct load control mechanism, the electricity provider alters the load based on the requirements of power systems, albeit adhering to the user requirements (Eid et al., 2016). The adaption of EV charge cycles to the conditions of power systems and the user requirements is known as 'Smart Charging' (IRENA, 2019).

Several studies have already investigated the economic feasibility of smart charging (e.g., Alghamdi et al., 2021; Eldeeb et al., 2018; Rashidizadeh-Kermani et al., 2018; van der Meer et al., 2018). All of them optimally scheduled the EV charging to maximize the profits of energy suppliers by considering the electricity market prices. Further studies ascertain that smart charging is feasible from both an economic and a technical perspective (Deilami et al., 2011; Franco et al., 2015; Richardson, 2011). These works developed an optimal solution for the efficient integration of EVs into the existing distribution systems. However, the acceptance of EV users, which is pivotal in large-scale adoption of smart charging, was rarely discussed in the studies mentioned above. This is somewhat counterintuitive since incentivizing the users is one of the most obvious ways to promote smart charging usage among EV users.

These studies on incentivizing the users to use smart charging mostly investigate the impact of monetary incentives on EV users' smart charging acceptance but less on the influence of non-monetary options. For example, Ensslen et al., (2018) developed a 'load-shifting-incentivizing' (dynamic) tariff which benefits both users and the energy suppliers. A smart charging trial in the UK found out that by implementing dynamic tariffs, most EV users shifted their charging events to off-peak periods (Greenflux, 2020). However, a recent report from the UK suggests that "over a quarter of EV users charge their vehicles during peak hours despite the cost benefits and carbon impacts" (Grundy, 2021, p.1). These contradictory results imply that monetary incentives alone might not suffice for large-scale adoption of smart charging (Will and Schuller, 2016). This ascertains that while developing an incentive scheme and strategies for smart charging, nudges should also be considered. Thaler and Sunstein (2008) define nudges as "any aspect of the choice architecture that alters people's behavior predictably without forbidding any options or significantly changing their economic incentives" (p.6). Incentives in contrast, refer to monetary benefits which arise from the choice of the desired alternative. Incentives and nudges could help ensure that smart charging is attractive to users and that they are willing to accept a certain degree of discomfort. Our research in progress study aims to better understand the behavioral component in smart charging systems and, specifically, the role of incentives and nudges for smart charging. We thus formulate two research questions:

RQ1: Which incentives and nudges in the context of smart charging are regarded as most attractive regarding user perception?

RQ2: What is the user's motivation for regarding certain incentives and nudges as attractive?

Figure 1 depicts an overview of our approach to answer these research questions. We first conducted an integrative literature review in different streams of research. Based on the literature review results, we identified incentives and nudges, which could be important from a smart charging perspective. We conducted three focus groups with 13 EV users in Luxembourg to get first insights into how attractive they perceive different incentives and nudges.

Preliminary results in this research in progress paper are that different motivations for EV usage seem to influence which incentives and nudges EV users prefer. The three motivations were ecological, economic, and technological. We will analyze focus group material using qualitative content analysis

(QCA) as a method. We will conduct a large-scale survey in a follow-up full paper to validate and determine which factors affect the perception of incentives and nudges.

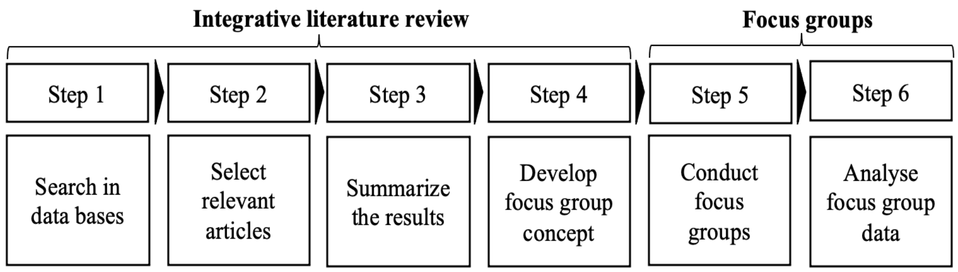

Figure 1. Research Approach.

2 Integrative literature review

Previous research has already described the impact of incentives and nudges on smart charging adoption to a small degree. Still, the number of those studies is limited. Therefore, we conducted a first integrative literature review, bringing together smart charging, energy saving and information system (IS) intersecting sustainability literature (e.g., Green IS, ICT4D). As a lens for our methodological proceeding, we used the guidelines for integrative literature reviews (Torraco, 2016). We searched in the SCOPUS and Google scholar data bases with combinations of search strings of two categories (Table 1). The search strings of the first category refer to smart charging and related concepts. Related concepts are similar to smart charging as they have the same underlying principle where the energy consumption is adapted based on the user requirements (e.g., residential). We also consider studies on energy savings. These are mostly referred to in the existing literature on incentives and nudges for smart charging (e.g., Huber et al., 2019b). The search strings of the second category are related to incentives and nudges.

Our search comprised two steps: The first step was structured with the aim to find as many relevant papers as possible about incentives and nudges for smart charging. We searched with the search strings of the first category (e.g., "smart charging") and combined them with those of the second category (e.g., "incentive"). We looked further into the identified papers using the forward-backward search to find more relevant papers. We also included papers focusing on incentives and nudges for vehicle to grid technology, a further development of smart charging technology that allows the power flow from the EV batteries to the power grid. In the second step, we focused on the papers that designed incentives and nudges to other similar concepts that could be theoretically transferred to smart charging. We combined the search strings of the first category (e.g., "EV adoption") with those of the second category (e.g., "nudge"). As there is a lot of literature on this in related fields, we aimed to get an overview of the literature and not cover the whole literature. Thus, we followed a narrative approach. In our team, we discussed and evaluated the applicability of incentives and nudges from other sectors to smart charging. The combination of the structured and narrative approach should yield a broad understanding on which incentives and nudges exist and are potentially effective for smart charging.

	Category 1		**Category 2**
Step 1 Structured approach	"smart charging" OR "flexible charging"	AND	"incentive" OR nudge" OR "behavior change" OR "consumer perspective" OR "user perspective" OR "motivation" OR "persuasion"
Step 1 Narrative approach	"load shift" OR "demand shift" OR "demand side management" OR "demand response" OR "EV adoption" OR "EV acceptance" OR "energy saving" OR "energy-efficient" OR "smart home management" OR "green information system"	AND	

Table 1. Search strings for the integrative literature review in step 1 and step 2.

Inclusion criteria for papers were the following: Papers needed to be in English or German and should state or measure the effect of incentives and nudges. In the first step, to find as much smart charging incentive literature as possible, we considered empirical papers, theoretical papers, conference papers, journal papers, doctoral theses, and university project reviews. In the second step, as fields related to smart charging were not the core focus of the paper, we mainly looked at the reviews and meta-analyses. In the first step, we found 12 papers[1]. In the second step, we selected 23 papers[2]. We looked more closely at those 35 papers. The results of the integrative literature review are that monetary incentives and the nudges *framing*, *feedback*, *gamification*, or *default-setting* can motivate people to use smart charging. In the following, we summarize this literature and provide details on related research.

First, *monetary incentives* in the context of smart charging, often refer to a discount on every kWh or the monthly base prize (Will and Schuller, 2016). Studies come to different conclusions regarding the effect of incentives and nudges on the use of smart charging. In the study of Schmalfuss et al., participants who tested smart charging for five months named monetary incentives most frequently as benefit for smart charging. Handke et al. (2012) claim that users need monetary incentives to accept smart charging. However, according to the survey results by Will and Schuller (2016), monetary incentives do not affect the acceptance of smart charging. Paetz et al. (2012b) tested a time-shifted charging concept for the charging of electric vehicles with 14 participants. The time-shifted charging mechanism allows users to adapt their charging schedule based on their requirements. For the participants of this study, however, monetary incentives were not the reason for time-shifted charging, but environmental aspects. The authors also doubt that time-shifted charging can work completely without monetary incentives.

Also, in the energy-saving literature, the effect of monetary incentives on energy-saving behavior is mixed. Some studies claim or find a positive effect (Alasseri et al., 2020; Azarova et al., 2020; Dütschke et al., 2013; Ito et al., 2018; Spandagos et al., 2021). However, a meta-analysis, which included 52 empirical studies, found a negative effect of monetary incentives on energy-saving behavior: Cost-saving information led even to higher energy consumption (Buckley, 2020). Despite disparate results, in the context of smart charging, monetary incentives may have a certain impact. According to Schmalfuß et al., (2015) and Tamis et al. (2018), EV users expect financial compensation for making their flexibility available to the energy provider. In summary, monetary incentives are potentially promising for smart charging. Previous smart charging studies mostly look at the perception of monetary incentives. Future studies on monetary incentives should also examine the impact of incentives on behavior change. But in practice, as monetary incentives are not effective for everyone, they should not be the only incentive (Tamis et al., 2018); nudges should also be considered.

Framing can be regarded as a nudge and "is the conscious formulation and description of the decision situation to encourage people to behave in a certain way" (Huber, 2020, p. 87). In the context of smart charging, this could mean using text messages to influence the decision-making situation so that EV users are more likely to use smart charging. Framing messages can be shown in an application before the user decides whether to use smart charging or not. In the study by Huber et al. (2019a), only cost frames were effective, environmental frames had no effect and social frames led even to a lower intention to use smart charging. Before charging, cost frames inform EV users to save money through smart charging (Huber et al., 2019b). Environmental frames make clear to the EV user that smart charging contributes to environmental protection (Huber et al., 2019b). Social frames show the user that the network is shared with other users and that everyone benefits from using smart charging (Huber et

[1] Selected papers in step 1: Antunes et al., 2018; Delmonte et al., 2020; Geske, 2014; Handke et al., 2012; Huber et al., 2019a; Huber et al., 2019b; Huber & Weinhardt, 2018; Jochem et al., 2012; Paetz et al., 2012b; Schmalfuß et al., 2015; Tamis et al., 2018; Will & Schuller, 2016.

[2] Selected papers in step 2: Alasseri et al., 2020; Allcott & Rogers, 2014; Azarova et al., 2020; Broman Toft et al., 2014; Buckley, 2020; Chatzigeorgiou & Andreou, 2021; Delmas et al., 2013; Dütschke et al., 2013; Frenzel et al., 2015; Günther et al., 2020; Horne & Kennedy, 2017; Ito et al., 2018; Johnson et al., 2017; Ming et al., 2020; Momsen & Stoerk, 2014; Morganti et al., 2017; Paetz et al., 2012a; Paetz et al., 2012c; Schaule & Meinzer, 2020; Soomro et al., 2021; Spandagos et al., 2021; Tiefenbeck et al., 2019; Vetter & Kutzner, 2016.

al., 2019b). In the energy-saving literature, Schaule and Meinzer (2020) had similar results: Cost frames led to an increased willingness to shift the run times of dishwashers and washing machines, and environmental frames showed no effect. "Social framing even showed a slight decrease in the readiness to shift run times for dishwashers" (Schaule and Meinzer, 2020, p. 1).

To summarize, especially cost framing messages seem to be successful. However, researchers should further investigate the effect of framing messages on the smart charging decision. Here, studies should investigate the effect of framing messages on real EV users' actual smart charging behavior.

Third, *Feedback* could be a significant nudge for smart charging. It can be given on the financial consequences or the respective carbon footprint of a user's charging behavior (Huber and Weinhardt, 2018). However, according to the meta-analysis of Delmas et al. (2013), feedback on cost savings in terms of energy savings leads to an increase in energy consumption and not a decrease (Delmas et al., 2013). Still, especially feedback on environmental contribution could be significant because eco-values, as well as ecological motives, are considered the main motivation for smart charging and the integration of renewable energy sources as the main acceptance factor (Frenzel et al., 2015; Geske, 2014; Huber et al., 2019a; Jochem et al., 2012; Paetz et al., 2012c; Schmalfuß et al., 2015; Tamis et al., 2018; Will and Schuller, 2016). Feedback on an environmental contribution would show users their contribution to environmental protection and motivate them to continue using smart charging. Schmalfuß et al. (2015) show in their survey study, for example, that EV users "are motivated by the feeling of doing something good" (p. 9) to use smart charging. The way feedback is given could be, e.g., historical, real-time, or socially comparative. Regarding the energy-saving literature, Chatzigeorgiou and Andreou (2021) regard historical feedback as a standard for feedback on energy consumption on mobile devices. Research results show that comparative social feedback and real-time feedback are particularly effective. Regarding comparative social feedback, US energy provider OPOWER received information every month about how their energy consumption varies compared to their neighbors (Allcott and Rogers, 2014). Even after the feedback reports were stopped for two years, there was an energy saving of 10-20% compared to when the feedback reports were received. According to Allcott and Rogers (2014), comparative social feedback could also be effective in the long term. Besides comparisons with other consumers, artificial norms can also be successful if the target group feels addressed (Soomro et al., 2021), e.g., encouraging hotel guests to reuse their towels. Concerning real-time feedback, Buckley (2020) concludes in his meta-analysis that real-time feedback is one of the most promising ways to give feedback. To give an example, hotel guests who "received real-time feedback on their energy consumption while showering used 11.4% (0.21kWh) less energy than guests in a control group" (Tiefenbeck et al., 2019, p.1). In addition to the distinction between historical, real-time, and social comparative feedback, feedback can be personalized or, for example, reflect the behavioral tendency. This is where personalized feedback seems most effective (Buckley, 2020; Delmas et al., 2013).

Fourth, gamification is "the use of game design elements in non-game contexts" (Deterding et al., 2011, p.9), e.g., tips, virtual currency, or badges (AlSkaif et al., 2018). It can be regarded as a form of feedback (Chatzigeorgiou and Andreou, 2021). The demarcations between gamification and feedback are blurred. Feedback and gamification differ, however, in their aims. Feedback aims to get the users to reflect on their behaviors. Gamification aims to engage the user and to enhance their activity and retention (Deterding et al., 2011). Game elements "vary widely in terms of the type of games, target, and features that might be appealing and motivating" (Morganti et al., 2017, p. 101). AlSkaif et al. (2018) classified the most important game elements for residential energy applications into the following categories: Information provision (e.g., tips), rewarding system (e.g., virtual currency), social connection (e.g., energy community), performance status (e.g., badges) and user interface (e.g., progress bar).

There is a lack of studies investigating the effect of gamification on the smart charging behavior of EV users. Still, in practice, current smart charging applications use numerous gamification elements (e.g., ev.energy, 2020). With regard to energy-saving behavior, studies find a positive effect of gamification elements (Chatzigeorgiou and Andreou, 2021; Johnson et al., 2017; Morganti et al., 2017). Gamification elements (e.g., personalized goals, feedback, social comparison, prizes, lottery) can enhance energy saving behavior and eco-driving (Günther et al., 2020; Ming et al., 2020). Regarding mobile energy applications, a limited number of studies examine the effect of gamification on behavior change (Beck et al., 2019). Also, existing studies often only consider individual gamification elements in isolation or differ in the combination of gamification elements they consider, e.g., compare the study of Ming et al. (2020) and Günther et al. (2020). It, therefore, seems difficult to describe the effect of the gamification elements on behavior change. However, some authors describe individual gamification elements further in literature and the effect on behavior: According to Buckley (2020), e.g. tips fall into the information provision category are very effective if individualized. According to their meta-analysis, general tips on saving energy even led to an increase in consumption. In general, the core principle behind tips is like feedback and framing. However, tips solely focus on improving user performance based on their behavioral patterns. Concerning social connection, Horne and Kennedy (2017) emphasize the role of social norms, which can be established via new technologies and can influence energy-related behavior. Peer pressure can be built up online and can impact the behavior of users (Spandagos et al., 2021).

Fifth, to set smart charging as a default is recommended by the UK Energy Task Force (Energy Task Force, 2019) and Delmonte et al. (2020), as this reduces user interaction with the smart charging system. In other areas, setting a desirable option as the default has proven effective, e.g., for organ donations (Shafir, 2013). Regarding the choice of environmentally friendly energy contracts, to set a contract with energy from renewables as the default was the only incentive that had an impact on whether people chose a contract where the energy came from renewable sources (Momsen and Stoerk, 2014): The default setting increased the proportion of those who opted for the green contract by 44.6%. In the study by Vetter and Kutzner (2016), the default setting also influenced whether a green contract was selected: Environmental attitudes did not influence the decision. For smart grids, the use of an opt-out frame leads to a significantly higher participation rate than the opt-in frame (Broman Toft et al., 2014). However, to make smart charging the default, smart meters and wall boxes should first be installed. If these conditions are met in the future, smart charging as a default could be possible. Still, EV users might just use it if there are no additional costs for purchasing infrastructure.

According to initial research results, different groups of people perceive incentives and nudges as differently attractive. Cultural and demographic factors and different motivations (e.g., ecological versus economic) influence, for example, how different they are perceived. Regarding cultural differences, e.g., monetary incentives are perceived as more attractive in Portugal than in the Netherlands; in contrast, social comparison is perceived as more negative in Portugal than in the Netherlands (Antunes et al., 2018). Besides cultural factors, different motivations for smart charging could also influence how attractive incentives and nudges are for different groups of EV users. Bailey and Axsen (2015) distinguish between EV users who could be motivated by cost-saving and those motivated by using electricity from renewable energy sources. In terms of how different consumers respond to demand response, Sharda et al. (2021) describe consumers based on the literature using four dimensions: Selfishness, importance of price, eco consumption, and demand responsiveness.

Concerning the price dimension, Sharda et al. (2021) distinguish between price optimizers (price prioritized over comfort), price-sensitive (tradeoff between comfort and price), and price-insensitive consumers (comfort prioritized over price). Regarding eco consumption, they distinguish between eco consumer (minimum power demand from the grid), the average consumer (average power demand from the grid), and waste consumer (comfort prioritized over price). Before incentives and nudges are applied, researchers need to conduct consumer research to investigate which incentives and nudges are appropriate for the respective target group. They "must fit the context and the targeted user group, as otherwise, they can backfire and even have adverse effects" (Huber, 2020, p. 68).

