Governance design for household participation in the energy system

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by

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To my partner in crime

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Sabine Pelka *Karlsruhe, 11th April 2024*

Content

Summary

Households possess an increasing potential to adapt their energy use to the conditions of the energy system, specifically whether renewable energy and grid capacity are available at any given moment. Two key trends are driving this increase: First, households with rooftop solar panels are investing in battery storage to reduce their energy consumption from the grid — a trend strengthened by the 2022 European energy crisis; and second, policymakers are incentivizing investments in electric vehicles and heat pumps to decarbonize the residential transport and heating sectors. However, this potential of households remains largely untapped due to shortcomings in consumer governance (i.e., the organization of household energy use). These shortcomings stem from both parts of consumer governance, namely the formal rules set by policymakers and services offered by intermediaries (e.g., retailers, service providers, and aggregators). The formal rules do not allow price signals, which express the conditions of the energy system, to be sent to households. Simultaneously, intermediaries offer only a few services to support households in adjusting their energy usage (e.g., smart charging services and variable tariffs). Currently, missing price signals and services are leading to uncoordinated energy use among households. This is resulting in inefficient energy system operation and missed opportunities for decarbonizing the residential sector.

Consumer governance needs to be updated to facilitate a coordinated energy use. We refer to coordinated energy use as household participation. Various proposals have been made, which cover some of the necessary aspects of consumer governance. The incohrerent proposals contain the risk of missing preconditions or a poor interplay with existing rules and services, which may hamper its implementation. For instance, supply contracts with a variable energy tariff send price signals to households without supporting them in how to respond.

Furthermore, conflicting household needs make combining the proposals into a coherent governance design challenging. An approach of arranging consumer governance to fulfill a need would conflict with another need. Hence, some design choices are mutually exclusive. Examples of common household needs include (i) contributing to the decarbonization of the energy system; (ii) realizing energy cost savings; (iii) limiting operational burden; (iv) safeguarding data privacy; and (v) meeting the need for control over consumption. Referring to the example above, supply contracts with a variable energy tariff allow households to retain control over their consumption. However, such contracts may also overburden them by requiring actions to realize the expected cost savings.

A research gap arises from the fact that a single governance design cannot meet all household needs and from the ambiguity of prioritising them. Such priorities are expected to vary between households and over time. In this dissertation, we contribute to the debate on consumer governance by (i) categorizing the existing proposals for governance design into a function-based inventory; (ii) providing insights into households' priorities; and (iii) identifying design choices that fit said priorities. We address the following research question:

> **How can one design governance that facilitates household participation in the energy system?**

Specifically, this dissertation provides recommendations for a needs-driven governance design in three steps, following a multi-method approach: First, in Chapter 2, we develop a framework for categorizing the functions of consumer governance as well as a literature-based inventory of design choices for each function. The inventory presents both mutually and non-mutually exclusive design choices. The non-mutually exclusive design choices offer a direct recommendation for the governance design since none conflict with another household need. Second, our empirical research identifies priorities for mutually exclusive design choices. In particular, a vignette survey presented in Chapter 3 examines tradeoffs between household needs when they decide to participate in the energy system. Complementarily, a field trial presented in Chapter 4 investigates households' priorities when they actively participate. Third, in Chapter 5, we deal with the case for which we identified no clear priorities for household needs in our empirical research. Therefore, we modify the governance design to find a reasonable balance between different conflicting needs. The developed agent-based model captures said needs and tests whether the modified design of consumer governance results in a reasonable balance between household needs.

The consumer governance framework, developed in Chapter 2, reveals how past proposals in the literature have determined the organization of household energy use. They have determined how certain organizational functions steer the technical functions of the energy system (i.e., energy generation, distribution, and consumption) toward household needs. The framework identifies the following three categories of organizational functions: (i) incentives determined by policymakers (i.e., market- and grid-based price signals and the allocation of administrative price elements); (ii) the organization of households' responses (i.e., preprocessing price signals for households and investing in and operating energy assets of households); and (iii) tasks that enable the intended response (i.e., data collection and billing).

According to the non-mutually exclusive design choices of the inventory, policymakers should set incentives based on price signals from the grid (e.g., based on variable network tariffs or flexibility markets) and avoid distortions that arise from volume-based administrative price elements. To respond to these price signals, intermediaries should facilitate different forms of investments in energy assets for households. Moreover, household energy use should be monitored and adapted based on high-frequency and -resolution data from smart meters.

The design choices for price signals from the energy market and the organization of responses to said signals are subject to conflicting household needs. Our empirical research presents an argument for organizing market-based price signals by aggregating and trading household energy on the wholesale market. Thus, the household priority of energy cost savings can be met most effectively and efficiently. If intermediaries adapt the energy use on households' behalf, then households would realize energy cost savings without a high operational burden. A governance design can meet the household need to retain control to some extent if intermediaries give households the right to overrule the automated adaptation. We explain how we arrived at these conclusions regarding the tradeoffs between conflicting household needs next.

The empirical research in this dissertation demonstrates that a governance design should focus on (i) enabling households to achieve energy cost savings, (ii) convincing them to participate by safeguarding their needs for control, and (iii) keeping them involved by limiting their operational burden. The results presented in Chapter 3 reveal that the most critical priority for households in the initial selection stage is realizing energy cost savings effectively and efficiently. They are willing to share their data if they realize cost savings. Their prioritization of energy cost savings leads us to recommend a governance design that provides market-based price signals by aggregating and trading their energy on the wholesale market.

Additional empirical results presented in Chapters 3 and 4 demonstrate that household priorities vary between the selection and participation stages (i.e., when deciding to participate vs. when participating). Retaining control over consumption is the second most crucial priority after realizing energy cost savings when deciding to participate (see Chapter 3). Households do not prioritize limiting the operational burden at this stage; however, this emerges as a priority during the participation stage. The field trial in Chapter 4 demonstrates that smart charging as the default charging mode leads to the highest cost savings. Other design choices, which require a self-dependent response from households, are less effective at realizing cost savings. In other words, if intermediaries adapt energy use on households' behalf, the households would realize energy cost savings with a low operational burden. Since households are allowed to override the default charging mode, this design choice partially meets their need to retain control. The extent to which the design choice meets said need for control depends on how the intermediary formalizes the right to overrule in service settings.

The design of service settings should balance conflicting household needs during the initial selection and participation stages. If households adjust the setting parameters to express their need for control, then they may intervene in optimization that realizes energy cost savings. In Chapter 5, we examine how to balance the tradeoff for households with electric vehicles and smart charging services. If they adjust the parameters of the smart charging default, then they run the risk of additional comfort-driven charging emerging, which would offset their energy cost savings. The modeling results presented in Chapter 5 demonstrate that determining both parameters (i.e., the targeted stage of charge and charging timing) at the same low level for cost savings is key to avoiding comfort-driven charging. If households intend to realize energy cost savings by reducing only one parameter, then the other parameter allows comfort-driven charging and offsets cost savings. The comfort-driven charging in the modeling results expresses common behavioral particularities known from empirical research, such as rebound effects. The design of the service setting should guide households to make conscious tradeoffs between comfort-driven and cost-optimal consumption.

The contributions of this dissertation cover both content-related and methodological aspects. Special emphasis is placed on methods that (i) ensure coherence in the governance design; (ii) identify changes in household needs during the different stages of participation; and (iii) capture the resulting tradeoff of needs in an agent-based model to test the impact of a modified governance design on household needs. Content-related contributions include the inventory of design choices developed in Chapter 2, which creates the basis for drafting new governance designs not only in this dissertation but also for future design iterations. Moreover, through covering different stages of participation within one research project, we reveal the conflict potential of intertemporal changes in household needs. Our methodological contributions include capturing charging behavior in an agent-based model. Specifically, we extend an existing optimization function of cost-minimizing household agents with a behavioral theory that explains common charging practices and then parametrize it with the empirical data of this dissertation. This extension enables us to iterate through a set of modified designs (without collecting new empirical data) and to identify the ones that result in a reasonable balance between the conflicting needs.

In addition, the research scope of consumer governance allows us to examine pathways for advancing the interfaces between households, intermediaries, and policymakers. Thus, we are able to derive policy recommendations. Policymakers should guarantee households access to real-time pricing and the freedom to choose between tariff designs. Simultaneously, they should mandate intermediaries to offer risk mitigation measures for countering the adverse effects of real-time pricing, such as price risk during moments of scarcity. Next to market-based price signals, policymakers should introduce incentives for ensuring the grid-friendly operation of residential energy assets, such as variable network tariffs or flexibility markets. Furthermore, regulators should ensure that distribution system operators provide grid access for energy assets and interoperable smart metering infrastructure. The widespread availability of smart meters avoids service-specific household investments and ensures a level playing field for intermediaries.

Moreover, we advise intermediaries to offer services that respond to price signals on households' behalf as much as possible. Aggregating and trading household energy on the wholesale market effectively and efficiently realizes energy cost savings. Intermediaries gain trust for such services by offering households the right to override the response. The services should include default settings that allow intermediaries to respond and optimize household energy use despite household inertia. If they could anticipate upcoming household needs in the design, make tradeoffs transparent, and create dedicated points for decision-making, then they would support households in making more informed decisions and taking on an active role in the energy system.

Samenvatting

Huishoudens beschikken over steeds meer mogelijkheden om hun energieverbruik aan te passen aan de omstandigheden van het energiesysteem (d.w.z. of er op dat moment hernieuwbare energie en netcapaciteit beschikbaar zijn). Twee belangrijke trends zorgen voor deze toename: Ten eerste investeren huishoudens met zonnepanelen op het dak in batterijopslag om hun energieverbruik van het net te verlagen. Deze trend werd versterkt door de Europese energiecrisis van 2022. Ten tweede stimuleren beleidsmakers investeringen in elektrische voertuigen en warmtepompen om de residentiële transport- en verwarmingssector CO_2 neutraalte maken. Dit potentieel van huishoudens blijft echter grotendeels onbenut door tekortkomingen in het consumentenbeheer (d.w.z. de organisatie van het energiegebruik van huishoudens). Deze tekortkomingen vloeien voort uit beide onderdelen van het consumentenbeheer, de regels van beleidsmakers en de diensten die worden aangeboden door tussenpersonen (bv. leveranciers, dienstverleners, aggregators). De regels maken het niet mogelijk prijssignalen, die de staat van het energiesysteem uitdrukken, naar huishoudens te sturen. Tegelijkertijd bieden tussenpersonen slechts enkele diensten aan om huishoudens te ondersteunen bij het aanpassen van hun energieverbruik (bv. slimme oplaaddiensten en variabele tarieven). Op dit moment leiden ontbrekende prijssignalen en diensten tot ongecoördineerd energiegebruik onder huishoudens, wat leidt tot inefficiënte werking van het energiesysteem en gemiste kansen voor het koolstofarm maken van de woonsector.

Er bestaan verschillende voorstellen om het consumentenbeheer te moderniseren, waarbij de nadruk ligt op aspecten die cruciaal zijn om de participatie van huishoudens te vergemakkelijken. Wetenschappers en uitvoerende partijen beschouwen echter verschillende aspecten als cruciaal. Als een voorstel slechts enkele aspecten regelt, kunnen ontbrekende randvoorwaarden of een onvoorziene wisselwerking met bestaande regels en diensten de uitvoering ervan belemmeren. Leveringscontracten met een variabel energietarief sturen bijvoorbeeld prijssignalen naar huishoudens zonder dat ze ondersteuning krijgen over hoe ze moeten reageren.

Bovendien maken tegenstrijdige behoeften van huishoudens het combineren van de voorstellen in een samenhangend bestuursontwerp lastig. De ene manier om consumentenbeheer in te richten om aan een bepaalde behoefte te voldoen, zou in strijd zijn met een andere behoefte. Daarom sluiten sommige ontwerpkeuzes elkaar uit. Hieronder volgen enkele voorbeelden van gemeenschappelijke behoeften van huishoudens in deze context: (i) bijdragen aan het koolstofvrij maken van het energiesysteem; (ii) besparingen op energiekosten realiseren; (iii) operationele lasten beperken; (iv) de privacy van gegevens waarborgen; en (v) voldoen aan de behoefte aan controle over het verbruik. Verwijzend naar het voorbeeld hierboven, stellen leveringscontracten met een variabel energietarief huishoudens in staat om controle te houden over hun verbruik. Ze kunnen huishoudens echter ook overbelasten door acties te vereisen om de verwachte kostenbesparingen te realiseren.

Een onderzoekskloof vloeit voort uit het feit dat een enkel bestuursontwerp niet aan alle behoeften van huishoudens kan voldoen en dat de prioriteiten van de behoeften van huishoudens dubbelzinnig zijn. De prioriteiten variëren naar verwachting tussen huishoudens en in de tijd. In dit proefschrift leveren we een bijdrage aan het debat over consumentenbeheer door

(i) de bestaande voorstellen voor bestuursontwerp te categoriseren in een op functies gebaseerde inventarisatie; (ii) inzicht te geven in de prioriteiten van huishoudbehoeften, en (iii) ontwerpkeuzes te identificeren die passen bij de (geprioriteerde) behoeften. We doen dit door de volgende onderzoeksvraag te beantwoorden:

> **Hoe kan men een bestuur ontwerpen dat de deelname van huishoudens aan het energiesysteem vergemakkelijkt?**

Specifiek biedt dit proefschrift aanbevelingen voor een behoefte gestuurd bestuursontwerp in drie stappen, volgens een multi-methodische aanpak: Ten eerste is het uitgangspunt een raamwerk voor het categoriseren van de functies van consumentenbeheer en een op literatuur gebaseerde inventarisatie van ontwerpkeuzes voor elke functie in hoofdstuk 1. De inventarisatie presenteert zowel wederzijds als niet wederzijds uitsluitende ontwerpkeuzes. Deze laatste ontwerpkeuzes bieden een directe aanbeveling voor het bestuursontwerp, omdat geen van de keuzes conflicteert met een andere huishoudbehoefte. Ten tweede identificeert het empirisch onderzoek in dit proefschrift de behoeften prioriteiten voor wederzijds exclusieve ontwerpkeuzes. Met name een vignettenonderzoek in hoofdstuk 3 de afwegingen tussen huishoudelijke behoeften onderzocht wanneer huishoudens besluiten om deel te nemen aan het energiesysteem. Als aanvulling hierop wordt in hoofdstuk 4 de prioriteiten van de behoeften van huishoudens wanneer ze actief deelnemen. Ten derde behandelt hoofdstuk 5 het geval waarin we in eerder empirisch onderzoek geen duidelijke prioriteit voor de behoeften van huishoudens hebben gevonden; daarom passen we het bestuursontwerp aan om een redelijk evenwicht te vinden tussen verschillende conflicterende behoeften. Het ontwikkelde ‘agent-based’ model legt deze conflicterende behoeften vast en test of het aangepaste ontwerp van consumentenbeheer resulteert in een redelijk evenwicht tussen de behoeften van huishoudens.

Het kader voor consumentenbeheer, ontwikkeld in hoofdstuk 1 laat zien hoe de voorstellen uit de literatuur de organisatie van het energiegebruik van huishoudens bepalen. Ze bepalen hoe bepaalde organisatorische functies, de technische functies van het energiesysteem (d.w.z. de opwekking, distributie en consumptie van energie) sturen in de richting van de behoeften van huishoudens. Het raamwerk identificeert de volgende drie categorieën van organisatorische functies: (i) prikkels bepaald door beleidsmakers (d.w.z., markt- en netwerk gebaseerde prijssignalen en de toewijzing van administratieve prijselementen); (ii) de organisatie van de respons van huishoudens (d.w.z., het voorbewerken van prijssignalen voor huishoudens en het investeren in en exploiteren van energiemiddelen van huishoudens); en (iii) taken die de beoogde respons mogelijk maken (d.w.z., gegevensverzameling en facturering).

Volgens de niet-uitsluitende ontwerpkeuzes , moeten beleidsmakers stimulansen instellen op basis van prijssignalen van het net (bv. op basis van variabele netwerktarieven of flexibiliteitsmarkten) en verstoringen vermijden die voortvloeien uit volume gebaseerde administratieve prijselementen. Om op deze prijssignalen te reageren, moeten tussenpersonen verschillende vormen van investeringen in energieactiva voor huishoudens vergemakkelijken. Bovendien moet het energieverbruik van huishoudens worden gemonitord en aangepast op basis van hoogfrequente en hoge resolutie gegevens van slimme meters.

De ontwerpkeuzes voor prijssignalen van de energiemarkt en de organisatie van de respons op de prijssignalen zijn onderhevig aan tegenstrijdige behoeften van huishoudens. Het empirisch onderzoek presenteert een argument voor het organiseren van, op de markt gebaseerde prijssignalen door energie van huishoudens samen te voegen en te verhandelen op de groothandelsmarkt. Zo kan op de meest effectieve en efficiënte manier tegemoet worden gekomen aan de prioriteit van huishoudens om energiekosten te besparen. Als tussenpersonen het energiegebruik namens huishoudens aanpassen, zouden de huishoudens besparingen op energiekosten realiseren zonder hoge operationele lasten. Een bestuursontwerp kan tot op zekere hoogte tegemoetkomen aan de behoefte van huishoudens om de controle te behouden als intermediairs huishoudens het recht geven om de geautomatiseerde aanpassing te annuleren. In de volgende paragrafen leggen we uit hoe we tot deze conclusies komen voor de afwegingen tussen conflicterende behoeften van huishoudens.

Het empirisch onderzoek in dit proefschrift toont aan dat een bestuursontwerp zich moet richten op (i) huishoudens in staat stellen om energiekosten te besparen, (ii) hen overtuigen om deel te nemen door hun behoefte aan controle te waarborgen, en (iii) hen betrokken houden door hun operationele last te beperken. De resultaten uit hoofdstuk 3 laten zien dat de belangrijkste prioriteit voor huishoudens in de eerste selectiefase het effectief en efficiënt realiseren van besparingen op energiekosten is. Ze zijn bereid hun gegevens te delen als ze kostenbesparingen realiseren. Hun prioriteit op het gebied van energiekostenbesparing brengt ons tot de aanbeveling van een bestuursontwerp dat marktgebaseerde prijssignalen biedt door hun energie samen te voegen en te verhandelen op de groothandelsmarkt.

Aanvullende empirische resultaten in de hoofdstukken 3 en 4 van dit proefschrift laten zien dat de prioriteit van huishoudens varieert tussen de selectie- en de deelnamefase (d.w.z. bij de beslissing om deel te nemen in tegenstelling tot de beslissing wanneerdeel te nemen). Controle houden over het verbruik is de op één na belangrijkste prioriteit na het realiseren van besparingen op energiekosten bij de beslissing om deel te nemen (zie hoofdstuk 3). Huishoudens geven in dit stadium geen prioriteit aan het beperken van de operationele lasten. Het beperken van de operationele lasten is echter wel een behoefte van huishoudens die tijdens de participatiefase naar voren komt. De veldproef in hoofdstuk 4 toont aan dat slim laden als standaard oplaadmodus leidt tot de grootste kostenbesparing voor huishoudens. Andere ontwerpkeuzes, die een zelfafhankelijke reactie van huishoudens vereisen, zijn minder effectief in het realiseren van kostenbesparingen. Met andere woorden, als tussenpersonen het energiegebruik namens de huishoudens aanpassen, realiseren de huishoudens besparingen op energiekosten met een lage operationele last. Aangezien huishoudens de standaard oplaadmodus kunnen opheffen, komt deze ontwerpkeuze gedeeltelijk tegemoet aan de behoefte van huishoudens om de controle te behouden. De mate waarin de ontwerpkeuze tegemoet komt aan de behoefte aan controle hangt af van de manier waarop de tussenpersoon het recht om af te wijken formaliseert in de service-instellingen.

Het ontwerp van de service-instellingen moet een evenwicht vinden tussen de tegenstrijdige behoeften van de huishoudens tijdens de eerste selectie- en participatiefasen. Als huishoudens de instellingsparameters aanpassen om hun behoefte aan controle uit te drukken, dan kunnen ze ingrijpen in de optimalisatie die besparingen op energiekosten realiseert. In hoofdstuk 5 onderzoeken we hoe we de afweging kunnen maken voor huishoudens met elektrische voertuigen en slimme laaddiensten. Als huishoudens de instellingen van de slimme oplaadstandaard aanpassen, lopen ze het risico dat er extra comfort gestuurd opladen ontstaat, waardoor hun besparingen op energiekosten teniet worden gedaan. De modelleerresultaten uit hoofdstuk 0 tonen aan dat het bepalen van beide parameters (d.w.z. de beoogde laadfase en laadtijd) op hetzelfde lage, kostenbesparende niveau de sleutel is tot het vermijden van comfort gestuurd laden. Als huishoudens van plan zijn om energiekosten te besparen door slechts één van de instellingen te verlagen, dan maakt de andere instelling comfort gestuurd laden mogelijk en compenseert de kostenbesparingen. Het comfort gedreven opladen in de modelresultaten geeft uitdrukking aan veel voorkomende gedragsbijzonderheden die bekend zijn uit empirisch onderzoek, zoals reboundeffecten. Het ontwerp van de serviceomgeving moet huishoudens helpen om bewuste afwegingen te maken tussen comfort gedreven en kosten optimaal verbruik.

De bijdragen van dit proefschrift bestrijken zowel inhoudelijke als methodologische aspecten. Er wordt speciale nadruk gelegd op methoden die (i) zorgen voor samenhang in het bestuursontwerp, (ii) veranderingen in de behoeften van huishoudens tijdens de verschillende fasen van participatie identificeren, en (iii) de resulterende afweging van behoeften vastleggen in een agent-based model om het effect van een aangepast bestuursontwerp op de behoeften van huishoudens te testen. Inhoudelijke bijdragen zijn onder andere de inventarisatie van ontwerpkeuzes ontwikkeld in hoofdstuk 1 die de basis vormt voor het opstellen van nieuwe bestuursontwerpen in dit proefschrift, maar ook voor toekomstige ontwerpiteraties. Bovendien laat onze aanpak van verschillende stadia van participatie binnen één onderzoeksproject het conflictpotentieel zien van intertemporele veranderingen in de behoeften van huishoudens. Onze methodologische bijdragen omvatten het vastleggen van laadgedrag in een agent-based model. Meer specifiek breiden we een bestaande optimalisatiefunctie van koste minimaliserende huishoudagenten uit met een gedragstheorie die gangbare oplaadpraktijken verklaart en parametriseren we deze met de empirische gegevens van dit proefschrift. Deze uitbreiding stelt ons in staat om een reeks gewijzigde ontwerpen te doorlopen (zonder nieuwe empirische gegevens te verzamelen) en de ontwerpen te identificeren die resulteren in een redelijke balans tussen de conflicterende behoeften.

De reikwijdte van het onderzoek naar consumentenbeheer stelt ons in staat om paden te onderzoeken voor het bevorderen van de raakvlakken tussen huishoudens, tussenpersonen en beleidsmakers. Beleidsmakers zouden huishoudens toegang moeten garanderen tot de werkelijke prijzen en keuzevrijheid tussen de tariefontwerpen. Tegelijkertijd zouden ze intermediairs moeten verplichten om risicobeperkende maatregelen aan te bieden om de nadelige effecten van werkelijke prijzen tegen te gaan, zoals prijsrisico tijdens momenten van schaarste. Naast mark gebaseerde prijssignalen moeten beleidsmakers prikkels invoeren om een netvriendelijke werking van residentiële energieactiva te garanderen, zoals variabele netwerktarieven of flexibiliteitsmarkten. Bovendien moeten de regelgevers ervoor zorgen dat de distributienetbeheerders toegang tot het net bieden voor energieactiva en operabele slimme meetinfrastructuur. De wijdverspreide beschikbaarheid van slimme meters voorkomt dienst specifieke investeringen van huishoudens en zorgt voor een gelijk speelveld voor tussenpersonen.

Bovendien adviseren we tussenpersonen om diensten aan te bieden die zoveel mogelijk reageren op prijssignalen namens de huishoudens. Door energie van huishoudens samen te voegen en te verhandelen op de groothandelsmarkt kunnen effectief en efficiënt besparingen op energiekosten worden gerealiseerd. Intermediairs winnen vertrouwen in dergelijke diensten door huishoudens het recht te geven om de reactie op te heffen. De diensten moeten standaardinstellingen bevatten waarmee tussenpersonen kunnen reageren en het energieverbruik van huishoudens kunnen optimaliseren ondanks de traagheid van huishoudens. Als ze in het ontwerp kunnen anticiperen op toekomstige behoeften van huishoudens, afwegingen transparant kunnen maken voor huishoudens en speciale punten voor besluitvorming kunnen creëren, dan zouden ze huishoudens ondersteunen bij het nemen van beter geïnformeerde beslissingen en een actieve rol kunnen spelen in het energiesysteem.

List of Abbreviations

ANOVA	Analyses of Variance
BSS	Battery Storage System
CPP	Critical Peak Pricing
DiD	Difference-in-differences
DR	Demand Response
DRS	Demand Response Service
EV	Electric Vehicle
FE	Fixed Effects
HH	Household
HP	Heat Pump
LMP	Locational Marginal Prices
PTR	Peak Time Rebates
PV	Photovoltaic
RTP	Real-Time Pricing
SD	Standard Deviation
SLP	Standardized Load Profile
SRQ	Sub-Research Question
TCE	Transaction Cost Economics
ToU	Time of Use Pricing
TWFE	Two-Way Fixed-Effects
VPP	Virtual Power Plants

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1 Introduction

1.1 Motivation

Households' potential to respond flexibly to the conditions of the energy[1] system, specifically to whether renewable energy and grid capacity are available at any given moment, is increasing (Glachant 2019; Wesche and Dütschke 2021). Two trends are driving this potential: First, households with rooftop photovoltaic (PV) systems are investing in battery storage to increase their self-consumption rate and avoid paying levies and taxes for the energy they consume from the grid (Sarfarazi et al. 2020; Klein et al. 2019) — a development reinforced by the surge in energy prices during the 2022 European energy crisis (Szymańska et al. 2023). Second, policies are incentivizing investments in electric vehicles (EVs) and heat pumps to decarbonize the residential transport and heating sectors. As such consumption can be adapted to the conditions of the energy system (Stute and Kühnbach 2023), it could play a significant role in integrating renewable energy and decarbonizing the electricity sector.

However, this potential for a coordinated energy use has hardly been used to date. The arrangements that determine how household energy use is organized do not enable them to adapt their use to the conditions of the energy system (Parrish et al. 2020). There are two kinds of arrangements, namely formal rules set by policymakers and service contracts between households and intermediaries, and both have shortcomings. Policymakers should adjust the formal rules to send price signals that convey the conditions of the energy system to households (O'Connel et al. 2014; Hu et al. 2015). Moreover, intermediaries such as aggregators, service providers, and retailers should offer services that support households in adapting their energy use to price signals (Nolden et al. 2016). Both types of arrangements form what is known as consumer governance. In the absence of price signals and supportive services, current arrangements have led to uncoordinated energy use. For instance, common supply contracts with a flat energy tariff allow households to consume energy under the same conditions whenever they want (Stute and Kühnbach 2023). Uncoordinated energy use leads to inefficient generation and grid infrastructure operations and potentially to high energy system costs (Kühnbach et al. 2021). Therefore, the current governance design does not take advantage of the potential of residential energy assets for decarbonizing the energy system.