3 Focus groups

Focus groups are a well-established method to get customers' and users' perspectives on new technologies or products (Paetz et al., 2012a). In that, focus groups allow a deep investigation of reasons underlying a product evaluation and thus go far beyond superficial responses (Mert and Tritthart, 2009). Participants get the possibility to „ask questions and also to stimulate each other in evoking associations and perceptions to discuss them as a group" (Paetz et al., 2012a, p. 28).

To analyze the feedback and input received in the focus group, we later plan to use qualitative content analysis (QCA) as a deductive and an inductive approach to analyze data (Cho and Lee, 2014): We will first deductively develop categories according to which the data will be coded. Afterward, we will derive further categories with the help of an inductive procedure.

3.1 Conduct of focus groups

The primary goal of our focus groups was to perceive the users' preferences for different incentives and nudges in the context of EV charging and understand the factors driving these preferences. We conducted three focus groups ($n_1 = 4$, $n_2 = 4$, and $n_3 = 5$) in Luxembourg with 13 EV users (2 female, 11 male). We selected the EV users who drove their EV for at least several months. Participation was voluntary. All the focus groups were recorded and transcribed.

We conducted the focus groups onsite with a predefined agenda: After a short introduction, this agenda contained three central building blocks lasting 30, 15, and 90 minutes. First, we asked the participants to share their EV usage patterns as it also might influence the perceived attractiveness of incentives. Second, we described the concept of smart charging. We illustrated the importance of customer flexibility, which served as a transition for the third part, "discussion about incentives." Third, we selected the incentives and nudges based on the results of the integrative literature review. We discussed the five incentive and nudge groups *monetary incentives*, *framing*, *feedback*, *gamification*, and *smart charging as a default* with the participants. Regarding gamification, we discussed four gamification elements: badges, credit points, tips, and energy communities. Each gamification element reflects a category of AlSkaif et al. (2018). We created a presentation containing a brief description of the incentives and nudges and discussion questions to guide the discussion. Respective discussion questions were to deduce the rationale behind the participants' interest/disinterest towards a specific incentive or nudge. After the discussion, we asked participants to rank first the five incentives and nudges and second, the four gamification elements according to attractiveness using a survey.

4 Preliminary results and discussion

In the following, we provide some preliminary results of the focus groups and the participants' ranking of incentives and nudges. Regarding the first research question, "Which incentives and nudges in the context of smart charging are regarded as most attractive regarding user perception?", the rankings provide the first results (see table 2). For example, out of 13 participants, five participants ranked monetary incentives as first. Overall, the participants regarded monetary incentives and smart charging as default as most attractive. Concerning gamification, they considered tips as most attractive.

Incentives/ Nudges	Ranking results
Monetary incentives	ranked 1st (n = 5), 2nd (n = 1), 3rd (n = 1), 4th (n = 2), 5th (n = 1)
Smart charging as default	ranked 1st (n = 5), 2nd (n = 4), 3rd (n = 3), 4th (n = 0), 5th (n = 1)
Feedback	ranked 1st (n = 0), 2nd (n = 3), 3rd (n = 4), 4th (n = 4), 5th (n = 0)
Framing Messages	ranked 1st (n = 1), 2nd (n = 2), 3rd (n = 2), 4th (n = 2), 5th (n = 4)
Gamification	ranked 1st (n = 0), 2nd (n = 1), 3rd (n = 2), 4th (n = 3), 5th (n = 5)
1. Tips	ranked 1st (n = 6), 2nd (n = 2), 3rd (n = 2), 4th (n = 2)
2. Credit points	ranked 1st (n = 5), 2nd (n = 4), 3rd (n = 3), 4th (n = 0)
3. Energy communities	ranked 1st (n = 1), 2nd (n = 3), 3rd (n = 4), 4th (n = 4)
4. Badges	ranked 1st (n = 0), 2nd (n = 3), 3rd (n = 3), 4th (n = 6)

Table 2. Ranking perceived attractiveness of incentives and nudges.

The ranking of the incentives and nudges was mostly consistent with the participants' answers during the focus group discussions. About the focus group discussions, we want to highlight two striking features. First, the participants, in general, were concerned about information overload. Thus, in the context of feedback, framing, and tips, they wanted to receive only a limited number of messages on their smartphone, e.g., one message per week or just when they open their smart charging application. Second, participants largely rejected most gamification elements in the discussion. However, participants in all three focus groups considered gamification elements might be attractive for the younger generation.

Regarding the second research question, "*What is the user's motivation for regarding certain incentives and nudges as attractive?*", participants' motivation seemed to be related to their motivation to purchase an EV. Three motivations for purchasing an EV were ecological, economic, and technological. Participants with an ecological motivation had their EV for ideological reasons, to contribute to environmental protection. They were mainly interested in nudges indicating their contribution to environmental protection (e.g., feedback, framing). Participants with an economic motivation owned their EV mainly because their company covered most of their purchase costs and partly charged their EV at work. They had a higher preference for monetary incentives. Participants with technological motivation purchased EVs for their driving experience. It was not clear which incentives or nudges they preferred.

As the three motivations seem to be related to different incentives and nudges, it might be useful to incentivize and nudge EV users differently. Analog to different contexts, individualization approaches foster an effective EV user targeting for smart charging. Besides different underlying motivations, also socioeconomic characteristics (e.g., age) may influence the perception of incentives and nudges.

The results of the integrative literature review inform researchers and practitioners which incentives and nudges can potentially be effective. The review is comprehensive as we looked at the incentives and nudges literature for smart charging and other relevant sectors. A limitation of the integrative literature review is that we only used two data bases. Future research should extend the literature review and include data bases as AIS E-library, IEE Xplore, ScienceDirect and SAGE Journals.

The focus groups helped to get an insight into which incentives and nudges are attractive for EV users. One limitation of the focus groups is that the sample size of 13 is small, and therefore its results cannot be generalized. This is the reason why after analyzing the focus group transcripts, we want to design a large-scale survey based on the focus group's results. One main goal of this large-scale survey is to obtain generalizable results on users' perceptions of different incentives and nudges. We aim at investigating which incentives and nudges are attractive for different EV users and which factors (age, nationality, income, education level, occupation, ecological, economic, and technological motivation) influence individuals' perception. Incentives and nudges and the above-mentioned factors are independent variables. Using multiple regression, we then want to investigate the influence of these independent variables on the perception of incentives and nudges. Here, we want to investigate how both EV users and non-EV users perceive the incentives and nudges and compare their perceptions—the rationale behind including non-EV users as they could serve as potential EV users. In addition, however, we want to test in an experiment within the framework of the survey which incentives and nudges are effective.

The results will help practitioners develop individualized incentive schemes in different contexts (e.g., different countries). In the academic field, we want to initiate research that further investigates the behavioral aspects of smart charging. Such research is highly relevant, as smart charging cannot be established without the acceptance of EV users.

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A3.3 Research Paper 3 - Empirical evaluation of behavioural interventions to enhance flexibility provision in smart charging

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

Hanna Marxen [a,*], Mohammad Ansarin [a,b], Raviteja Chemudupaty [a], Gilbert Fridgen [a]

[a] Interdisciplinary Centre for Security, Reliability and Trust (SnT), University of Luxembourg, Luxembourg, Luxembourg
[b] Trinomics BV, Rotterdam, Netherlands

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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

* Corresponding author.
E-mail address: hanna.marxen@uni.lu (H. Marxen).

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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.

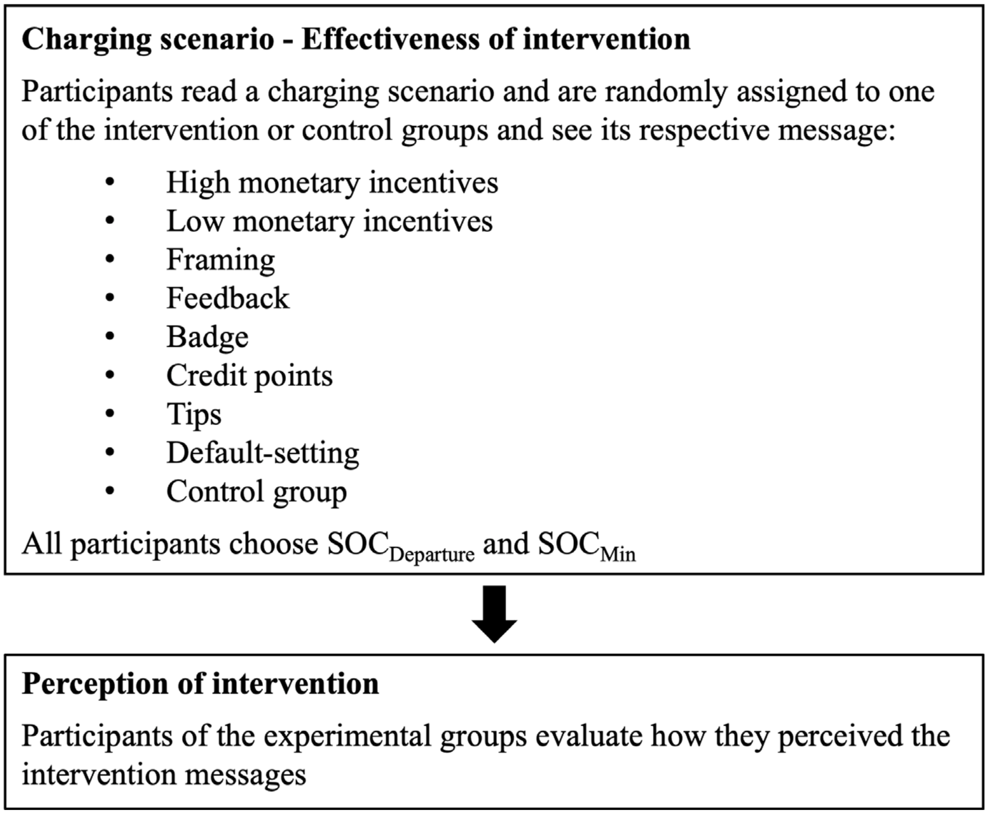

Fig. 1. Overview of the experimental survey design.

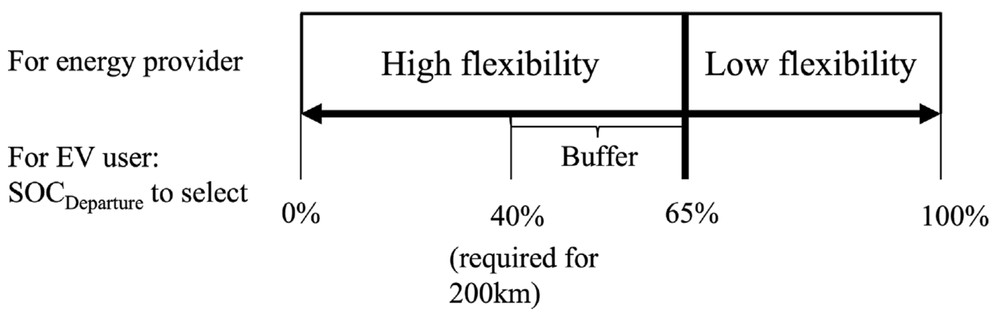

Fig. 2. Illustration of the simplified flexibility definition for the experimental design.

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

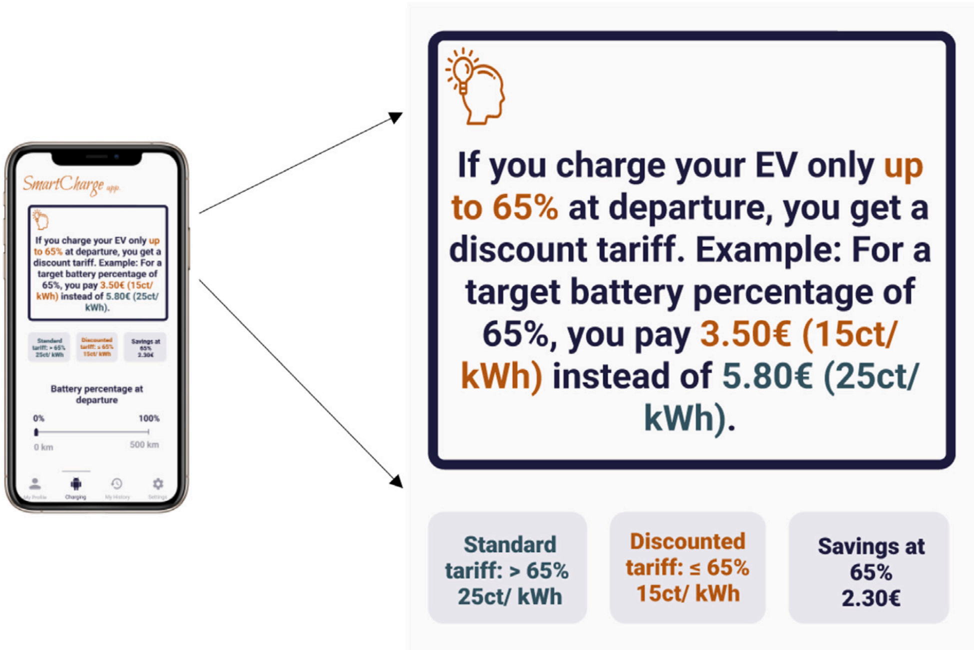

Fig. 3. Example of message for the high monetary incentives group.

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 $SOC_{Departure}$ up to 65%. b_0 indicates the (predicted) $SOC_{Departure}$ value of the control group. In contrast, b_i indicates the difference between the respective experimental and control groups concerning the selected $SOC_{Departure}$.

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 $SOC_{Departure}$.

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 $SOC_{Departure}$ 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 ($SOC_{Departure}$, 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 $SOC_{Departure}$ 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 $SOC_{Departure}$. 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 $SOC_{Departure}$. 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 $\text{SOC}_{Departure}$ values also report lower SOC_{Min} values and that SOC_{Min} correlates with risk aversion. These results suggest that factors associated with $\text{SOC}_{Departure}$, 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 $\text{SOC}_{Departure}$ 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 $SOC_{Departure}$ 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 $SOC_{Departure}$, 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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Survey related to the paper “Empirical evaluation of behavioral interventions to enhance flexibility provision in smart charging”

Dear participant,

thank you for your interest in this study.

This study is conducted at the department FINATRAX of SnT, University of Luxembourg. By your participation, you support our research project on behaviors in electric vehicle charging. It takes a maximum of 10-15 minutes to complete the survey.

There are no right or wrong answers, we are only interested in your true and honest perspective. To ensure that the results of our study are meaningful, we would ask you to answer the survey completely and seriously. Participation in the survey is voluntary and open to anybody aged 18 and over. You can terminate the survey any time without stating reasons. All data will be kept strictly confidential.

At the end of the study you can take part in a lottery for five Amazon vouchers (1* 100€, 1* 40€, 3* 20€).

Thank you for your participation!

Part 1

How familiar are you with smart charging of electric vehicles?

Please rate yourself on a scale from 0 (not familiar at all) to 7 (extremely familiar). Please select 0 if you have never heard about it.

not familiar at all (1)	(2)	(3)	(4)	(5)	(6)	extremely familiar (7)

In order to be able to answer the questions in the survey, it is important to understand the explanation of smart charging. Please read it carefully:

Smart charging is a technology that allows the **energy supplier** to manage the charging of electric vehicles (EVs): The energy supplier considers both the **requirements of the power system** and the **EV user needs**.

Requirements of the power system: If most EVs are charged at the same time (e.g., after rush hour), this can overload the electricity grid. Imagine a residential neighbourhood with several EVs plugged in overnight at their home charging stations. By using smart charging, the load can be distributed across the time period EVs are plugged in. Some of those EVs can for example be charged between 22:00 and 1:00, some between 1:00 and 4:00 and some between 4:00 and 7:00.

EV user needs: Before charging, EV users enter their needs in a smart charging application:

- Departure time: The user says when to leave the next morning.
- Battery percentage: The user specifies how much battery percentage he/ she wants at departure time.

This way, the **energy supplier** knows which preferences to consider when managing the charging.

Based on the explanation of smart charging you just read, please select the appropriate answer.

Smart charging ...

- takes into account the requirements of the EV user and the power system.
- gives the energy provider complete control over the charging of EVs without considering EV user needs.
- exclusively maximises the EV users' profit.

Please indicate whether you would allow your energy supplier to control the charging process of your EV. Your energy supplier would ensure that your EV is charged to the desired battery percentage at departure.

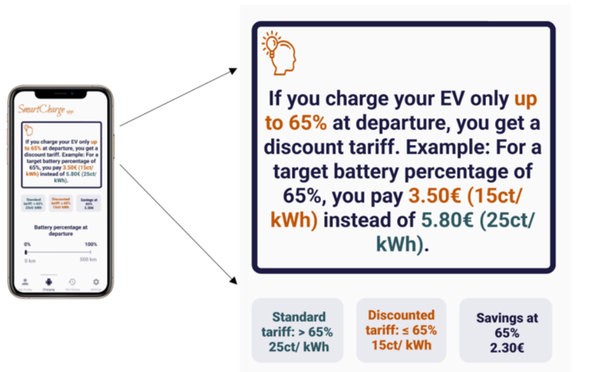
	Strongly disagree	Disagree	Some-what disagree	Neither agree nor disagree	Some-what agree	Agree	Strongly agree
I would have the charging process of my EV controlled by my energy supplier.							

Please imagine this scenario to answer the next questions:

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 200km (round trip).

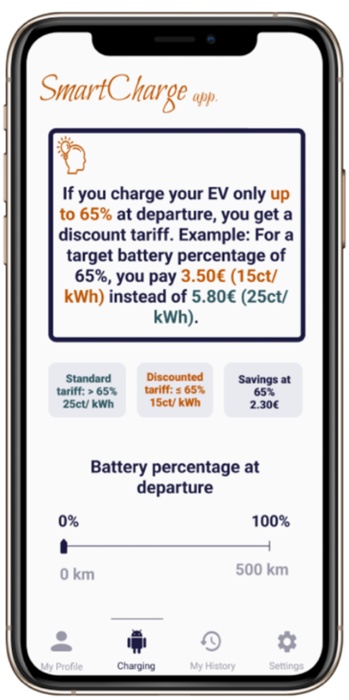
You have told your smart charging app that you have to drive 200km the next day.