Furthermore, while proposals to update consumer governance exist in the literature, they have only determined some of its arrangements. For instance, supply contracts with a variable energy tariff send price signals to households without supporting them in how to respond (Darby and McKenna 2012). Aggregators respond on households' behalf and trade household energy as a virtual power plant on the wholesale market (Morstyn et al. 2018). However, they do not facilitate households' investments in energy assets, which is an activity performed by energy communities that organize collective investments in energy assets (Lowitzsch et al. 2020). If

[1] The electrification of heating and transport is going to make electricity the main energy carrier at the household level. Transport and heating technologies are expected to use electricity that is provided by the electricity system. However, we account for interlinkages between the electricity, heating, and transport sectors by using the term "energy" instead of "electricity".

proposals to update consumer governance only define some of the arrangements, then missing preconditions or a poor interplay with existing arrangements may hamper their realization.

Moreover, where existing proposals outline new arrangements for consumer governance, they relate to specific subsets of household needs that they recognize (Parrish et al. 2020). The heterogeneity of household needs is the reason for such variety in proposals. Financial, environmental, social, and hedonistic needs are common household requirements (Steg et al. 2018). However, conflicting household needs make it impossible to combine the proposals into a coherent governance design. Some choices for this design are mutually exclusive; for instance, collective investments in energy assets fulfill the environmental and social needs of households. However, efforts to coordinate the investment of multiple parties may conflict with households' hedonistic needs. This situation is further complicated by the expectation that household needs will vary between household groups (Abrahamse and Steg 2009; Yilmaz et al. 2021) as well as over time (Sloot et al. 2023).

This dissertation provides advice for a coherent consumer governance design that facilitates a coordinated energy use of households. We refer to the coordinated energy use as household participation in the following. We identify mutually exclusive design choices that result from conflicting household needs and reveal the priorities of said needs.

1.2 Background: Perspective of common economic theories on household participation

Economics theories provide insights into why households have hardly participated in the energy system thus far and which barriers must be removed to change this. The insights differ depending on the underlying assumptions of the theory on how households make decisions and which variables influence said decisions. Neoclassical economics states that in a perfect market, prices—which are determined by the costs of the supply and the utility of the demand—optimally allocate resources. Transaction cost economics expands the notion of costs, while behavioral economics questions the notion that decisions are solely based on a tradeoff between costs and utility. In this section, we examine the relevance of these three theories for household participation. They are summarized in Table 1-1:

Table 1-1: Perspective of three common economic theories on household participation

Theories	**Assumption on the decision making of households**	**Variables that influence decision making and how they are related**	**Main barriers to be removed for household participation**
Neoclassical economics	Welfare-optimizing individuals	Benefits > price	Imperfect market with a lack of price signals
Transaction cost economics (Williamson 2000) and bounded rationality (Simon 1987)	Individuals striving for satisfying outcomes (as subject to transaction costs)	Benefits > transaction cost	High transaction costs of alternatives to current governance design
Dual process theory (Kahneman 2003) and nudging (Thaler 2017; Thaler and Sunstein 2009)	Individuals have two systems for decision making: consumption decisions mainly made by intuition (and not rational reasoning)	Heuristics- and bias-driven (e.g., present bias)	The context in which households make consumption decisions favors uncoordinated consumption

Neoclassical economics states that imperfect information on prices impedes individuals' welfare maximization. In the context of household participation, variable tariffs could convey the price signals of the wholesale market to households and improve their level of information (Sorrell et al. 2003). Since households do not possess risk management capabilities and have limited time to monitor prices, they may outsource the market transaction to intermediaries, who will respond on their behalf.

Acknowledging limitations in time and other resources, Herbert Simon proposes that households are bound in their rationality for welfare maximization and create satisficing outcomes rather than cost-optimal ones (Simon 1987). In line with bounded rationality, transaction cost economics contrasts the benefits of performing a market transaction with its costs (Williamson 2000; Ramesohl 2003). Governance shapes market transactions by affecting their benefits and costs, and it is designed viably if the benefits offset the costs of transactions. In this context, transaction costs are affected by the frequency of transactions, their uncertainty, and asset specification (Dahlman 1979). A new governance design that facilitates household participation would only be attractive if the tradeoff between transaction costs and benefits is more favorable than that under the current governance design (Ramesohl 2003).

Behavioral economics questions whether individuals solely make decisions based on a tradeoff between costs and benefits. Daniel Kahneman's dual-system theory states that daily household decisions are based on intuition rather than rational reasoning (Kahneman 2003). Therefore, they are prone to biases and rely on heuristics. In the case of household participation, rational reasoning may determine planned household decisions, such as investing in energy assets or selecting a service that supports their operation. However, intuition determines the daily decisions of households when operating energy assets; thus, the context of households steers their decision-making. Subtle changes in the decision context can stimulate behavioral change if they address households' intuition. Such changes are called nudges (Thaler 2017; Thaler and Sunstein 2009).

In summary, the design of consumer governance is centered on the assumption that a design is attractive if the benefits offset the costs. Households can reduce their energy costs by responding to price signals. However, their response to price signals is subject to other costs (i.e., transaction costs) and behavioral biases. The economic theories presented in this section encourage a broader definition of costs and benefits to meet household needs with a new governance design.

1.3 Problem description & research objectives

Existing proposals for an updated design of consumer governance have focused on arrangements perceived as necessary to facilitating household participation. However, scholars and practitioners differ in their perspectives on which arrangements are necessary and which household needs should be fulfilled. These diverging perspectives have led to not only incoherent proposals that only define some arrangements but also conflicting ones that provide mutually exclusive designs for the same arrangement.

Translating the manifold household needs into a coherent design for consumer governance is highly complicated. This motivates the main research question addressed in this dissertation, which is as follows:

**How can one design governance
to facilitate household participation in the energy system?**

To answer this research question, we apply the design process of Knops and de Vries (2005) and Dym et al. (2014) to the case of consumer governance. This process consists of three steps, to which we add one extra step at the beginning to base the design process on state-of-the-art research on consumer governance. The four steps are as follows:

I. We create an inventory of existing design proposals;
II. We identify the design requirements;
III. We draft a preliminary design based on the design requirements;
IV. We test whether the preliminary design meets the design requirements and revise it until it does.

Other scholars have applied the design process to other parts of the electricity system, such as the balancing market (Poplavskaya and Vries 2019; Piao et al. 2017) and the distribution system (Piao et al. 2017). In the following paragraphs, we tailor the design process to the case of consumer governance to address the research problems highlighted in Section 1.1:

Creating a coherent governance design: Consumer governance consists of a range of formal rules and contracts that jointly determine how household energy use is organized. If a design proposal defines only some of those rules and contracts, it runs the risk of failing in the implementation phase due to missing preconditions or a poor interplay with existing arrangements. As part of design step I, we develop a comprehensive list of required arrangements.

Managing mutually exclusive design choices due to conflicting household needs: Some household needs are conflicting, as they cannot be met with the same design and create dilemmas for households. Households may reveal latent priorities when they face mutually exclusive design choices. The design inventory that we create in design step I identifies mutually exclusive design choices. In design step II, we examine households' priorities on the basis of these design choices.

If no clear priorities for household needs are identified, then we combine both design choices when drafting a preliminary design in design step III. The following three outcomes are possible: The modified design meets needs to the fullest extent, partially, or not at all. If the modified design does not meet needs at all, then it is considered a failure and must be revised. Meeting needs to the fullest extent possible is desirable but unlikely, since conflicting household needs exist for the modified design. We test the impact of the modified design on household needs in design step IV and revise it if necessary.

Incorporating a group-dependent variation of household needs: Households' priorities are expected to vary among household groups. Sociodemographic characteristics are well known to explain household energy use. By contrast, sociotechnical characteristics (e.g., the ownership of flexible technologies) determine the capability to adapt energy use (Abrahamse and Steg 2009; Parrish et al. 2020). We involve household groups with different flexible technologies and perform a technology-specific analysis in design step II, which concerns households' priorities.

Incorporating a time-dependent variation of household needs: The economic theories presented in Section 1.2 indicate that households' priorities are likely to differ between when they select a service and when they operate it. On the one hand, the transaction cost of seeking information may result in a gradual increase in knowledge for the household over time. Thus, households would make more informed decisions at a later stage of participation. On the other hand, households are expected to make daily decisions about their energy use based on intuition, which is prone to biases (e.g., immediate gratification and present bias). A discrepancy between the initial decision for a service and its operation is often also associated with the intention–action gap (i.e., households' intention to participate does not match their actions). In design step II, we test households' priorities during both stages to explore the differences over time.

Next, we summarize the design steps, which motivated the four sub-research questions (SRQs) answered by this dissertation. After each SRQ is answered, the consumer governance design is further specified. Figure 1-1 depicts the design process of this dissertation:

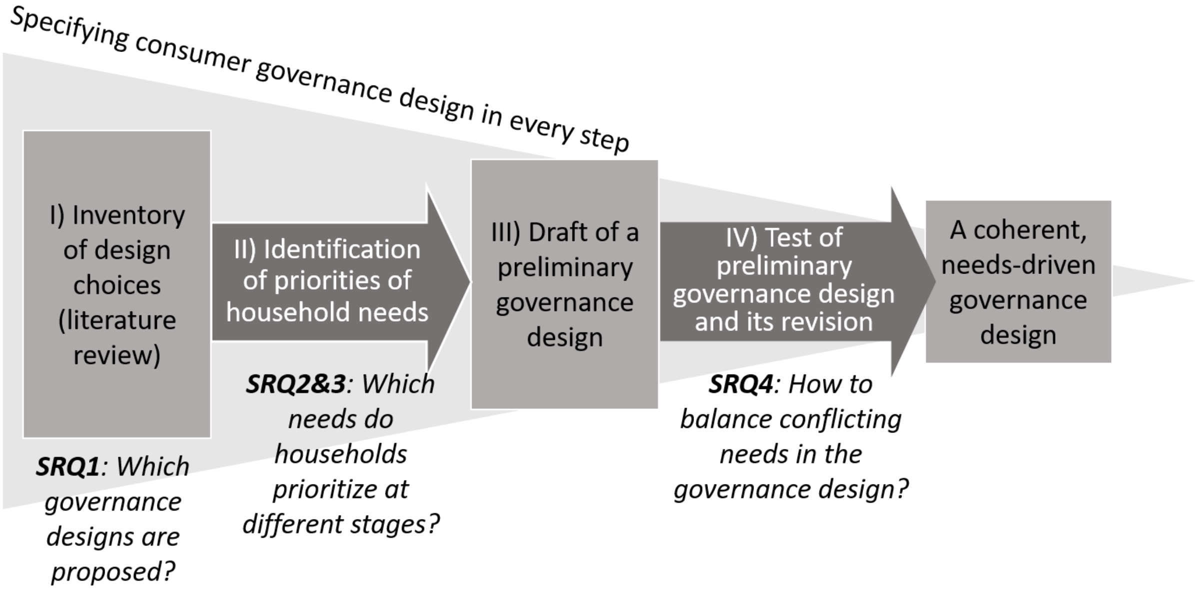

Figure 1-1: Design process applied in this dissertation, including the sub-research questions (SRQs)

Design step I – Creating an inventory of governance designs: We decompose, group, and organize the existing design proposals for consumer governance in terms of their organization of household energy use. Then, we map their performance by the degree to which their benefits offset their transaction costs. The results of the organization and performance form an inventory of design choices, which is presented in Chapter 2. The structure of the inventory ensures a coherent design that defines all required arrangements for organizing household energy use.

The following three types of design choices are expected:

i. Those that can be excluded from further analysis since they do not facilitate household participation (e.g., flat retail tariffs);
ii. Viable ones that target the same household need;
iii. Viable ones that target different household needs.

The third type of design choice is controversial since it creates a dilemma for the selection of the design. In the next step, we clarify which of the mutually exclusive design choices are preferred by households.

This design step motivates the first SRQ, which is answered in Chapter 2:

SRQ 1. Which governance designs are proposed in the literature for facilitating household participation in the energy system?

Design step II – Identifying households' priorities: The design requirements define the design space; they further restrict which design choices are viable for consumer governance. In this dissertation, the design requirements originate from household needs and policy objectives for a decarbonized, cost-efficient, and secure energy system. Which household needs should be prioritized for the governance design is examined based on the mutually exclusive design choices of the previous design step.

Notably, some household needs and policy objectives reinforce each other. For instance, if households adapt their consumption to price signals, then the total energy system costs and household costs are reduced simultaneously. This dissertation focuses on household needs. It only deals explicitly with policy objectives if they contradict the household needs.

Households' priorities are expected to vary between both participation stages as well as between the flexible technologies they possess. We collect data from households with different flexible technologies and at different stages, including when they decide to participate and when they participate on a daily basis. Furthermore, we perform technology-specific analyses on household priorities for the initial decision and for participation.

This design step is divided into one SRQ per participation stage, and they are answered in Chapter 3 (SRQ 2) and Chapter 4 (SRQ 3):

SRQ 2. Which needs do households prioritize when deciding to participate?

SRQ 3. Which needs do households prioritize while participating?

Design step III – Drafting a preliminary governance design: A preliminary design for consumer governance is drafted based on the inventory of design choices and households' priorities. Chapter 2 presents the design choices that are viable for household participation but not mutually exclusive (i.e., design choices that do not conflict with other household needs). The preferences for the mutually exclusive design choices (i.e., that target different household needs) are presented in Chapters 3 and 4. If no clear preference exists, then we modify the design by combining the design choices at the beginning of Chapter 5. Since design step III is answered in different chapters, we assign it no SRQ.

Design step IV – Testing the preliminary governance design and revising it: This step tests the degree to which the modified design balances the conflicting needs. Different modified designs are tested to identify the one that results in the optimal balance between needs.

This design step motivates the fourth SRQ, which is answered in Chapter 5:

SRQ 4. How can conflicting household needs be balanced in the governance design?

With the design process completed, we have a proposal for updating consumer governance. In the following section, we outline and explain the motivation behind the methodological choices for each SRQ.

1.4 Overall approach & methodology for each sub-research question

A design process combines the systematic approach of engineering with the strengths of economics and other social sciences to understand household needs. By applying the design process to the case of consumer governance, this interdisciplinary dissertation combines conceptual, empirical, and model-based research. Figure 1-2 illustrates how the design process of this dissertation is operationalized:

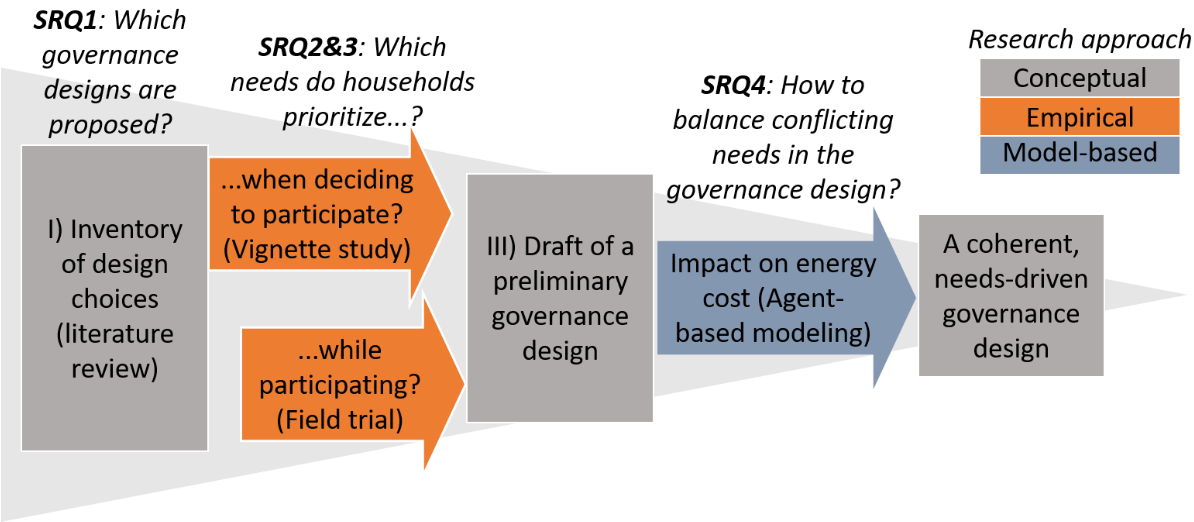

Figure 1-2: Operationalization of the design process in this dissertation

As the figure indicates, the starting point of the design process is the literature-based inventory of design choices, which is created as a response to SRQ 1. Our empirical research clarifies households' priorities for mutually exclusive design choices. We examine the priorities when households choose a service to participate (SRQ 2) and when they operate the service (SRQ 3). Then, we test how the chosen design meets those needs with an agent-based model in response to SRQ 4.

The methodological choices for SRQs 2 and 3 are differentiated by how households make decisions at each participation stage. Different forms of data collection and evaluation are required to capture these decisions adequately. Households can report the conscious decision to choose a service as a stated choice. We collect data in a survey at this stage. By contrast, households tend to be less aware of their intuitive decisions during service operations. If they cannot state their needs based on their experience, then they are more likely to provide socially desirable answers instead. We observe the needs at this stage as revealed choices in a field trial. The order of both questions and the chosen methods naturally reflects the participation stages in real life—from selecting a service in exchange with an intermediary to operating it privately at home.

We discuss the methodological choices for each SRQ in the following subsections.

1.4.1 SRQ 1: Which governance designs are proposed in the literature for facilitating household participation in the energy system?

In Chapter 2, we develop a design framework for consumer governance based on the functions that need to be performed to organize household energy use. Functions are the smallest element of consumer governance that serves an objective. Following the approach of Knops and de Vries (2005), we choose them to decompose the different design proposals uniformly without creating redundancy between the decomposed parts. The result is an inventory of state-of-the-art design choices for each function of consumer governance.

Moreover, the inventory offers guidance for choosing a governance design by categorizing its performance. Based on insights from the literature, we evaluate the designs according to the degree to which the benefits offset the transaction costs. As evaluation criteria, we apply the determinants of transaction cost economics and common household needs from the literature (see Section 2.2).

1.4.2 SRQ 2: Which needs do households prioritize when deciding to participate?

In Chapter 3, we determine households' priorities when they are deciding *under which conditions to participate in the energy system*. In particular, through a survey, we examine the dilemmas that households face when choosing a demand response service with conflicting attributes. The attributes reflect the mutually exclusive design choices in Chapter 3. We determine the priorities for choosing the demand response services for the entire sample and for sub-groups. The sample consists of households in Germany (n = 962) that own an EV, a heat pump, and/or a stationary battery or that intend to purchase one of these flexible technologies. We examine group- or time-dependent variations by testing the impact of the type of flexible technology to which the service is applied and whether the household owns this technology or only intends to purchase it.

The choice options in such a survey must be concrete enough that households can relate to them as well as generic enough to be applicable to all sub-groups. We balance both requirements by developing a vignette study that combines the strengths of choice experiments and mixed-methods studies. The vignette study forces participants to decide between conflicting service attributes, as is done in choice experiments. Furthermore, as is usually done in mixed-methods studies, the vignette study describes the services at a higher level of abstraction, which is applicable to all sub-groups. We present an overview of the literature on which our survey design is based in Subsection 3.2 and explain our survey design in Subsection 3.3.1.

1.4.3 SRQ 3: Which needs do households prioritize while participating?

In Chapter 4, we examine households' priorities *while participating in the energy system.* We determine the priorities for the mutually exclusive design choices by testing different interventions for optimizing household energy use in a randomized controlled field trial in Germany (n = 111). Since the sending of price signals to households has not yet been widely established in Germany, the participants optimize their energy use by consuming electricity from their own rooftop PV system. We examine which intervention is most effective at enabling households to increase their self-consumption.

We test the effect of three sequentially applied interventions based on the smart meter data of households. Each applied intervention reflects one design choice. All three interventions are designed as nudges since they are expected to be effective at stimulating behavioral change. The interventions are randomly assigned to participants on their digital devices to monitor self-consumption. We reveal the causal effects of the interventions using the so-called difference-in-differences (DiD) approach. It effectively absorbs confounding factors, such as weather and price shocks, in the context of the 2022 European energy crisis. Over the 1.5 years of the field trial, smart meters delivered a sufficient number of observations for this method to be employed. The observations also include measurements from a baseline period and a control group. We provide further information on the experiment design in Subsection 4.2.2 and on the statistical methods in Subsection 4.2.3.

As in the vignette study, we examine group- or time-dependent effects for the field trial. In particular, we compare the effects of households that own an EV on their self-consumption with those that do not. Moreover, we examine the effects over time in an event study to identify signs of fatigue.

1.4.4 SRQ 4: How can conflicting household needs be balanced in the governance design?

In Chapter 5, we test which modified design results in a reasonable balance between conflicting household needs. The tested designs partly consist of the chosen designs from Chapters 2–4, while other parts of the design range between the mutually exclusive design choices for which the households could not decide due to conflicting needs.

We extend an agent-based model to test the impact of the designs on conflicting household needs. The existing agent-based model simulates how households minimize their energy costs as a response to price signals from the wholesale market. The cost minimization reflects households' financial needs. We extend their optimization objective to other consumption needs. Depending on the identified conflict in Chapter 2, we choose and implement a behavioral theory to capture these conflicting needs in the optimization function. The existing model and its extensions are described in Subsection 5.3.2.

The parameters in the optimization function capture the consumption needs of the households as well as how they adjust their needs in response to the modified design. The empirical research in Chapters 3 and 4 provides data for these parameters. Households report their consumption needs in the vignette study in Chapter 3. For instance, parameters based on these data express a household's need to retain control over consumption. The field trial in Chapter 4 presents how households respond to different governance designs. Since the optimization in the field trial and the agent-based model have a similar optimization logic, the empirical data can be easily translated into model parameters. One example is the targeted stage of charge that households determine when optimizing the charging process of their EVs in the field trial. The input data for the model are presented in Subsection 5.3.3.

Additionally, we analyze which compromises on cost savings households must accept if they want to safeguard other consumption needs. Thus, the impact of a modified design on costs ranges between two extreme cases, namely a non-optimized consumption behavior and one that minimizes energy costs without considering other consumption needs. We identify which governance design results in the optimal tradeoff between minimizing energy costs and safeguarding other consumption needs.

2 Design choices for consumer governance to facilitate household participation in the energy system[2]

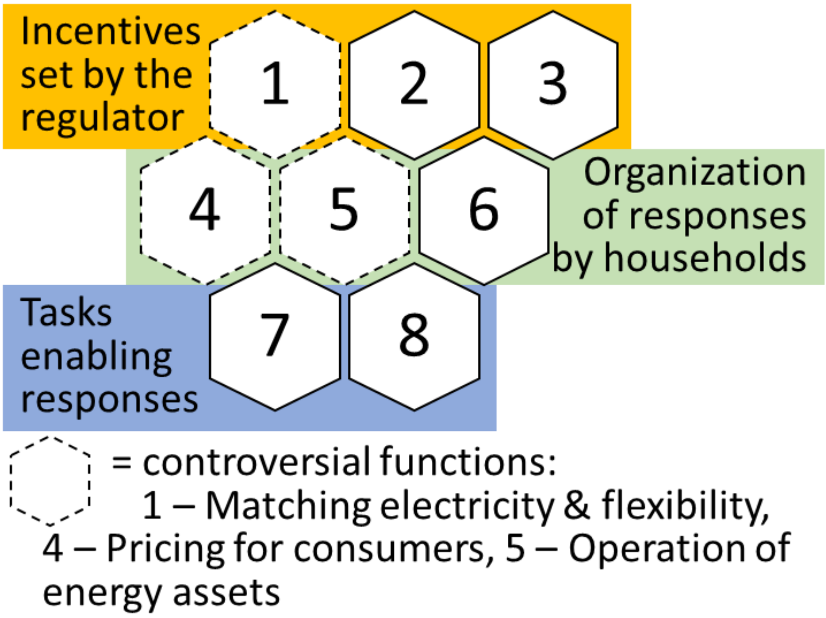

Figure 2-1: Graphical summary based on the design choices for SRQ 1

Households' limited time makes operating their energy assets in an electricity system–friendly manner challenging. Numerous proposals for governance designs that facilitate household participation exist in the literature. By decomposing them into functions and how they are performed, we identify four prominent and commonly structured design archetypes. None of them performs all of the required functions. While energy communities focus on investing, the other archetypes—variable tariffs, local energy markets, and virtual power plants—are characterized by the matching and operation of the assets. All four are positioned to target key tradeoffs that consumers face when choosing a design. While the trust-building features of the first three archetypes primarily target normatively motivated consumers, the virtual power plant facilitates profit-oriented consumers with its efficient aggregation.

2.1 Introduction

Households own a growing number of energy assets capable of supplying or consuming electricity in a flexible manner. Their self-generated electricity or demand-side flexibility can be

2 This chapter has been published as Pelka S., Chappin E., Klobasa M., De Vries L., Participation of active consumers in the electricity system: Design choices for consumer governance, Energy Strategy Review, 2022

offered to the electricity system. Still, it is unlikely that households will spend time or awareness trading them as professional traders do.

New service providers can provide an intermediary role in organizing the electricity-system-friendly operation of the assets on behalf of the consumers. From the perspective of Transaction Cost Economics (TCE), they facilitate participation by reducing the transaction costs for consumers (Nolden and Sorrell 2016; Williamson 1981). Such arrangements are considered attractive if the benefits offset the induced transaction costs of consumers (Sorrell 2007).

The intermediary faces two challenges while creating attractive arrangements. First, the agreements need to reflect the heterogeneous consumer requirements and be formalized in a contract. Second, the contractual arrangements need to align with the electricity market design and its regulatory arrangements. The latter involves, in particular, incentives in the form of price signals from the electricity grid, the market, or administrative price elements. If the challenges are successfully managed, both levels of arrangements form a new governance design that facilitates an electricity-system-friendly operation of energy and flexibility assets owned by consumers.

This literature review aims to compare the design and attractiveness of such governance for active electricity consumers. First, we analyze the designs proposed in the literature by decomposing and grouping them into the functions required for the facilitation. We present similarly structured archetypes of governance designs and check them for shortcomings, such as an incomplete coverage of the required functions. Second, we assess to which degree the designs meet the heterogeneous consumer requirements and offset the imposed transaction cost. We highlight the strengths, weaknesses, and tradeoffs of the designs.

The decomposition approach originates from Dijkema (2001), who recommends assessing a complex design based on its smallest elements that serve an objective, its functions, and how they are performed, the design choices. Knops and de Vries (2005) formalized this recommendation for the electricity system in a so-called Function-based Design Analysis. It has been applied for other analyses of the electricity system so far, such as the balancing market (Poplavskaya and Vries 2019; Piao et al. 2017) and distribution system (Piao et al. 2017). It states that the governance design is characterized by the performance of its organizational functions, which steer the technical functions of electricity supply (e.g., generate, distribute, consume) towards the objectives of the electricity system (e.g., cost-efficient electricity supply) (Knops et al. 2005). The design choices are defined by the regulatory and contractual arrangements.

This literature review is structured in five sections. Section 2.2introduces the consumer requirements, the functions, and other key terms used in this review. We present design choices for each function in Section 2.3. Based on this inventory, in Section 2.4, we group the design proposals in the literature based on the design choices and categorize them by the degree of attractiveness for the consumers. Conclusions are presented in Section 2.5.