Your smart charging app displays the following message:[1]

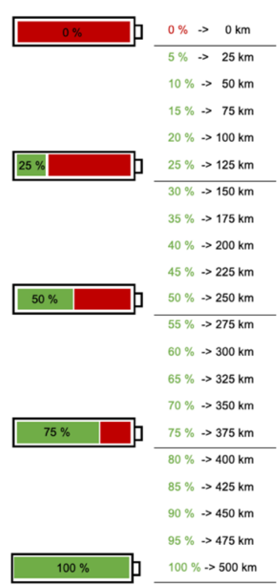


Your smart charging app asks you what battery percentage you want the next morning.

Reminder scenario: You come home at 18:00 with your EV. Your battery percentage is 15%. The next day, you have to leave at 8:00 and drive 200km (round trip).



Here you can read how far you can drive with different battery percentages. The physical conditions of your car and the weather conditions for the next day are considered.



Which battery percentage would you like to have at departure the next morning?

Please choose a battery percentage from 0-100%. (Participants can select a value from 0-100%)

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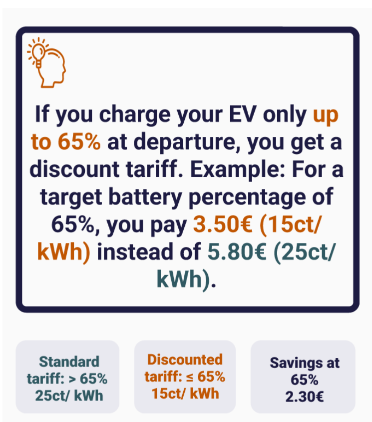
[1] The intervention message is just illustrated for the high incentives group, but the other messages can be found in the paper.

Which battery percentage should your EV always have as a mininum in case of unforeseen emergencies? (This implies that your EV would be always charged to that level at maximum charging power when plugged in.) This question does not refer to the previously described scenario.

Please choose an absolute minimum battery percentage from 0-100%. (Participants can select a value from 0-100%)

What information did you perceive on the mobile phone screen?

- Information on ...
- how I can save money.
- how I can get money in form of digital vouchers.
- that I saved CO_2.
- how I can obtain more energy from renewables when charging.
- that I am among the 20% top smart chargers and received an environmental badge.
- the default battery percentage.
- that my EV is connected to the charging station.
- which battery percentage is best for the battery of my EV.



[2]

How did you perceive the following message (see screenshot below)? Your answers should reflect you personally and should not reflect any ideal case from your point of view. Please note that there are no right and wrong answers. Please choose a value from 1-7 in each row.

My judgement of this message is ...

Unpleasant (1)	(2)	(3)	(4)	(5)	(6)	Pleasant (7)
Annoying (1)	(2)	(3)	(4)	(5)	(6)	Nice (7)
Irritating (1)	(2)	(3)	(4)	(5)	(6)	Likeable (7)
Undesirable (1)	(2)	(3)	(4)	(5)	(6)	Desirable (7)

[2] The intervention message is just illustrated for the high incentives group, but the other messages can be found in the paper.

Part 2

The following questions are about your mobility behavior and vehicle usage.

Which of those transportation means cover currently the most of your mobility needs?

Please select 1-3 answers that apply to you.

- Electric vehicle
- Plug-in hybrid
- Combustion engine vehicle
- Public transport
- Bicycle
- Other:

How often do you drive an electric vehicle*?

Please select the answer that applies to you.

*Electric vehicles (EVs) are vehicles that are electrically powered (only fully battery-powered vehicles are considered in this study). They use electric motors for propulsion, which are powered by a battery.

- Never
- Once or twice a year
- Once or twice a month
- Once or twice a week
- Many times a week
- Every day
- Many times a day

How many vehicles does your household own?

- 0
- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10

How many of all your vehicles are electric vehicles?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6

How many people in your household have a driving licence?

- ○ 0
- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6
- ○ 7
- ○ 8
- ○ 9
- ○ 10

Please indicate how many kilometres on average you daily drive your vehicle. (in km)

Part 3

The following questions are about your electric vehicle usage.

The electric vehicle I am using is ...

- ○ a bought EV
- ○ a leased EV
- ○ a company EV
- ○ Other:

How many kilometres can your electric vehicle roughly drive in electric mode? (in km)

What is the battery capacity of your electric vehicle in kWh? (in kWh)

Please indicate how many kilometres on average you daily drive your electric vehicle. (in km)

For how long is your electric vehicle standing at home on average on a weekday? (in hours)
(participants can select a value between 0-24h)

For how long is your electric vehicle standing at home on average on a weekend day? (in hours)
(participants can select a value between 0-24h)

Where do you mostly charge your electric vehicle?

- ○ At home
- ○ At work
- ○ At a public charging station
- ○ At commercial places
- ○ Other:

Part 4

In the following, we ask you for your reasons to drive an electric vehicle. Your answers should reflect you personally and should not reflect any ideal case from your point of view. Please note that there are no right and wrong answers.

For each statement, please indicate how much you disagree or agree.

I drive an electric vehicle, because ...

	Strongly disagree	Disagree	Some-what disagree	Neither agree nor disagree	Some-what agree	Agree	Strongly agree
it is comfortable to drive due to its silent motor.							
it is easy to drive (e.g. no changing of the gears).							
it is fun to drive due to its quick acceleration.							
I like to try new technologies.							
I can be part of the sustainability movement.							
it is healthier due to lack of fumes and pollution.							
I can be environmentally friendly. it helps me spend less on fuel.							
it gives me governmental incentives (e.g. no taxes, no tolls, free parking spaces).							
considering all costs, it is cheaper for me than driving conventional cars.							
it helps me show others my personal values. it makes me feel proud. it is part							

of my identity. I am judged favourably by others.							
it gives me governmental incentives (e.g. no taxes, no tolls, free parking spaces).							
considering all costs, it is cheaper for me than driving conventional cars.							
it helps me show others my personal values. it makes me feel proud. it is part of my identity. I am judged favourably by others.							
it makes me feel proud. it is part of my identity.							
I am judged favourably by others.							

Are there other important reasons why you drive an electric vehicle?

If yes, please feel free to share them.

In the following, you see statements about environmental concerns and on the role of risk in life. Your answers should reflect you personally and should not reflect any ideal case from your point of view. There are no right and wrong answers.

For each statement, please indicate how much you disagree or agree.

	Strongly disagree	Disagree	Some-what disagree	Neither agree nor disagree	Somewh at agree	Agree	Strongly agree
Humans are severely abusing the environment.							
Despite our special abilities humans are still subject to the laws of nature.							
The earth is like a spaceship with very limited room and resources.							
The balance of nature is very delicate and easily upset.							
If things continue on their present course, we will soon experience a major ecological catastrophe.							

	Strongly disagree	Disagree	Some-what disagree	Neither agree nor disagree	Some-what agree	Agree	Strongly agree
I do not feel comfortable about taking chances.							
I prefer situations that have foreseeable outcomes.							

Before I make a decision, I like to be absolutely sure how things will turn out.							
I avoid situations that have uncertain outcomes.							
I feel comfortable improvising in new situations.							
I feel nervous when I have to make decisions in uncertain situations.							

Part 5

In this last part of this survey, we would like to ask you to provide some personal information. Your information will be kept anonymous and strictly confidential. However, this Information is important for our research.

What is your gender?

- Male
- Female
- Transgender Female
- Transgender Male
- Gender Variant/ Non-Conforming
- Prefer not to disclose
- Other:

How old are you? (in years)

(Participants can select a value between 18-100)

What is your nationality?

Please name the country or countries that apply. If you have several nationalities, please select the last option (other) and specify.

(Participants can select their nationalit(y)/(ies) out of a list of all nationalities)

Which highest degree of education do you have?

- No school diploma
- Some high school
- Highschool/ GED
- Some college
- Associates' degree
- Bachelor's degree
- Master's degree
- Doctoral degree
- Other:

What is your current occupation?

- Working professional (full-time)
- Working professional (part-time)
- Student Pensioner
- Housewife/ househusband

- Unemployed
- Other:

To which of the following industries is/ was your work or study field primarily related?

- Business, consultancy or management
- Accountancy, banking or finance
- Charity and voluntary work
- Creative arts or design
- Energy and utilities
- Engineering or manufacturing
- Environment or agriculture
- Healthcare
- Hospitality or events
- Computing or IT
- Law
- Law enforcement and security
- Leisure, sport or tourism
- Marketing, advertising or PR
- Media or digital
- Property or construction
- Public services or administration
- Recruitment or HR
- Retail
- Sales
- Science or pharmaceuticals
- Social care
- Teacher training or education
- Transport or logistics
- Other

What is your monthly net income?

- less than 1000 €
- 1000-2999 €
- 3000-4999 €
- 5000-6999 €
- 7000-8999 €
- ≥ 9000 €

In which country do you live?

(Participants could choose between all possible countries)

Do you feel that this survey has changed your attitude towards the topic of electric vehicles charging?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
This survey has changed my attitude towards the topic of electric vehicles charging.							

Thank you for your participation in this study.

In the following, you are invited to read information about the background and aim of this study. If you want to participate in the lottery, you can enter your email address in the next comment field. You can also indicate whether you would like to take part in two more of our surveys on smart charging in the future.

A3.4 Research Paper 4 - Impact of minimum energy requirement on electric vehicle charging costs on spot markets

Impact of minimum energy requirement on electric vehicle charging costs on spot markets

Raviteja Chemudupaty[1], Mohammad Ansarin[1,2], Ramin Bahmani[1], Gilbert Fridgen[1], Hanna Marxen[1], Ivan Pavić[1]
[1]Interdisciplinary Centre for Security, Reliability and Trust (SnT), University of Luxembourg, Luxembourg, Luxembourg
[2] Trinomics BV, Rotterdam, Netherlands
Email: [raviteja.chemudupaty, ramin.bahmani, gilbert.fridgen, hanna.marxen, ivan.pavic]@uni.lu,
mohammad.ansarin@trinomics.eu

***Abstract*—Simultaneous charging of electric vehicles (EVs) increases the peak demand and might lead to higher electricity prices. This could increase EV charging costs and make EVs unattractive. Smart charging utilizes the flexibility provided by EVs and adapts charging behavior in response to the electricity market price signals. However, some studies indicate users' reluctance to participate in smart charging programs, as they perceive the risk of their vehicle not being charged sufficiently at required times. As a countermeasure, several researchers use the concept of minimum state of charge (SOC_{min}). It is the percentage of the battery up to which the EV is charged uncontrollably at full power right after it is connected to the charger. Depending on the users' SOC_{min} requirement, there might be an impact on EV flexibility and subsequently on EV charging costs. We developed a novel flexibility algorithm which quantifies EV flexibility in terms of both energy and power as a function of time. To calculate the EV charging costs, we developed a two-stage scenario-based stochastic optimization model. Optimization utilizes flexibility input and minimizes charging costs while participating in both day-ahead and intraday markets. We found that in most cases where EVs provide some flexibility, there was no significant increase in charging costs. However, we observed a 50% increase in costs when EVs do not provide flexibility. Therefore, EVs possess high flexibility potential. This flexibility can be provided almost without any loss of user comfort for high monetary gains.**

***Index Terms*—Electric vehicles, Flexibility, Electricity markets**

I. Introduction

During the last couple of years due to its environmentally positive effects, we have seen a rapid increase in electric vehicle (EV) penetration. This trend is expected to continue in the coming years [1]. However, the introduction of EVs brings new challenges to the existing power system. When EVs charge simultaneously, it could lead to an increase in peak power demand. This could subsequently lead to significant increase in wholesale market prices [2]. Furthermore, existing power grid capacities should be increased to prevent the grid from overloading and voltage issues [3]. All these factors would increase the costs of electricity procurement, which is reflected in the user's bill, making EVs unattractive.

This caveat could be addressed by using demand response (DR) programs [4]. DR refers to the alteration of user demand in response to signals coming from the power system. In that notion, the charging behavior of EVs can be used as flexibility service where charging adapts to the power system conditions and to the user mobility requirements. This is commonly termed as smart charging. The electricity prices are usually lower during the off-peak periods. Therefore, charging EVs at lower prices would simultaneously reduce the procurement costs of energy suppliers and reduce the peak demand.

Several studies have developed optimization models for smart charging of EVs with the objective to maximize the revenue of EV aggregator while participating in electricity markets [5], [6]. To consider uncertainties of electricity market prices and vehicle availability, [7]–[9] proposed two-stage stochastic optimization models with objective to maximize the revenue of EV aggregators. These studies optimally scheduled EV charging while considering price uncertainty in electricity markets and different travel patterns for EVs. However, all the above studies assumed that users would participate in smart charging programs and thus provide full flexibility throughout the charging session.

There are some studies that indicate users' reluctance to participate in smart charging programs [10], [11]. This is because users perceive certain risks in smart charging programs, including fear of losing control and not being charged sufficiently at the required times. As a countermeasure, several researchers and practitioners use the concept of SOC_{min} [12]–[14]. SOC_{min} is the percentage of the battery up to which the EV will be charged in an uncontrolled manner at full power right after it is connected to the charger. SOC_{min} plays a large role in the acceptance of smart charging and counteracting range anxiety [15]. [15] evaluated the charging costs incurred for smart charging with this additional user requirement, i.e. SOC_{min}, while participating in the German day-ahead electricity market. We extend their work by considering several cases with different possible SOC_{min} values and we evaluate EV flexibility for each of the cases. Additionally, we evaluate monetary value of EV flexibility when participating in both day-ahead and intraday markets. In our paper, we strive to answer the following research questions:

- RQ1: How does the SOC_{min} requirement impact the EVs flexibility potential?
- RQ2: What is the monetary value of EV flexibility depending on SOC_{min} when participating in wholesale electricity spot markets?

To answer RQ 1, we propose a novel flexibility algorithm

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to quantify flexibility. We quantify EV flexibility in terms of both energy and power as a function of time. This will tell us the amount of power that can be varied in each timestep whilst maintaining the required energy level to satisfy user requirements. To evaluate the flexibility algorithm, we use synthetic mobility dataset based on German mobility behavior. We then use this flexibility as an input to our optimization model to simulate EV charging.

To answer RQ 2, we developed a two-stage scenario-based stochastic optimization model with the objective to minimize the charging costs while participating in both day-ahead and intraday markets. To consider the uncertainty in the intraday market, we modelled different prices scenarios. We used German day-ahead and intraday electricity market data to evaluate our optimization model.

II. Mathematical Framework

In this section, we present the mathematical formulation used for flexibility algorithm and optimization model used to optimize the EV charging behavior.

A. Flexibility algorithm

The flexibility provided by an EV varies for each charging session based on the user charging requirements. These requirements include $E^{arrival}$, the energy level of the EV battery at the time of arrival ($t^{arrival}$). $E^{departure}$, the energy that should be transferred to EV by the time of departure ($t^{departure}$). $E^{minimum}$, the energy that should be transferred to satisfy the SOC_{min} requirement. The maximum charging power of EV is $P^{EV,max}$. As we only consider unidirectional charging, we can only use $E^{departure}$ for flexibility provision.

We only consider the part of EV battery capacity which offers flexibility, $E^{departure}$, and model the flexibility metrics - energy and power metrics accordingly. The energy metrics are minimum energy level (E_t^{min}) and maximum energy level (E_t^{max}). The minimum energy level represents the minimum cumulative energy that must be transferred to the EV at time t to satisfy the user's energy requirements. As we assume a linear charging of the EV, we calculate E_t^{min} by using Equation (1), where charging power at time t is P_t. The charging process to determine E_t^{min} is divided into three phases within its plugin duration (Equation (2)). The first phase is between $t^{arrival}$ and time taken for the minimum energy transfer, which is t^{min}. The second phase is between t^{min} and $t^{critical}$, where $t^{critical}$ is the time after which the P_t should be maximum to satisfy the user's energy requirement. The third phase is the time between $t^{critical}$ and $t^{departure}$. Hence, the P_t in the first phase, second phase, and third phase are $P^{EV,max}$, 0, and $P^{EV,max}$ respectively.

$$E_t^{min} = E_{t-1}^{min} + P_t \times \Delta t \tag{1}$$

$$P_t = \begin{cases} P^{EV,max} & t^{arrival} < t \leq t^{min} \\ 0 & t^{min} < t \leq t^{critical} \\ P^{EV,max} & t^{critical} < t \leq t^{departure} \end{cases} \tag{2}$$

The maximum energy level (E_t^{max}) represents the maximum cumulative energy that can be transferred to the EV at time t. As we assume a linear charging of EV, the maximum energy level at time t , E_t^{max} is calculated by Equation (3). The charging process to determine E_t^{min} is divided into two phases (Equation (4)). The first phase is between $t^{arrival}$ and $t^{instant}$. $t^{instant}$ is the time it takes to transfer $E^{departure}$ when charged at full power. The second phase is between $t^{instant}$ and $t^{departure}$ where there is no energy transfer. Hence, the charging power in first phase and second phase is $P^{EV,max}$ and 0 respectively.

$$E_t^{max} = E_{t-1}^{max} + P_t \times \Delta t \tag{3}$$

$$P_t = \begin{cases} P^{EV,max} & t^{arrival} < t \leq t^{inst} \\ 0 & t^{inst} < t \leq t^{departure} \end{cases} \tag{4}$$

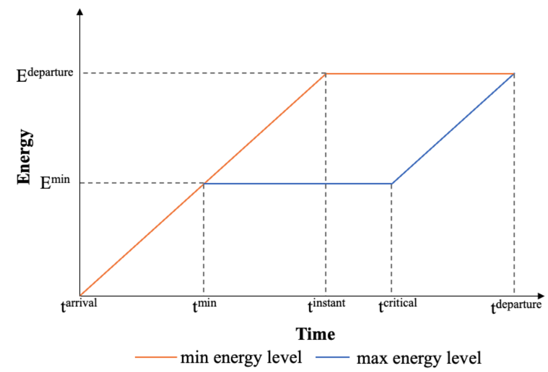

Fig. 1. Representing EV flexibility in energy vs. time graph.