2.2 Review framework

We review the literature based on the Function-based Design Analysis by Knops and de Vries (2005) to group its numerous, overlapping design proposals and categorize them by the degree to which the perceived benefits offset the transaction costs. According to Dahlman (Dahlman 1979), the intermediary can influence the level of transaction costs by the asset specificity, uncertainty, and the frequency of the interactions. The first is distinguished between human (e.g., knowledge, expertise) and physical asset specificity (e.g., smart metering), whose recent developments for consumers are elaborated in section 2.2.1. The benefits depend on the consumer requirements presented in section 2.2.2. The requirements of the electricity system shown in section 2.2.3 and the response of the intermediary to both requirements shown in section 2.2.4 imply the functions required for organizational support.

2.2.1 Technological developments: Distributed energy assets, smart metering, and load forecasting

The political agenda to decarbonize the electricity sector has led to advancements in technologies for distributed generation assets, storage systems, and sector coupling (e.g., electric vehicles and heat pumps) (Parag and Sovacool 2016; Mengelkamp et al. 2018). Over time, the reduction in the cost of such technologies has enabled increasing numbers of consumers to impact the electricity system by feeding self-generated electricity into the grid, shifting electricity consumption from the grid using flexible appliances, and using electricity storage systems (Wesche and Dütschke 2021). Information and communication technologies allow the electricity system to access the assets (Siano 2014). Smart metering and other sensors monitor the operation of the assets and enable remote control.

For the participation of the assets, a plan needs to be forecast and announced in advance to ensure a balance of electricity taken from and fed into the grid. For households, a standardized load profile (SLP) is usually applied to simplify the forecasting procedure. As power trading requires the recognition of load shifts or generated electricity, more accurate forecasting is needed than the SLP (He et al. 2013). Automated data analytics based on artificial intelligence and synergies between data sets reduce the effort to produce accurate forecasts (vom Scheidt et al. 2020; Andoni et al. 2019). Furthermore, larger balancing groups with one aggregated plan tend to offset deviations of single assets (He et al. 2013).

2.2.2 Design requirements by the electricity consumers

Steg et al. (2018) identified four motivations of electricity consumers: Egoistic consumers aim to minimize costs. Altruistic consumers focus on ways to support others, and biospheric consumers care about the consequences for the environment. The latter two motivations are summarized as normative motivation. Hedonistic consumers desire pleasure and low effort, which is valid for all consumers to a certain degree and reflected in the transaction cost.

Most consumers become active to minimize their supply cost (egoistic motivation) and support the decarbonization of the electricity system and renewable integration (normative motivation) (Hirsch et al. 2018; Abrahamse and Steg 2009; Roth et al. 2018). For some consumers, this is linked to mistrust in incumbent players and results in additional objectives for trust-building (Stenner et al. 2017), such as creating transparency for pricing, the origin of electricity (Hackbarth and Löbbe 2020; Mengelkamp et al. 2019), and the usage of smart meter data (Haring et al. 2016; Globisch et al. 2020; Brown et al. 2018), as well as empowering local and sustainable initiatives (Sagebiel et al. 2014; Koirala et al. 2018; Wolsink 2012).

As all types of consumers co-exist and each consumer may exhibit multiple motivations and requirements, the governance design needs to adapt to their specific requirements to varying degrees, as shown in Table 2-1.

Table 2-1: Requirement of active consumers

Motivation	Consumer requirement	Source
Egoistic	Minimize their electricity cost	(Wesche and Dütschke 2021), (Koirala et al. 2018), (O'Connel et al. 2014)
Hedonistic	Minimize their transaction cost	(Nolden and Sorrell 2016), (Good et al. 2017), (Parrish et al. 2020)
Normative	Decarbonize their electricity supply,	(Hirsch et al. 2018), (Abrahamse and Steg 2009), (Roth et al. 2018)
	safeguard data privacy,	(Haring et al. 2016), (Globisch et al. 2020), (Brown et al. 2018)
	create price transparency and enable control,	(Hackbarth and Löbbe 2020), (Mengelkamp et al. 2019)
	empower local and sustainable initiatives	(Sagebiel et al. 2014), (Koirala et al. 2018), (Wolsink 2012)

2.2.3 Design requirements and functions stemming from the rest of the electricity system

Generation, storage, distribution, consumption, and measurement of electricity are the main technical functions of the electricity system. They are operated to serve the needs of consumers, but these needs do not necessarily comprise all the requirements for the system. In general, electricity policy needs to balance the following objectives (European Commission 2020):

- Security of supply,
- Cost-efficiency and,
- Decarbonization of the electricity supply.

Price signals are a key mechanism for achieving all three objectives. The low marginal cost of renewable electricity results in low wholesale market prices. This leads to the primary consumption of decarbonized electricity. Price peaks during the absence of renewables incite investments in flexibility assets. Thereby, the security of supply is also maintained (Sovacool and Mukherjee 2011). The importance of price signals is manifested in the EU decision for a zonal energy-only market (European Commission 2020). This means, first, that only electricity that has been produced is remunerated and not its mere readiness like in capacity markets (Bjarghov and Doorman 2018). Second, grid congestions are managed after the gate closure of the wholesale market and are not reflected in the market price (Knops et al. 2001). These principle decisions concerning electricity market design create the basis for assessing consumer governance design.

Alongside the market price signals, other price signals from the electricity grid and administrative elements of the retail price also incite an electricity-system-friendly operation of the assets. Such regulatory arrangements are defined in section 2.3 as design choices. Regulatory arrangements also aim to orchestrate other involved actors, such as grid operators, to support consumers and behave in an electricity-system-friendly way by themselves.

2.2.4 Intermediaries facilitate the functions of the electricity supply

Intermediaries act as brokers between consumers and the electricity system to organize electricity supply. On behalf of consumers, they manage the interactions with the grid operator and the market (Nolden and Sorrell 2016). Economies of scale combined with legal, commercial, financial and technical expertise allow them to organize the electricity supply more efficiently than an individual consumer (Poplavskaya and Vries 2020).

In terms of TCE, intermediaries minimize transaction costs of the consumers by reducing the frequency of interaction, bearing price and forecasting uncertainty, and providing the human and physical assets required for the interactions (Nolden and Sorrell 2016). The most traditional form of an intermediary is a retailer offering a flat retail tariff. The retailer organizes grid access with the grid operator and purchases electricity from the wholesale market based on a contract. Electricity flow is unidirectional, and a flat retail price is charged by the intermediary to the actors involved, as illustrated in Figure 2-2.

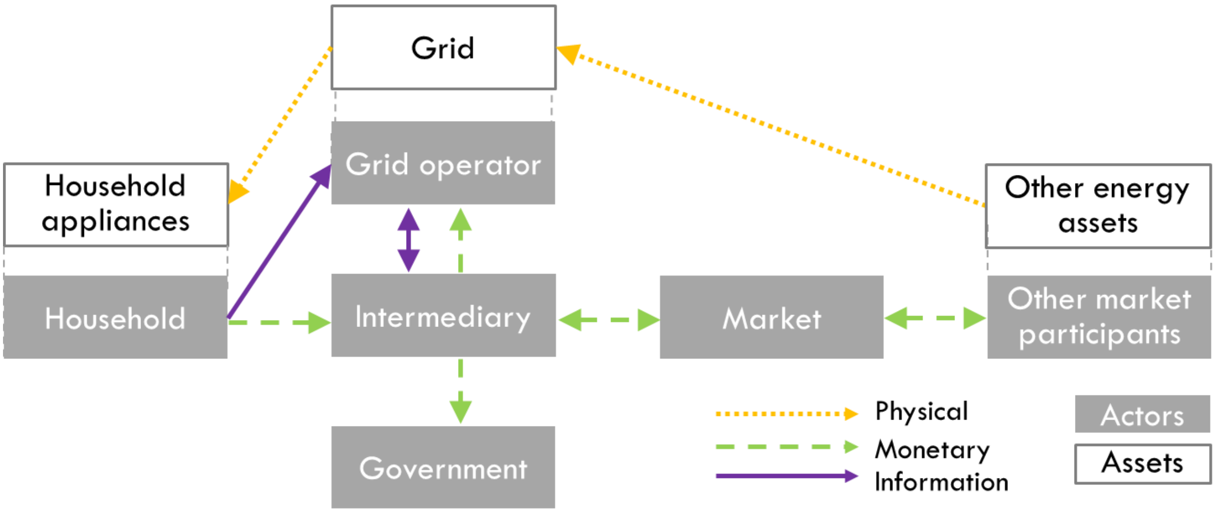

Figure 2-2: Actors, roles, and interactions in traditional electricity exchange

The interactions are different for active consumers: The intermediary receives price signals and translates them for the consumers. As a response on the household level, electricity flows between the consumers and other market participants. The intermediary receives consumption data and payments allocated to the involved actors. New governance designs that follow this interaction pattern are specified in the form of design choices and assessed in section 2.3. Depending on the governance design for active consumers, such intermediaries are called aggregators (e.g., (2018), (2020)), energy service providers (e.g., (2019), (2016)), or community energy operators (e.g., (2016), (2021)).

2.3 Design choices for a governance design for active electricity consumers

Design choices represent different ways of performing functions. In sub-sections 2.2.1 and 2.2.3, we identified eight functions for organizing the electricity supply of households that are listed in Table 2-2. Functions 1 - 3 are incentives for system-friendly consumption behavior set by the regulator. Functions 4 - 8 represent actions in response to them, which are specified in a contract between the consumer and the intermediary. Functions 7 and 8 are about implementation choices enabling the other functions. The design choices for each function are presented in the following sub-sections.

Table 2-2: Functions (F1-8) and their design choices (A, B, or C) for the electricity exchange

Function 1-3: Incentives set by the regulator	Function 4-6: Organization of the response by households to the incentives	Function 7-8: Tasks enabling the response of households
F1. Matching electricity and flexibility A. Aggregation B. Local energy market ***F2. Congestion management*** A. Technical intervention B. Congestion pricing C. Flexibility market ***F3. Allocation of administrative price elements*** A. Volume-based B. Capacity-based C. Fixed	***F4. Pricing for consumers*** A. Variable tariff B. Flat tariff C. Business model ***F5. Operation of energy assets*** A. Indirect coordination B. Direct coordination ***F6. Investment in energy assets*** A. Individual investment B. Collective investment C. Investment-as-a-service	***F7. Data collection*** A. Yearly metering B. High resolution and frequency of metering ***F8. Billing*** A. Yearly/monthly billing B. Continuous billing

2.3.1 Matching electricity and flexibility

Price signals from the wholesale market steer the matching of demand and supply. Whether it is accessible for small assets owned by households depends on the market access regulation and prequalification requirements. Small assets can be aggregated to meet the requirements. Alternatively, intermediary markets with lower entrance thresholds can be created (Morstyn et al. 2018). In the literature, such markets are frequently restricted to a small geographic area and called local energy markets. Their restricted market access serves at the same time as a guarantee of origin for the participating consumers (Löbbe et al. 2020). There are two main design choices, aggregation and local energy market.

Regarding the design choice aggregation, Glachant (2019) describes aggregators as reverse retailers who provide flexibility and electricity from the consumers to the wholesale or other markets. Heterogeneous assets in a well-combined portfolio complement each other and create electricity products that meet the needs of the market (Poplavskaya and Vries 2020). A central control system connects them to one entity (Plancke 2015).

In contrast to the design choice aggregation, which aims to comply with the conditions of established markets, the local energy market creates a two-sided market platform with its own conditions and trading processes (Glachant 2019). Consumers represent both sides of the market and interact in close proximity, connected by a public or private grid (Löbbe et al. 2020). The trading process includes both local interactions and those with the wholesale market and the grid (Löbbe et al. 2020).

Without standardization by a regulator, different market architectures of local energy markets may emerge with regard to two aspects. On the one hand, the dispatch of demand and supply can be organized in a market with auctions and bids, or hierarchically by an optimization process considering the objectives and constraints of the participants (Parag and Sovacool 2016; Sousa et al. 2019; Capper et al. 2022). Common market-based organizations in the literature are peer-to-peer and transactive energy markets, common hierarchical organizations are associated to community or collective self-consumption (Capper et al. 2022). On the other hand, the geographic dimension and dispatch levels may differ (Parag and Sovacool 2016; Koirala et al. 2016; Capper et al. 2022). Larger markets with auctions are more liquid and transparent. At the same time, smaller hierarchical systems have lower entrance barriers and thus can activate and involve larger numbers of participants (Parag and Sovacool 2016).

2.3.2 Congestion management

If more grid capacity is used than installed, price signals can reallocate the utilization of the capacity. The literature proposes two design choices with price signals for congestion management. On the one hand, congestion can be priced into the electricity price or as a variable network tariff. A special form is peak pricing, which deviates from the flat tariff only during periods of congestion. On the other hand, a reallocation can be traded in flexibility markets (He et al. 2013; Ilieva and Gramme 2019; Plancke 2015; Lehmann et al. 2019). At present, the grid utilization of small assets is not adapted by price signals, but by direct technical interventions of the grid operator. There are three design choices when it comes to congestion management, technical interventions, congestion pricing, and flexibility market.

In the case of technical interventions, they are scheduled based on the announced consumption and supply plan and are communicated in advance to electricity assets. In return, the assets receive cost reimbursement (van Blijswijk and Vries 2012). For small assets without an announced plan, the grid operator relies on stochastics for the interventions, making communication in advance and cost reimbursement more difficult. For flexible appliances, rules for more extensive technical interventions may be formalized in the grid connection agreement or an additional contract for flexibility provision (Gonzalez Venegas et al. 2021).

One implementation of the design choice congestion pricing is the locational marginal prices (LMP) that considers the grid capacity in the dispatch process of the electricity market. In case of capacity limitations, LMP results in different prices for every node of the electricity grid at every time step (Gonzalez Venegas et al. 2021). If the wholesale market is determined as one pricing zone, variable network tariffs create similar effects to LMP.

Modeling studies demonstrate the efficiency of congestion pricing on the distributional level for small assets (Yusoff et al. 2017; Li et al. 2014; Verzijlbergh et al. 2014; Abdelmotteleb et al. 2017), but uncertainties on both sides remain. For the grid operator, translating capacity limitations into variable network tariffs carries the risk of not recovering grid costs. For the consumers, geographical differences in pricing tend to be considered unfair, create price uncertainties, and additional monitoring efforts. Both aspects need to be addressed by the tariff design (Gonzalez Venegas et al. 2021; Savelli and Morstyn 2021), which is discussed in sub-section 2.3.4.

The last design choice, the flexibility market, follows a different paradigm. Instead of pricing the grid usage rights, the consumers own them and trade them on a flexibility market. The grid operator announces a flexibility demand concerning the amount of power required, the location, and the level of reliability (Heilmann et al. 2020). Flexibility can be traded as short-term products (e.g., adapted grid usage for 15 minutes) or long-term contracts (e.g., right to adapt the load for one year) (Gonzalez Venegas et al. 2021). One grid operator needs to coordinate the flexibility usage with other grid operators on the same voltage level and higher ones. Calculating the optimal auction outcome is easier for smaller geographical market areas, but a higher degree of coordination is required afterward (Heilmann et al. 2020). Professional support is required at consumer level to forecast the flexibility and for bidding.

2.3.3 Allocation of administrative price elements

The design of taxes, levies, and other elements of the retail price impact the market-based price signals and thereby the incentives for system-friendly operation (Klein et al. 2019). The three design choices for its allocation logic are volume-based, capacity-based and fixed allocation.

Volume-based price elements incite consumption reduction but diminish the price signals sent by the grid and market. Capacity-based price elements allow price signals to evolve their incentives for system-friendly behavior if exemptions exist for capacity overruns during these times. Technical installations, such as a fuse or a smart meter, need to monitor and penalize capacity overruns. Fixed-price elements have a similar effect as capacity-based ones without technical monitoring. To set the fixed price, an economically sustainable and non-discriminating calculation logic needs to be determined (Pérez-Arriaga 2013).

2.3.4 Pricing for consumers

Independently of the origin of the price signal, they are transformed into tariffs or other business models for the consumer (He et al. 2013; Glachant 2019). Apart from the traditional flat tariff, different forms of variable tariffs exist. Most design choices require smart metering that labels the consumption per price level with a time stamp.

Various variable tariffs that differ in the intensity of price signals are proposed in the literature (presented in order of decreasing intensity): Real-Time Pricing (RTP), Time of Use Pricing (ToU), Critical Peak Pricing (CPP), and Peak Time Rebates (PTR) (Khan et al. 2016; Dutta and Mitra 2017; Hu et al. 2015; Darby and McKenna 2012). Pre-determined price levels, a long duration, and small price differentials decrease the incentives for system-friendly behavior and the price risks for consumers (Dutta and Mitra 2017). For instance, while RTP sends price signals in the same resolution as on the wholesale market, ToU announces them in advance for a specific day, week, or season. The simplest ToU form is the peak and off-peak tariff, which can be metered by an analog double-rate meter in contrast to the other tariffs. The CPP and

PTR only deviate from their flat tariff in rare moments of extreme wholesale prices or grid utilization (Khan et al. 2016).

Next to the variable tariff as one design choice, the flat tariff with one price level involves no price risks for consumers and no incentive for system-friendly consumption behavior.

Next to the volume-based tariffs, more complex pricing schemes with bonuses and fees exist and are labeled as business models. For instance, additional services, in particular the direct coordination strategy in function 5, are charged by the intermediary in the form of a fee. In the case of aggregated trading portfolios, it is almost impossible to trace the contribution of a single entity to the overall revenue, so a lump-sum bonus is paid. Ex-ante determined fees or bonuses decrease the risks for consumers (He et al. 2013).

2.3.5 Operation of energy assets

When consumers receive price signals, they are responsible for responding to them by adapting their consumption or generation. They can be supported through optimized load control by the intermediary. Dependent on the coordination role of the intermediary, the design choices is called indirect or direct coordination.

In the case of indirect coordination, the consumers control any adjustment of consumption by themselves after receiving the price signals. This increases price transparency and awareness but also the level of effort and the price risk.

In the case of direct control, the intermediary has direct control over the assets according to their operation parameters and consumer requirements. This case is especially applicable for batteries and large, flexible appliances with regular usage patterns and distributed generation, for which intermediaries optimize for increased self-consumption or offer trading services. The requirements can be updated more frequently to avoid comfort losses for appliances with irregular usage patterns (e.g., electric vehicles).

2.3.6 Investment in energy assets

If their current infrastructure does not allow consumers to respond to price signals, additional investments, e.g., in a photovoltaic system, can enable them to become active. These require the financial means and the capacity for technical planning and administrative processes. If this exceeds what an individual consumer is capable of, collective investments and investment-as-a-service are design choice alternatives next to the individual investments (Silva et al. 2022).

In the case of the design choice individual investment, individual households cooperate with energy service providers on technical planning, financial matters, and administrative processes. They tend to dimension the installed capacity to their consumption needs since the trading of excess electricity involves additional administrative obligations (Sarfarazi et al. 2020).

In the case of the design choice collective investment, larger installed capacities are realized by the collective investments of several households. Instead of being limited to one house, the most suitable location for the efficient operation of the energy asset is selected. Households with a small budget can participate as well (Hertig and Teufel 2018; Lowitzsch et al. 2020; Busch et al. 2021). Additional contractual arrangements are required to define the ownership rights, access, and compliance rules (Bourazeri and Pitt 2018). Since the financial means and the social complexity increase with the number of participants, it is recommended to install control and conflict resolution mechanisms (Cayford and Scholten 2014; Wolsink 2012).

In the case of investment-as-a-service, intermediaries invest in energy assets instead of households and offer their utilization in return for a fee that covers the cost for operation, maintenance, and repair. This innovative business model, which began in the software industry (software-as-a-service), shifts the financial burden and risk to the intermediary (Singh and Klobasa 2021).

2.3.7 Data collection

After the functions are performed, the consumers send metering data to the intermediary. We differentiate between data granularity and transfer frequency for the design choices (Good et al. 2017; O'Connel et al. 2014).

In the case of yearly metering, flat tariffs are billed based on yearly consumption data, which can be provided by an analog meter.

Most variable tariffs, cost optimization and trading services require the other design choice, the high resolution and frequency of metering data (Doostizadeh and Ghasemi 2012). The data are provided by smart meters, which collect the data according to the tariff design, store them temporarily and distribute them after a short period (Siano 2014).

2.3.8 Billing

In return for the shared data, the intermediary gives the consumers reports about the performance. Reporting can involve a more detailed price breakdown, information on the origin of the electricity, data usage, or a peer comparison (He et al. 2013). For the design choices, we differentiate the frequency of reporting. There are two billing choices, yearly or continuous billing.

Regarding the first one, the consumers receive a paper-based bill for their energy consumption once a year based on the yearly metering.

The second design choice, more frequent billing, increases price transparency and consumer awareness. On average, energy savings of 8% are reported for more frequent billing(Zangheri et al. 2019). At the same time, it is recommended to combine this with other motivational interventions (e.g., goal setting), as increased awareness alone does not necessarily result in behavioral changes (Abrahamse et al. 2005). To convey the information, alternatives to the paper-based bill are an electronic bill or direct reporting via in-house displays and smartphones (Zangheri et al. 2019).

2.4 Archetypes of governance designs for active electricity consumers

Several governance designs have been implemented in practice or proposed in the literature. Following section 2.3, we break them down into design choices to understand and categorize their performance. This breakdown highlights characteristic design choices and white spaces, for which the design still needs to be specified. It results in an overview of archetypes of new governance designs, which match the different design requirements of consumers and the electricity system.

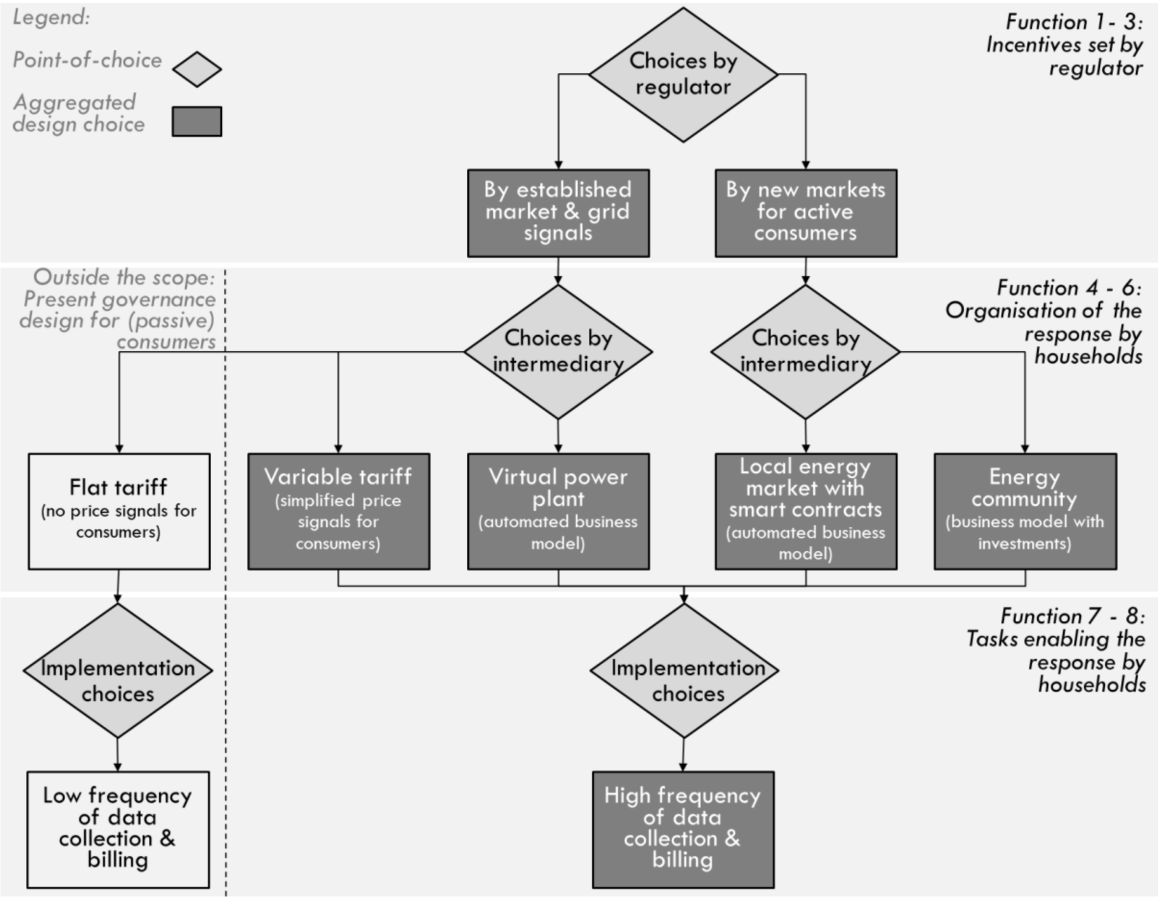

Figure 2-3: Summary of archetypes of new governance design w.r.t. the design choices from Section 2.3

Figure 2-3 summarizes the key design choices for each category of functions. Regarding the first category, the identified governance designs follow two different incentive logics set by the regulator. They are either based on existing market and grid signals, or new markets for active consumers are implemented. Concerning the first incentive logic, the governance design of virtual power plants (VPP) and variable tariffs are based on the wholesale market's price signals. Concerning the second incentive logic, the local energy market with smart contracts and energy communities form new decentralized markets. In contrast to the traditional governance design, the flat tariff, the new tariffs require a higher frequency of data collection and billing.

The four archetypes of governance design are based on a few characteristic design choices in combination with their dependent design choices. For instance, indirect coordination as an operation strategy (F5) is applied for variable tariffs (F4), whose enforcement is the responsibility of the consumers. In contrast, direct coordination (F5) is positioned as a business model with fees and bonuses (F4). The fees include the costs for forecasting, trading, and enforcement services. The lump-sum bonuses result from aggregated trading portfolios, in which it is almost impossible to determine the contribution of single entities.

Some unspecified design choices, such as congestion management mechanisms (F2) or investments (F6), result in fragmented governance designs. The literature suggests combinations of archetypes to complete the design. Table 2-3 presents the characterized and unspecified design choices, synonyms, and specifications of each archetype from the literature.