The minimum and maximum energy levels can be represented in the energy vs. time graph as illustrated in Figure 1 above. From the Figure 1 it is quite evident that EV does not provide any flexibility until t^{min}. The power flexibility metrics are minimum power (P_t^{min}) and maximum power (P_t^{max}) at time t. The (P_t^{min}) when there is no flexibility, that is until t^{min}, is equal to $P^{EV,max}$. When EV offers flexibility, from t^{min} to $t^{departure}$, (P_t^{min}) is equal to 0. The maximum power (P_t^{max}) during the whole plugin duration is equal to $P^{EV,max}$.

The flexibility provided by an EV during its plugin duration is quantified by using energy (E_t^{min}, E_t^{max}) and power parameters (P_t^{min}, P_t^{max}). These parameters will convey the amount of power with which EV can be charged while maintaining upper and lower limits of cumulative energy transfer.

In our study, we calculate the individual flexibilities of each EV separately and then aggregate them (i.e, summation of the flexibility metrics of individual EV) to obtain the aggregated flexibility of all EVs. We represent the corresponding aggregated energy and power flexibility metrics as $E_t^{min,agg}$, $E_t^{max,agg}$ and $P_t^{min,agg}$, $P_t^{max,agg}$. Thus, it represents a virtual battery with minimum and maximum power and energy levels.

B. Optimization model

This section presents the mathematical model to minimze the energy provider's costs incurred for EV charging. We developed a two-stage scenario-based stochastic optimization model considering the price uncertainty of the intraday market. To consider intraday price uncertainty, we generate scenarios for intraday electricity prices first and employ them as optimization input afterwards.

We consider the uncertainty of intraday prices by utilizing probability density function (PDF) to create scenarios based on historical data and to model probabilistic nature of intraday market behavior. We employ normal PDF to generate scenarios for intraday prices as illustrated in Equation (5) below [16].

$$PDF(x) = \ 1/(\delta\sqrt{2\pi})\ exp(-(x-\mu)^2/(2\delta^2\ )). \quad (5)$$

using normal PDF, we generate different scenarios for intraday price. The value for each scenario and its corresponding probability are calculated using Equations (6) and (7) respectively:

$$\chi_{x,\ n_x} = \frac{1}{\rho_{x,\ n_x}} \times \left(\int_{x_{start,\ n_x}}^{x_{end,\ n_x}} x.PDF\,(x)\,dx \right), \qquad n_x = 1, 2,\ \ldots,\ N_x \quad (6)$$

$$\rho_{x,\ n_x} = \int_{x_{start,\ n_x}}^{x_{end,\ n_x}} PDF\,(x)\,dx \ \ , \qquad n_x = 1, 2,\ \ldots,\ N_x. \quad (7)$$

where $\chi_{x,\ n_x}$, $\rho_{x,\ n_x}$, and n_x are value, probability, and number of intervals for the scenario x,respectively. In this paper, we consider 7 intervals illustrating 7 scenarios for intraday prices of each time period.

The objective function in this paper is to minimize the costs of energy provider using our two-stage scenario-based stochastic optimization method. One prominent feature of two-stage stochastic optimization is the division of decisions in two stages. The energy provider takes some decisions in the first stage, and compensates any unfulfilled resource allocation in the second stage of the optimization. The objective function used in our paper is illustrated in Equation (8):

$$\sum_{t\in T} (P_t^{DA} \times c_t^{DA}\ )\Delta t + \sum_{w\in W}\sum_{t\in T} \rho_w \times (P_{t,w}^{RT} \times c_{t,w}^{RT}\ )\Delta t. \quad (8)$$

The objective function is divided into two parts. The first part is the total cost of energy provider in day-ahead market in the optimization period T, and the second part is expected cost of the energy provider in intraday market under various scenarios, W. The energy provider purchases the required power from the day-ahead market in the first stage, and compensates the rest of the required power based on the occurring scenario in the second stage. We use the generated scenarios from the previous section as input for the stochastic optimization. P_t^{DA} and c_t^{DA} are power purchased from the day-ahead and day-ahead price, respectively at time t. ρ_w is the probability of occurrence of each scenario w. Moreover, $P_{t,w}^{RT}$ and $c_{t,w}^{RT}$ are variable and parameter illustrating the purchased power from intraday market and intraday market prices at time t for scenario w.

In the scenario-based stochastic optimization used in this paper, P_t^{DA} is the same for all the scenarios. Therefore, the power balance between day-ahead and intraday is attained by using the Equation (9) below:

$$P_t^{DA} + P_{t,w}^{RT} = \quad P_{t,w}^{agg} \quad \forall\ t \in T, w \in W. \quad (9)$$

$P_{t,w}^{agg}$ is the variable for aggregated charging power of EVs, which is restricted by the connected vehicles to the grid, illustrated in the Equation (10):

$$P_t^{min,agg} \ \leq P_{t,w}^{agg} \ \leq \ P_t^{max,agg} \quad \forall\ t \in T, w \in W. \quad (10)$$

$P_t^{min,agg}$ and $P_t^{max,agg}$ are inputs from the flexibility algorithm from previous section and are restricting the allowed charging power for EVs.

In this paper, we assume that all the EVs connected to the grid create a large virtual battery. This virtual battery can describe the characteristics of the connected vehicles while giving a proper understanding for mathematical modeling of EVs. By aggregating the effect of all connected EVs in $E_{t,w}^{agg}$ variable, Equation (11) can depict the virtual battery energy balance:

$$E_{t,w}^{agg} = E_{t-1,w}^{agg} + P_{t,w}^{agg} \times \Delta t - E_t^{cars,disconnected} \qquad \forall\ t \in T, w \in W. \quad (11)$$

In this regard, $E_{t,w}^{agg}$ is the variable illustrating the energy capacity of virtual battery which is affected by $E_{t-1,w}^{agg}$, $P_{t,w}^{agg}$, and $E_t^{cars,disconnected}$ which are energy capacity of virtual battery in prior time step, aggregated charging power of EVs at current time step t for scenario w, and the energy capacity related to EVs which left their chargers at current time step t, respectively. $E_t^{cars,disconnected}$ resulted from the flexibility calculations and is the same for all scenarios. Moreover, $E_{t,w}^{agg}$ is restricted by the aggregated energy metrics of connected EVs as illustrated in the following Equation (12):

$$E_t^{min,agg} \leq \ E_{t,w}^{agg} \leq \ E_t^{max,agg} \quad \forall\ t \in T, w \in W \quad (12)$$

where $E_t^{min,agg}$ and $E_t^{max,agg}$ are minimum and maximum energy levels of connected EVs, respectively.

III. Testing and validation

A. Datasets

We use existing synthetic mobility data to derive the required inputs for calculating the EV flexibilities [17]. We consider mobility data of 1000 EVs with battery capacity of 75 kWh and max charging power of 7.4 kW. For the SOC_{min} values, we generate different cases where all the EV users chose a specific SOC_{min} value in each case. The cases are illustrated in Table I below. We analyze only the home charging case, with following assumptions 1. all vehicles will predominantly charge at home, and 2. all vehicles are always plugged in while parked at home. 3. all vehicles are charged until 100% SOC is reached or max SOC that can be reached within parking duration.

Please note that our model results hold, even if users decide to charge their battery only up to, e.g., 80% of their capacity to avoid battery degradation. In that case, 100% SOC would just correspond to 80% of the battery capacity. However, for reasons of simplicity, we will not make this distinction in the following.

TABLE I
EV CASES BASED ON SOC_{MIN} REQUIREMENT

Case	Description
0% SOC_{min}	All vehicles offer full flexibility
x% SOC_{min}	All vehicles have SOC minimum requirement of x%
100% SOC_{min}	All vehicles offer zero flexibility (uncontrolled charging)

We used German wholesale electricity market price data to calculate procurement costs. For day-ahead prices, we use historical data for January 2020 [18]. We generate scenarios individually for one day and compile intraday price scenarios for the whole month. In Figure 2, we illustrate the average electricity prices of German day-ahead and intraday market of a typical representative day of January.

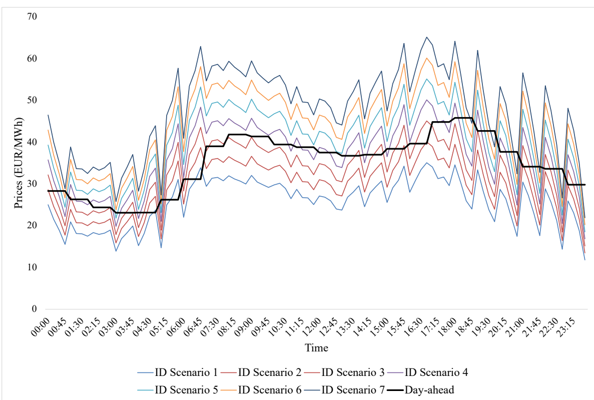

Fig. 2. Average day-ahead and intraday scnearios electricity prices.

B. Results

We calculate EV flexibilities for all the SOC_{min} cases for one month using the flexibility algorithm described in Section II-A. EV flexibilities are timeseries of energy ($E_t^{min,agg}$ and $E_t^{max,agg}$) and power ($P_t^{min,agg}$ and $P_t^{max,agg}$) flexibility metrics. Used timeseries data are for the range of one month and resolution of 15 minutes.

We model the EV as virtual battery, albeit only with the possibility of charging. Therefore, the energy metrics - $E_t^{min,agg}$ and $E_t^{max,agg}$, can be interpreted as minimum and maximum energy level of the virtual battery at time t. The power metrics - $P_t^{min,agg}$ and $P_t^{max,agg}$, can be interpreted as minimum and maximum charging capacity of the virtual battery.

Figure 3 illustrates the average power metrics for a typical day in month of January. As depicted in Figure 3, the maximum power curve for all the cases is the same. This is because maximum power is simply the sum of maximum charging power of all EVs connected to the charger. The value of $P_t^{max,agg}$ is maximum between midnight and 06:00, which is basically when the most EVs are connected to the charger. The $P_t^{min,agg}$ is zero when all EVs offer full flexibility at time t. Therefore, in the 0% SOC_{min} case the minimum power curve is always zero. In other SOC_{min} cases, EVs do not offer full flexibility until their SOC_{min} requirement is satisfied. Therefore, there are very few instances where $P_t^{min,agg}$ value is little over zero. This is because for most EVs, the $SOC_{arrival}$ is already greater than or equal to the SOC_{min} values. For EVs, whose $SOC_{arrival}$ value is already less than their SOC_{min} values; the power required to satisfy their SOC_{min} requirement is not significant. Therefore, the variation in minimum power curves for all SOC_{min} cases is not very significant.

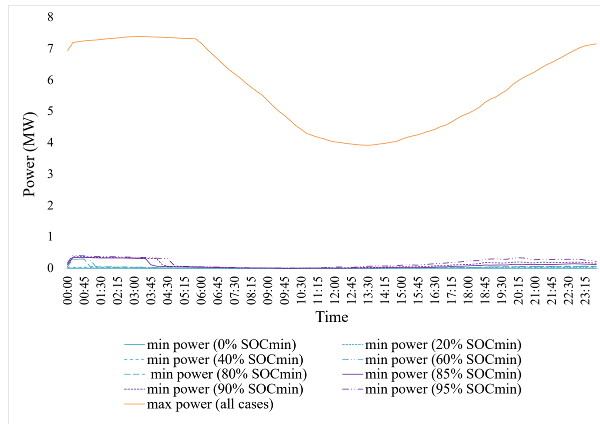

Fig. 3. Power metrics.

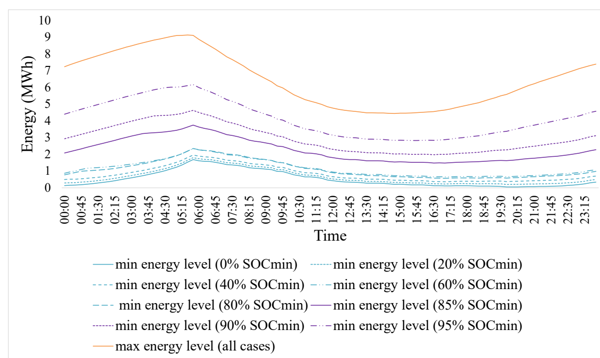

Fig. 4. Energy metrics.

Figure 4 illustrates the average energy metrics of a typical day in January. The maximum energy curve is the same for all cases as it just gives the sum of maximum allowable energy level of the EVs connected to the charger. The minimum energy level gives the cumulative energy that must be transferred at each time interval to satisfy the user requirements. Therefore, as the value of SOC_{min} increases, the value of the minimum energy level curve also increases. The difference between minimum and maximum energy gives the operational energy capacity of the virtual battery. As power metrics are almost similar for all cases, a higher operational energy capacity represents greater flexibility. Therefore, we can see a reduction in flexibility as the value of SOC_{min} increases.

We will illustrate how we optimally scheduled the electric vehicle charging using the modelled flexibilities. In Figures 5 and 6, we can observe the power procured from day-ahead and intraday market for EV charging on a random day (y axis scales are different in two figures, values in y-axis of Figure 5 are lower). The objective of energy provider is to minimize the overall costs. Therefore, the energy provider prefers to procure the power when the prices are low. Due to lower prices in the intraday market, most of the power is purchased from intraday market. In this regard, as illustrated in figure 6, most of the power for charging EVs is procured at 00:45, 04:00, 20:45, and 21:45, when the prices are lowest. Moreover, at times such as 02:00 and 04:00 some part of the required power can be provided from the day-ahead market, where the prices are lower in the day-ahead market.

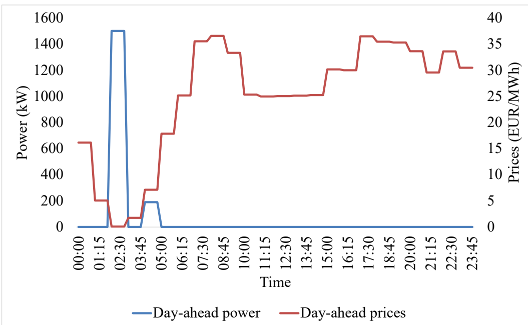

Fig. 5. Aggregated power procured for EV charging on a random day from day-ahead market

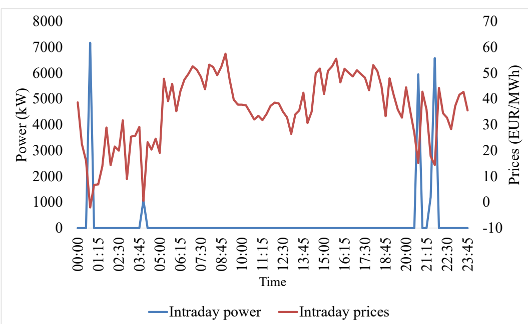

Fig. 6. Aggregated power procured for EV charging on a random day from intraday market

The total energy consumed to charge the EVs is 200 MWh for one month. From Figure 7, we can observe that the majority of the energy is procured from the intraday market for all SOC_{min} cases. However, as the flexibility decreases, the share of energy procured from the day-ahead market increases. It is evident that the intraday market prices are quite volatile as depicted in Figure 2. Prices can be extremely high or extremely low compared to the day-ahead market. As flexibility decreases, the probability of purchasing energy at lower prices decreases. This results in a slight increase in share of energy procured from the day-ahead market.

We illustrate the corresponding costs incurred to procure the required energy from the electricity markets for all SOC_{min} cases in Figure 8. We can observe that as the flexibility decreases, the costs increase. The charging costs until 80% SOC_{min} are almost similar. The charging costs starts to increase from 85% SOC_{min} case. However, the difference in

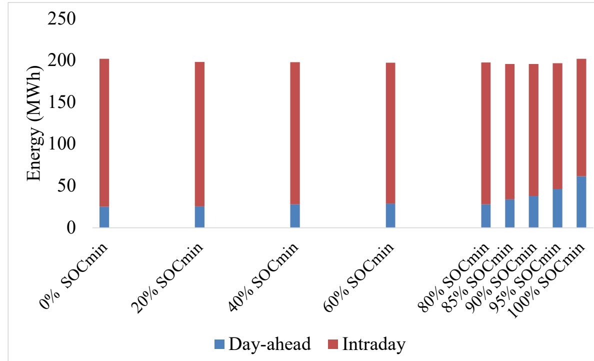

Fig. 7. Energy procured for EV charging

costs between the cases where the EVs offer flexibility and no flexibility is quite considerable. Costs increased by almost 50% for the 100% SOC_{min} case even when compared to the 95% SOC_{min} case.

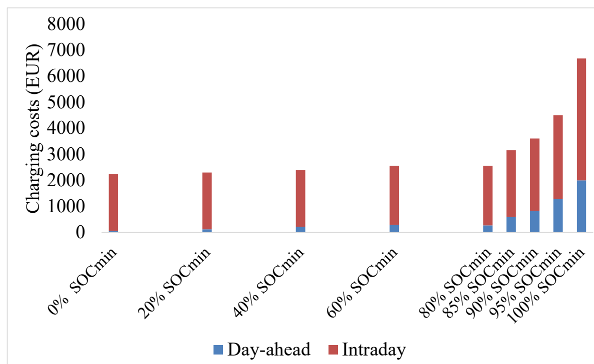

Fig. 8. EV charging costs

IV. Discussion

We found that as the SOC_{min} value increases, the flexibility decreases. However, the reduction in flexibility was considerable only for the cases where SOC_{min} value was greater than 80% compared to 0% SOC_{min} case. This is because for most EVs, the battery percentage rarely drops below 80% due to their mobility patterns, given available charging options. The same holds true for charging costs where the costs were almost similar until the 80% SOC_{min} case and increased only for the cases where the SOC_{min} was above 85%. However, even compared to the case of 95% SOC_{min}, the charging costs for the case where EVs do not offer flexibility were 50% higher. This further ascertains the importance of flexibility for the energy providers.