Table 2-3: Synonyms, specifications, characteristics and unspecified design choices for the four archetypes of governance design

Governance design archetype	Synonyms & key words in the literature	Specification in the literature	Characteristic design choices	Unspecified design choices	Source
Variable tariff	Dynamic tariff	Real-time pricing, tariff of use, (critical) peak pricing, peak time rebate	Variable tariff (F4) + indirect coordination (F5)	A specific form of variable tariff (F4), investment in energy assets (F6)	Gelazanskas and Gamage (2014), Doostizadeh and Ghasemi (2012), Khan et al. (2016), Yan et al. (2019), Nicolson et al. (2018), Hu et al. (2015), Dutta and Mitra (2017), Campillo et al. (2016), Darby and McKenna (2012), O'Connel et al. (2014)
Virtual power plant	Aggregation	-	Aggregation (F1) + direct coordination (F5)	Congestion management (F2), investment in energy assets (F6)	Lehmbruck et al. (2020), Morstyn et al. (2018), Glachant (2019), Poplavskaya and Vries (2020), Plancke (2015)
Local energy market with smart contracts	Decentralized electricity market design, micro energy markets, distributed generation in smart grids, local energy platform	Peer-to-peer trading, microgrid, electricity island, (regional) flexibility market, smart contracts & blockchains	Local energy market (F1) + direct coordination (F5)	Congestion management (F2), investment in energy assets (F6)	Morstyn et al. (2018), Sousa et al. (2019), Parag and Sovacool (2016), Glachant (2019), Haring et al. (2016), Heilmann et al. (2020), Mengelkamp et al. (2018), Rassa et al. (2019)
Energy community	Community-based markets, community-electricity systems, community-based energy initiatives	Collective actions, co-ownership, prosumer communities, self-consumption, prosumer group model, cooperatives	Collective investments (F6)	Matching of electricity and flexibility (F1), congestion management (F2), pricing for consumers (F4), operation of energy assets (F5)	Koirala et al. (2018), Sousa et al. (2019), Bauwens (2017), Lowitzsch et al. (2020), Roth et al. (2018), Sagebiel et al. (2014), Hertig and Teufel (2018), Sarfarazi et al. (2020), Bourazeri and Pitt (2018), Cayford and Scholten (2014), Espe et al. (2018)

In the following, the characteristic design choices and their performance are presented for the four archetypes based on the available information in the literature. To determine which archetype is attractive for which consumer, further empirical research needs to substantiate the tradeoffs between the highlighted benefits and transaction costs.

2.4.1 Variable tariff

The design of variable tariffs is characterized by how they convey prices to consumers (F4.A) and how consumers respond to them (F5.A). They are designed for consumers who like to control the operation of their assets and appreciate transparent price information. The consumers select a variable tariff with an appropriate level of information by balancing these requirements and the monitoring effort. This is discussed further in Section 2.3.4.

Regarding the performance of variable tariffs, the field tests report a reduction in generation capacity and an improvement in the economic efficiency with four limitations from a system perspective. First, seasonal differences are reported. Hot months show significantly higher responsiveness than mild and cold ones (Hu et al. 2015). Second, peak prices often result in new and higher peak demands at different times (the so-called avalanche effect) (Yan et al. 2018), which can provoke new price peaks or grid congestions. Third, in some countries, the incentives are mitigated by volume-based levies, taxes, and network tariffs (O'Connel et al. 2014). Adaptations in the design of the administrative price elements are discussed in section 2.3.3. Fourth, the reliability of the provided flexibility depends on the implemented control strategies, such as explained in section 2.3.5.

Solutions for the latter also address the limitations of consumers and intermediaries. Intermediaries report a high integration effort compared to a small specific potential per asset (Darby and McKenna 2012). Likewise for consumers, high social acceptability costs occur in the form of risk of welfare loss, price uncertainty, and monitoring effort (Da Silva and Santiago 2018; Dutta and Mitra 2017). Fatigue and rebound effects are observed, which decrease the provided flexibility in the medium term (Khan et al. 2016). These limitations could be limited by combining variable tariffs with an automated load control (Darby and McKenna 2012).

Additional technological costs and limited control for the consumers need to be considered in this case. Also, the flexibility provided by active changes in the daily routine cannot be made accessible by it (e.g., a postponed departure for a longer charging period of an electric vehicle), since the awareness and commitment of the consumer are required (Darby and McKenna 2012; Silva et al. 2022). ToU is more frequently tested in field experiments than RTP and CPP. The experiments with CPP report the highest level of peak shifting but a limited shifted volume in total due to the rare peak times. The resulting low-cost saving leads to dissatisfied consumers. RTP and ToU lead to a similar level of peak shifting. Its highest level is observed for experiments combining variable tariffs and automated load control (Yan et al. 2018).

All in all, the monitoring effort, the price uncertainty, and the communication cost for small and less reliable flexibility potential leads to a high level of transaction cost compared to the savings for the consumer. Especially in the case of rapidly changing tariffs, a combination with automated load control is recommended (Silva et al. 2022). The acceptance of this combination depends on whether the transparency needs of the consumers are met with the targeted information at a low level of effort.

2.4.2 Virtual power plant

The design of VPP is characterized by an aggregation of electricity and flexibility for trading on the wholesale market (F1.A), which is directly enforced by the intermediary (F5.B). The consumer pays a trading fee and receives the trading revenue in return (F4.C). If locational information of the assets is provided, the VPP can participate in different congestion management mechanisms (F2).

The combinations of different technologies and locations in VPP portfolios create valuable electricity products traded efficiently on the wholesale market (Sarfarazi et al. 2020; São José et al. 2021). Large portfolios in combination with a high fixed cost of forecasting and trading realize scale effects (Kelm et al. 2019; Poplavskaya and Vries 2020). Direct control leads to increased reliability for the electricity system but limits the control for the consumers. VPP is mainly dedicated to all generation assets, as well as flexible appliances, whose usage routine provides a predictable potential. To involve consumers with a more intermittent usage routine, combinations of VPP and the local energy market are discussed (Morstyn et al. 2018).

All in all, VPP trades electricity and flexibility from distributed assets efficiently to a low level of transaction costs for the consumers. Thereby, it especially meets the requirements of profit-oriented consumers.

2.4.3 Local energy markets with smart contracts

The local energy market (F1.B) is combined with automatically executed contracts (F5.B) to enable the local trading at a reasonable effort for the consumers. The automatically executed contracts take into account the preferences of the consumers, in particular the accepted price level, the origin of electricity, or the constraints for load shifting. The contract can be linked to smartphone apps for adapting preferences (Morstyn et al. 2018; Rassa et al. 2019). In the case of blockchain technology, the contracts are called smart contracts, which serve as a decentralized protocol for managing the interactions (Andoni et al. 2019; Morstyn et al. 2018; Mengelkamp et al. 2018; Kirli et al. 2022). Also without blockchain technology, adaptable contracts are combined with trading on the local energy market (He et al. 2013; Morstyn et al. 2018; Rassa et al. 2019; Capper et al. 2022; Abrishambaf et al. 2019).

The main revenue streams in a local energy market are based on the consumers' willingness-to-pay for local electricity or remunerations for grid-friendly consumption. Concerning the latter, local dispatch automatically prevents the utilization of higher voltage levels (Schreck et al. 2020; Dehler et al. 2017). As an inherent element of the bids, the locational reference also enables participation in congestion management mechanisms, such as flexibility markets and congestion pricing (Garella 2019; Ilieva and Gramme 2019; Morstyn et al. 2018).

The willingness-to-pay for local electricity is ambiguously discussed in the literature (Mengelkamp et al. 2019; Sagebiel et al. 2014; Wagner et al. 2021; Capper et al. 2022). While Rommel et al. (Rommel et al. 2016) report a willingness-to-pay of up to 6,9 ct/kWh, Mengelkamp et al. (2019) identify a negative utility. Potential losses of living quality explain it due to the proximity of the assets.

At the same time, the proximity of the intermediary in a local energy market coincides with knowledge about local conditions and trust, which is presented as an advantage for the activation of local assets (Morstyn et al. 2018; Lehmann et al. 2019; He et al. 2013). Another trust-building characteristic is the local processing of data (Haring et al. 2016; Globisch et al. 2020; Capper et al. 2022).

Little is known about the transaction cost, as most local energy markets are still in a research state (Capper et al. 2022; Abrishambaf et al. 2019). A high degree of automation in combination with smart contracts and smartphone apps, as well as risk management by the intermediary in the form of forecasting services and price caps, are key design specifications for low transaction cost on the consumer side (Wagner et al. 2021; Lehmann et al. 2019). On the intermediary side, these services lead to high transaction cost, which needs to be counterbalanced by scale effects (Capper et al. 2022). If these challenges are handled, the local energy market is a promising governance design for consumers with normative motivation and trust-building needs.

2.4.4 Energy community

The energy community is the only presented governance design focusing on investments, in particular community-based investments (F6.B). It can be complemented by the previously presented design choices for operation. While the trust-building characteristics of the local energy market reinforce its community spirit, the VPP increases its cost-efficiency. In either way, reciprocal effects are observed for combined investment and operation activities: Consumers co-owning renewable assets are more open to load shifting (Roth et al. 2018).

Two legal definitions exist on the EU level: the renewable energy community focusing on investments in renewables and the citizen energy community involving all activities along the energy value chain. Both communities are voluntary, non-profit-oriented cooperation of natural persons, small businesses, and public administration, which enable joint investments in larger, more efficient assets at the most suitable locations (Lowitzsch et al. 2020).

Renewable subsidy schemes, tax exemptions, and research projects led to a rise in energy communities over the last three decades (Wierling et al. 2018). Apart from the active citizens and municipalities as first movers (Gregg et al. 2020), most consumers state that they are interested in the participation and are willing to pay for it (Sagebiel et al. 2014). Still, they are not willing to steer an energy community (Koirala et al. 2018). It is recommended to partner with professional players to facilitate coordination and lower the transaction cost for the consumers (Nolden and Sorrell 2016).

A more professional approach needs to be balanced with the social and sustainable objectives of the community. A targeted involvement of consumers is required for strengthening the local democratic processes (Busch et al. 2021) and stimulating the activation of social norms and high trust capital (Bauwens 2017).

2.5 Conclusion

In this literature review, we structured the possible designs of consumer governance in the electricity market based on the functions required for organizing the electricity-system-friendly operation of assets owned by consumers and the design choices that are available. The eight identified functions concern, on the one hand, price signals (matching electricity and flexibility, congestion management, allocation of administrative price elements) and, on the other hand, the consumers' response towards (pricing for consumers, operation of energy assets, investment in energy assets, data collection and billing). Based on the inventory of the functions and design choices, we grouped the proposals in the literature and assessed the degree to which their benefits offset the induced transaction costs of consumers. This approach structures a large number of existing, partly overlapping proposals, which not only differ with respect to their design choices but also with respect to the consumer requirements they aim to meet.

We identified four archetypes of governance design, which are positioned to target the key tradeoffs that consumers face when choosing a design. None of the designs performs all functions required for organizing the consumer's response. The first archetype, energy communities, is characterized by the function of investing. Energy communities reduce investment barriers and increase trust capital.

The other three archetypes are characterized by the functions of matching and operating energy assets. Variable tariffs send price signals from the wholesale market to consumers so that they can adapt their energy assets themselves. They improve price transparency and consumers' control over their consumption. Local energy markets directly coordinate the assets but trade them on their own geographically limited market. They ensure local value creation and data privacy. Virtual power plants also directly coordinate the assets and aggregate them for trading on the wholesale market. While the trust-building features of the first three archetypes primarily target normatively motivated consumers, the design of a virtual power plant facilitates profit-oriented consumers due to its efficient aggregation.

The categorization reveals two shortcomings for further research. With regard to the design, the archetypes can be combined with each other to cover the so far unspecified functions and provide comprehensive organizational support for the active consumers. For instance, the electricity produced by the investments of an energy community can be traded in a two-stage trading process combining a local energy market and a virtual power plant to ensure an efficient electricity supply with local value creation. Further conceptualization and empirical research are needed to assess the performance and limitations of such combinations.

With regard to the attractiveness of the design, more empirical studies about the highlighted tradeoffs are needed to confirm which archetype is attractive for which consumer type. This concerns, in particular, the acceptable degree of automated load control considering the consumers' need for control and data privacy.

3 Priorities of households in the selection stage: Insights on demand response dilemmas in Germany[3]

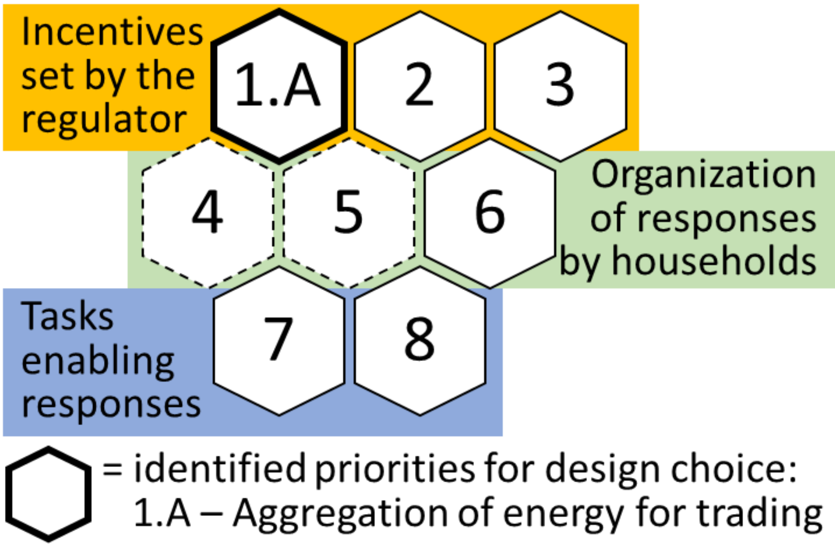

Figure 3-1: Graphical summary based on the design choices for SRQ 2

Households equipped with flexible technologies, such as electric vehicles, can support the energy transition by shifting electricity consumption to times of high renewable supply and by preventing consumption peaks that cannot be covered by existing grid and generation infrastructure. Demand response services support households in performing these consumption shifts. Households ask for specifications of services that stand partly in contrast to each other. For instance, while electric vehicle owners tend to insist on retaining control over their charging, others prefer data-driven automation to minimize their active involvement. Recent studies exploring the acceptance of demand response services focused either solely on specific household groups (e.g. electric vehicle users) or on a broad representative sample without further differentiation. Complementarily to fill this gap, we examine differences in preferences for contrasting service designs between household groups. Specifically, we consider: (i) the type of flexible technology to which demand response is applied, and (ii) the adoption level, i.e., whether the households plan to, or currently own, a flexible technology.

In a vignette survey, we examine the preferences towards four contrasting service designs with German households that either own or have expressed interest in acquiring a flexible technology (n=962). Our results show that the preferences do not fundamentally differ between the kind of flexible technology and adoption level. Generally, participants prefer automated demand response services with data sharing. The added value of realizing energy cost savings

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effectively and efficiently stands out as the main driver for the diffusion of demand response services, outweighing data privacy concerns. Contrary to our expectations, electric vehicle owners did not show a special need for control and households not yet owning flexible technologies did not express a need for little effort. We discuss the implications of our findings for demand response service providers and outline pathways of future research in this domain.

3.1 Introduction

Coordinated consumption shifts of flexible household technologies, such as electric vehicles (EV), heat pumps (HP), or battery storage systems (BSS), support a cost-efficient and secure decarbonization of the energy system. These technologies can be leveraged to consume energy during periods of high renewable supply and to prevent consumption peaks that exceed the capacity of existing energy infrastructure (Noel 2017; Stute and Kühnbach 2023). While households recognize the value of these consumption shifts, their limited time and other priorities often prevent them from actively implementing such changes in consumption. Demand response services (DRS) by service providers, such as variable electricity tariffs or energy management systems with direct load control, are emerging to facilitate the required consumption shifts (O'Connel et al. 2014; Powells and Fell 2019). Different specifications of the services exist to please the households' needs for participation in DRS (Gelazanskas and Gamage 2014; Morstyn et al. 2018). Some popular but contrasting specifications create dilemmas for households and force them to decide between these contrasting options (Parrish et al. 2020; Pelka et al. 2022). This paper reveals households' preferences on the most prominent demand response (DR) dilemmas in current literature.

Shifts in the operation of flexible technologies align with the households' needs as long as they do not violate their primary purpose (e.g., heating and mobility needs). This compatibility tends to differ between the kind of flexible technology and its adoption level. Specifically, studies with EV-owners report a strong need to stay in control of charging processes (Libertson 2022b; Bailey and Axsen 2015; Geske and Schumann 2018). Comfort losses and a high operational effort discourage households – especially if participation in DRS requires prior investments in flexible technologies (Sloot et al. 2023; Naghiyev et al. 2022). While most studies focus on households with one specific flexible technology (e.g., (Bailey and Axsen 2015), (Geske and Schumann 2018), (Huber et al. 2019a), (Libertson 2022b), (Delmonte et al. 2020)) or a broad representative sample without further differentiation into subgroups (e.g., (Broberg and Persson 2016), (Buryk et al. 2015), (Dütschke and Paetz 2013), (Lehmann et al. 2022), (Li et al. 2017), (Lackes et al. 2018)), we compare the preferences towards contrasting DRS designs between households with different flexible technologies and with different adoption levels. Our comparison demonstrates whether the household groups require fundamentally different DRS designs (e.g., variable electricity tariffs for current EV-owners and direct load control for late adopters) or if there is a general alignment in preferences, suggesting a 'one-size-fits-all' service approach. We summarize our research objective in the following research questions: How do households decide when confronted with dilemmas of contrasting attributes in DRS? In these dilemma situations, do households' choices of DRS attributes vary based on their current ownership of a flexible technology? And does it matter which kind of flexible technology they own?

Based on the literature, we specify the research questions and postulate three hypotheses that illustrate the prevalent design contrasts for specific household groups. We choose a simplified vignette study to investigate the hypotheses. The simple design with a limited set of attributes and binary attribute specifications allows to examine preferences of different household groups in one study and challenges the households to choose between contrasting DRS designs. We combine the advantages of the two most common research approaches for the acceptance of DRS design, qualitative studies describing contrasting design aspects more comprehensively (e.g., (Libertson 2022b), (Naghiyev et al. 2022), (Delmonte et al. 2020)) and choice experiments forcing the households to decide (e.g., (Yilmaz et al. 2021), (Lehmann et al. 2022), (Broberg and Persson 2016), (Globisch et al. 2020)). Thereby, we find a balance with the vignettes: making them as descriptive as possible (especially for households interested in but not yet owning a flexible technology), while keeping them sufficiently abstract to involve different household groups (with different technologies) within a single study.

In the vignette study, participants are asked to state their preferences based on a short description of a situation. In each situation, four variables are implemented in a way that the contrasting attributes of DRS vary between situations. Thus, each situation contains one positively specified attribute, leading to a total of four DRS designs (for details see Section 3). The hypothetical setting is made tangible for participants with a descriptive reference to familiar dilemmas and technologies. We recruited participants (n=962) from Germany who either own or have expressed interest in purchasing a flexible technology, aiming to compare their preferences. This specific sample is more suitable to respond to the vignettes than a representative sample because the ownership of flexible technologies is a technical prerequisite for participating in DRS (Sloot et al. 2023; Schuitema et al. 2017). Since DRS are hardly offered in Germany (apart from field experiments with variable electricity tariffs and a curtailment product offered by German distribution system operators), operating flexible technologies is the most relevant experience for assessing the consequences of shifting their operation. Thereby, our paper extends the existing literature by examining the preferences of different household groups towards contrasting DRS designs by presenting dilemmas.

The following section (Section 3.2) reviews the relevant literature on key dilemmas and introduces the tested hypotheses on DRS. Section 3.3 presents the experimental design, the collected data, and the methods of the present study, while Section 3.4 outlines the results of the statistical analyses. Finally, Section 3.5 discusses the results and their implications.

3.2 Literature Review and Hypotheses

The range of discussed DRS in the literature indicates a lacking consensus on their design. For instance, variable electricity tariffs (e.g., (Dütschke and Paetz 2013), (Yan et al. 2018), (Ruokamo et al. 2019)) and energy management systems with direct load control (e.g., (Parrish et al. 2020), (Naghiyev et al. 2022), (Buryk et al. 2015)) are two frequently mentioned examples with a contrasting design, which target different needs of the households. While variable electricity tariffs empower households to shift their consumption by themselves, energy management systems automate the shifts and reduce the effort for households. To create a targeted design for a broad adoption of DRS, scholars and service providers need to understand which needs drive DRS adoption. Since the needs are likely to differ between households, we also explore their heterogeneity. For instance, research shows that some households dislike frequent disruptions while others dislike rare but extreme events (Parrish et al. 2020).

3.2.1 Common study designs for testing the DRS adoption

Present DRS studies differ not only in the examined methodological design but also in the abstraction level of the design and the targeted household groups (see Table 3-1). Regarding the abstraction level, focus groups (e.g., (Naghiyev et al. 2022)), interviews (e.g., (Delmonte et al. 2020)), and mixed-method studies (e.g., (Libertson 2022b)) revealed (mainly) qualitative drivers on a higher abstraction level (e.g., maintaining control, reducing operational effort, mitigating risks). At the same time, choice experiments (e.g., (Yilmaz et al. 2021), (Lehmann et al. 2022), (Broberg and Persson 2016), (Globisch et al. 2020)) explored the value of specific design features leading to less abstraction. The latter assessed, for instance, the timing of the consumption shift (e.g., point in time, frequency, and duration, (Broberg and Persson 2016), (Lehmann et al. 2022)), its relevant interactions (e.g., advance notifications, right to opt-out, data sharing, (Yilmaz et al. 2021), (Globisch et al. 2020)), additional services (e.g., technical support, device monitoring, smart home services, (Richter and Pollitt 2018), (Globisch et al. 2020)) and monetary aspects (e.g., compensation and fees, (Buryk et al. 2015), (Dütschke and Paetz 2013)). The associated value of the specific features is partly hard to assess in a generalizable fashion since it varies over time depending on the participants' socio-temporal conditions (Libertson 2022a). While qualitative studies describe contrasting DRS design aspects more comprehensively, the comparative approach of choice experiments reveals preferences between DRS designs. Acknowledging the strengths and limitations of both approaches, we choose a simplified vignette study, which forces participants to decide between contrasting DRS designs after their comprehensive description.

Regarding the targeted household groups, present DRS studies focus either on early adopters of specific flexible technologies, such as EV-owners (e.g., (Bailey and Axsen 2015), (Geske and Schumann 2018), (Huber et al. 2019a), (Libertson 2022b), (Delmonte et al. 2020)) whose experience prequalifies them for more valid judgment on shifting the particular technology, or a representative sample (e.g., (Broberg and Persson 2016), (Buryk et al. 2015), (Dütschke and Paetz 2013), (Lehmann et al. 2022), (Li et al. 2017), (Lackes et al. 2018)), also capturing the perspectives of potential future adopters. Combining both advantages, we follow the approach of Delmonte et al. (Delmonte et al. 2020) to involve households who own or are interested in acquiring flexible technologies. Combined with the decision for a simplified vignette study, this allows to involve (prospective) owners of different flexible technologies in one study and compare their preferences while achieving valid responses.

Table 3-1: Literature overview w.r.t. to method and sample, tested DRS service attributes, main determinants for the adoption of DRS and other outcomes; sorted by method (i.e., qualitative studies, choice experiments, surveys separated by a horizontal double line) and sample (i.e., households (=HH) with or without flexible technologies separated by a horizontal bold line); grey cells mark the tested attributes; among them, the dark grey cells highlight the ones that are confirmed as drivers of DRS adoption

Source	**Method**	**Sample**	**Control of shifts**	**Effort of perform-ing shifts**	**Data sharing**	**Cost savings**	**Other attri-butes**	**Other determinants & outcomes**
(Libertson 2022b)	Mixed method	EV-owners (n=24-1428)	Reduced charging power					Participants driven by uncertainty & anxiety, and constrained by external factors (e.g., access to charging stations)
(Delmonte et al. 2020)	Semi-struc-tured inter-views	EV-owners or with purchase intension (n=60)	Third-party control	User-mana-ged charging		Financial incentive		Preferences towards user-managed charging due to control
(Huber et al. 2020)	Online nudge experi-ment	EV-owners (n=164)	State of charge buffer			Financial incentive	Social or enviro-nmental benefits	No change for social & environmantal benefits
(Naghiyev et al. 2022)	Field trial with focus groups	HH with white goods (n=18-72)	Third-party control	Conven-ience, user interface				Financial incentives for initial user interaction
(Bailey and Axsen 2015)	Choice exper-iment	EV-owners or with purchase intension (n=1470)	Third-party control		Degree of data sharing	Financial incentive	Share of renew-able consumption	More driven by financial than environmental benefits

(Geske and Schumann 2018)	Choice exper-iment	EV-owners (n=611)	Min. range, timing of charging			Financial incentive	Access to board com-puter	Even without financial incentives, high acceptance rates
(Yilmaz et al. 2021)	Choice exper-iment	HHs (10 % with EVs, 50 % with HPs, n=556)	Number of inter-ventions, prolongation of charging, override, notification			Financial incentive		Financial benefits for HP DR, overriding options for EV DR
(Lehmann et al. 2022)	Choice exper-iment	HHs (n=1034)	Frequency, duration, time period of inter-ventions			Financial incentive		
(Broberg and Persson 2015)	Choice exper-iment	HHs (n=918)	Third party control, time period of interventions		Degree of data sharing	Financial incentive	Heating or electri-city	
(Buryk et al. 2015)	Choice exper-iment	HHs (n=160)		Ease of effort		Financial incentive	Environmental or system benefits	Other determinants: environmental or system benefits
(Dütschke and Paetz 2013)	Choice exper-iment	HHs (n=160)		Degree of automa-tion			Granula-rity of variable tariffs & price spreads	Need for simple tariffs, increased acceptance in case of practical experience
(Globisch et al. 2020)	Choice exper-iment	HHs (n=985)	Response time		Degree of data sharing	Financial incentive	Smart home features	
(Lackes et al. 2018)	Survey	HHs (n=653)	Retain control	Conven-ience	Data security, data privacy	Financial incentive	Environmental benefits	Other determinants: technical safety, data privacy

(Li et al. 2017)	Survey	HHs (n=835)				Financial incentive	Smart techno-logies, actions for energy saving	Limited familiarity with smart grid technologies

Note: Sorted by method (i.e., qualitative studies, choice experiments, surveys separated by a horizontal double line) & sample (i.e., households (=HH) with or without flexible technologies separated by a horizontal bold line); grey cells mark the tested attributes; among them, the dark grey cells highlight the ones that are confirmed as drivers of DRS adoption of DRS

3.2.2 Acceptance of control loss, operational effort, and other requirements for DRS

Table 3-1 displays the heterogeneity of service attributes that are identified as drivers for the adoption of DRS. Financial benefits and means to retain control over consumption are key drivers in many studies. In some of them, both are reported as important (e.g., (Lehmann et al. 2022), (Yilmaz et al. 2021)). In others, financial benefits overrule means to retain control (e.g., (Huber et al. 2019a), (Delmonte et al. 2020)), or vice versa (e.g., (Bailey and Axsen 2015), (Geske and Schumann 2018), (Broberg and Persson 2016)). Yilmaz et al. (Yilmaz et al. 2021) explain this discrepancy with the involved flexible technologies. Other studies identify convenience, comfort, and simple information (e.g., (Buryk et al. 2015), (Dütschke and Paetz 2013), (Lackes et al. 2018)) or data privacy (e.g., (Bailey and Axsen 2015), (Globisch et al. 2020)) as more important than financial benefits. Duetschke et al. (Dütschke and Paetz 2013) underline that the acceptance increases with the DRS experience level. This distinction may explain differences between studies with non-experienced and experienced participants.

The need for control over consumption, operational effort, level of data sharing, and energy cost savings are reoccurring attributes of DRS in the literature, whose specifications influence each other. Still, their importance for the adoption of DRS is hardly compared to each other within one study. Our study tackles this gap in the literature based on the following insights on the attributes, the role of flexible technology, and experiences with them from the literature.

DRS need to be designed in a way that the secondary purpose of the flexible technology, participating in DRS, does not impede its primary purpose (e.g., providing heat or mobility). The compatibility between both purposes depends on how households use flexible technologies. For instance, for most households, the usage of EVs is an integrated part of their daily routine, which depends on socio-temporal configurations (Powells and Fell 2019; Libertson 2022a). Since charging is restricted to plugin times and the households rely on their EV for performing their daily activities, households tend to charge immediately after arrival and in larger quantities to cover their mobility needs (Delmonte et al. 2020; Libertson 2022b; Will and Schuller 2016). Relying on public charging or having an inflexible daily schedule reinforces this charging practice (Libertson 2022a; Gschwendtner et al. 2021). For instance, when operating an HP, most households request that the temperature stays within a specific acceptable range, especially during the colder season (Broberg and Persson 2015). In contrast to EVs and HPs, the primary purpose of BSSs is to provide flexibility, and therefore they are inherently compatible with DRS. Comparing the three flexible technologies, a special sensitivity to participation in DRS may apply for EV-owners because EV use is closely linked to households' daily routine (Libertson 2022b). This is in line with research showing that compatibility of an EV with household needs predicts EV purchase intention (Burghard and Dütschke 2019). Given the strong interlinkages with their daily routine, a more substantial reluctance towards control loss is assumed for electricity-only (e.g., EVs) than heating technologies (e.g., HP) (Ruokamo et al. 2019). Households consider the right to opt-out of a DRS more important for EVs than for HPs (Yilmaz et al. 2021; Geske and Schumann 2018). Research shows similar service features that drive EV-owners' decisions for DRS, such as (i) an ensured minimum state of charge (Yilmaz et al. 2021) and (ii) an immediate charge button (Gschwendtner et al. 2021). This highlights the special sensitivity of EV-owners towards losing control over consumption shifts.

Owning a flexible technology is not only a technical prerequisite for DRS but also demonstrates openness towards technological innovations, which increases the likelihood of participating in DRS. One could state that technology openness leads to a higher acceptance of the downsides of innovations in early adopters compared to households with less or no technology openness. Parrish et al. (Parrish et al. 2020) explain that a socio-technical differentiation of households (e.g., technology adoption) explains the usage likelihood of DRS better than socio-demographic variables. Put differently, the access and ability to use a flexible technology influence the intention to use a DRS more than, for instance, income or age. Abrahamse and Steg (Abrahamse and Steg 2009) support that socio-demographics explain the household's overall energy usage well but not whether households can change their energy consumption. The latter is better explained by socio-psychological values, such as social norms, environmental awareness, and openness towards innovations (Sloot et al. 2023).

In particular, the literature recognizes differences in the acceptance of DRS based on the adoption level of corresponding technologies. For instance, a higher acceptance of shifting energy consumption is recognized for households owning generation technologies (Roth et al. 2018), EVs (Yilmaz et al. 2021), and smart home devices (Li et al. 2017). For greater participation in DRS beyond the early adopters of flexible technologies, the need for enabling technologies that ease participation is emphasized (Buryk et al. 2015).

Easing the participation of prospective owners of flexible technologies and safeguarding the control need of EV-owners are two key requirements for participation in DRS. While their importance is especially prevalent for specific household groups, they are also generally more important than other aspects (Broberg and Persson 2015; Delmonte et al. 2020). While investments in flexible technologies are driven by their economic viability, participation in DRS depends on the corresponding effort and compatibility with the households' habits and comfort (Sloot et al. 2023). In field experiments examining variable electricity tariffs, households reported that the effort of monitoring the tariffs exceeded its financial benefit (Hu et al. 2015; Khan et al. 2016; Naghiyev et al. 2022). In some cases, even households with a high level of motivation showed fatigue effects after executing consumption shifts manually for a while (Khan et al. 2016; Parrish et al. 2019).

Automated, data-driven consumption shifts (also called direct load control) reduce the effort for consumers (Parrish et al. 2019; Crawley et al. 2021). This service specification creates two other dilemmas. Firstly, households fear that the automated shifts are incompatible with their routines and that they will lose control over their consumption (Parrish et al. 2019; Naghiyev et al. 2022). In surveys, households asked for financial compensation for their electricity consumption being controlled in general (Broberg and Persson 2015) or for having less favorable DR conditions (e.g., the electricity consumption being controlled over long periods of time) (Lehmann et al. 2022). At the same time, field experiments showed that the reservations towards automated consumption shifts diminished after a period of familiarizing with it (Parrish et al. 2019; Snow et al. 2022) - underlining the importance of distinguishing between current and prospective owners of flexible technologies.

Secondly, calculating and determining the automated consumption shifts requires sharing sensitive consumption data with the service provider (Snow et al. 2022). Surveys demonstrated that households are only willing to share their data if they receive financial compensation (Richter and Pollitt 2018; Globisch et al. 2020). Inconsistencies in determining the compensation level were identified when short-term rewards of data sharing (e.g., an efficient realization of energy cost savings) were traded against its long-term risks (e.g., perceived surveillance of daily routines by the service provider). This can be explained by a lack of information for the household about the consequences and biases toward short-term rewards (Acquisti and Grossklags 2007; Bhatia and Breaux 2018).

Requests for high compensations in surveys or drop-outs in field experiments indicate that staying in control of consumption and limiting the operational effort are basic requirements for participating in DRS (Parrish et al. 2019). These requirements need to be fulfilled before households shift their energy consumption for electricity cost savings. Based on the reviewed literature, safeguarding data privacy (i.e., no data sharing) tends not to be one of the basic requirements.

3.2.3 Summary and hypotheses

Summarizing households' needs for participating in a specific DRS, one can state that how the DRS is designed seems to be tantamount to the objective it aims to achieve. Based on previous research, we chose the following four attributes of DRS because they seem to influence household participation in DRS: control of consumption shifts, the effort of performing the shift, consumption data sharing (i.e., sharing more consumption data than with other DRS), and electricity cost savings. Combined with the households' two most prevalent, distinctive characteristics, the kind of flexible technology and its adoption level, we conclude the following three hypotheses for our study:

H1 "Consumption control and limited effort as basic DR requirements": **Participants are less likely to use a DRS that violates the need for control of the electricity consumption andthe operational effort than a DRS that violates the objective of saving electricity costs and data privacy.**

H2 "Need for consumption control of EV-owners": **Participants with EVs are less likely to choose a DRS with low control than participants with other flexible technologies.**

***H3 "Need for effort limitation for interested householdshouseholds":* Participants who do not yet own flexible technologies are less likely to choose a DRS with higher operational effort than participants who already own flexible technologies.**

While Hypothesis 1 *"consumption control and limited effort as basic DR requirements"* does not differentiate between the household groups and involves all attributes, Hypothesis 2 *"need for consumption control of EV-owners"* and 3 *"need for effort limitation for interested householdshouseholds"* focus on specific groups and highlighted attributes.

In our study, a simplified vignette design based on the four highlighted service attributes and its carefully combined and described specifications convey the dilemmas of DRS coherently and meet the German participants' limited experience with DRS. While more complex vignette studies and choice experiments randomly combine 3 to 5 specifications of 3 to 5 DRS attributes with each other, we choose binary attribute specifications. The vignettes are embedded in a realistic and concrete context, which makes it easier for the participants to relate to and reveal their judgment – this applies especially for households that do not yet own a flexible technology (Atzmüller and Steiner 2010). At the same time, the vignettes' attributes are abstract enough to apply for households with different flexible technologies. A too specific contextualization is avoided to obtain generalizable results (Atzmüller et al. 2016).

3.3 Materials and Methods

The following section illustrates how we test the previously introduced hypotheses. In particular, we explain the experimental design (Section 3.3.1), the resulting data (Section 3.3.2), and the statistical methods applied to the data (Section 3.3.3). The study design including the hypotheses has been pre-registered and is available at https://aspredicted.org/blind.php?x=9Q3_3QG

3.3.1 Experimental design, survey, and measures

We conducted a vignette study in an online survey to test which of the four DRS attributes (control of consumption shifts, the effort of performing the shift, consumption data sharing, and electricity cost savings) are preferred by which household group based on their adoption level of different flexible technologies. The experiment targeted German households with some level of experience with flexible technologies. Thus, we surveyed households who reported in a pre-screening questionnaire that they own an HP, an EV, or a BSS (different flexible technologies) or considered purchasing one in the past half year (different adoption levels).

To implement the dilemmas based on the literature and the four outlined DRS specifications, we developed four different stylized DRS and included each DRS in a vignette. Each DRS was characterized by one negatively specified attribute, respectively. The other three attributes were framed positively. To have sufficient power for comparing the household groups, we decided to present all vignettes to each participant and limit the number of vignettes to four, the smallest sub-set of vignettes capturing dilemmas. The order of the services (each presented in a vignette) stayed the same for each participant, proceeding from the most to the least widespread DRS in Germany. In fact, it started with the DRS on losing control (similar to a curtailment product offered by German distribution system operators), followed by the one with high effort (i.e., performing the shifts by themselves; similar to the field experiments on variable electricity tariffs) and the DRS with data sharing. Lastly, the DRS having lower energy cost savings (as a consequence of minimizing control loss, effort and data sharing) was presented. The unified order ensures a logical flow from the participants' perspective (Podsakoff et al. 2003). After presenting one DRS, we assessed the DRS usage likelihood, the dependent variable, by asking participants how likely it is that they choose this DRS.

All four vignettes with the stylized DRS were introduced with a general explanation of DRS and a scenario of an electricity consumption shift from the evening to the night hours. This scenario was carefully chosen to create similar conditions for different flexible technologies owned, assuming that most participants are at home during these hours independent of their individual routines. The two specification levels for each attribute, the four stylized DRS, a short form of the introduction, and a text example of one DRS are illustrated in Figure 3-2. The vignette text for the three other DRS is provided in Appendix F.

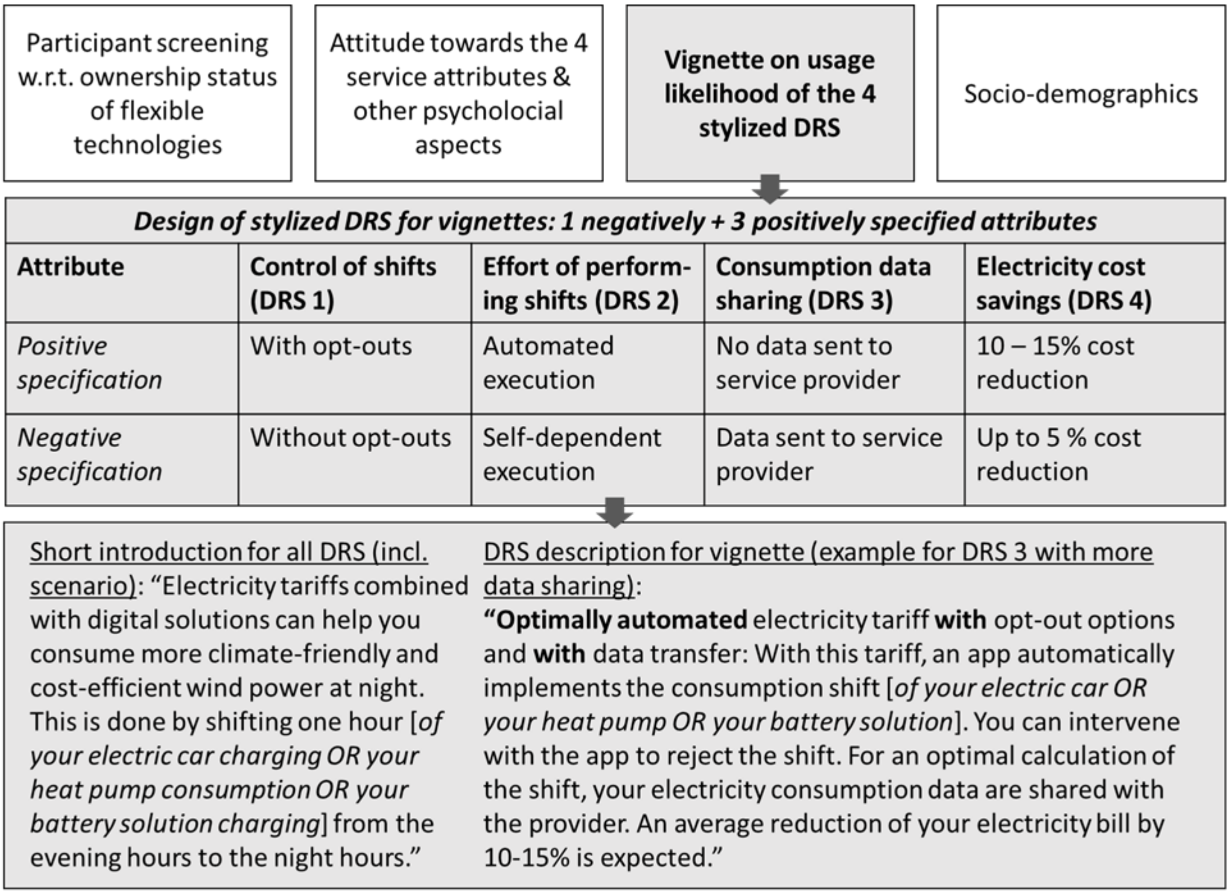

Figure 3-2: Flow chart of the survey, vignette part shaded in grey with one text example of a vignette

The technologies mentioned in the questionnaire were individually adjusted for those the participants owned or were interested in, which was asked beforehand. If multiple technologies were indicated in the pre-screening, the most prevalent one in the German population was displayed as a specific technology, ranking from HP and EV to BSS (see Figure Annex 9-1).

We also collected socio-demographics (after the vignettes) and socio-psychological aspects (mainly before the vignettes, see in Table 3-2) in the survey to explain the likelihood of using each of the four DRS. The latter consists of items testing the attitude towards the four service specifications and other aspects from literature motivating DR participation, in particular, environmental awareness (e.g., Sloot et al. 2022, Sloot et al. 2023), technology openness (e.g., Globisch et al. 2020), and social norms (e.g., Gamma et al. 2021)[4]. The implemented measures are presented in Table 3-2.

In the context of the increased electricity prices in 2022 and their impact on consumption behavior, we asked participants for the change of their electricity tariffs since the beginning of 2022, ranging from a strong increase (coded as 5), no change (coded as 3) to a strong decrease (coded as 1). If appropriate, we conducted Cronbach's α to examine the reliability of the implemented scales. All measures appear reliable (Cronbach's α >.70; see Table 3-4).

Table 3-2: Psychological measurements of the vignette study

Measure	Item	Reference	Position w.r.t. the vignettes
Attitude toward control loss	I do not want my daily routine to be affected by limited use of [my heat pump OR my battery storage OR my electric car]. [a]	(Lackes et al. 2018)	Prior
	It is important to me to maintain control over the use of [my heat pump OR my battery storage OR my electric car]. [a]	(Lackes et al. 2018)	Prior
	I accept limited use of [my heat pump OR my battery storage OR my electric car], provided I am notified in a timely manner.	(Lackes et al. 2018)	Prior
	I accept limited use of [my heat pump OR my battery storage OR my electric car] provided it saves me money.	(Lackes et al. 2018)	Prior
Attitude toward effort	I am confident in using digital solutions to save electricity, or I am already using them confidently.	(Burghard and Dütschke 2019)	Prior
	The functionality of digital solutions for saving electricity is easy to understand.	(Burghard and Dütschke 2019)	Prior
	It would be easy for me to find information on how to use digital solutions to save electricity.	(Rizun and Strzelecki 2020)	Prior
Attitude toward data privacy	Sharing my electricity usage data puts me under surveillance.	(Bhatia and Breaux 2018)	Prior
	I have concerns about security breaches that could compromise the privacy of my electricity usage data.	(Bhatia and Breaux 2018)	Prior

[4] For the control loss measurements with EV as the reference technology, we refer to the usage of electric vehicles and not the usage of the charging point, since a limited usage of the latter results ultimately in a limited usage of the electric vehicle.

	I am concerned that my electricity usage data will be misused.	(Bhatia and Breaux 2018)	Prior
	I am concerned that my electricity usage data will be shared with third parties.	(Bhatia and Breaux 2018)	Prior
Attitude toward cost savings	I am motivated to keep my electricity costs below a certain level.	(Park et al. 2018)	Prior
	The price of electricity plays an important role for me when choosing my electricity tariff.	(Park et al. 2018)	Prior
	I am concerned that the initial cost of a digital solution will exceed the potential savings.	(Park et al. 2018)	Prior
Environmental awareness	I think I am someone who behaves in an environmentally friendly way.	(van der Werff et al. 2014)	Posterior
	I think the environment is more important to me than to other people.	(van der Werff et al. 2014)	Posterior
	I think environmentally friendly behavior is an important part of me.	(van der Werff et al. 2014)	Posterior
Technology openness	I'm very curious about new technical developments.	(Globisch et al. 2020)	Posterior
	I quickly take a liking to new technologies.	(Globisch et al. 2020)	Posterior
Social norm	The people I care about like digital solutions for saving electricity.	(Burghard and Dütschke 2019)	Prior
	Digital solutions for saving electricity have a positive image in society. [b]	(Burghard and Scherrer 2022)	Prior
Instruction: Please indicate to what extent the following statements apply to you. 5-point Likert scale ranging from 1 - fully disagree to 5 - fully agree Notes: [a] reversely coded, [b] excluded due to a reliability analysis assessing Cronbach's α			

3.3.2 Data and sample

The data were collected in Germany by a market research institute from March to June 2022. They cleaned the data and excluded participants based on the following criteria: (1) incomplete questionnaire, (2) participants answering the two implemented quality control questions incorrectly, and (3) participants who reported in a pre-screening questionnaire that they did not own and were not interested in purchasing a flexible technology. Of the resulting sample of 1,116 participants, the ones who did not disclose their gender, home tenure, education, or income level were also excluded to ensure maximum power for the analyses. This reduced the sample to 962 participants. Testing the hypotheses, we arrive at the same pattern of results with the full (n=1,116) and the reduced sample (n=962).

The data present a non-representative subset of the German population, who is already experienced with or has seriously thought about purchasing flexible technologies and, thereby, is likely to answer questions on DRS meaningfully and reliably. In contrast to the German population, the socio-demographic variables show that a higher share of this sub-sample owns their home, is older and more often represented by male individuals, and has a higher income and education level (Table 3-3). This is in line with recent findings in the literature (Plötz et al. 2014; Burghard and Dütschke 2019).

The sample involves five household groups regarding their ownership of flexible technologies, including HP, EV, and BSS (Table 3-3): participants (1) owning more than one flexible technology (also called multiple owners in the following, 27%), (2) owning only an HP (20%), (3) owning only an EV (10%), (4) owning only a BSS (5%) and (5) having considered to purchase at least one of the mentioned flexible technologies in the last six months (37%). An analysis of the statistical power shows that BSS owners cannot be separately evaluated in the following analyses due to their small sample size (n=52). Most multiple owners own an EV and a BSS (31%), followed by owning all three technologies (30%), an EV and an HP (25%), and an HP and a BSS (13%). Most participants indicated that they do not have experiences with digital services for optimizing their consumption yet (69%) but are interested or very interested in them (63%).

Table 3-3: Sample characterization in relation to the German population (n = 962)

Socio-demographic variables	**Sample (n=962)**		**German population**
	Absolute	%	%
Gender			
Female	367	38.15%	50.50%
Male	595	61.85%	49.50%
Age			
Average	55.50	-	45.70%
Household type			
Single	106	11.02%	41.44%
Couple	338	35.14%	28.83%
Couple with child(ren)	462	48.02%	13.83%
Other	56	5.82%	15.90%
Dwelling type			
Detached house	578	60.08%	27.50%
Non-detached house	224	23.28%	13.70%
Flat	136	14.14%	56.10%
Other	24	2.49%	2.70%

Monthly net income of household			
<1000 EUR	10	1.00%	9.45%
1000 -2999 EUR	247	25.70%	49.20%
3000-4999 EUR	439	45.60%	26.71%
> 5000 EUR	266	27.70%	14.63%
Educational level			
No degree	1	0.10%	4.20%
Secondary school degree	74	7.69%	3.80%
General certificate of secondary education	497	51.66%	31.10%
Higher education	390	4.54%	33.90%
Home tenure			
Owner	902	93.76%	62.40%
Tenant	60	6.24%	37.60%
Employment status			
Full-time	570	59.25%	40.40%
Part-time	144	14.97%	15.65%
Retired	177	18.40%	29.63%
Other	71	7.38%	14.32%
Flexible technologies (1 = differentiation between sole and multiple owners for our sample, no such data available for the German population, only presentation of the share of households owning the technology)			
Owning (only)[1] HP	192	19.96%	3.23%
Owning (only)[1] EV	101	10.50%	3.60%
Owning (only)[1] stationary battery	52	5.41%	1.08%
Owning more than one flexible technology[1]	261	27.13%	-
Purchase intention of at least one flexible technology (but not owning any)	356	37.01%	-
PV panel ownership	345	35.86%	3.25%
Own calculations based on (Institut Arbeit und Qualifikation der Universität Duisburg-Essen 2022a), (Institut Arbeit und Qualifikation der Universität Duisburg-Essen 2022b), (Statista 2022b), (BNetzA 2019), (BNetzA 2021), (BNetzA 2023)			

3.3.3 Statistical method

The hypotheses deal with differences in DRS preferences between their specifications (H1) and the household groups (H2 and H3). Exploratory analyses provide insights into why participants have chosen one DRS specification over the other. The following illustrates the statistical methods for the hypothesis testing and the exploratory analysis.

Whether households respond more sensitively towards violating the attributes of staying in control and limiting effort than the ones of electricity cost savings, and data sharing (H1) is tested with (non-parametric) Wilcoxon signed-rank tests including a Bonferroni correction (instead of paired t-tests because the differences in ratings, i.e. the dependent variable, were not normally distributed; but see (Stone 2010)). It compares the DRS with the hypothetically prioritized specifications to the ones with hypothetically secondary specifications. Therefore, Hypothesis 1 is decomposed into four sub-hypotheses (Figure 3-3): To be confirmed, DRS 1 with loss of control is expected to have a lower usage likelihood than DRS 3 with data sharing and DRS 4 with fewer energy cost savings. As for DRS 1, the same applies to DRS 2 with more effort. To detect differences in the usage likelihood between hypothetically prioritized or hypothetically secondary specifications, respectively, comparisons between DRS 1 and 2, as well as 3 and 4, are conducted as an exploratory analysis. The Bonferroni correction is applied to minimize the risk of α inflation.

Design of stylised DR service for vignettes: 1 negatively + 3 positively specified attributes				
DR service / (sub-)sample	... with less control (1)	... with more effort (2)	...with more data sharing (3)	...with fewer cost savings (4)
All	**H1 comparison dimension (Wilcoxon signed-rank test)**			
Owning only HP	**H2 comparison dimension (Kruskal-Wallis-test)**	**H3 comparison dimension (Kruskal-Wallis-test)**		
Owning only EV				
Owning only stationary battery				
Owning more than one flexible technology				
Only with purchase intention				

Figure 3-3: Hypothesis testing with regard to the sub-samples (vertical) and service specifications (horizontal)

Hypotheses 2 and 3 focus on the DRS preferences between the household groups for the DRS 1 with control loss and DRS 2 with more effort (Figure 3-3). Therefore, we conducted (non-parametric) Kruskal-Wallis tests (as Shapiro-Wilk tests indicated that the dependent variables were again not normally distributed). To confirm Hypothesis 2, EV-owners should show a lower usage likelihood for DRS 1 than the other participants. For Hypothesis 3, prospective owners of flexible technologies (i.e. participants with a purchase intention only) should show a lower usage likelihood for DRS 2 than current owners of flexible technologies. As part of the exploratory analysis, Kruskal-Wallis tests were also conducted for DRS 3 and 4 to explore preferences among the household groups towards these DRS.

The hypotheses ask for comparisons between the DRS that reveal the importance of one attribute in relative terms, i.e., relative to the other three reversely specified attributes of the same DRS. The results do not explain whether the difference in usage likelihood results from the positively or negatively specified attributes of one service. Therefore, we additionally conduct one linear regression for all services to explore which attribute drives the difference in the usage likelihood between two services. Since the design of the stylized service vignettes makes the attributes correlate, we choose a ridge regression for the analysis. Its penalty term mitigates the impact of collinearity, such as demonstrated by (Mohanpurkar and Suryanarayanan 2013), (Muhammad Yousaf Raza et al. 2021), (Qin Zhu and Xizhe Peng 2012). The general psychological measurements in Table 3-2 are an additional source for explaining differences among the household groups.

As a further exploratory analysis, we conduct a linear hierarchical regression for the most popular DRS to understand the explanatory factors behind its usage likelihood. In Table Annex 9-5 – 9-7, the results of a linear hierarchical regression for the other three DRS can be found. In line with previous analyses and the explanatory variables in the literature, four hierarchical levels are applied:

- The attitude towards each of the four DRS specifications
- The adoption level of the different flexible technologies
- Other most common psychological aspects in literature or timely topics: environmental awareness, technology openness, social norm, energy price change
- Socio-demographics: Age, gender, tenure, education, income

The dependent variable for all analyses is the usage likelihood of the DRS rated on a 5-point Likert scale (ranging from 1 - fully disagree to 5 - fully agree). For validation, we also conducted all analyses with the ranked usage likelihood as dependent variable (ranging from 1 – most likely to be used to 4 – least likely to be used, see Appendix E).An analysis of the statistical power showed that the sample size is considered to be sufficient to identify even small effect sizes for all analyses.

3.4 Results

In the following, we present the results of the previously described statistical methods that were applied to test the hypotheses (Section 3.4.2). Then, we explain why the participants preferred one DRS specification over the other (Section 3.4.3). Beforehand, we introduce the descriptive statistics of (i) the psychological variables, including the attitude toward the DRS specification, and (ii) the usage likelihood for the four stylized DRS (Section 3.4.1).

3.4.1 Descriptive statistics

As the first step of the analysis, we examined the descriptive statistics of the psychological aspects (Table 3-4). The analysis shows that, on average, participants rated all variables high with means above the scale's midpoint. The importance of energy cost savings was rated highest (compared to the other variables). In contrast, the importance of data privacy is, on average, the lowest and its standard deviation (SD = 1.05) the highest (compared to the other variables), indicating different attitudes toward data privacy among respondents. However, the mean of the importance of data privacy is still high. Apart from the importance of data privacy (3), Spearman's correlation analyses show a positive correlation ($p < .01$) between variables associated with the DRS specifications and the psychological variables from the literature (5, 6, 7). The positive correlations indicate that a strong social norm, high environmental awareness, and high technology openness are associated with more tolerance towards the downsides of the DRS (e.g., the need to accept additional effort). However, the size of the correlations varies from weak (e.g., correlations between 5, 6, 7 and the importance of cost savings) to relatively strong (e.g., correlation between 6, 7 and acceptance of effort). Spearman correlations smaller than .10 can be considered negligible (Rea, L. M. & Parer, R.A. 1992). Descriptive statistics on these variables for each household group are provided in Table Annex 9-1.