For EV users, it makes little difference whether their EV is charged instantaneously every day to a SOC_{min} of 80% or 100%. Even for an emergency at night (e.g., to the nearby hospital), a SOC_{min} of 80% would be sufficient for most. However, people are used to fill the tank of conventional cars immediately to their full capacity; thus, full charging of EVs is rather standard [19]. This standard needs to be changed as it is quite evident that it might not affect user comfort to a relevant amount.

There are some limitations in our paper that we would like to address in our future research. We assumed that all vehicles have the same specifications and undergo the linear charging process without efficiency losses. In reality, vehicle specifications will be different and the charging process is not linear. In principle, all EVs do not charge every day, but only a couple of times a week, depending on the user. We assumed that we know the user mobility patterns and corresponding requirements. However, these limitations will not have a major influence on the final outcome, i.e., high monetary value for the flexibility of EVs. In future research, we will consider more stochastic user scenarios and evaluate their impact on EV flexibility and charging costs.

V. Conclusion

In our paper, we evaluate the impact of the minimum SOC requirement on EV flexibility potential and charging costs. We developed a flexibility algorithm to quantify flexibility using energy and power metrics as a function of time. We then calculated the flexibility for each case and use it as input to the optimization model to simulate EV charging. To evaluate the monetary value of flexibility, we developed scenario-based stochastic optimization model with the objective of minimizing EV charging costs while participating in both the day-ahead and intraday markets. We modelled 7 different intraday prices scenarios to consider the uncertainty in the intraday market.

In summary, EVs possess high flexibility that can be provided without almost any loss of comfort (80% of the SOC is sufficient for almost all daily driving needs) for high monetary gains (160% reduction in charging costs). Therefore, it is vital that EV users provide this kind of flexibility. Energy providers could motivate users to provide flexibility by incentivizing them. These incentives can be financed by revenues generated from the flexibility of EV users.

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A3.5 Research Paper 5 - Maximising smart charging of EVs: The impact of privacy and money on data sharing

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Maximizing Smart Charging of EVs: The Impact of Privacy and Money on Data Sharing

Hanna Marxen
SnT - Interdisciplinary centre for security reliability and trust, University of Luxembourg, hanna.marxen@uni.lu

Raviteja Chemudupaty
University of Luxembourg, raviteja.chemudupaty@uni.lu

Gilbert Fridgen
University of Luxembourg, gilbert.fridgen@uni.lu

Tamara Roth
University of Luxembourg, tamara.roth@uni.lu

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Completed Research Paper

Hanna Marxen
SnT, University of Luxembourg
Luxembourg, Luxembourg
hanna.marxen@uni.lu

Raviteja Chemudupaty
SnT, University of Luxembourg
Luxembourg, Luxembourg
raviteja.chemudupaty@uni.lu

Gilbert Fridgen
SnT, University of Luxembourg
Luxembourg, Luxembourg
gilbert.fridgen@uni.lu

Tamara Roth
SnT, University of Luxembourg
Luxembourg, Luxembourg
tamara.roth@uni.lu

Abstract

Smart charging has the potential to shift peak load to times of lower demand, which better exploits renewable generation and enhances grid resilience. For increased effectiveness, smart charging requires access to data that consumers might be hesitant to share. To explore which data consumers would share and which factors influence this decision, we adopt the Barth and de Jong's risk-benefit calculation framework to smart charging and conduct an online-survey (n = 479). We find that most respondents who would share charging details with a smart charging application, are ambivalent about location data and would never share calendar details. When presented with concrete monetary rewards, participants lose their initial reservations and would share all data for an amount dependent on the data's sensitivity. Thus, our study contributes to research on the privacy paradox by highlighting the importance of calculations between perceived risks and benefits for the decision to share data.

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

Introduction

The use of electric vehicles (EVs) has increased rapidly in recent years. Governmental incentive schemes and sales bans on combustion vehicles will likely bolster this trend (Shepardson et al., 2021). What appears at first glance to be a big step towards more sustainability also puts tremendous pressure on the energy grid (IEA, 2022). Managing thousands of simultaneous EV charging events combined with regular peaks in electricity consumption and volatility of renewable energy sources (RES) could strain the grid and threaten energy security (Papaefthymiou et al., 2018). However, if EVs are charged in a controlled manner, i.e., through smart charging, they could instead become a flexible asset and support grid stability. Smart charging means that energy providers can optimally adjust the EV charging schedule in response to power system signals (e.g., RES generation) while meeting user requirements (IRENA, 2019).

To fully exploit the flexibility potential of EVs and implement smart charging, it is imperative for energy providers to understand the charging patterns of EVs. Understanding and accurately predicting these charging patterns helps energy providers tailor their services to individual EV users and support grid resilience. Charging patterns typically manifest for different types of data: Historical charging behavior and smartphone location data will help predict future charging behavior. Data linked to a person's schedule (e.g., via a calendar) can be even more accurate and helpful to optimize EV charging. Advances in pattern prediction may further automate smart charging so EV users become less involved.

Despite the advantages of accurate charging pattern prediction, consumers might be reluctant to share their data due to privacy concerns (Aloise-Young et al., 2021; Barth et al., 2019; Smith, 2008; Smith et al., 2011). They fear losing control of who has access to and can use their data (Cichy et al., 2021). At the same time, consumers readily share data in online contexts, such as social media or e-commerce, sometimes forgetting their initial concerns about data privacy (Chakraborty et al., 2013; Kokolakis, 2017). This ambiguous relationship between privacy and data sharing is often termed as the 'privacy paradox' and is a well-researched phenomenon (Buckman et al., 2019; Kim et al., 2019; Wu et al., 2020). Moreover, studies on social-hedonic and financial rewards have indicated that risk-taking behavior, such as excessive private data sharing, depends on the ratio of perceived benefits versus perceived risks (Turel, 2021).

Most privacy paradox studies focus on the active sharing of information with an online service provider. However, the findings of these studies may not be fully applicable in the context of smart charging. Cichy et al. (2021) argue in their research on data sharing for connected cars, which – much like location data sharing for smart charging – relies on IoT devices, that common data sharing reservations in online service contexts may not apply to IoT devices. "IoT devices (1) tend to be 'always on' and generate continuous data streams, (2) give users little or no power to control the data flows, (3) require unrestricted data access to fully function, and (4) invade users' virtual and physical space given the increasingly powerful actuators—components that transform electric impulses into physical actions—they are equipped with" (p. 1864). These four characteristics distinguish data sharing mechanisms of IoT and connected cars from data sharing mechanisms in online contexts, such as social media and e-commerce (Cichy et al., 2021). For example, sharing data on social media or online shopping does not typically require a user's current location or access to their calendars. Thus, smart charging comes with different privacy concerns than social media or online shopping.

Since most observations focus on the privacy paradox in e-commerce and social media interactions, there is a need to investigate factors influencing the readiness to share data in an IoT context, such as smart charging. Although studies have highlighted the importance of sensitive data for smart charging (Bhusal et al., 2021; Habbak et al., 2022), we just found one study that examined whether privacy concerns, perceived risks, and potential environmental benefits influence data sharing with EVs (Alotaibi et al., 2023). The study explored the general data sharing behavior for different EV services. Still, it does not elaborate on the readiness to share data for smart charging nor does it say anything about the sharing behavior of different data types with varying degrees of sensitivity. The study also did not investigate whether people would be more willing to share their personal information when presented with some form of monetary compensation (Hirschprung et al., 2016; Wagner et al., 2018). The relevance of monetary compensation to balance perceived risks is well known from financial economics (e.g., Caraco et al. 1980; Payne et al. 2017), so our study aims to explore its applicability to data sharing with a smart charging application. We therefore asked the following research questions:

RQ1: What data types do individuals intend to share for smart charging?

RQ2: Which factors impact individual's intention to share data with their smart charging application?

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

We conducted a large-scale survey to answer our research questions. For RQ1, we explored which data types participants would be most comfortable sharing to enable smart charging. For this evaluation, we included three different types of data (charging history, smartphone location, calendar data). Each of these data types came with varying degrees of sensitivity. To answer RQ2, we used the theoretical framework of Barth and de Jong (2017), commonly applied in privacy paradox research, which integrated key theories on mobile computing. Unlike the thematically related framework of Cichy et al. (2021), the Barth and de Jong (2017) framework specifically focuses on data sharing in mobile computing, making it more suitable for our context. We also explored attitudes towards data sharing and perceived risks and benefits of using the smart charging application, building on theories like foraging and risk sensitivity (Turel, 2021). We additionally assessed data sharing habits and their effect on participants' data sharing intentions. To evaluate the impact of monetary incentives, we introduced an experimental setting to our survey with one experimental and one control group. To answer RQ3, we explored the amount participants would request from the energy provider for sharing data with varying degrees of sensitivity. Answering these research questions contributes to both theory and practice.

Our contributions are three-fold. First, we apply the framework of Barth and de Jong to the context of smart charging. We add to this framework by investigating data sharing behavior for data with varying degrees of sensitivity. Specifically, we look into the differences between moderately and highly sensitive data and how far the framework would still apply. Second, we provide a deeper understanding on the trade-off between perceived risks and benefits by applying a risk-sensitivity and foraging theory perspective. Third, we demonstrate the effect of monetary rewards on data sharing behavior, even for highly sensitive data.

The rest of the paper is structured as follows. The theoretical background elaborates on smart charging and the role of data, Barth and de Jong's (2017) theoretical framework and a short introduction to risk-sensitivity and foraging theory. In the third section, we describe our method, data collection, and analysis. In the fourth section, we present the findings of our SEM and the calculation of monetary incentives. In the fifth section, we critically discuss our findings, elaborate on our theoretical and practical contributions, and outline related limitations. We conclude with a summary of our study.

Theoretical Background

Smart charging and the role of data

Adapting the charging behavior of EVs in response to the power system signals whilst considering the user requirements is known as smart charging (IRENA, 2019). Smart charging algorithms help shift the EV charging process to low-demand periods, drastically reducing the need for additional generation capacities (Pawlowski & Dinther, 2020; Schmidt & Busse, 2013). Moreover, EV charging can be synchronized to the availability of energy from RES to reduce grid imbalances due to generation peaks and simultaneously maximize RES consumption (Eldeeb et al., 2018; van der Meer et al., 2018). To best leverage the potential of smart charging solutions, it is vital to accurately predict the flexibility provided by each EV. Flexibility in the context of smart charging describes the amount of energy that the energy provider can shift until the EV battery has reached the desired percentage within the indicated parking time (Develder et al., 2016; Guthoff et al., 2021; Saxena et al., 2015). Practitioners typically use mobility data (e.g., arrival time, departure time, distance traveled), charging requests (e.g., energy required at the departure time), EV specifications (e.g., battery capacity and maximum charging power) to calculate the flexibility (Daina et al., 2017; Fridgen et al., 2014).

For smart charging solutions to function efficiently, they require bidirectional data exchange between EV users and the energy provider. This data exchange comes with two obstacles: First, regulations, such as the GDPR (General Data Protection Regulations in Europe), require a high degree of user privacy, complicating the collection of relevant data. Second, users are often cautious when sharing sensitive data (Strüker & Kerschbaum, 2012).

There are a variety of technical and sociotechnical measures to overcome these obstacles. Studies on technical measures aim to increase privacy by design without impeding access to (relevant) data (Teng et al., 2022). Examples of such privacy measures are differential privacy (Fernández et al., 2022), homomorphic encryption (Teng et al., 2022), and distributed learning techniques (McMahan et al., 2017). These measures can also be leveraged for smart charging to improve confidence in the data sharing process. They are, however, not subject to this paper.

Sociotechnical measures typically support the acceptance of data sharing. Although sociotechnical measures have already been established in other contexts, they have not been tested for the acceptance of data sharing in smart charging. Monetary incentives are a prominent sociotechnical measure influencing users' intention to share data in various contexts. Thus, we also investigated their effect in our study along with the type of data people would share with the smart charging application and the factors influencing this decision.

We ground our investigations in the rational risk-benefit calculation framework (Barth and Jong, 2017) and make links to IS theories on risk-sensitivity and the privacy paradox. Based on these theories, we derive our hypotheses and research model.

Rational risk-benefit calculation framework (Barth and de Jong, 2017)

Our study is grounded in the theoretical framework of Barth and de Jong (2017), which is related to the privacy paradox, which describes the contradictory behavior of individuals who express concerns about privacy but often share their data freely. Barth and de Jong (2017) aimed to uncover the factors behind this paradox. They summarize and explain theories of private information sharing with mobile apps. They differentiated between rational and biased decision-making theories in the absence or presence of risk factors and consolidated these ideas in a theoretical framework. Barth and de Jong's framework was referred to in different contexts as health technologies (Fox, 2020) and e-commerce (Kolotylo-Kulkarni et al., 2021). Unlike social media and mobile apps, the privacy paradox hasn't been explored in smart charging, so we applied their rational decision-making framework to this context.

According to the rational decision making framework (Barth & de Jong, 2017), individuals choose the option with the greatest benefits. Attitudes towards information disclosure affect context factors and ultimately influence the readiness to disclose certain information. These attitudes can be privacy concerns, general (institutional) trust, or personality traits. Context factors encompass situational factors or individual and environmental characteristics. Individuals weigh perceived risks against perceived benefits, which affects their disclosure intentions and actions. While Barth and de Jong (2017) tie together multiple literature streams to elaborate on risk-benefit calculations, the perspective introduced by risk sensitivity and foraging theory might suit the context of smart charging. These theories include factors such as esteem and self-actualization that may present interesting angles of explanations for our observations in the users' strive to optimize their gains (Turel, 2021).

Risk sensitivity theory and foraging theory in information systems

The assessment of perceived risks and benefits is also at the core of two theories adapted from behavioral biology. Foraging theory suggests that individuals aim to maximize their benefits while considering the dangers of the activities involved in receiving the benefits (Payne et al., 2017; Stephens & Charnov, 1982). They typically base their decision-making on assessing one particular problem, a 'currency' by which they decide between options, and considering external and internal constraints (Stephens & Krebs, 1986).

Risk sensitivity theory (RST) extends foraging theory by adding flexibility to the interplay between internal and external motivators and constraints. Suppose that perceived benefits, for instance, social-hedonic rewards for displaying 'green' behavior in smart charging, outweigh the perceived risks, such as sharing personal data to maximize energy flexibility. In that case, the reward-utility curve may switch from risk averse to risk prone (Mishra & Fiddick, 2012). Thus, people may share sensitive data in high-risk high-reward contexts (Caraco et al., 1980).

Turel (2021) has only recently adapted both theories to analyze technology-mediated dangerous behaviors. More specifically, he explored the role of social-hedonic rewards on risk-taking in social media contexts and found significant overlap with foraging behavior. Such behavior depends on several external and internal context factors that influence the risk proneness and, dependent on their expression, may drive risk-shifting (Cartar, 1991). That is, the relationship between perceived risks and benefits fluctuates, highly dependent on the information provided (Turel, 2021). The level of provided information is also crucial for privacy considerations, especially in the context of smart charging. – where the use of data is unclear for EV users.

Development of hypotheses and research model

In the following section, we describe the development of our hypotheses derived from the literature. Figure 1 illustrates our research model and hypotheses. As noted earlier, attitudes towards disclosure of information play a crucial role in shaping the decision-making context and, consequently on the perception of risks and benefits (Barth & de Jong, 2017). Such attitudes can encompass general privacy awareness and trust towards the provider who manages the smart charging application. People who are generally more concerned about how their data are handled tend to perceive greater risks and have higher levels of risk awareness (Fortes et al., 2017; Van Slyke et al., 2006). Thus, we propose the following hypothesis:

H1a: Privacy awareness is positively related to perceived risks with the smart charging application.

An energy provider typically controls smart charging applications. The level of trust people have in their energy provider can significantly impact their perception of smart charging applications (Utz et al., 2023). Studies conducted in various areas, such as IoT and e-commerce, suggest that lower trust in the service provider leads to greater perceived privacy risks (Kim et al., 2019; Kim et al., 2008). This concept could be applied to smart charging applications since consumers would have a more direct relationship with their energy provider than with other online service providers. Thus, we hypothesize the following:

H1b: Trust in the energy provider is negatively related to perceived risks with the smart charging application.

If people's trust in their energy provider influences the perceived risks of smart charging applications, it can also affect the perceived benefits. Such benefits could encompass the optimal use of sustainable energy, contributing to stable and sustainable grid infrastructure, and reduced charging costs (Brey et al., 2021). Individuals who have built experience-based trust in their energy provider may perceive the potential benefits of the smart charging application more strongly (Utz et al., 2023). In the study by Söllner et al. (2016), trust in the application provider predicted the perceived usefulness of an application. Thus, we formulate the following hypothesis:

H1c: Trust in the energy provider is positively related to perceived benefits with the smart charging application.

Research indicates that prior behavior can be a reliable indicator of future behavior (Ouellette & Wood, 1998). In an experimental setting, Söllner et al. (2022) demonstrated that habitual use of an application positively influences continuous information system (IS) use. Such IS usage habits might also extend to data sharing habits. Barth and de Jong (2017) included this in their model as an antecedent for data sharing. For this reason, we suggest the following hypothesis:

H2: Prior data-sharing habits are positively related to the intention to share data for smart charging.

According to the framework of Barth and de Jong (2017), attitudes influence the intention to share data and resulting data sharing behavior (Theory of Reasoned Action/ Theory of Planned Behavior, Ajzen, 1985; Ajzen and Fishbein, 1980). Data sharing is often considered risky, as some personal data are sensitive. In the context of smart charging, different data types, such as charging history, smartphone location, and calendar data, can help identify behavioral patterns and create user profiles. We want to determine which types of data individuals would share with a smart charging application.

Data sharing decisions typically depend on evaluating risks against potential benefits (Privacy calculus theory, Culnan and Armstrong, 1999). In the context of smart charging, violation of user privacy could be the greatest perceived risks (Bailey & Axsen, 2015), along with the fear that personal data are used for purposes beyond smart charging (Xu et al., 2012). According to risk-benefit calculation theories, such as privacy calculus theory (Culnan & Armstrong, 1999) or risk-sensitivity theory (Mishra & Fiddick, 2012), the perceived risks and benefits of the smart charging application will influence the intention to share data. According to Alotaibi et al. (2023), the privacy calculus is also crucial to explain data sharing with EV services. Based on this, we formulate the following hypotheses:

H3: (H3a) Perceived risks are negatively, and (H3b) perceived benefits are positively related to the intention to share data for smart charging.