Table 3-4: Mean, standard deviation, and Spearsman's correlation analyses for the psychological variables (incl. Cronbach's α for each scale)

	Mean	SD	1	2	3	4	5	6	7	8
1 - Acceptance of control loss	3.65	.74	.803	.242**	-.036	.150**	.217**	.135**	.304**	.044
2 - Acceptance of effort	3.38	.71		.625	-.0096**	.106**	.241**	.504**	.463**	-.008
3 - Importance of data privacy	3.00	1.1			.925	.037	.051	-.033	-.171**	.054
4 - Importance of cost savings	4.12	.70				.658	.183**	.119**	.234**	.161**
5 - Environmental awareness	3.68	.79					.769	.273**	.235**	-.017
6 - Technology openness	3.87	.92						1	.291**	-.013
7 - Social norm	3.57	.78							.883	.083*
8 - Electricity tariff change in 2022	3.90	.82								

Note: Diagonal shows Cronbach's α

* $p < .05$, ** $p < .01$, *** $p < .001$. n=962

When examining the overall preference of households (i.e., usage likelihood of each DRS), we received the following descriptive results: DRS 3 with more data sharing is most likely to be used, followed by DRS 2 with more effort and DRS 1 with less control. Participants are least willing to compromise on cost savings, rating the usage likelihood of DRS 4 as the lowest (Figure 3-4). If the participants are forced to decide *between* the DRS (i.e., rank them starting with the most preferred one), they respond consistently, ranking DRS 3 most often as the first choice and DRS 4 most often as the last choice (Figure 3-5).

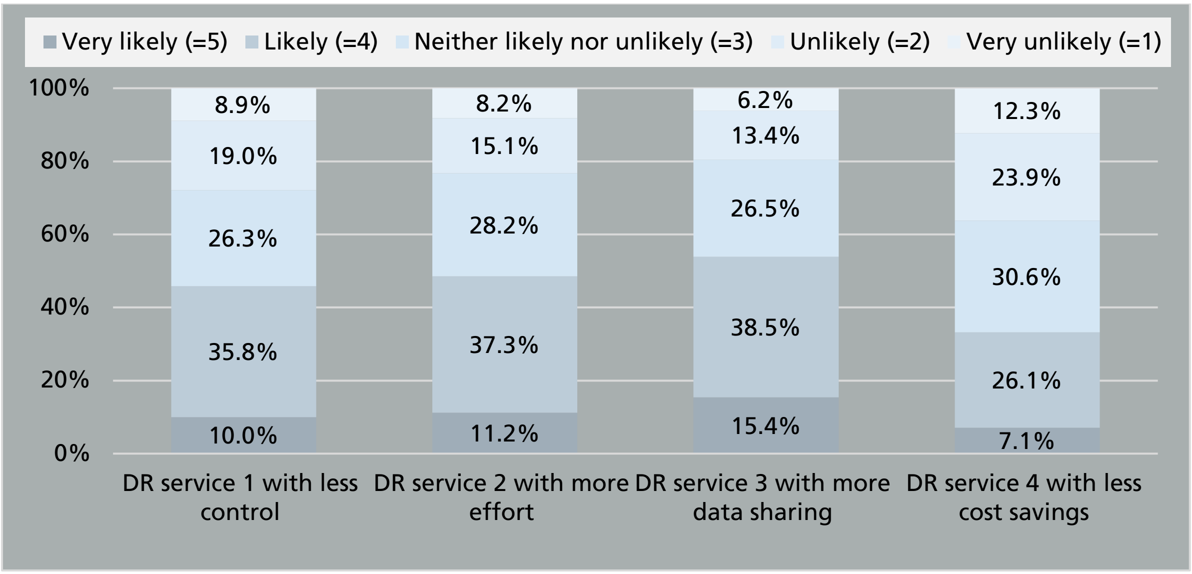

Figure 3-4: Usage likelihood of DRS (rated on a 5-point Likert scale ranging from 1 – very unlikely to 5 – very likely)

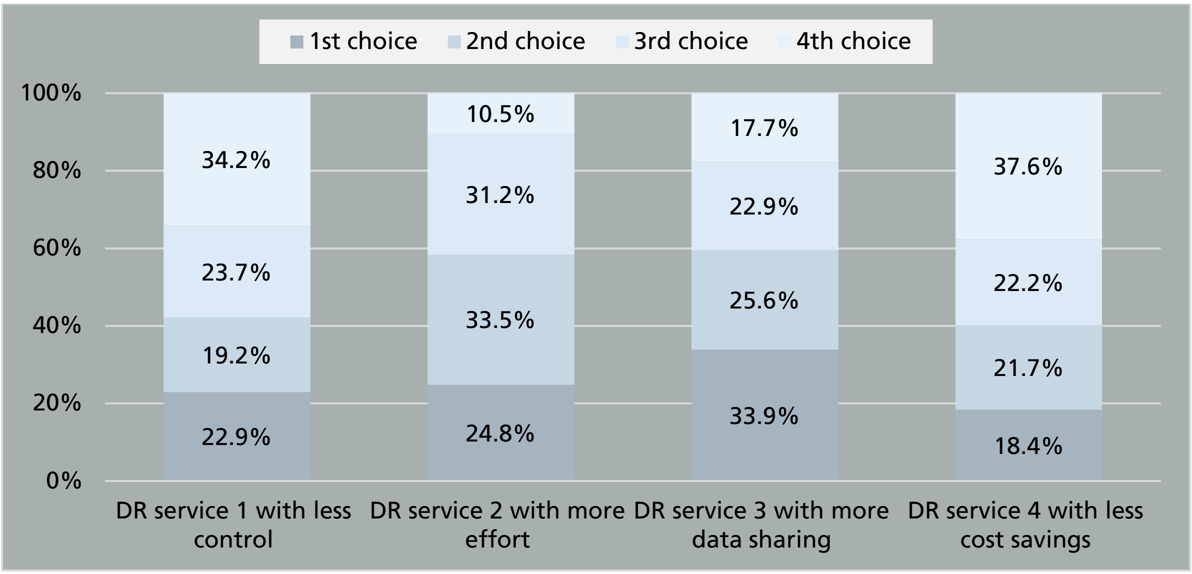

Figure 3-5: Usage likelihood of DRS (ranked from the first choice as the most likely one to the fourth choice as the least likely one)

3.4.2 Hypotheses testing

The Wilcoxon signed-rank test supports only partially Hypothesis 1 *"consumption control and limited effort as basic DR requirements"*. We expected that DRS 1 with less control and DRS 2 with more effort are less preferred than the other two DRS (i.e., DRS 1 and 2 have a significantly lower usage likelihood compared to DRS 3 and DRS 4).. The results of the four comparisons (sub-hypotheses 1a-d) are illustrated in Table 3-5 and Table 3-7. As expected, DRS 1 with less control had a significantly lower usage likelihood than DRS 3 with more consumption data sharing (a). In contrast, DRS 1 had a higher usage likelihood than DRS 4 with less cost savings (b), not confirming the hypothesis. The same applied to DRS 2 with more effort. DRS 2 showed a lower usage likelihood than DRS 3 (c) but a higher usage likelihood than DRS 4 (d). Consequently, households are less willing to compromise on consumption control and limited effort than on limited data sharing. But they are least willing to compromise on realizing energy cost savings.

The responses on the most popular DRS 3 (more consumption data sharing) and the least popular DRS 4 (less cost savings) show that participants prefer data-driven, automated DRS, which achieve energy cost savings effectively and efficiently. Staying in control over their consumption and limiting operational efforts are only important basic requirements if the cost-saving potential is realized. They are willing to share their consumption data if all three aspects can be covered with data-driven, automated services.

The extreme positions of the DRS that impact data privacy (DRS 3) and cost savings (DRS 4) are confirmed by sign test based on the ranked usage likelihood (see Table Annex 9-9). In contrast, the results based on the ranked dependent variable show more extreme tendencies for the services that imply control loss (DRS 1) and effort (DRS 2) than the results based on the rated dependent variable. In particular, we find no significant difference between services that increase the effort (DRS 2) and that mitigate data privacy (DRS 3). The same applies to the services that increase the control loss (DRS 1) and that mitigate cost savings (DRS 4).

The relative importance of realizing cost savings over safeguarding data privacy is reinforced by the findings on the absolute importance of one attribute based on the ridge regression in Table Annex 9-8. It analyses the effect of each attribute (coded in a binary way indicating whether the attribute was positively or negatively specified) on the usage likelihood of all DRS. While compromises on the cost savings strongly (β=-.27) and on the need for control slightly (β=-.02) decrease the usage likelihood, the automation in return for data sharing strongly (β=.22) and the self-dependent execution slightly (β=.08) increase the usage likelihood.

A small ($r < 0.1$) to medium ($0.1 < r < 0.3$) effect size is recognized for the six t-tests (Cohen 1988).

Table 3-5: Results of Wilcoxon signed-rank Test testing Hypothesis 1

#	DR service	Z	Effect size r	Asymp. Sig. (2-tailed)	Relevant aspects to test Hyp. 1: Lower usage likelihood for DR service with...	Result
1	1 vs. 2	-2.14^{b}	.069	.033	-	-
2	1 vs. 3	-5.49^{b}	.177	.000***	less control than more data sharing	supported
3	1 vs. 4	-5.18^{c}	.167	.000***	less control loss than less energy cost savings	not supported
4	2 vs. 3	-3.29^{b}	.106	.001**	more effort than more data sharing	supported
5	2 vs. 4	-8.07^{c}	.260	.000***	more effort than less energy cost savings	not supported
6	3 vs. 4	-10.81^{c}	.349	.000***	-	-

a. Wilcoxon Signed Rank Test,
b. Based on negative ranks,
c. Based on positive ranks.

Adj. p-value based on Bonferroni Correction: p-value / 6; * p <.0083, ** p <.0017, *** p <.0002

Testing Hypothesis 2 *"need for consumption control of EV-owners",* the Kruskal-Wallis-test shows no significant difference in the usage likelihood between the five household groups for DRS 1 with less control (see Table 3-6). The Kruskal-Wallis test is non-significant, leading to no required subsequent analyses. Thus, Hypothesis 2 is not supported. We have chosen a nonparametric Kruskal-Wallis test to test Hypothesis 2 due to the significant Shapiro-Wilk tests indicating a violation of the ANOVA assumption that the dependent variable (i.e. adoption likelihood of DRS 1) is normally distributed within each household group. Nonetheless, the ANOVA results with planned contrast are displayed in the Annex, showing the same non-significant result (see Table Annex 9-4). Interestingly, Hypothesis 2 is descriptively supported as the group of EV-owners reported the lowest likelihood to adopt DRS 1 compared to the other groups (non-significant result, see also Table Annex 9-4).

Testing Hypothesis 3 *"need for effort limitation for interested households"*, a significant difference between the household groups is recognized for DRS 2 with more effort by conducting the Kruskal-Wallis test (see Table 3-6). Participants with a purchase intention of flexible technologies (interested only) are less likely to use DRS 2 than participants owning more than one flexible technology. No significant differences between participants owning one technology and the ones with purchase intention were identified. The related descriptive statistics are displayed in Table Annex 9-4. Therefore, Hypothesis 3, assuming a lower usage likelihood of interested participants than others for the DRS 2 with more effort, is only partially supported. A medium effect size ($0.1 < r < 0.3$) is recognized (Cohen 1988). We conducted a Kruskal-Wallis test due to the same reasons as for testing Hypothesis 2. In contrast, we performed further subsequent analyses (non-parametric Kruskal-Wallis pairwise comparison with Bonferroni correction) to identify between which groups the differences in preference for DRS 2 exist. A summary of the results from hypothesis testing (as pre-registered) and the results from the exploratory analyses is presented in Table 3-6.

These findings are confirmed by the results based on the ranked usage likelihood (see TableAnnex 10): Participants owning multiple flexible technologies are more likely to use DRS than heatpump owners and interested ones. In the case of the ranked dependent variable, the analysis for DRS 1 provided significant results. The analysis for DRS 2 is not significant.

Table 3-6: Results of Kruskal-Wallis test testing Hypothesis 2 based on DRS 1 and Hypothesis 3 based on DRS 2, The results for the gray-shaded DRS 3 and 4 are complementary, explorative analyses

	DRS 1 with less control	DRS 2 with more effort	DRS 3 with more data sharing	DRS 4 with fewer cost savings
Asymp. sig. for Kruskal -Wallis –Test (n = 962)				
Household groups	.754	.000***	.000***	.001**
Significance adjusted for Bonferroni corrections - pairwise comparison based on Kruskal - Wallis –tests (effect size r for significant outcomes)				
only HP vs. only interested	-	.601	1.000	1.000
only HP vs. only EV	-	.935	.266	1.000
only HP vs. multiple	-	.000***[1] (.206)	.002**[1] (.175)	.009**[1] (.156)
only interested vs. only EV.	-	1.000	.210	1.000
only interested vs. multiple	-	.023*[1] (.123)	.000***[1] (.168)	.002**[1] (.149)
only EV vs. multiple	-	.724	1.000	.195

*** p < .001, ** p < .01;*[1] p <.0083, **[1] p <.0017, ***[1] p <.0002; n = 910 if not stated differently - For pairwise comparison, owners of BSS only were excluded from these analyses due to a small subgroup size and power issues.

Hypothesis	Selection & aggregation: Sample	Selection & aggregation: DRS	Test	Results of hypothesis testing
H1 *"consumption control and limited effort as basic DR requirements"* Decomposed into four sub-hypotheses: *"lower usage likelihood of DRS...*	All	1, 2, 3, 4	Wilcoxon signed-rank tests with Bonferroni corrections	Partially confirmed, in particular:
a) with less control than with more data sharing" (1 vs. 3)				a) Supported
b) with less control than with fewer cost savings" (1 vs. 4)				b) Not supported
c) more effort than more data sharing" (2 vs. 3)				c) Supported
d) more effort than fewer cost savings" (2 vs. 4)				d) Not supported
Exploratory: 1 vs. 2 & 3 vs. 4				No significant difference between DRS 1 with less control and 2 with more effort, but a preference for DRS 3 with more data sharing over 4 with less cost savings
H2 *"need for consumption control of EV-owners"*	EV- , HP-, multiple owners, interested participants	1	Kruskal-Wallis –test with Bonferroni corrections	Not supported (not significant)
H3 *"need for effort limitation for interested households"*		2		Partially supported (only when comparing "only interested" and "multiple")
Exploratory: Higher usage likelihood of a group for DRS 3?		3		For DRS 3 and 4: Higher usage likelihood of multiple owners than participants with purchase intention or owning HP.
Exploratory: Higher usage likelihood of a group for DRS 4?		4		
Exploratory: Which factors determine the usage likelihood of the most popular DRS?	All	With the highest usage likelihood	Hierarchical linear regression	Significant predictors: all attitudes towards the DRS specifications, EV-ownership, technology openness, social norm, gender

Table 3-7: Overview of the results for hypotheses testing and the exploratory analyses

3.4.3 Exploratory analysis: Kruskal-Wallis test of psychological factors and regression for DRS 3 with more data sharing

To interpret the results of the hypothesis testing more comprehensively, we also conduct Kruskal-Wallis tests between the household groups on the corresponding psychological measurements from Table 3-1. The statistical figures on technology openness (general), the importance of data privacy and cost savings (ref. to H1), the acceptance of control loss (ref. to H2), the acceptance of effort (ref. to H3) can be found in Table Annex 9-2.

Across all three significant Kruskal-Wallis tests in Table 3-6, participants owning multiple technologies significantly differ from HP owners and those with purchase intention. Participants owning more than one flexible technology show a higher usage likelihood than participants with purchase intention. They are also more likely to use the DRS than participants with only an HP. This is not only proven for DRS 2 in the hypothesis testing but also for DRS 3 with more data sharing and DRS 4 with less energy cost savings in the exploratory analyses. Testing the most apparent difference between them, the Kruskal-Wallis test on technology openness proves that multiple owners have a higher technology openness than those participants who own only one technology or have a purchase intention.

Remarkably, the household groups with a lower usage likelihood than multiple owners also show a higher sensitivity toward cost savings. In particular, participants with a purchase intention assign higher importance to cost savings than multiple owners and EV-owners. This is also the case for HP owners compared to EV-owners. In contrast to the importance of cost savings, no group differences are identified for the characteristic attribute of the most popular DRS, the importance of data privacy.

While the group differences in usage likelihood for DRS 1 are insignificant, significant differences are recognized for its characteristic attribute, the acceptance of control loss. Participants owning an EV show significantly lower acceptance of control loss than those owning an HP or multiple flexible technologies. The discrepancy between the general measurement and the DRS indicates that other variables, such as technology openness and social norm, may influence DRS usage more than the acceptance of control loss.

To summarize the comparison between the household groups, all participants like and dislike the same kind of DRS, but the multiple owners show an overall stronger interest in all DRS than others. Descriptively, we find that DRS 3 is liked the most by all groups (except for owners of only a BSS who like DRS1 the most). DRS4 is least preferred by all groups (but for owners of multiple flexible technologies as preferred as DRS 1, see Annex Table 9-4). There are only slight descriptive differences between the groups regarding their preferences of DRS 1 and DRS 2. The common preferences among the household groups speak for a unified design across technologies and adoption levels.

After understanding the differences between the DRS and household groups, we explore the reasons behind the usage likelihood with a hierarchical linear regression (Table 3-8). The analysis is conducted for the most popular DRS, namely DRS 3 with more data sharing. Four models test how (i) the attitude towards the service specification (four predictors), (ii) the technology ownership (four predictors), (iii) established psychological aspects (four predictors), and (iv) the socio-demographics (five predictors) impact the usage likelihood of DRS 3. The four models are able to explain 18.9 % of the participants' choices (see adjusted R^2), which is relatively low. Model 1 on the attitude towards the service specifications explains 14.8 % of the participants' choices. This model also validates the participants' perception of the stylized DRS (construct validity). For the case of DRS 3 with more data sharing, this means that participants who are concerned about their data privacy are expected to indicate a lower usage likelihood, which is the case. The following three hierarchical regression models (Model 2-4) explain additional variance in the DRS preferences, but only with a decreasing tendency (i.e., the increase of the adjusted R^2 decreases across models).

The strongest predictor in Model 1 is the importance of data privacy, followed by the acceptance of control loss and the acceptance of effort. While we expected the design of the service specification of DRS 3 to "provoke" this response for importance of data privacy (i.e., data sensitive participants are less likely to choose DRS 3), the other two predictors require some interpretation. On the one hand, participants may associate the automated shift of DRS 3 with the need to share control over their energy consumption. On the other hand, they may assume that the operation of a DRS involves some effort, even if it is automated. Consequently, a higher willingness to face a certain level of control loss and effort may lead to a higher interest in participating in DRS 3.

The variables on other psychological aspects (Model 3) and socio-demographics (Model 4) explain the usage likelihood better than the technology ownership (Model 2). Only the ownership of an EV is a significant predictor of the usage likelihood of DRS 3. At the same time, its explanatory power is shifted to other variables when we add the variables of Models 3 and 4. Technology openness, a strong social norm, identifying as male, and paying attention to cost savings better explain a high usage likelihood than owning an EV. A similar shift of explanatory power can also be recognized for the acceptance of effort, when the variables of Model 3 and 4 are added.

A logit regression based on the ranked usage likelihood (see Table Annex 9-11) confirmed acceptance of control loss, importance of data privacy, technology openness, social norm and gender as significant predictors for the usage likelihood of DRS 3.

Table 3-8: Results of hierarchical linear regression on usage likelihood of DRS 3 with more data sharing

	Model 1: Service specifications		Model 2: Technology ownership		Model 3: Other psychological aspects		Model 4: Socio-demographics	
	Coefficient [a]	p-value	Coefficient [a]	p-value	Coefficient [a]	p-value	Coefficient [a]	p-value
Acceptance of control loss	.163***	.000	.169***	.000	.160***	.000	.156***	.000
Acceptance of effort	.186***	.000	.172***	.000	.084*	.029	.069	.075
Importance of data privacy	-.242***	.000	-.251***	.000	-.240***	.000	-.242***	.000
Importance of cost savings	.036	.233	.076*	.015	.056	.082	.069*	.034
Owning only HP (1 = yes, 0 = no)			-.051	.225	-.052	.209	-.058	.180
Owning only EV (1 = yes, 0 = no)			.126**	.001	.102*	.010	.074	.072
Owning only stationary battery (1 = yes, 0 = no)			-.004	.911	-.004	.910	-.010	.775
Purchase intention (but not owning) (1 = yes, 0 = no)			-.066	.204	-.071	.166	-.071	.175
Environmental awareness					-.040	.209	-.031	.340
Technology openness					.139***	.000	.120**	.001
Social norm					.072*	.035	.082*	.016
Electricity tariff change in 2022					.013	.658	.008	.782
Age							-.047	.156
Gender (1=male, 0=female)							.100**	.002
Tenure							-.009	.781
Education							.024	.459
Income							.000	.988
Adjusted R^2	.148***		.169***		.184***		.189***	

a. standardised beta coefficient, * p < .05, ** p < .01, *** p < .001. n=962

3.5 Discussion

Our simple vignette design allowed us to involve households with different flexible technologies and adoption levels in one study and challenge them to choose between contrasting DRS designs. We show that the preferences of German households are more homogeneous than expected. Independent of whether they are prospective or actual owners of flexible technologies and which technology they (prospectively) own, they prefer data-driven, automated DRS, which achieve energy cost savings effectively and efficiently. They are least willing to compromise on realizing the full cost-saving potential, followed by staying in control over their consumption and limiting their operational effort. Households owning more than one flexible technology are more likely to use DRS than households with no or only one flexible technology.

In the following paragraphs, we contrast our findings with the ones from the literature and reflect on our methodological choices and limitations, particularly the design of the vignette study and the selection of the sample.

Complementarily to studies with one household group (e.g., Libertson 2022b, Bailey and Axsen 2015), we show that safeguarding control needs is no distinctive driver for the participation in DRS of EV-owners, but are equally important for all household groups. This is also the case for reducing the operational effort and participants with purchase intention. Participants are more willing to compromise on both attributes than demonstrated in other studies (e.g., Yilmaz et al. 2021, Buryk et al. 2015). On the one hand, participants might respond more indifferent since such operational attributes are harder to assess or due to the order effects of the vignette. On the other hand, the participants might assign more importance to the attribute cost savings than expected due to the data collection during the energy crisis or the prerequisite of investing in flexible technologies. Especially, the ones with purchase intention might associate the monetary-driven investment decision with the more effort- and comfort-driven participation decision (Sloot et al. 2023). We further discuss the reasons behind the discrepancy with the existing literature in the following.

The lower usage likelihood of DRS with limited energy cost savings is likely to be affected by the timing of the survey. The evolving energy crisis and increasing energy prices during the data collection from March to June 2022 raised concerns about high energy bills among households. A new dimension of awareness for energy cost savings was triggered. Households owning energy-intense technologies (e.g., HPs) and having no alternatives to limit the impact of the prices (e.g., the interested households with no generation and flexible technologies so far) were especially affected. This may also explain the high preference for energy cost savings assigned by participants who own an HP or do not yet own any flexible technology.

The literature states that the passive operation of HPs leads to a higher acceptance of DRS than interactive technologies, such as EVs since the consumption shifts are less noticeable (Ruokamo et al. 2019; Yilmaz et al. 2021). Our results show the opposite. HP owners are less likely to use DRS than others. One alternative interpretation of the role of interaction may be that the interaction with flexible technologies better qualifies the participants to assess the impact. Due to the lack of experience, consumption shifts of passive technologies, such as HPs, may be more intimidating and lead to a lower usage likelihood of DRS. The contradicting results on passive and interactive technologies require further research.

The chosen vignette design with four attributes and binary attribute specifications allowed us to position contrasting attributes as salient information and describe them comprehensively for non-experienced participants. We refrain from the common practice of having more than two specifications for each attribute (Auspurg and Jäckle 2012) since it would not be beneficial for analyzing the contrasting attributes but overwhelms the participants. The largely consistent responses for the general service statements, rated, and the ranked usage likelihood support their validity (Liebe and Meyerhoff 2021; Treischl and Wolbring 2022).

Within the household group that owns multiple technologies, the participants responded consistently to the vignettes, although their technology references on the vignette were different, depending on which of their owned technologies is most prevalent and long-established in the German population. This confirms our initial assumption that their response is not limited to the referred technology. The other owned flexible technologies are salient in their minds as well. Alternatively to our predefined hierarchy for reference selection, participants could have also selected a reference technology by themselves (e.g., the most frequently used one).

To have sufficient power for the comparison of the household groups, we decided to present all vignettes to each participant and limit the number of vignettes to four, the smallest sub-set of vignettes for defining each attribute once reversely to the other three (i.e., one attribute per vignette was positively specified while the other attributes were negatively specified). A reason for this decision was also the overall research aim to examine the dilemma in relative terms between the attributes.

The attribute specifications can be combined more diversely for future studies without a power-demanding sub-group comparison. The ridge regression in Table Annex 9-8 indicates that the relative importance of one attribute is consistent with its absolute importance. Still, the data collected from our limited vignette sets creates collinearity between attributes, making the regression coefficients vulnerable to inaccuracy. The penalty term of the ridge regression mitigates this risk (see Figure Annex 9-3). A vignette with only positively or negatively specified attributes would have created a comparison baseline and prevent the collinearity. This would allow for a more systematic and robust analysis of each attribute. This greater variety in the vignettes would also enable the determination of isolated utilities per attribute.

We follow the recommendation of Treischl and Wolbring 2022 for a unified order of vignettes and attributes to ensure a logical flow and create a more comprehensible running text. Thereby, we refrain from the common practice of randomizing the order within and between the vignettes (Podsakoff et al. 2003). Having the same order of attributes within each vignette creates the risk that participants relate the adjoining attributes more closely to each other than the other attributes. We limit this risk by positioning all attributes briefly next to each other in the title of each vignette (see vignette description in Appendix A).

By asking the participants to rate one vignette after the other and rank them relative to each other, inconsistencies between both measurements indicate order and learning effects. While the participants responded consistently for three of the four vignettes based on the descriptive analysis, only the one on control loss is less popular in the ranking than in the rating. The signed test based on ranked usage likelihood (see Table Annex 9-9) shows that both DRS with less extreme ratings are closer to both DRS with more extreme ratings, when looking at the ranked usage likelihood: There is no significant difference between the DRS with control loss and fewer cost savings, nor between the DRS with data sharing and more effort. For control loss, this finding is also confirmed by the psychological factors in the regression: a higher acceptance of control loss leads to a higher usage likelihood. Its position as the first presented vignette might have led to an over-rating due to learning effects, meaning that the first response is less reliable and consistent than the others in the course of the vignette, since participants become more knowledgeable and reflected (Plötz et al. 2014). A stronger unwillingness to compromise on control loss is also in line with the findings in the literature (Geske and Schumann 2018; Broberg and Persson 2015; Delmonte et al. 2020).

Auspurg and Jäckle (Auspurg and Jäckle 2012) argue that the immunity towards order effects increases with the assigned importance of attributes by the participants, which might be the case for the three consistently answered vignettes. The consistency also indicates that participants rate the value of each vignette independently instead of the incremental change from one vignette to another. If a prior vignette is used as a reference point for the rating of the current vignette, the switch from the negatively specified attribute to the positively specified attribute would lead to a more favorable rating of the current vignette. Since we do not recognize a more favorable perception in the rating than in the ranking, we conclude no or only a marginal effect of the incremental change between the vignettes.