The theoretical framework of Barth and Jong (2017) assumes that contextual factors can influence decision making. In this study, we focus on two contextual factors: The desired level of automation of the smart charging application and monetary incentives. Some studies, for instance, Xu et al. (2008), have treated these factors as inherent benefits of data sharing. We did not include automation as a benefit, as it is unclear if it will become the norm. Instead, we explore the desired level of automation as a variable and its effect on the intention to share data.

Resource exchange theory suggests that users are willing to share some of their data in exchange for services (Donnenwerth & Foa, 1974; Foa, 1971). Services can be personalized and automated (Shah, 2015), or come in the form of monetary rewards. However, to increase service automation, the smart charging application requires more data that users who want automation should be willing to share. This assumption is supported by Kim et al. (2019), who found that people share their data for better personalized services without considering privacy risks. Thus, we hypothesize the following.

H4: The desired app automation is positively related to the intention to share data for smart charging.

We consider monetary incentives as both a context factor and a benefit of smart charging. This approach enables us to test how monetary incentives impact data sharing. Previous studies indicated that privacy comes at a cost with different 'price tags' depending on the sensitivity of shared data (Hirschprung et al., 2016) or the context in which the data are shared (Acquisti et al., 2013).

Other immaterial rewards could also play a role, such as increased user convenience or social-hedonic rewards (Turel, 2021). They are, however, difficult to measure in this context and may have different effects on the readiness to share data. Social-hedonic rewards, for instance, could backfire if users' social network criticizes their readiness to share important data for smart charging instead of applauding their contribution to the environment. Thus, we focus primarily on material rewards whose use is established in the literature (Acquisti et al., 2013; Hirschprung et al., 2016). Monetary rewards have also been proven to be effective in related contexts, such as the general acceptance of smart charging (Kramer & Petzoldt, 2022; Wong et al., 2023). They might effectively encourage data sharing (Cichy et al., 2021). We thus propose the following hypothesis:

H5: *Participants who receive monetary incentives have a higher intention to share data for smart charging than participants who do not.*

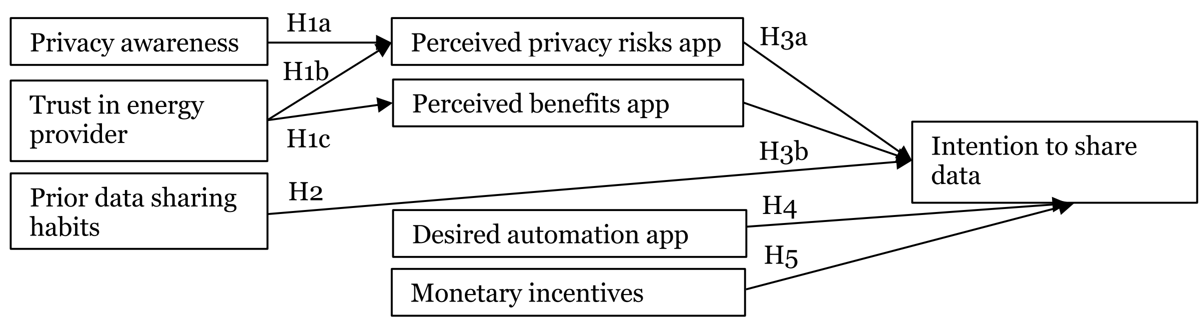

Figure 1. Representation of the hypotheses and research model

Methods

Before conducting the survey, we did a pre-test survey with 20 participants. We included a comment section in the survey to receive impromptu feedback from our pilot group. Feedback primarily concerned the complexity of questions and statements. We changed the survey accordingly and submitted the final draft to the university's ethics committee. After receiving approval from the ethics committee, we started disseminating the survey. Our goal was to get a sample of EV and non-EV users. To achieve this, we distributed the survey widely, including social media and EV user forums, as well as to prolific academics. The survey, which included a questionnaire and a related experiment, was available in English and German. It took about 10-15 minutes to complete the survey.

At the beginning of the survey, we asked participants if they were smartphone users. If they answered "Yes", they received questions about their data sharing habits, such as how many apps they use a month and how many continuously track their location. We measured data sharing habits, as people have many smartphone applications that require location sharing. Additionally, participants rated their familiarity with smart charging on a scale from 1 "not familiar at all" to 7 "extremely familiar". Regardless of their answer, they received a short explanation of smart charging, including potential benefits and requirements. In this way, we wanted to ensure they can make informed decisions when answering our survey.

Participants also received information on how sharing certain data can help the application become more automated and tailored to the charging patterns of users. We assure them that the data would only be shared with the energy provider and not transferred to a third party. Once they finished reading, participants rated the importance of three proposed benefits – facilitating an optimal use of sustainable energy, contributing to a stable energy grid, and reducing charging costs – when using the smart charging application (Brey et al., 2014). They also replied to items on perceived risks during usage (Secondary use of personnel information by Xu et al., 2012) and answered a related attention question. Participants responded to partially adapted scales on privacy awareness (Ponnurangam Kumaraguru & Cranor, 2005), and trust in the energy provider (Döbelt et al., 2015). They indicated their agreement to the respective items on a 7-point Likert scale (1 "Strongly disagree" – 7 – "Strongly agree").

The participants continued with a hypothetical smart charging scenario. They saw a screenshotted mock-up of the smart charging application, which depicted the charging preferences. They selected their preferences by responding to three questions written below the mock-up. These questions inquired about the state of charge (SOC) at arrival, desired SOC at departure, and parking duration. To measure the desired level of automation, participants replied to how often they would want to enter such information manually (1 "before every trip / settings manually" – 9 "once when installing the app / mostly automated").

For the experiment, we randomly assigned participants to the control or experimental group. Participants in the experimental group were notified that they could recover some of their electricity costs if they shared their data with the application. Participants in the control group did not receive this information. After that, we asked all participants which data they would share with the application. They each indicated their willingness to share charging times and preferences, smartphone's location, and full calendar details on a 7-point Likert scale (1 "Strongly disagree" – 7 – "Strongly agree"). In the experimental group, participants also had to imagine that they were frequent drivers with a monthly charging cost of 100 euros. We asked them to indicate how much of the total charging costs they wished to be redeemed for sharing each data type. They could also choose not to share any data type for money. At the end of the survey, participants were informed about the background and purpose of the study and could provide feedback on the survey. To honor their participation, they could sign up for a lottery.

We used structural equation modeling (SEM) to address RQ1 (*What data types do individuals intend to share?*) and answer H1-H5. To calculate the dependent variable, the intention of sharing data, we used a standardized mean of the three data sharing items (composite score). To answer RQ2 (*Which factors impact individual's intention to share data with their smart charging app?*) and RQ3 (*How much does the monetary incentive need to be for individuals to share different data types?*), we analyzed our results descriptively.

Sample

To determine the necessary sample size for the SEM, we used a sample size calculator (Soper, 2022) based on Cohen (2013) and Westland (2010). This analysis indicated that we needed a sample of n = 314 (considering a medium effect and a power of 0.8) to calculate our model and detect effects. 501 participants completed the survey. We eliminated participants (n = 22) for the following reasons: 1) Participants were not smartphone users (n = 10), 2) we detected multivariate outliers according to the Mahalonibis statistical measure (n = 12) and/or they answered the survey in less than three minutes or had evident response patterns for different items (n = 4). We conducted the analysis with 479 participants.

225 participants (46.97%) were in the experimental group to measure monetary incentives and 254 (53.03%) were in the control group. Most of the participants identified either as men (55.95%), female (40.71%) or diverse (3.34%). They were students (50.31%), worked full time (37.37%), or had other occupations (12.32%). Most of the participants had a master's (44.05%), a bachelor's (21.71%), or different degrees (34.24%). Participants predominantly lived in Luxembourg (50.73%), Germany (33.83%), France (6.26%), Belgium (2.71%), and other countries (6.89%). The three main nationalities were German (31.11%), Luxembourgish (16.70%), and French (6.26%). The mean age was 31.78 (SD = 13.03). While 28.18% of participants were EV users and 71.82% were non-EV users, our sample isn't specific to or representative of EV users. Our study primarily examines the willingness to share data for smart charging, irrespective of personal EV experience. Therefore, both EV and non-EV users can answer the survey in the same way.

Results

To answer RQ1, we calculated the mean values of the three data sharing variables for the control and experimental groups. We measured data sharing with a 7-point Likert scale (1 "Strongly disagree" – 7 – "Strongly agree"). Values above 4 indicate that people intend to share these data. The results indicate that the participants are comfortable sharing their charging history and patterns (Exp. Group: *M* = 5.47, *SD* =1.48, *Md* = 6 – "agree", Control group: *M* = 5.65, *SD* = 1.28, *Md* = 6 – "agree") and their location on the smartphone irrespective of monetary incentives (Exp. Group: *M* = 3.92, *SD* = 1.95, *Md* = 4 – "neither agree nor disagree", Control group: *M* = 4.13, *SD* = 1.85, *Md* = 5 – "somewhat agree"). In contrast, participants are not comfortable sharing full calendar details (Exp. Group: *M* = 2.75, *SD* = 1.86, *Md* = 2 – "disagree", Control group: *M* = 2.57, *SD* = 1.77, *Md* = 2 – "disagree").

To test RQ2 and hypotheses 1-5, we calculated a structural equation model, using the package "Lavaan" for "R" (Rosseel, 2012). We checked for the one-dimensionality of the measured items. Each item loaded on its respective underlying concept, and all loadings were significant (see Table 1). The scales' construct reliabilities (CR) were good (Hair, 2017), except for the composite score of intention to share data. Due to variance in the composite score of intention to share data, we additionally calculated three single SEMs with the dependent variables charging history (SEM2), location of the smartphone (SEM3), and calendar details (SEM4).

	Standardized factor loadings			
	SEM1	SEM2	SEM3	SEM4
	Composite score	Historical data	Location data	Calendar data
Privacy awareness	**(CR =.73)**	**(CR = .73)**	**(CR = .73)**	**(CR = .73)**
Consumers have lost all control over how personal information is collected and used by companies. (inverted)*deleted in the analysis				
Most businesses handle the personal information they collect about consumers in a proper and confidential way.	.773	.772	.773	.773
Existing laws and organizational practices provide a reasonable level of protection for consumer privacy today.	.740	.740	.740	.740
Trust Energy provider	**(CR =.81)**	**(CR = .81)**	**(CR = .81)**	**(CR = .81)**
My consumption data is being managed securely by my energy supplier.	.652	.652	.651	.650
My energy supplier is billing my consumption correctly.	.757	.757	.757	.756
I can rely on my energy supplier.	.884	.884	.885	.886
Perceived privacy risks with the application	**(CR =.92)**	**(CR = .92)**	**(CR = .92)**	**(CR = .92)**
I am concerned that a smart charging app may use my personal information for other purposes without notifying me or getting my authorization.	.873	.874	.874	.873
When I give personal information to a smart charging app, I am concerned that the app may use it for other purposes.	.910	.908	.910	.910
I am concerned that a smart charging app may share my personal information with other entities without getting my authorization.	.876	.878	.875	.876
Perceived benefits with the application	**(CR =.75)**	**(CR = .76)**	**(CR = .76)**	**(CR = .76)**
Facilitating optimal use of sustainable energy	.837	.822	.846	.859

	Standardized factor loadings			
	SEM1	SEM2	SEM3	SEM4
	Composite score	Historical data	Location data	Calendar data
Facilitating contribution to a stable energy grid	.689	.700	.685	.677
Facilitating reduced charging costs	.597	.604	.592	.586
Intention to share data	**(CR =.63)**			
The location of my smartphone	.726			
My charging times and preferences	.573			
Full details of my calendar (time, subject, location, and other details of all items in your calendar)	.508			

Table 1. Scales of the research model with respective factor loadings and composite reliability (CR). Note: All factor loadings are statistically significant.

The fit of the model with the composite score intention to share data as dependent variable suggests that the model fits the data ($\chi^2 = 237.598$, $df = 110$, $p < .001$, Comparative Fit Index [CFI] = .945, Tucker Lewis Index [TLI] = .934, Root Mean Square Error of Approximation [RMSEA] = .053, Standardized Root Mean Square Residual [SRMR] = .068). Yet, fit indices for the three models with the single data sharing types as dependent variables suggest that the separate models fit even better to the data. The fit indices are as follows: For charging history and patterns as dependent variable ($\chi^2 = 138.965$, $df = 82$, $p < .001$, CFI = .972, TLI = .965, RMSEA = .041, SRMR = .057), for the location of the smartphone ($\chi^2 = 141.326$, $df = 82$, $p < .001$, CFI = .971, TLI = .963, RMSEA = .042, SRMR = .059) and for the calendar details ($\chi^2 = 152.446$, $df = 82$, $p < .001$, CFI = .965, TLI = .956, RMSEA = .046, SRMR = .060). Since privacy awareness and trust in the energy provider were highly correlated, we tested this correlation in all four models. Table 2 illustrates the standardized path coefficients and if the hypotheses could be confirmed or rejected for the four models.

	Composite score	Historical data	Location data	Calendar data
	SEM1	SEM2	SEM3	SEM4
	Standardized path coefficients (t-values)			
H1a: Privacy awareness -> Perceived privacy risks app use	.261***	.430***	.430***	.433***
H1b: Trust in energy provider -> Perceived risks app use	-.164**	-.163*	-.164**	-.166**
H1c: Trust in energy provider -> Perceived benefits app use	.261***	.260***	.255***	.247***
H2: Prior location sharing habits -> Intention to share data	.278***	.052 $p = .089$	.153***	.123***
H3a: Perceived privacy risks app use -> Intention to share data	-.457***	-.278***	-.277***	-.336***
H3b: Perceived benefits app use-> Intention to share data	.339***	.379***	.234***	-.025 $p = .559$
H4: Desired automation of the app -> Intention to share data	.047*	-.003 $p = .872$	.055**	.014 $p = .452$
H5: Monetary incentives message -> Intention to share data	-.049 $p = .614$	-.081 $p = .321$	-.083 $p = .313$	.149 $p = .079$
Privacy awareness <-> Trust in energy provider	-.356***	-.356***	-.356***	-.354***

	Composite score	Historical data	Location data	Calendar data
	SEM1	SEM2	SEM3	SEM4
	Standardized path coefficients (t-values)			

Table 2. Empirical evaluation of hypotheses and standardized path coefficients, *p < .05, **p < .01, ***p < .001.

To answer RQ3, we grouped the amount of money participants would need to recover from their charging bill to share data. We can interpret the desired amount as percentages since we asked participants to imagine that their electricity bill was 100 euros. Figure 2 illustrates the results. The more sensitive the data is (from charging history to calendar details), the more reluctant participants are to share their data, and the higher the monetary reward participants request. We observed that more than 50% of participants would share their data for money for all three data types,

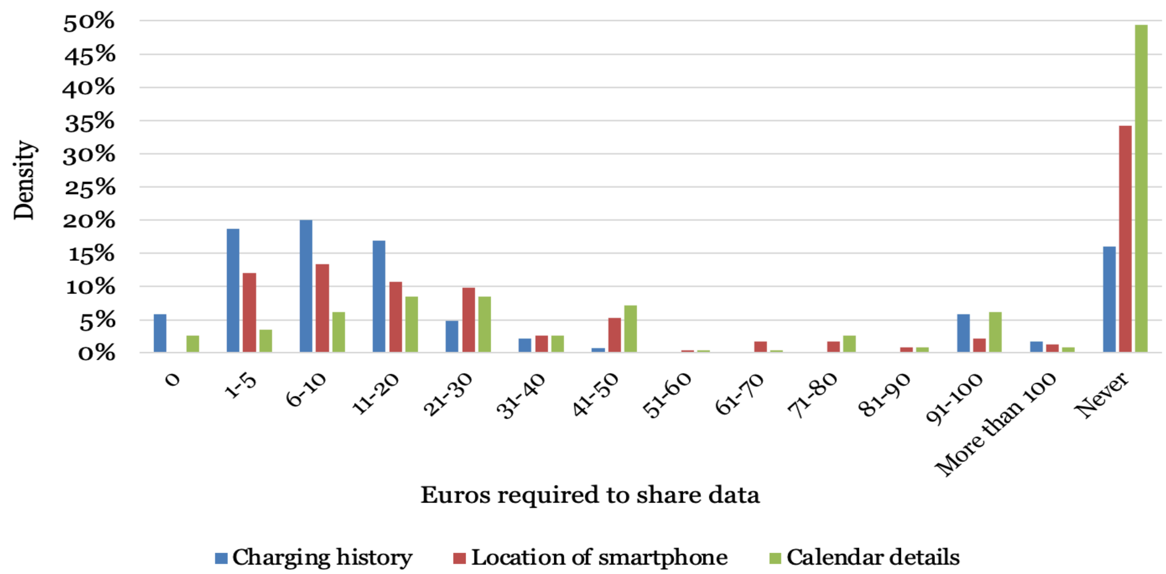

Figure 2. Euros which participants require back to share their data

We calculated the correlations between demographic variables and our main variables in an exploratory analysis. Women were less willing than men to share their calendar data (r_{Sp} = -.12, p = .012) and perceived more benefits with the smart charging application (r_{Sp} = .11, p = .017). Also, increasing age had a direct negative effect on the willingness to share location data (r = -.13, p = .005) and a direct positive effect with greater trust in their energy provider (r = .13, p = .006).

Discussion

Our findings provide food for thought about the applicability of the privacy paradox to smart charging. In our answer to RQ1 (*What data types do individuals intend to share for smart charging?),* we found that most people would share their charging history with a smart charging application. Participants are more ambivalent about their smartphone location data and are reluctant to share their calendar details. These findings are consistent with previous studies on data sharing with websites (Malhotra, 2012; Smith et al., 2011) and indicate that the readiness to share data decreases with increasing data sensitivity.