Some aspects of decision-making are hard to capture by stated preferences (Alberini 2019). The specific contextualization of the vignette makes the questions more assessable for the participants. We selected the described shift of the electricity consumption from the evening to the night hours in the expectation that most households are at home during these hours and are impacted similarly. Still, some attributes might be easier to assess than others. The quantitative description of the energy cost savings may be more tangible and persuasive for participants than the qualitative ones of the other attributes. Also, the cost attribute relates to the objectives for participating in DRS, while the others to how they are operated (e.g., automated shifts). The ones related to the objective might be more salient in the households' decision-making process than the operational ones. Still, the operational aspects are key for keeping households involved over time, especially in the context of fatigue effects. Studies with revealed preferences are more suitable to capture them (Alberini 2019).

The low explainability of the regression on the DRS with more data sharing (18.9 %) and the inconsistent responses of EV-owners on the general control statement and DRS 1 with control loss imply the need for additional variables explaining the usage likelihood of DRS. In the latter case, EV-owners might be willing to deviate from their general control need if they trust in the DRS. Research on other data-driven services highlights trust in the service provider and digital literacy as drivers for the acceptance of a service (Delmonte et al. 2020; Acquisti and Grossklags 2007; Bhatia and Breaux 2018; Lackes et al. 2018).

We are aware of the criticism of single-item measures for dependent variables. Nonetheless, using single-items after a vignette is a common approach in vignette experiments. Since the to-be-measured construct (i.e., adoption of the DRS) can be considered as not multidimensional (in comparison to other psychological constructs, see (Allen et al. 2022)), we follow the literature on efficient questionnaire design and vignette experiments and used a single-item measure for the dependent variable (see also Ausprung). Nonetheless, further studies building on our results could use a multi-item measure (also for comparison of results).

By focusing on (prospective) owners of flexible technologies, our study represents only a specific part of the German population. One non-represented group is tenants relying on their landlords for investments in their homes and low-income households. Both have hardly access to (rather) technology-derived demand response but to (rather) socially-derived demand response. Our study does not cover the drivers and barriers of the latter. Another non-represented group is the potential owners of flexible technologies without purchase intention. The observed differences between the actual and prospective owners might magnify for this group. The prospective owners have a lower income level and weight the importance of cost savings higher than the actual owners. Still, the socio-demographics and psychological factors are relatively homogeneous among actual and prospective owners (see Table Annex 9-1). We recommend repeating the study later (with a more heterogeneous, representative sample) when an increasing diffusion of DRS creates further insights.

Our non-representative sample collected during exceptional circumstances creates insights into the diffusion of DRS over time. The realization of energy cost savings is likely to remain a key driver. The results on the usage likelihood for DRS, the technology ownership status, and the technology openness confirm that the attitude of early adopters of flexible technologies makes them more likely to participate in DRS. Their assumingly high intrinsic motivation makes them more tolerant towards the effort and comfort losses of DRS. Vice versa, the diffusion of DRS among households not yet owning flexible technologies cannot be driven by their intrinsic motivation but (currently) depends on external incentives in energy cost savings. This was demonstrated for households with a purchase intention and is also likely to be the case for the ones without a purchase intention yet, which are not represented in the survey.

The need for realizing energy cost savings effectively and efficiently will gain importance for these prospective owners of flexible technologies to participate in DRS. Thus, we recommend that providers of DRS consider cost savings in their design. However, due to the rapid developments in flexible technologies, their adoption rate, and the availability of DRS, changes are not unlikely - especially for households who do not own a flexible technology yet. Thus, DR research should continuously monitor and examine the driving factors for participation in DRS to develop empirically-driven recommendations for DRS providers.

3.6 Conclusion

Our vignette study examined the preferences of households towards contrasting DRS designs, considering both the type of flexible technologies they have and their adoption levels. Our results show that preferences do not fundamentally differ between the household groups. Generally, households prefer data-driven, automated DRS - independent of whether they are current or prospective technology owners, or the specific technology they currently own or intend to own. The primary motivator for adopting DRS is the potential for efficient and effective energy cost savings, which dominates concerns about data privacy. The hypothesized special control needs of EV-owners and comfort needs of households not yet owning flexible technologies were not confirmed. Households whose technology openness already led to the ownership of more than one flexible technology are more likely to use DRS compared to those who own (or plan to own) only one (e.g., EV or HP).

The design process for DRS by service providers demands empirical evidence, especially when prioritizing contrasting service attributes. External incentives in the form of energy cost savings are shown to drive a broad diffusion among current and prospective owners of flexible technologies. Thereby, existing and new flexibility potential can be unlocked, which supports the decarbonization of the energy system in a two-fold manner. The unlocked flexibility can increase the consumption of fluctuating renewable energy generation, and it can help to avoid load peaks that would lead to complications or additional investments in the existing infrastructure, such as electrical distribution grids. Both the energy system and the households themselves profit from the coordinated use of flexible technologies facilitated by DRS. It is crucial that the industry develops DRS grounded in empirical findings and that policymakers provide incentives for such systems. Only then notable cost savings and alleviated pressure on the energy infrastructure can be ensured.

4 Priorities of households in the participation stage: Evidence on behavioral interventions from a field trial in Germany[5]

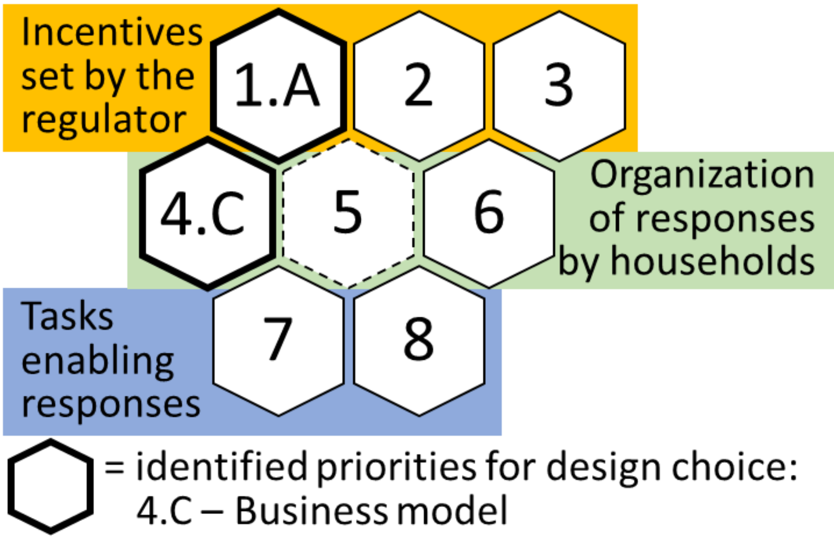

Figure 4-1: Graphical summary based on the design choices for SRQ 3

Aligning prosumers' electricity consumption to the availability of self-generated electricity decreases CO_2 emissions and costs. Nudges are proposed as one behavioral intervention to orchestrate such changes. At the same time, fragmented findings in the literature make it challenging to identify suitable behavioral interventions for specific households and contexts - specifically for optimizing self-consumption. We test three sequentially applied interventions (feedback, benchmark, and default) delivered by digital tools in a field experiment with 111 German households with rooftop-photovoltaics. The experiment design with a control-group, baseline measurements, and high-frequency smart-meter-data allows us to examine the causal effects of each intervention for increasing self-consumption. While feedback and benchmark deliver small self-consumption increases (3-4 percent), the smart changing default leads to a 16 percent increase for active participants. In general, households with controllable electric vehicles show stronger effects than those without. For upscaling behavioral interventions for other prosumers, we recommend interventions that require little interaction and energy literacy because even the self-selected, motivated sample rarely interacted with the digital tools.

5 This chapter has been published as Pelka S., Kesselring A., Preuß S., Chappin E., de Vries L., Can nudging optimize self-consumption? Evidence from a field experiment with prosumers in Germany, Smart Energy, 2024

4.1 Introduction

Shifting consumption to the times of self-generated electricity of households with rooftop photovoltaic (PV) is a key measure to decarbonize the residential energy sector. Coordinated consumption shifts ensure a viable return-on-investment for households (Nyholm et al. 2016; Schopfer et al. 2018; van der Stelt et al. 2018) and a more efficient operation of the existing energy infrastructure (Venizelos Venizelou et al. 2018; Dehler et al. 2017; Rasmus Luthander et al. 2015). Optimization models demonstrate that households can increase their self-consumption with consumption shifts by 2 to 50 percentage points, depending on the optimized technology. White goods are at the lower end (Luthander et al. 2016), while stationary battery systems (Linssen et al. 2017; Nyholm et al. 2016; Kaschub et al. 2016; Kuckshinrichs et al. 2023; Schopfer et al. 2018; Rasmus Luthander et al. 2015) and EVs (Higashitani et al. 2021; Kern et al. 2022) are more promising. To unlock the emerging flexibility potential of the latter, households need to establish a new routine for using these flexible technologies (Kern et al. 2022).

Orchestrating consumption shifts is an understudied use case for behavioral interventions (Wolske et al. 2020; Rasmus Luthander et al. 2015). Behavioral interventions, as subtle changes in one's choice environment, complement price incentives. Price incentives shape the terms of household consumption and address rational reasoning (e.g., higher return-on-investment from tax exemption (Gerarden et al. 2017; Sunstein 2021; Alipour et al. 2021). Behavioral interventions provide ongoing support for households to respond to these terms (e.g., stimulating flexibility) and to make intuitive decisions [20]. Nudges are one of the most researched behavioral interventions (Thaler and Sunstein 2008). The ongoing rise of digital tools leads to a broader application since behavioral interventions can be easily implemented in the user interface [18,19].

Behavioral interventions can guide households in the way the choice task is structured, and the choice option is described (Hummel and Maedche 2019b; Johnson et al. 2012). The first category about structuring the choice task is known as more effective but also invasive in terms of paternalism. A frequently applied example is defaults (Hummel and Maedche 2019a). In contrast, the second category about describing the choice options (e.g., feedback) is more subtle (Hummel and Maedche 2019a). The majority of interventions for energy savings belong to this category. For instance, the realized energy savings for feedback ranged between 5 and 13 percent (e.g. Bager and Mundaca (2017), Myers and Souza (2020), Houde et al. (2013), Asensio and Delmas (2015), Ruokamo et al. (2022), Dominicis et al. (2019), Schleich et al. (2017),). In some studies (e.g., Dominicis et al. (2019), Schleich et al. (2017)), the effect persisted over a period of up to two years. However, most field trials took four weeks to 11 months and did not report long-term effects.

Although automated consumption shifts enable behavioral interventions from the first category (i.e., structuring the choice task), the few existing studies on consumption shifts apply behavioral interventions from the second category about the description of choice options (e.g., environmentally friendly framing). These studies show one-digit improvements of provided flexibility (Wolske et al. 2020; Sunstein 2021). Although this seems small, the effects are economically meaningful given the strong evidence that price incentives alone are insufficient for energy decision-making (e.g., Gerarden et al. 2017, Schneider et al. 2013) the similar magnitude, the existing literature's focus on other incentive mechanisms, and the missing utilization of automation encourage us to explore further behavioral intervention of both categories for households with rooftop-PV and EVs. Thereby, we consider that these prosumers have a different asset base and, therefore, more flexibility potential in the operational phase than the general population. We contribute to the broader research question "Can behavioral interventions delivered through digital tools help prosumers increase their self-consumption?" by testing empirically the impact (i) of interventions from both categories (i.e., changing the description of choice options and the structure of the choice task) and (ii) for prosumers with and without EVs.

The range of findings in the literature makes it challenging to determine which kind of behavioral intervention fits which household and context. The efficacy of such interventions is highly context-specific, as the intervention accounts only for part of the outcome variation (self-consumption in our case) in real-life environments. Insights on the group- and context-dependent fit are therefore important but largely missing (Andor and Fels 2018), while publication bias reinforces the evidence gap (Maier et al. 2022). At the same time, methodological challenges exist: First, generally established techniques for stated preferences are less suitable for capturing intuitive choices and intervention effects of everyday life (Andor and Fels 2018). Second, shortcomings in the research design of revealed preference approaches (e.g., underpowered sample, no control-group, no baseline measurement) impede applying methods for causal effects (Hummel and Maedche 2019b). Studies with larger, more heterogeneous samples tend to result in smaller effect sizes (Andor and Fels 2018). Third, behavioral intervention studies are highly context-specific, hindering interventions' comparability across single interventions (Abrahamse et al. 2005).

Under consideration of the content-related and methodological challenges, we examine the understudied use case of behavioral interventions for consumption shifts based on smart-meter-data. In a German field experiment of the Horizon 2020 funded project NUDGE, three sequentially applied interventions support 111 participating households in shifting their electricity consumption to times of their self-generated electricity. The first two interventions adjust the description of the choice option (i.e., second category), specifically through visualization in the digital tool in the form of (a) feedback and (b) benchmarking. The third intervention is a default targeting EV charging (i.e., first category). Recent intervention studies based on smart-meter-data (e.g., (Imbens and Wooldridge 2009), (Weigert et al. 2022), (Bager and Mundaca 2017), (Brown et al. 2013), (Schleich et al. 2022), (Myers and Souza 2020)) successfully applied a difference-in-differences approach (DiD) to reveal the causal effect of interventions. We also selected this approach and compared the relative developments in self-consumption between the treatment- and control-groups over time.

We create a new comparability level by testing three interventions within the same experiment setting to minimize context-specific differences and present new evidence specific to EV-users. Learning effects during the interventions are managed by establishing previously tested interventions as new basic settings and calculating only the incremental change for each intervention. We investigate group-specific effects for prosumers with and without controllable EVs and fatigue effects during the nudging period.

In Section 2, we present the applied methodology. Section 4.3 contains the results with the overall, time- and group-dependent effect for each intervention. Section 4.4 includes the discussion, whereas we conclude our study in Section 4.5.

4.2 Methodology

4.2.1 Sample

We analyzed the self-consumption of 111 participating households living in, or near Mannheim, Germany. The participants are customers of the service provider Beegy[6] and responded voluntarily to its call for participation via e-mail. Smart-meter-data were collected continuously at high-frequency resolution and aggregated to daily average values at household-level for analysis. Our estimation sample starts in January 2022 and ends in June 2023. Supplementary data on household equipment and a socio-demographic survey were also recorded (see supplementary-material 1.2).

The majority are families with children (57 percent) living in a single- or semi-detached house (69 percent) (Gabriel et al. 2022). The average age is 56.34 (Gabriel et al. 2022). All households have rooftop-PV with an average installed PV-capacity of 8.16 kWp (Gabriel et al. 2022). A sub-group of 39 participants owns a controllable EV (in the following called "EV-group"). 105 participants are equipped with battery-storage-systems and 29 with heatpumps. We divided the sample into a treatment-group (n = 54) and a control-group (n = 57) with random assignment before the first intervention. Both groups are similar in installed PV-capacity, number of controllable EVs (n = 18 in the treatment- and n = 21 in the control-group), wall boxes, heatpumps, and other technical dimensions (see supplementary-material). Equipment changes during the intervention period (see supplementary-material) were considered in a robustness check.

4.2.2 Design and Procedure

4.2.2.1 Interventions and Experiment Design

In the following, we describe the interventions and their implementation. Each intervention was presented to participants for a specific period during the experiment (see Figure 4-2). Two tools, a webportal, and a smart-charging-app, exposed the participants to the interventions. The smart-charging-app is only available for participants with controllable EVs. The tools were already in use before the experiment. This real-life embedding creates authentic insights but also places restrictions on the intervention design (e.g., no social comparison is possible due to data privacy).

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[6] Further information on the service portfolio of Beegy can be found: https://www.beegy.com/one-pager-en/ (last visited: 27/12/2023)

Flexible technologies such as battery-storage-systems (n=105) and heatpumps (n=29) were automatically optimized for increasing self-consumption (see Section 4.4).

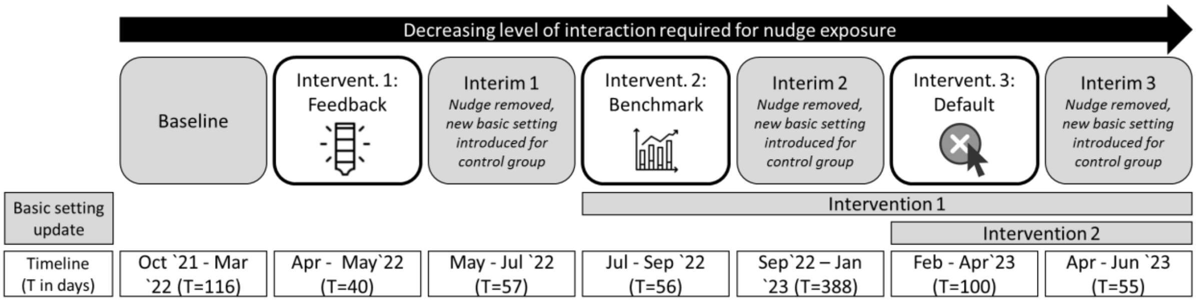

Figure 4-2: Timeline of the experiment

Given concerns about fatigue effects for participants, we first implement two interventions that change the description of the choice options (but leave the choice task as before, i.e., second intervention category) and end with an intervention that simplifies the choice task (i.e., first intervention category). The two earlier interventions are visualizations that bundle more than one design element. They present information on how behavior translates to savings in both monetary terms and CO_2 emissions. They are designed to require more active user engagement than the last intervention.

The two earlier interventions describe the choice options more appealingly based on concurrent timing (first intervention, feedback) or more competitively with a dynamic framing (second intervention, historical benchmark). The feedback combines simple indicators on a dashboard with signaling colors (see Figure 4-3). The historical benchmark with prompts reports on the previous and upcoming self-consumption in a bar chart and provides recommendations on how to adjust the consumption (see Figure 4-4). The consumption recommendations are based on a forecast of self-generated electricity and are communicated with prompts. They encourage households to use their dishwasher or laundry during the hours of forecasted generation.

The third chosen intervention, a default intervention, changes the choice tasks and aims to establish new charging behaviors with low awareness and interaction requirements (see Figure 4-5)[7]. Therefore, a new charging mode for participants with controllable EVs was introduced. The existing charging mode of the smart-charging-app maximized self-consumption during charging, given the specified target state of charge and departure time. The new charging mode is activated on the webportal and charges the EV only with self-generated electricity[8]. Once the participants accepted the new charging mode in the webportal, it was always activated when the EV was plugged in at home.

Simultaneously with the smart-charging-default, an additional feature as part of the third intervention was introduced for all participants to keep participants without controllable Evs engaged. The feature aggregates the savings in terms of cost savings and CO_2 emissions in the form of a downloadable energy report (see Figure Annex 10-3).

[7] Figure 2-4 illustrates the three interventions in the webportal, which are similarly implemented in the smart-charging-app (see Appendix B).

[8] Provided it is not overruled by new settings in the smart-charging-app.

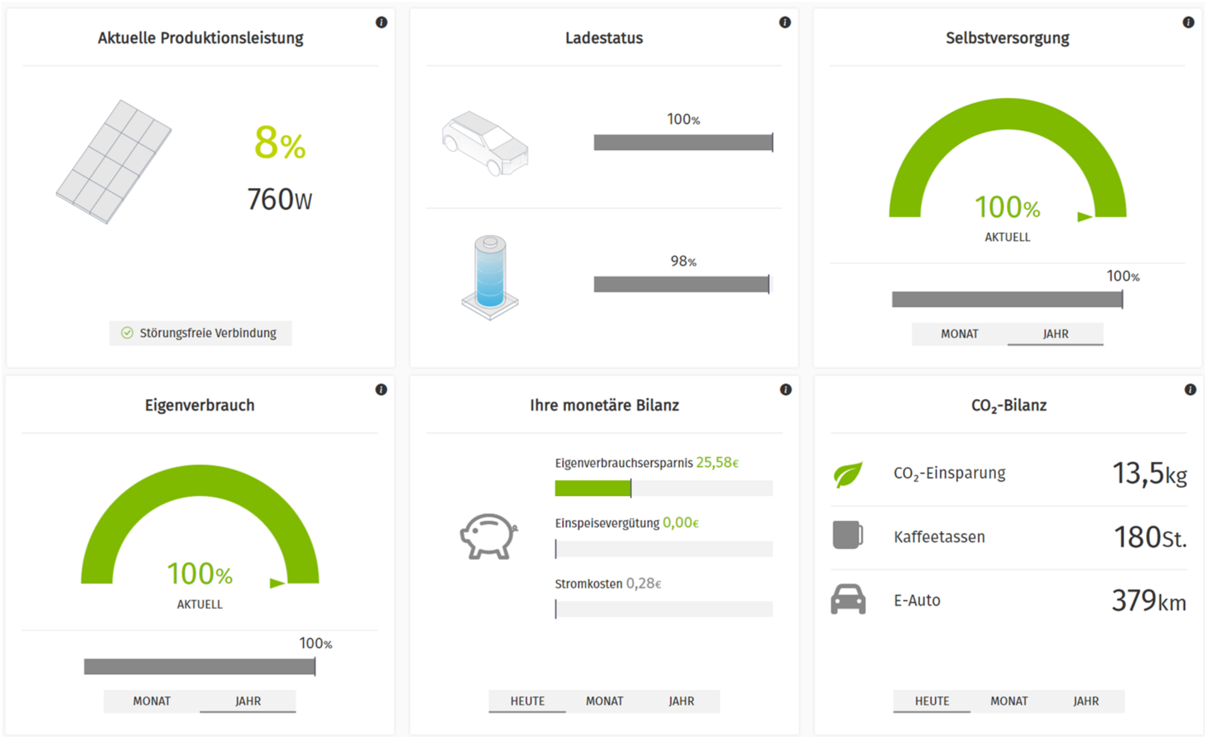

Figure 4-3: Intervention 1 for the PV- and EV-group providing simple indicators in signaling color to stimulate consumption shifts or additional consumption during PV-generation by the participants, as presented to the participants and thus, in German language, see supplementary material for further information.

Figure 4-4: Intervention 2 for the PV- and EV-group providing benchmark of previous and current self-consumption (top) and forecast of PV-generation with recommendations for actions (bottom) to stimulate consumption shifts or additional consumption during PV-generation by the participants, as presented to the participants and thus, in German language, see supplementary material for further information.

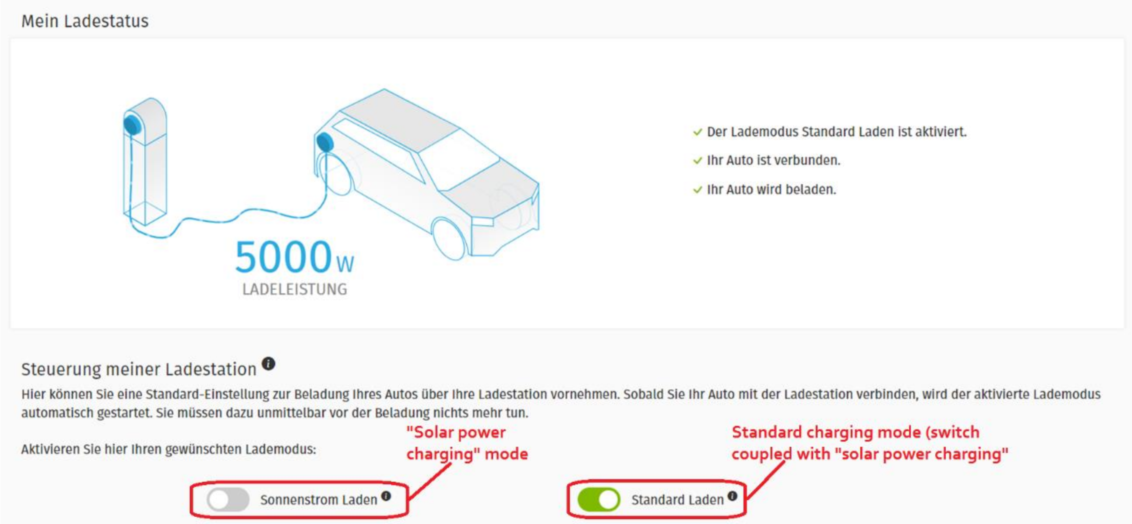

Figure 4-5: Intervention 3 for the EV-group providing a new charging mode that charges the EV automatically with excess electricity from the local PV ("solar power charging" – switch on the left side, which is deactivated until its first activation). If activated, the switch on the right side for the existing charging mode "standard charging" is deactivated.

The first intervention is implemented on the dashboard, which is the landing page of the tool (i.e., the page that is shown once the tool is opened). The second and third interventions are implemented on pages that are accessed via the sidebar of the tools (i.e., "statistic" and "forecast" for the second and "download" and "e-mobility" for the third intervention). The participants were informed about the updates via a one-time e-mail at the beginning of the intervention and via a "new" sticker next to the page name on the sidebar.

Two special constellations in the experiment design allow us to evaluate the respective effect of each intervention. First, multi-treatment designs have to consider learning effects, which makes it difficult to separate individual interventions from the compound effect. To mitigate this issue, we introduced interim periods without an intervention after each treatment period. Second, to distinguish between persistent learning and the effect of the following intervention, we transformed the previous intervention into a basic setting for the following intervention. This means that the previous intervention was visible to the control- and treatment-groups when the following intervention was introduced. To allow the control-group to internalize the new basic setting, we have already introduced the previous intervention to them during the interim period. The difference between the treatment- and control-group provides incremental change since the control-group has only seen the previous intervention before the next treatment begins.

4.2.2.2 Main Measures for Treatment and Control Group

We tested the three interventions sequentially in the same setting. To respond to the interventions, participants can either shift their existing consumption or additionally consume self-generated electricity. We computed two measures to analyze participants' responses to the nudging interventions: an absolute one (self-consumption) and a relative one to the overall consumption (autarky-rate) (Klein et al. 2019; Klingler and Schuhmacher 2018). While in other studies (e.g., Luthander et al. 2016, Venizelos Venizelou et al. 2018) the latter is also called self-sufficiency-rate, we call it autarky-rate to avoid terminological confusion with sufficiency-research.

The absolute measure recognizes both responses but is prone to random consumption changes (e.g., vacations, construction works). The relative one absorbs these consumption changes (including additional consumption in response to the intervention).

As outlined above, the composition of the treatment- and control-group is comparable; this also applies to the mean outcome variables (see Table 4-1). Self-consumption is calculated as the mean hourly value over a 24-hour period. Autarky-rate is the ratio of self-consumption to total consumption, calculated from the respective daily means. The autarky-rate takes values between 0 and 1. The final column shows the number of observations (Obs) in the panel comprising 422 days, after excluding few cases with missing values in the smart-meter reporting. The standard deviation, minimum and maximum indicate a high variation within each group across individual households. Overall, the participants' energy consumption is above the German average but falls in line with estimates addressing prosumers and EV ownership (e.g., (Kern et al. 2022), (Linssen et al. 2017)).

Table 4-1: Summary statistics by group

	Mean	**SD**	**Min**	**Max**	**Obs**
Treatment-group (n = 54)					
Consumption [Wh]	755.58	586.12	0.05	7503.91	23029
Self-consumption [Wh]	445.49	358.8	0	3863.78	23029
Autarky-rate [percentage]	0.55	0.24	0	1	23029
Control-group (n = 57)					
Consumption [Wh]	720.18	565.57	0	5987.11	24010
Self-consumption [Wh]	459.33	370.57	0	4188.53	24010
Autarky-rate [percentage]	0.60	0.23	0	1	24010

Notes: Descriptive statistics for estimation sample from January 2022 to June 2023 at daily aggregation. Self-consumption is the difference between total consumption and output to grid. Autarky-rate is the ratio of self-consumption to total consumption.