For RQ2 (*Which factors impact individual's intention to share data with their smart charging app?),* we calculated the structural equation model four times, once with the intention to share data composite score (SEM1), the intention to share charging history (SEM2), the intention to share the location of the smartphone (SEM3), and the intention to share calendar details (SEM4) as dependent variables. In general, our analysis indicates that Barth and de Jong's model is also valid in data sharing with a smart charging application. However, depending on the sensitivity of the data to be shared, not all factors, especially contextual ones, impact the intention to share data.

For all four models, trust and privacy awareness had a statistically significant negative impact on perceived risks and a positive effect on perceived benefits. That is, people who trusted their energy provider perceived fewer risks and more benefits with the smart charging application. While the role of institution-based trust is well-researched for customer loyalty (Utz et al., 2023) and e-commerce (McKnight & Choudhury, 2006), it also appears to play an important role for the readiness to share sensitive data with a service provider. Furthermore, people with greater awareness of privacy perceived greater risks. The general perception of greater risks in a data sharing context highlights the importance of information on data use and full transparency. This is in line with findings on risk-taking behavior, which show that the information available to individuals has a significant influence on their risk behavior (Turel, 2021).

For SEM1-3, perceived risks had a negative influence, and perceived benefits had a significant positive impact on the general intention to share data. These results align with the risk-benefit calculation since perceived benefits are often weighed against the risk probability. The higher the benefits, the easier it is to level perceived risks (Barth & de Jong, 2017; Culnan & Armstrong, 1999). However, for calendar data (SEM4), the perceived benefits of the smart charging application did not influence the intention to share data. They were insufficient to push the curve from high-risk low-benefit to high-risk high-benefit, which encouraged risk-averse behavior (Turel, 2021). The perceived risk of sharing sensitive data outweighed the perceived benefits of personalized charging, which has created a negative reward-utility balance and triggered risk averse behavior (Turel, 2021). These explanations from risk-sensitivity and foraging theory explicate risk-benefit calculations of Barth and de Jong's (2017) framework, wherein users refrain from sharing data when the risk probability is unfavorable. However, the underscoring of perceived benefits as opposed to the perceived risks of sharing sensitive data for smart charging can have significant implications for the design of smart charging applications. Either users enter their charging preferences for every charging event, which will be inconvenient, or smart charging will be limited. The success of smart charging depends on the ability to collect and analyze data to optimize charging processes.

Prior location-sharing habits had a statistically significant impact on the intention to share data for the composite score (SEM1), location data (SEM3), and calendar data (SEM4) but not for charging history (SEM2). This finding aligns with research on data sharing habits in the context of the privacy paradox (Awad & Krishnan, 2006). Despite privacy concerns, people overshare sensitive data on, for instance, social media (e.g., Chakraborty et al. 2013). Since experience-based trust might also be extendable to the action and not tied exclusively to the institution, people right- or wrongfully assume that sharing previously disclosed data does not carry any substantial risk (McKnight et al., 1998).

Our analysis of contextual factors demonstrated that the desired automation of the application positively influenced the intention to share data for the composite score (SEM1) and location data (SEM3) but not for historical data (SEM2) or calendar data (SEM4). This reflects findings from previous research on the privacy paradox wherein controlling the terms under which sensitive information is acquired and used was a key component of user privacy (Awad & Krishnan, 2006). While automation of data sharing would tremendously improve personalization and user experience, users appear reluctant to share such information unconditionally.

Despite the level of desired control, our analysis of RQ3 (*How much does the monetary incentive need to be for individuals to share different data types for smart charging?*) revealed that more than 50% of the participants would share all data types (historical data/pattern, location data, calendar data) in exchange for money. The more sensitive the data, the higher the expected monetary reward. For charging history data, over half of the participants required 20% of their monthly charging costs to be recovered. For the location of the smartphone, more than half of the participants wanted 40% of their monthly charging costs to be recovered. For calendar details, more than half of the participants required at least 100% of their monthly charging costs to be recovered. These findings reflect behavior explained in risk-sensitivity and foraging theory. The higher the risk, the higher the required benefits to switch from risk-averse to risk-prone behavior (Stephens & Charnov, 1982; Stephens & Krebs, 1986). However, the required monetary compensation may exceed what electricity companies would be willing to pay for the data.

Moreover, the results of RQ3 appear to contradict those of the model. Although the SEM model indicates that people would not share their data for money, more than 50% of our participants were willing to share all data types when explicitly asked how much (RQ3). However, the desired monetary compensation was exceptionally high for sensitive data, which is not always consistent with previous research. Dependending on the survey design, previous studies yielded different results: Braghin and Del Vecchio (2017), for instance, conducted a study in which only 36% of the participants agreed to share their browsing habits on an app for money. In contrast, Barak et al. (2013) conducted a field study asking participants for the amount required to share their location data. They found that 80% of the participants would share their location data for significant monetary rewards, while 20% would not share their data at all. Wagner et al. (2018) reviewed the existing literature on data monetarization and concluded that the monetary value of privacy is still unclear. They noted that the value people assign to their private information is generally low and that some people would sell data for only a little money. Also, Acquisti et al. (2013) suggest that privacy valuation depends on the situation's context and framing.

Theoretical and practical implications

Our research has both theoretical and practical implications. The theoretical implications of our study lie in the extension of Barth and de Jong's (2017) theoretical framework for smart charging applications. Since Cichy et al. (2021) argue in their study on data sharing for connected cars that common data sharing reservations in online service contexts do not apply to IoT devices, we demonstrated that the privacy paradox and typical data sharing reservations apply to smart charging applications. Depending on the type of data they share, users can decide on the level of personalization with a high level of control over their private information (Awad & Krishnan, 2006; McKnight et al., 1998).

However, the framework does not apply to highly sensitive calendar data. In this case, the perceived benefits of the smart charging app had no impact on the intention to share data. This demonstrates the influence of behavioral principles from foraging theory and risk-sensitivity on the data sharing intention. More specifically, some data carry inherent high-risk characteristics, which cannot be balanced even by high perceived rewards from a usability and knowledge perspective (Stephens & Charnov, 1982; Stephens & Krebs, 1986). However, findings on the effects of monetary rewards indicate differences in the value of rewards. That is, experience-based values, such as usability or convenience, appear less influential than material values in the form of concrete monetary rewards. Thus, adding of foraging and risk-sensitivity theory principles to the framework enhances Barth and de Jong's (2017) explainability of discrepancies between perceived risks and benefits.

Our findings on the effect of monetary rewards also highlight the importance of the research design to reliably catch such tendencies despite self-reporting bias. While undefined monetary rewards did not affect the readiness to share data, a direct question on the amount of money for which participants would share their data yielded different results. More than 50% of the participants were willing to share all data types. Thus, researchers might require more direct questions in their studies on the privacy paradox to reliably capture the impact of monetary incentives on data sharing.

Regarding practical implications, we found that customers are willing to share their data if they receive monetary compensation. However, the requested amount is often unrealistically high, especially for sensitive data such as calendar and smartphone, and may not be financially attractive to energy providers.

In addition, we found that perceived risks and benefits of the smart charging app have a significant impact on people's willingness to share data. Energy providers should, therefore, ensure that customers are well-informed about the benefits of their application and the use of data for smart charging to lower perceived risks. Explanatory videos might help convey the required information.

Furthermore, it is a good idea for energy providers to limit data collection to only the essential information needed to further optimize the charging process. This approach will help to avoid the unnecessary collection of data that may concern users.

Trust in the energy provider also influences how participants perceive the risks and benefits of the application. It is therefore important for energy providers to build trust with their customers. This can be done by being transparent about how they collect, process, and use data, or through, for instance, customer loyalty programs based on transparency-enhancing technology (e.g. Utz et al. 2023).

Limitations and future work

Our research comes with some limitations. First, we measured the intention to share data but not the actual behavior. There may be a gap between intention and actual behavior (Sheeran & Webb, 2016). A field study measuring the actual behavior could help us fill the gap but would have to be postponed until smart charging is more widely adopted. This is also the reason why we restricted our study to the intention of sharing data.

Second, we applied the rational decision-making framework to smart charging, which assumes that data sharing is rational. However, our decisions are also influenced by biases such as heuristics and situational cues (Barth & de Jong, 2017). To meet this limitation, future research could carry out a pilot focusing on irrational factors influencing decision-making.

Third, we asked participants for the amount of money rewards required to share their data. However, this self-assessment may not necessarily correspond to the actual values at which they would share their data. To overcome this limitation, a randomized experimental study could be conducted to test for how much money participants would be willing to share their data.

Fourth, we need to consider the possibility that our findings may not generalize to other cultural groups. Researchers claim that people from individualistic cultures value privacy more and show more privacy-protective behaviors, while in collectivistic cultures, privacy is less protected (Li, 2022). A cross-cultural study would help us evaluate the generalizability of our findings. However, previous cross-cultural studies on social networks often did not show differences between individualist and collectivist cultures (Li, 2022).

Conclusion

Our research aimed to investigate the types of data individuals would share with a smart charging application for EVs, such as charging patterns, smartphone location, and calendar details, and the factors influencing their decision. We applied the theoretical framework of Barth and de Jong (2017) and conducted a large-scale online survey to explore our hypotheses. We also investigated if participants would share their data for monetary rewards and, dependent on the data type, for how much. We used the IS theories of the privacy paradox (e.g., Barth and de Jong, 2017), foraging theory, and risk sensitivity theory to explore this behavior (e.g., Turel 2021)

We found that most individuals would share their charging history but would not share more sensitive data, such as calendar details. Participants were also ambivalent about sharing the location data. To determine which factors influenced the decision to share data, we calculated four SEM models, each with one dependent variable – charging details, smartphone location, calendar data – and a composite score of all three variables. The perceived risks and benefits of the smart charging application determined the intention to share charging details and smartphone location. However, perceived benefits did not influence the decision to share sensitive calendar data, while perceived risks had a significant influence.

Moreover, we discovered that different contextual factors influenced the data sharing decision for different data types. For instance, the desired degree of automation, influenced the intention to share location data but not the intention to share the charging history and calendar data. Interestingly, proposed monetary rewards did not have a significant impact on the intention to share data in any of the SEM models. However, when we asked participants from the monetary rewards group how much money they would share their data, most participants indicated willingness to share data for a monetary reward. The requested amount increased with the sensitivity of the data. Therefore, the energy supplier needs to decide if it is worth paying these rewards to get access to relevant data for smart charging.

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A3.6 Research Paper 6 - The role of gender in data sharing for smart charging of electric vehicles

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The Role of Gender in Data Sharing for Smart Charging of Electric Vehicles

Hanna Marxen
SnT - Interdisciplinary centre for security reliability and trust, University of Luxembourg, hanna.marxen@uni.lu

Muriel Frank
Interdisciplinary Centre for Security, Reliability and Trust (SnT), muriel.frank@uni.lu

Gilbert Fridgen
University of Luxembourg, gilbert.fridgen@uni.lu

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Completed Research Full Paper

Muriel-Larissa Frank
SnT, University of Luxembourg
muriel.frank@uni.lu

Hanna Marxen
SnT, University of Luxembourg
hanna.marxen@uni.lu

Gilbert Fridgen
SnT, University of Luxembourg
gilbert.fridgen@uni.lu

Abstract

Uncontrolled EV charging creates spikes in electricity consumption, risking power system stability. A solution to this is smart charging, where energy suppliers take advantage of EV users' flexibility to charge the EVs at low-demand periods. However, the user acceptance of smart charging is highly dependent on perceived benefits. It also relies on the willingness of EV users to facilitate smart charging by sharing sensitive information such as charging, location or calendar data. No prior research has investigated how individual factors, such as gender, may impact the willingness to share data for smart charging. Drawing on privacy calculus and social role theories, we explore gender differences in data sharing for smart charging and analyze the effect of monetary incentives. Analyzing survey data (n = 383), our results demonstrate that gender significantly influences decisions to share information related to smart charging, which has implications for decision makers in energy companies.

Keywords

Smart charging, gender differences, data sharing, social role theory.

Introduction

As a cleaner alternative to conventional vehicles, electric vehicles (EVs) are on the rise (Van Der Kam et al. 2019). In 2022, 14% of all new cars sold worldwide were electric and with ambitious government programs in place, this positive trend is likely to continue (IEA, 2023). But as the use of EVs increases, so too does electricity demand (Eising et al. 2014; Ensslen et al. 2018). One solution to avoid grid congestion is smart charging of EVs, i.e. adopting the charging of EVs both to the needs of the power system and EV users (IRENA 2019).

While the technical aspects of smart charging have received much attention in the past (e.g., Sanchez-Martin et al. 2016), the human dimension has often been neglected (Baumgartner et al. 2023). This is highly problematic as the success of smart charging largely depends on EV users' willingness to cooperate with suppliers, for example by sharing information about their charging and mobility behavior as well as charging preferences (Baumgartner et al. 2023; Daina et al. 2017). By understanding the charging patterns of EV users, energy suppliers can not only optimize the charging cycle but also gain a competitive advantage and generate revenue (Bin Humayd and Bhattacharya, 2017). The more sensitive the shared data is, the higher the value for the energy supplier. For instance, calendar data might offer more accurate predictions of future charging patterns compared to historical charging patterns and location data.

However, due to privacy concerns and fear of data loss, EV users do not readily share personal data (Alotaibi et al. 2023). Over the past years, researchers have investigated user privacy concerns related to smart grid infrastructure (Döbelt et al. 2015), user willingness to use (Schmalfuß et al. 2015) and user acceptance of smart charging systems (Will and Schuller 2016). A lens that still needs to be explored is gender differences in user acceptance of smart charging and their willingness to share their charging-related data. This lens is becoming increasingly important as there is growing evidence that women and men use IT differently and have different attitudes towards privacy (Lin and Wang, 2020). For instance, subjective norms and perceived ease of use have a stronger impact on women's decision to use a new technology, whereas perceived utility has a stronger impact on men's decision (Venkatesh and Morris, 2000). The same holds true for the sharing of personal data through apps or online social networks, revealing gender disparities (Lin and Wang 2020; Park 2015). However, it may be inappropriate to assume that findings from e-commerce and social media studies can be transferred to smart charging data sharing (Cichy et al. 2021). This is because data sharing for smart charging, often enacted through connected cars, relies on the Internet of Things (IoT) with sensors that are always active and may constantly invade users' physical and virtual spaces (Cichy et al. 2021).

As sharing personal and sensitive data is important to realize the full potential of smart charging systems (Habbak et al. 2022), it is crucial to understand users with different characteristics, including different genders. It is also essential to understand how users' intentions to share data vary, and to identify the types of personal data with different levels of sensitivity that people are willing to share. We are therefore investigating how intentions to share different types of data with varying degrees of sensitivity differs between men and women. Focusing on charging, location, and calendar data - representative of different levels of sensitivity - our first research question is as follows:

RQ1: How does the intention to share data for smart charging (charging, location, and calendar data) differ between men and women?

Limited data for charging of EVs might hinder optimization, risks financial losses for suppliers and may reduce the use of renewable energy (Marxen et al. 2023). It is therefore important to explore how different types of users can be encouraged to share data. Research indicates that people tend to share their data for monetary incentives (Alfnes and Wasenden 2022), and that they require higher financial compensation as the sensitivity of data increases (Hirschprung et al. 2016). Yet, findings regarding the impact of gender on the willingness to share data in exchange of money remain inconclusive (Ackermann et al. 2022; Weydert et al. 2019). Thus, we investigate for the case of smart charging how women and men react to monetary incentives and whether they differ in their threshold for selling sensitive data of different sensitivities, such as charging, location or calendar data. This will allow for the development of targeted incentive schemes. Our second research question is as follows:

RQ2: To what extent do men and women differ in their intention to share smart charging data for money?

To answer our research questions, we analyzed survey data from 383 individuals using descriptive, group and mediation analyses. Our findings illustrate that gender has a statistically significant impact on users' intentions to share data for smart charging, and on users' demands for financial compensation for providing such data. This has important implications for the design of smart charging systems, including communication and future incentives for sharing sensitive data with these systems. In addition, our results suggest that energy suppliers and/or other aggregators need to offer appropriate benefits to EV users so as not to hinder their intention to share data.

Theoretical Background

Smart Charging, Gender, and Privacy Concerns

Smart charging means adapting the EV charging cycle to both the power system requirements and user preferences (IEA 2022). It optimizes EV charging by taking advantage of the EV's flexibility and low demand periods. Smart charging algorithms rely on various user input data, including mobility patterns (e.g., arrival and departure times and distance traveled), charging requirements (e.g., energy needed at departure), and EV specifications (Fridgen et al. 2014). Related data provides valuable indications about the extent to which energy suppliers can adjust charging rates while still meeting user requirements (Chemudupaty et al. 2023). With this flexibility information and real-time electricity market signals, energy suppliers can optimize EV charging schedules (Haupt et al. 2020; Sanchez-Martin et al. 2016).

However, a significant challenge arises from the assumption that user data is readily accessible. In reality, privacy concerns often restrict the availability of such data (Alotaibi et al. 2023).

Smart charging research so far did not investigate how gender impacts data sharing decisions. However, literature on electric mobility already finds that men and women differ significantly in terms of behavior, attitudes and values (Sovacool et al. 2018, 2019). According to Sovacool et al. (2018), this research stream on electric mobility focuses on gender differences in travel behavior, environmental values, preferences for different mobility forms, and societal gender roles. In Nordic countries for example, less women own an EV than men (Sovacool et al. 2019). Additionally, women exhibit higher environmental awareness levels and a stronger inclination toward convenience and safety. This underscores how gender differences shape the transport sector (Sovacool et al. 2019). Therefore, we aim to explore gender differences in the transport sector, with a focus on data sharing for smart charging.

Privacy Calculus Theory

In order to make rational decisions about the sharing of personal information in the smart charging context, the privacy calculus theory suggests that individuals will evaluate the perceived benefits and the expected risks (Culnan and Armstrong, 1999; Dinev and Hart, 2006). This is especially true in a technological environment, where not sharing any data is sometimes simply not possible (Sah and Jun, 2023).

Privacy calculus theory is supported by protection motivation theory (Maddux and Rogers, 1983; Rogers, 1975), which states that individuals evaluate the consequences of their actions. It means that they will change behaviors if they perceive the risks of the current actions higher, and that they will refrain from adjusting their behavior if they perceive the benefits of doing nothing higher. Over the past decades, the privacy calculus theory has been successfully applied in various fields, ranging from e-commerce (e.g., Dinev and Hart, 2006) to IoT services (Sah and Jun 2023) and thus provides a sound framework for studying information disclosure for smart charging. Realizing the full potential of smart charging technologies requires sensitive data, such as location-based or charging data, which compromises the privacy of those using EVs. Thus, EV users are faced with the decision of whether to share sensitive data with energy suppliers to receive better services, or not to share sensitive data to avoid privacy violations.

Gender Differences and Social Role Theory

Gender differences influence decision-making processes (Venkatesh et al. 2000). One important theory that helps dissect gender-based differences in behavior is social role theory (SRT). Archer (1996) posited that all types of social behavior can be framed in terms of two distinctions that transcend gender: that women are communal and that men are agentic. SRT posits that gender differences are a result of social construction and perception of gender-related roles according to cultural and social norms (Eagly and Wood, 2016; Venkatesh and Morris, 2000). These differences in behavior result from the typical characteristics of roles that women tend to play compared to men. Men, for example, are more technology oriented, while women are more socially oriented.

In mobility studies, too, we see that men and women behave in strikingly different ways, reflecting the different social roles expected of them (Singh 2020). Literature also acknowledges the nature of gender relations and roles that set certain expectations and assign women the role of household managers (Solá 2016; Sovacool et al. 2018). SRT has been confirmed as helpful in explaining gender differences in the information systems domain. For example, SRT has been used to examine the decision to share information on social networking sites (Lin and Wang 2020). It has also been demonstrated to be valid for studying information disclosure in location-based services (Li et al. 2021).

Hypotheses

We aim to examine how gender influences the intention to share personal data to facilitate smart charging. Existing research, such as Ackermann et al. (2022), indicate that men tend to be more open to share personal data compared to women. As stated above, social role theory suggests that these differences come from social constructions (Venkatesh and Morris, 2000). In the context of information sharing, men and women have different styles (e.g., Li et al. 2021), with men being more technology-focused and valuing extrinsic benefits (Eagly and Wood, 2016; Spence and Helmreich, 1978). For smart charging, we expect men to be more likely than women to see the benefits and usefulness of data sharing, leading them to share data for tailored services and cost savings. However, women may be more concerned about privacy risks, with fears of data misuse and surveillance (Dym and Fiesler, 2018). Therefore, they might feel that giving away sensitive data as location data can lead to surveillance and makes them more prone to misuse of data. Hence, our first hypothesis is that men are more willing to share data with energy suppliers than women:

H1: Men are more willing to share charging data (H.1.1), location data (H.1.2) or calendar data (H1.3) for smart charging than women.

Early research on information privacy demonstrates that individuals' privacy concerns also relate to unauthorized secondary use of data (Smith et al. 1996). This means that people are concerned about data being utilized for undisclosed purposes (McKnight et al. 2011). We find initial confirmation that these concerns are also relevant in the energy context, where consumers of smart grid infrastructure are concerned about unauthorized disclosure of detailed energy data (Döbelt et al., 2015). More recently, Alotaibi (2022) found that EV users are hesitant to share their location despite benefits. Drawing on privacy calculus and protection motivation theory, EV owners weigh risks and perceived benefits and engage in actions that promise to minimize negative outcomes. In the context of data sharing with energy suppliers for smart charging, we hypothesize that perceived loss of control over data will impact whether men and women are willing to share charging, location, and calendar data:

H2: Fear of secondary use of personal information mediates the relationship between gender and intention to share (H2.1. charging data, H2.2. location data, H2.3. calendar data) for smart charging.

There is some initial evidence that individuals may share personal information with third parties when offered incentives (e.g., Jai and King, 2016). Studies on monetary incentives find a positive effect on individuals' willingness to share information. For example, Alfnes and Wasenden (2022) uncover that consumers are willing to make a tradeoff between giving up some of their privacy by sharing their data for money. However, their willingness to do so depends heavily on contextual characteristics, e.g., the type of data (Ackermann et al., 2022; Roeber et al., 2015). With regard to gender differences, social role theory indicates that men are more concerned with egoistic benefits than women (Sun et al. 2015). However, findings on the impact of gender on an individual's decision to share sensitive data in exchange for desired financial benefits are inconclusive. While some studies find that men are more willing to trade data for money (Ackermann et al. 2022), others find no impact of gender (e.g., Weydert et al., 2019). Lastly, we aim to understand gender differences in disclosing charging, location, and calendar data with energy suppliers for financial reward, hypothesizing the following:

H3: Men are more likely than women to share (H3.1. charging data, H3.2. location data, H3.3. calendar data) for smart charging if they receive financial compensation.

Methodology

Research Design

To gain a better understanding of gender differences in data sharing for smart EV charging, we relied on survey data from Marxen et al. (2023). For the sake of clarity, we will still briefly outline the approach used for data collection. First, a pre-test was conducted with 20 participants. Based on their feedback, minor adjustments were made to the wording for the main study. The online survey was then shared on EV forums and through social media channels, and respondents were invited to participate in a lottery. It was stressed that their responses would be kept confidential (Podsakoff et al. 2003).

For the main survey, participants were first given a brief description of smart charging, including how smart charging works and how they could potentially benefit from smart charging of their EVs. This ensured that the participants had a good understanding of the technology and would be able to make a conscious decision. Participants also saw a screenshotted mock-up of the smart charging application, to get a feeling on how a smart charging application looks like in practice. Subsequently, participants indicated their agreement with three items, adapted from Xu et al. (2012), measuring the fear of secondary use of information when using the smart charging application. Answers were collected on a 7-

point Likert scale ("strongly disagree" - "strongly agree"). A sample item is "When I give personal information to a smart charging app, I am concerned that the app may use it for other purposes". In our study, Alpha's Cronbach for this scale was $\alpha = .91$.

For investigating data sharing intentions, all subjects were made aware of the benefits of data sharing, including reduced charging costs, grid stability and environmental benefits. It was emphasized that data sharing would be limited solely to the energy supplier. All participants then indicated to which extent they would share (1) charging times and preferences, (2) the location of their smartphone, and (3) full details of their calendar (subject, location, and other details of their items in their calendar). They indicated their agreement on a 7-point Likert scale. All participants were randomly assigned to either the control group or the experimental group. Participants in the experimental group were informed that they can claim back a share of their electricity costs by providing their data to the energy supplier, while participants in the control group did not receive this information. Those in the experimental group were then asked to indicate how much money they would like to receive back in return for charging smartphone location, and calendar data respectively. They were asked to imagine their monthly charging bill as 100 Euros. If they did not want to share their data for any money, they were instructed to indicate 1000.

Sample

Our sample consisted of both EV and non-EV users living in Europe, primarily in Germany, Luxembourg, and France. The purpose was to survey EV users as well as non-EV users as the latter group represents potential future EV users. Due to the current limited use of smart charging, neither EV nor non-EV users are expected to have practical experience.

For the analyses, we collected data from 391 respondents who either identified as women or men. To ensure accuracy, we excluded multivariate outliers using to the Mahalanobis statistical measure ($n = 1$), non-smartphone users ($n = 5$), subjects with noticeable response patterns ($n = 1$) and with completion times of less than three minutes ($n = 1$). After applying these exclusion criteria, 383 datasets remained for the final analysis. Within these datasets, $n = 204$ participants were in the control group and $n = 179$ in the experimental group. Our sample consists of 87 EV users (22.72%) and 296 non-EV users (77.28%). In terms of gender, we have a slightly higher number of male participants (55.10%) than female participants. Half of the participants (55.35%) are students and the majority lives in Luxembourg (62.66%). Participants of the sample are on average 32.23 ($SD = 13.42$) years old. Our sample has a relatively high level of education, with most respondents having at least a university degree (73.11%). Our analyses involved SPSS and R, with Hayes Process Macro for mediation analyses (Hayes 2018).

Results

To answer RQ1 and to test H1.1-1.3, we used Mann-Whitney U tests to assess gender differences in intentions to share charging data (H1.1), location data (H1.2) and calendar data (H1.3). We chose this approach due to the non-normal distribution of the intention to share data across the three types. The results reveal that our hypotheses are only partially supported. Men and women do not differ significantly in their intentions to share charging data ($U = 17399.00$, $p = .445$) or calendar data ($U = 16432.00$, $p = .071$). However, men intend to share location data more than women ($U = 16007.50$, $p = .040$).

For H2.1-3, we calculated three mediation analyses (Table 1). Notably, males were coded as "1" and females as "2". The fear of secondary use of personal information statistically significantly mediates the relationship between gender and all three data sharing intentions: Charging (H2.1.), location (H2.2.), and calendar data (H2.3.). We do, however, not find a direct effect of gender on intentions to share charging, location, or calendar data.

To address RQ2, we performed a median difference test using Yate's Continuity Corrected Asymptotic Sig., comparing the expected financial compensation for data sharing between men and women in the experimental group. We opted for a median comparison over a mean comparison test to compare the distributions in terms of financial compensation, avoiding potential skewing effects from high values in one group. We excluded participants who indicated an unwillingness to share data (value of 1000) or indicated a value greater than 1000, due to possible misinterpretation. Results indicate that women expect statistically significantly higher financial compensation for sharing their location ($Mdn = 15$) than men (*Mdn* = 30), $\chi^2(1{,}114) = 5.70$, $p = .028$. For charging data, men were not more likely to share data (*Mdn* = 10) than women (*Mdn* = 15), $\chi^2(1{,}148) = 2.08$, $p = .202$. Neither for calendar data, men were more likely to share their data (*Mdn* = 30) than women (*Mdn* = 4), $\chi^2(1{,}85) = 2.64$, $p = .160$.

				BC 95% CI		
Dependent Variable	Effect of gender on SecU (a)	Unique effect of SecU (b)	Indirect effect (ab)	Lower	Upper	Direct effect (c)
Sharing intention charging data	.38 (.12), *p* = .002	.-.22 (.06), *p* < .001	-.08 (.03)	-.16	-.03	-.03 (.13), *p* = .799
Sharing intention location data	.38 (.12), *p* = .002	-.38 (.08), *p* < .001	-.14 (.05)	-.26	-.05	-.21 (.19), *p* = .283
Sharing intention calendar data	.38 (.12), *p* = .002	-.37 (.07), *p* < .001	-.14 (.06)	-.27	-.04	-.27 (.18), *p* = .136
Notes. SecU: The fear of secondary use of information. All coefficients reported for paths a, b, and ab are unstandardized slopes with the corresponding standard errors in parentheses.						

Table 1. Mediation analyses between gender and intention to share data, SecU as mediator

Figure 1 presents those results graphically, illustrating the proportion of individuals requesting to share charging, location, and calendar data and the corresponding amounts of money. Regarding sharing charging data, men and women make roughly the same indications, with a majority willing to share their data for monetary benefits and only about 20% refusing to share. For location data, roughly 35% of men and women express reluctance to share, but women tend to request higher compensation. For calendar data, 50% of both men and women indicate their unwillingness to share. As expected, the more sensitive the data, the less willing people are to share it.

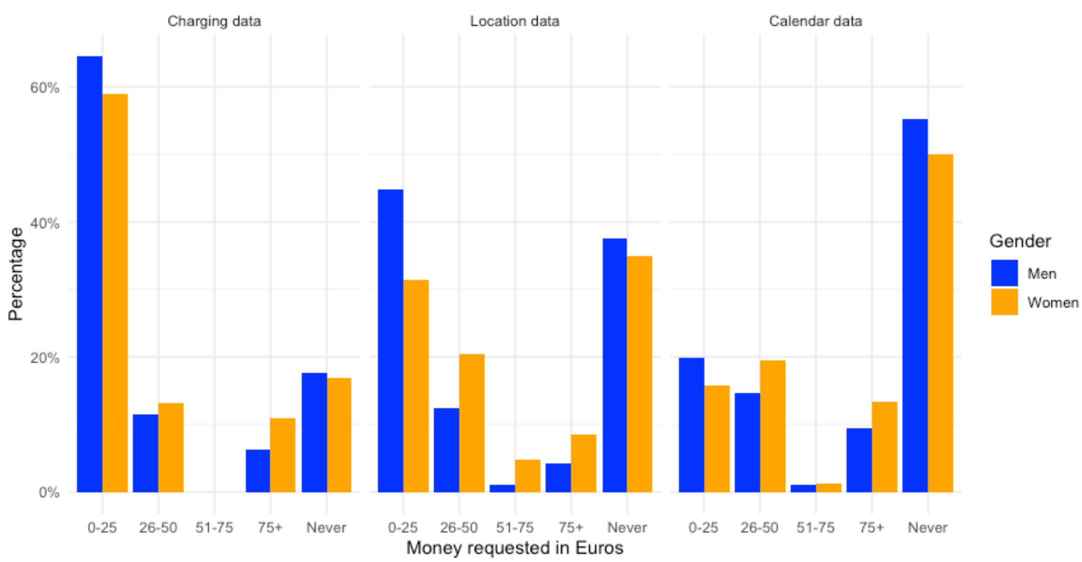

Figure 1. Distribution of the money men and women request to share charging, location, calendar data

Discussion and Conclusion

Realizing the full potential of smart charging technologies highly depends on the active participation of EV users, making it crucial to understand their concerns, preferences, and needs (Baumgartner et al. 2023). While previous research has acknowledged gender differences in behaviors and decisions, gender differences in smart charging technologies and information disclosure remained unexplored. Our study aimed to fill this gap by examining gender differences in the willingness to share different data types for smart charging and determining whether financial compensation influences these decisions. Analyzing responses from 383 participants, we discovered noteworthy variations in the behavioral patterns of men and women which we will discuss below.

Theoretical and Practical Implications

By investigating the behavior of women and men in relation to smart charging, our study makes several theoretical and practical contributions. First, our work contributes to the growing stream of gender studies in the energy context, stressing that gender can be relevant in influencing user preferences for sustainable energy mobility modes (Sovacool et al., 2018, 2019). More specifically, our results reveal that women are less inclined to share location data and tend to request higher compensation for sharing such information in comparison to men. Interestingly, we do not find these differences in charging and calendar data. One explanation for these differences between men and women about sharing their location may be explained by technological anxiety of female users. According to prior studies, men tend to be more skilled with technology and feel more comfortable surrounding technology (Huffman et al. 2013). They are also less concerned with leakages of personal information (Lee 2020). Hence, it's plausible that women's heightened awareness of privacy concerns makes them reluctant to share location data. Overall, our work advances research on gender differences in emerging technology use, contributing to a better understanding of how men and women conform to social roles in the smart charging context.

Second, we find that privacy concerns mediate the relationship between gender and sharing of charging, location, and calendar data. According to privacy calculus theory (Milne and Gordon, 1993) and protection motivation theory (Maddux and Rogers, 1983; Rogers, 1975), individuals must weigh the benefits of sharing charging or location data against revealing sensitive information. This involves giving up their privacy as well as risking secondary use of data. Our findings confirm that women seem to perceive sharing sensitive data with their energy supplier as riskier than men. They might feel that giving away their location data can lead to surveillance and makes them more prone to misuse of data (Dym and Fiesler, 2018). In contrast, men, who tend to be more task-oriented, prioritize the benefits of sharing sensitive data for smart charging over the risks of misuse. This is in line with studies on location-based social network services stating that men tend to focus on utilitarian benefits (Sun et al. 2015).

Third, our findings also suggest that small monetary incentives do not necessary lead to desired levels of data sharing. Depending on the sensitivity of the data, EV users can be more or less motivated by financial incentives to share information with energy suppliers. We find that the more sensitive the data, which allows to extract the exact whereabouts of a person, the higher the price people attach to their data. This corresponds to earlier findings by Wagner et al. (2020). Monetary incentives, as in the study by Ioannou et al. (2021), appear to encourage a large proportion of respondents to share personal information. However, according to our analysis, the amounts requested by most respondents, especially for location and calendar data, may be unrealistic for an energy supplier. Surprisingly, we observed no difference between men and women concerning calendar data. This might be attributed to both genders perceiving calendar data as equally sensitive.

Fourth, our results have an impact on policy decisions of energy suppliers. Knowing that men and women differ in their decisions to share sensitive data and in the demand of financial compensation, clearly influences the use of data plans and the promotion of smart charging technologies. Energy suppliers who want to motivate users to share personal information need to find a balance between collecting as much information as possible to facilitate smart charging systems and their customer's needs and fears.

Limitations and Future Research Avenues

As with any research endeavor, we need to be aware of limitations that point to future research opportunities. First, one limitation is to rely on participants' intentions to share charging, location, or calendar data, which may not fully reflect actual behavior. Since energy suppliers do not yet offer applications for customers to exchange sensitive data, we argue that intentions are a suitable measure (Marxen et al. 2023). Furthermore and in line with Fishbein and Ajzen (1975), intentions are a good proxy for behavior. However, in a future study, the generalizability of our work can be improved by carrying out an experiment and observing EV users' actual behavior in smart charging contexts.

Second, our sample consists only of people living in Europe, which seems appropriate when studying gender differences. In future studies, it would certainly be interesting to see if the differences are also visible in other parts of the world. Even if certain stereotypes remain the same, cultural influences can play an important role and lead to different results.

Our work opens further possibilities for future work on gender-related differences in sharing data with smart charging systems and energy suppliers. Since our results suggest that monetary incentives only partially increase sharing intentions, it would be interesting to test alternative motivators for male and female EV users to share data with energy suppliers. Alternative motivators could be nudges. Previous studies on digital nudging, for instance, suggest that nudging with presentations are effective (Ioannou et al. 2021). Furthermore, further research could explore the impact of both social benefits and utilitarian benefits on gender-specific disclosure intentions for smart charging. For location-based services, for example, women put more emphasis on sharing their current whereabouts as they feel that this helps them to receive offers in a timely manner (Li et al. 2021).

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