Figure 4-6 plots the data for both groups over time to complement the static representation. The three solid, vertical black lines indicate the treatment start dates of the interventions, with the dashed line indicating the end of the intervention for the treatment-group. This partitions the study period into four blocks of interest: the baseline (N=0) and the interventions N = {1,2,3}. For the DiD approach, it is important that treatment- and control-groups are comparable and do not exhibit differential patterns at baseline (parallel trends assumption, see, e.g., Angrist and Krueger (1999)). The graphical illustration supports this assumption. Both groups are similar in levels and trends, and the strong, common fluctuation over time is driven by weather conditions, as expected. The variability in August 2022 is attributable to missing values due to problems with a central data platform. We conducted a robustness check with a restricted sample to ensure that this does not bias the estimation results. The same pattern holds qualitatively for both outcomes (self-consumption and autarky-rate), despite higher volatility for self-consumption.

The parallel development between the groups also holds when comparing the particular EV-group and the group without controllable EVs (in the following called "PV-group"), providing further support for successful randomization in the design. For details, refer to the supplementary-material 1.3. The figure does not support a visible divergence during the intervention, which indicates that average effects may be small and weather effects may dominate patterns over time. We will consider these first insights in the formal analysis.

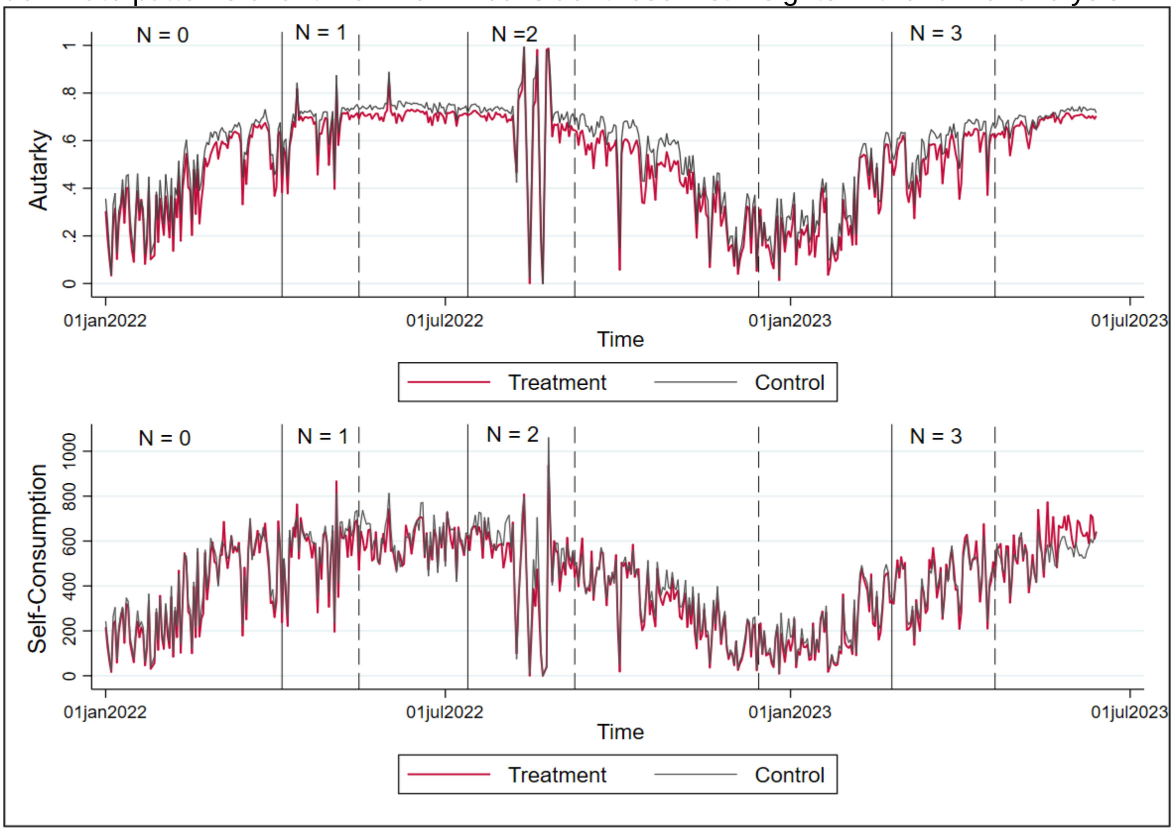

Figure 4-6: Outcomes by group over time

4.2.3 Statistical Models for Analysis

As outlined above, the main identification strategy is a DiD approach. The objective is to identify the causal effect of the behavioral intervention after accounting for differences across groups and differences across time that would otherwise correlate with the nudging effect. We evaluate the effect of the intervention assignment (i.e., intention-to-treat), which may include participants that did not actively interact with the content. However, this approach indeed provides a realistic projection of the expected effect of intervention in real-world settings for policy-makers and practitioners.

The model is estimated for the two outcome variables. Autarky-rate is the preferred outcome in light of the wide variation across individuals depicted in Table 4-1. For self-consumption, we log-transform the dependent variable to address the long right tail with high-value outliers in the distribution of the raw data.

There are two challenges to obtaining credible estimates in our setting. First, the European energy crisis: We address this with time-fixed effects at the daily level absorbing shocks in the environment that are common to both groups. This includes behavioral adjustments driven by price spikes and political announcements. For example, Pelka et al. (2023) document that search volume on Google Trends accounts for part of the variation in self-consumption. Time-fixed effects also account for weather variation, which applies to both groups and shows in the raw data (see Figure 4-6). Second, we want to compare the three nudging treatments with each other. We, therefore, estimate separate coefficients for each intervention instead of a single treatment effect.

With these considerations, we chose a two-way fixed-effects model (TWFE) with multiple treatment periods (see e.g., (Greene 2001)). Formally, the regression equation (1) is:

$$y_{it} = a_i + b_N T_{it} N_t + c G_i + d N_t + p_t + e_{it} \tag{1}$$

Where i indicates individuals and t indicates time periods (days). The indicator T equals 1 for the treatment-group, and zero for the control-group. N is a categorical variable that takes value 0 at baseline and then has six non-zero values. The three active intervention periods $N = 1$, $N = 2$, $N = 3$, and the interim periods (see Figure 4-6). The coefficient of interest is b_N for all $N = \{1,2,3\}$, which captures the DiD treatment effect from the interaction of T and N. The estimate represents the differential development of the treated households during the nudging period measured relative to the control-group.

The TWFE model absorbs individual-specific intercepts (a_i) and period-specific intercepts (p_t, see discussion above). The individual fixed-effects a_i absorb level differences across households in a within-transformation. This accounts for time-constant factors such as household size, stock of appliances, or pre-existing behavioral differences. Robust standard errors are calculated with the common Huber-White adjustment. From a purely statistical perspective, the model obtains coefficients also for the interim periods: $\mathrm{N} = \{0,1,\ldots 6\}$ (see supplementary-material 1.3). The interim coefficients $b_{N>3}$ capture the relative difference across groups, not the counterfactual development without any nudging.

Overall, we chose the methodology in light of the data structure and the objective to deliver causal effects. The DiD is state of the art (Andor et al. 2019), and allows us to leverage the experiment design with control group and panel data. The addition of two-way fixed effects provides further control over the granularity in the time-series and cross-sectional variation (Collischon and Eberl 2020; Imai and Kim 2021; Gangl 2010). Relative to simpler regression designs, we lose degrees of freedom, but gain the ability to address the complex variation pattern.

We then add heterogeneity analysis and robustness checks. First, we consider the dynamic nature of the treatment effect by running an event study for all three interventions. This addresses concerns that the treatment effect diminishes over time due to fatigue. By contrast, the behavior might change with a time lag to treatment, so the prediction is ambiguous. Additionally, the pre-treatment coefficients support parallel trends assumption.

The second extension is a sub-group analysis for the EV and PV-group. This is implemented through an additional interaction term in the main regression equation for the sub-groups. The working hypothesis predicts a stronger effect on the EV-group because this sub-group receives the treatment with an additional interface – the smart-charging-app. This analysis is particularly interesting for Intervention 3, since that intervention is a two-part treatment with additional functionalities specific to the EV-group. We then use additional information from the tool to test whether tool users were able to shift self-consumption from the evening hours (in which they tend to charge (Morrissey et al. 2016)) to the midday-PV-peak. Formally, this is tested with a regression (2) specific to Intervention 3 using data at *hourly* frequency:

$$y_{it} = a_i + b_H A_{it} H_t + c H_t + p_t + e_{it} \tag{2}$$

Where A is an indicator for households that actively engage with the app, and H is a categorical variable for AM (6-10am), midday (11am-3pm), and PM (4pm-8pm). The base level is AM, and we exclude night-time hours. The coefficient of interest is b_H, which indicates whether active app users realize larger shifts during a specific Time Block H . We again use a TWFE model and robust standard errors.

4.3 Results

4.3.1 Treatment Effects

The analysis based on the DiD approach delivers treatment effects for each intervention. For interpretation, two particular aspects of our design are important (see Section 4.2). First, the treatment effects are measured relative to the control-group, which has never seen the respective intervention before. Second, the treatment effects capture incremental changes: each coefficient gives the effect of the newly introduced intervention. Table 4-2 presents the main regression results, with autarky-rate as the dependent variable in the upper panel and the natural logarithm of self-consumption in the lower panel. Throughout all results, we refer to self-consumption meaning this logarithmic transformation for ease of exposition. The first column shows the basic model with no controls or fixed effects. Column (2) adds time-fixed effects to address day-specific shocks common to both groups. Column (3) is a two-way fixed-effects model with both time and household-specific fixed effects. This very conservative estimation is most demanding regarding variation but also most credible in eliminating the potential confounders discussed previously. Note that the group and period indicators are omitted due to the collinearity with the fixed effects. Column (4) replaces the time fixed-effects with the continuous variable solar radiation based on the insights from Figure 4-6. The household fixed-effects are kept. The number of observations is lower because radiation data are not available for December 2022 (interim period after Intervention 2) and after May 2023 (last part of Intervention 3).

Before turning to treatment effects, we assess model selection. We use the coefficient of variation (R^2) in the bottom panel as proxy for model fit. Moving from column (1) to columns (2) and (3), the R^2 increases substantially with the addition of fixed effects. The simplest model explains 26 percent of the variation in the outcome autarky, which increases by more than 30 percentage points when time-fixed effects are added. After adding household-fixed effects, the TWFE model in column (3) accounts for 78 percent of the variation. Notably, substituting time-variant weather controls for the time-fixed effects results in a substantial drop in the R^2, suggesting that time patterns are not driven entirely by weather as an exogenous force. We find a very similar pattern for self-consumption in the lower panel. For both outcomes, the sign of the coefficients is robust across all four columns, but the effect sizes and the standard errors increase as we build towards the TWFE model. This indicates that care must be taken in accounting for household and time heterogeneity, as the simpler models tend to understate the estimated treatment effect.

Based on these preliminaries, we consider column (3) the main estimate of the analysis. In the following, we focus on this column. For the feedback intervention (N=1), there is a small, positive treatment effect. The coefficient for autarky indicates that the intervention increased autarky by 2.1 percentage points, a moderate improvement of 3.8 percent when evaluated against the mean outcome of 0.55 (Table 4-1 for reference). The coefficient on self-consumption indicates a 2.9 percent increase in self-consumption. Evaluated at the sample mean, this translates to an improvement of 13 Wh per hour on average. While the effect sizes are similar for both outcomes, the estimate is highly significant for autarky, but not for self-consumption (only at the 10 percent-level of confidence).

Regarding the benchmark intervention (N=2), the effects are again positive and of similar magnitude as Intervention 1. For self-consumption, the effect sizes vary substantially across columns, and the result is not statistically significant in the conservative estimates (Columns 3 and 4). This likely reflects the higher volatility of self-consumption relative to autarky-rate, which leads to unstable coefficients in specifications that do not control for heterogeneity across households. Comparing the estimates in the TWFE model, a Wald test fails to reject the null hypothesis of equal coefficients (p-value = 0.955 for autarky-rate, p-value = 0.961 for self-consumption, see supplementary-material). This indicates that the feedback and the benchmark intervention do not differ in their effectiveness.

Table 4-2: Main results for DiD design

Panel A: Results for Autarky-Rate				
	(1)	(2)	**(3)**	(4)
	Basic	Time FE	**Twoway FE**	Weather
N = 1	0.0146**	0.0185***	**0.0209*****	0.0201***
	(2.09)	(3.45)	**(5.57)**	(4.40)
N = 2	0.0145*	0.0201***	**0.0212*****	0.0180***
	(1.77)	(3.72)	**(5.05)**	(2.65)
N = 3	-0.00868	-0.00493	**-0.00935****	-0.000671
	(-1.22)	(-0.87)	**(-2.26)**	(-0.05)
R2	0.255	0.582	**0.778**	0.639
Obs	46409	46409	**46409**	34004
FE	none	time	**time+ household**	household
Panel B: Results for Self-Consumption				
	(1)	(2)	**(3)**	(4)
	Basic	Time FE	**Twoway FE**	Weather
N = 1	0.0160	0.0291	**0.0291***	0.0259
	(0.54)	(1.23)	**(1.73)**	(1.25)
N = 2	0.0450	0.0606**	**0.0280**	0.0165
	(1.25)	(2.15)	**(1.32)**	(0.59)
N = 3	0.0569**	0.0704***	**0.111*****	0.105*
	(2.09)	(3.43)	**(6.64)**	(1.81)
R2	0.111	0.473	**0.702**	0.525
Obs	45928	45928	**45928**	33564
FE	none	time	**time+ household**	household

Notes: DiD estimation for dependent variables autarky (upper panel) and self-consumption (lower panel). Robust standard errors (Huber-White) in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. N = {1,2,3} refers to interventions 1 and 2, and 3, respectively. Columns differ in the fixed-effects structure, indicated in the bottom row.

The consistent picture of small, positive effects from the first two interventions does not carry to the default intervention (N=3). For autarky, the effect size is negligible from an economic perspective despite the statistical significance. Yet, for self-consumption, there is a sizable increase of 11 percent in self-consumption. Evaluated at the hourly sample mean, this translates to an increase of 49 Wh. Wald tests against Intervention 1 and Intervention 2 reject equality of coefficients for both outcomes (all p-values < 0.001), indicating that Intervention 3 does indeed work differently.

When self-consumption rises, but autarky remains unaffected, the likely explanation is that households simultaneously increased total energy consumption. Autarky-rate as the ratio would then be constant. To substantiate this interpretation, we also ran the same model with total energy consumption as the outcome variable (not shown here). We found a significant increase of about 8 percent, which suggests that households increased both the denominator and the numerator of the autarky-rate. Intervention 3 is found to be more effective in increasing self-consumption, but ineffective for autarky. This finding suggests that more is needed to understand the mechanism of Intervention 3 compared to the other two interventions. We explore this further in the following sections.

Finally, we conduct a number of robustness checks and run the regression separately for each intervention to support the stability of the estimates. The list of robustness checks is included in Appendix C. Code and documentation are available from the authors upon request.

4.3.2 Short-Run Effects

One explanation for the small average effects in the main results above could be that consumers quickly lose interest rather than adapting their routine due to the interventions (Sunstein 2017). We test this with the event study design displayed in Figure 4-7. Time is centered to zero as the day a specific intervention becomes effective. For a better overview, the specification reports only 20 lead and lag terms (daily coefficients before and after the intervention started) and aggregates the other daily coefficients as endpoints (see (Callaway and Sant'Anna 2021)). Individual coefficients are plotted as black circles; the endpoints are represented as hollow circles. Across all interventions and for both outcome variables, the point estimates are clustered closely around the horizontal line at zero. The confidence intervals also span zero in the vast majority of cases. Corresponding to the main results, the time pattern appears less volatile for autarky than self-consumption at least for Interventions 1 and 2. Overall, the event study does not support a clear time trend within the study period. In fact, individual coefficients are insignificant, which indicates that single-day effects are small and the positive average found in the main result emerges only in the aggregate. Given power constraints with the small cross-section relative to the number of parameters, this is expected. On the flip side, the study also lends credibility to the parallel trends assumption, as the pre-treatment effects are tightly clustered around zero. In economic terms, the event study further supports that the three tested interventions have small effects within the ecosystem of prosumers' energy consumption.

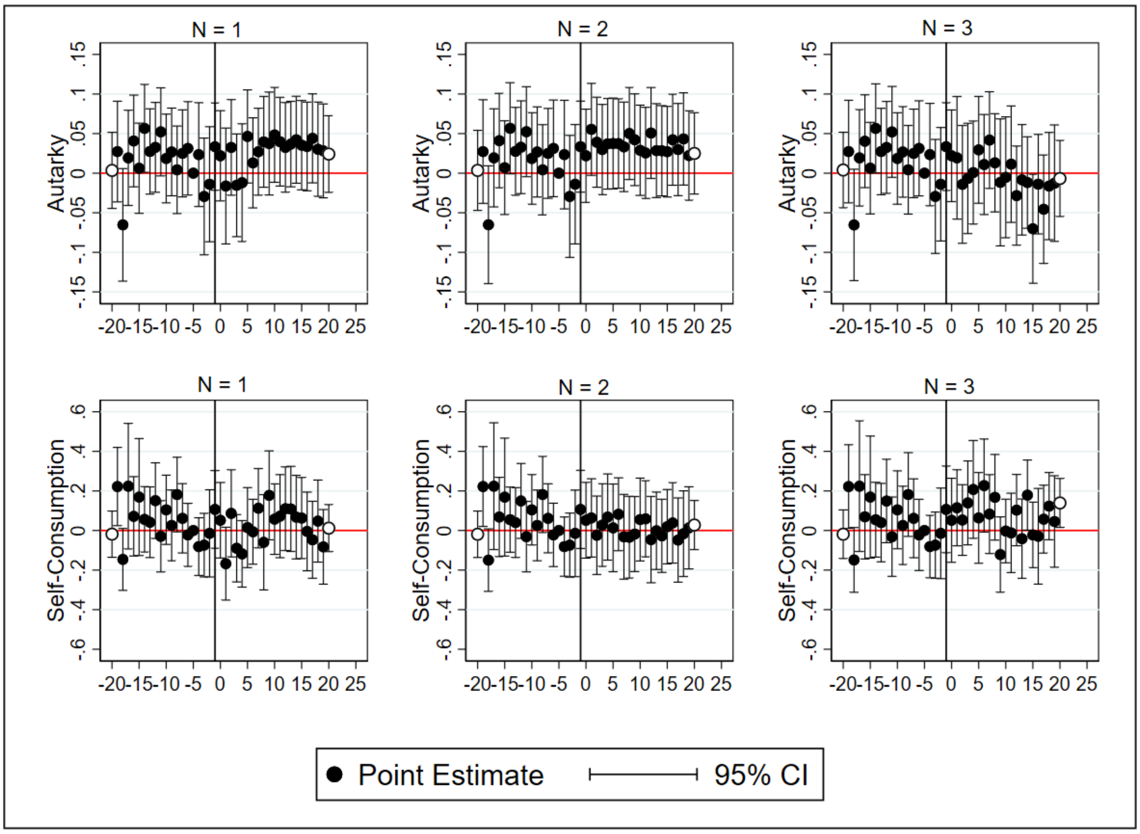

Figure 4-7: Event study results

4.3.3 Sub-Group Analysis

A unique feature of the experiment is the sub-division into the participants without ("PV-group") and with controllable EVs ("EV-group"). We estimate the effects separately for these sub-groups to explore heterogeneity. This is shown in Figure 4-8. The specification is the same TWFE model as in the main results but displayed in graphical form for exposition: the circle and diamond symbols represent the coefficients, i.e., point estimates for the marginal effect, and the vertical extensions the 95 percent confidence interval. Autarky-rate is displayed in the upper panel, self-consumption (log-transformed) in the lower panel. The columns correspond to the three interventions.

For Interventions 1 and 2, the EV-group appears more responsive than the PV-group. While the confidence intervals overlap for autarky-rate, the sub-group differences are statistically significant for self-consumption. The EV-group has self-consumption treatment effects in the range of 10-12 percent, which is substantially above the average effect of 2-3 percent in the main analysis. Across both outcomes, the analysis suggests that the positive average effect is driven more by the EV-group.

However, this does not hold for Intervention 3. The confidence intervals of the two sub-groups overlap substantially for both outcomes, and the associated p-values do not support sub-group differences (not reported here). This result is surprising because especially Intervention 3 was targeted to the EV-group. The PV-group only received the energy report, whereas the EV-group had a new charging mode. The sub-group analysis does not support the interpretation that the increase in self-consumption is driven by the EV-group, which was the working hypothesis derived from the main results.

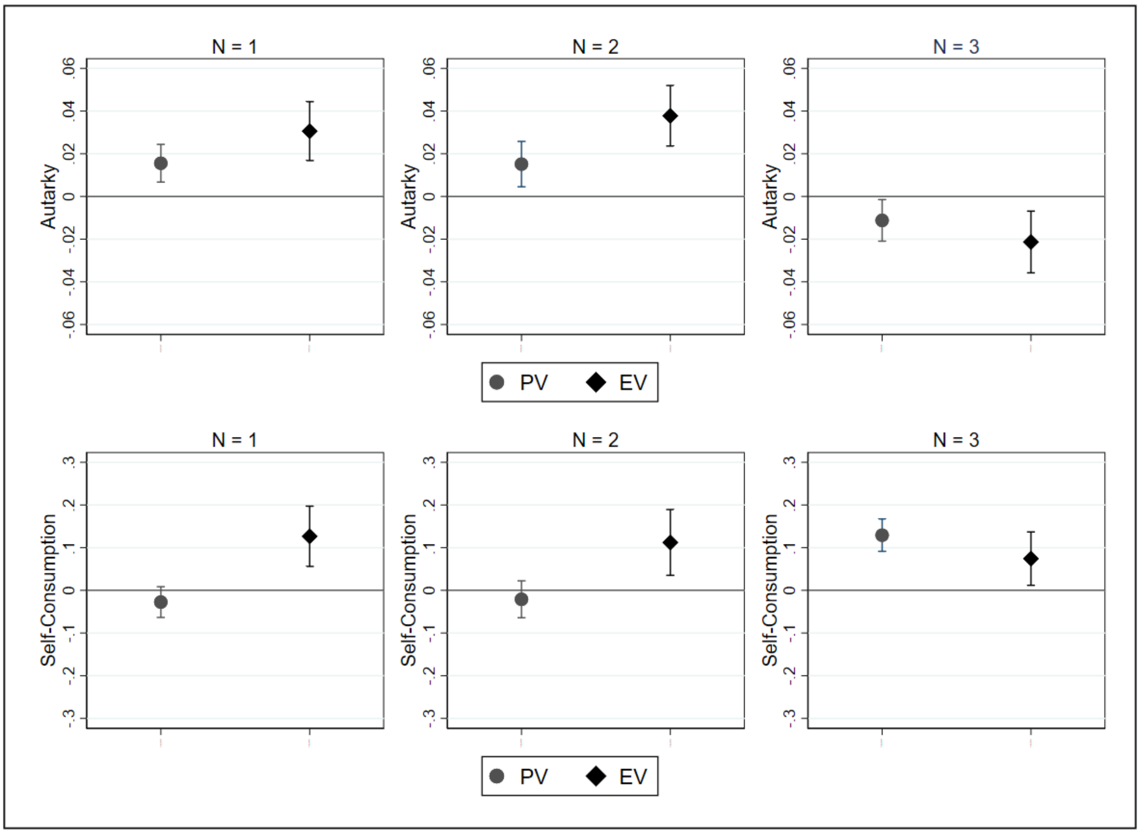

Figure 4-8: Sub-group analysis

However, the presented effects come from assignment to the treatment-group (intention-to-treat effect). Using the additional information available from the smart-charging-app, we explore intraday-shifts separating those households that activated the new charging mode of Intervention 3 (n=9), and those that did not. The hypothesis is that the active group changed their charging behavior to longer plug-in times, so the smart-charging-mode would shift consumption to the midday-PV-peak. We add energy consumption (again log-transformed) based on the insights from the main result.

The regression results are shown in Table 4-3 below. The coefficients of interest are in bold in the top two rows: the interaction terms reveal whether the active group shifts more into midday (11am-3pm), i.e., relatively more than the control-group. For each outcome, the first column uses all inactive households as the control-group; the second column uses only those in the EV-group, i.e., only participants who had access to the mode. This means a loss of observations but serves as a robustness check against concerns that those in the PV-group are not suitable control-group for the EV sample. As before, the results show no significant effects for autarky-rate but a strong positive shift to the midday hours for self-consumption and total consumption (Active x Midday). The effect sizes of 15-17 percent for self-consumption are substantially larger than the main result. Total consumption increases by a similar magnitude. We do not find significant differences in the evening hours (Active x PM) across all outcomes, which indicates that the midday increase is not offset by opposite changes during evening hours. The base effects for Midday and PM in the lower rows conform to expectations from normal load profiles. The results are interpreted as revealing the potential of the new mode, thus indicating that the weak effects in Figure 4-8 stem from a low activation level. By contrast, participants that activate the new charging mode are able to use their PV-generation more effectively. In brief, the default intervention has a high potential for consumption shifts that is not captured in the overall sample because a relatively small sub-group drives it.

Table 4-3: Intra-day shifts during intervention 3

	(1)	(2)	(3)	(4)	(5)	(6)
	Autarky-rate		Self-Consumption		Total Consumption	
Active x Midday	**-0.00217**	**0.0132**	**0.165****	**0.157****	**0.165****	**0.135***
	(-0.15)	(0.94)	(2.28)	(2.17)	(2.26)	(1.84)
Active x PM	**0.0114**	**-0.00871**	**-0.0587**	**-0.130**	**-0.0117**	**-0.0313**
	(0.42)	(-0.32)	(-0.39)	(-0.87)	(-0.15)	(-0.39)
Midday	0.184***	0.173***	0.721***	0.802***	0.176***	0.260***
	(80.26)	(44.97)	(66.91)	(42.21)	(23.91)	(20.68)
PM	-0.0209***	0.00600	0.118***	0.260***	0.0972***	0.170***
	(-7.42)	(1.29)	(8.59)	(11.25)	(13.83)	(14.69)
R^2	0.352	0.322	0.200	0.193	0.250	0.196
Obs.	72802	26325	69347	25270	72802	26325
Control-group	All	EV only	All	EV only	All	EV only

Notes: Regression testing for intra-day shifts during Intervention 3. Data at hourly frequency. Baselevel is AM (6:00-10:00). Active is an indicator for interaction with the app. Robust standard errors in parentheses. Significance Levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Connecting the insights from sections 2.2 and 2.3, the question is whether the default intervention can also induce more regular and, thus, sustainable behavior changes. With the small sample and limited uptake, we can only provide indicative, descriptive evidence here.

Testing for variance equality (Levene-test) shows a minor *increase* in the variance of self-consumption, but fails to reject the null hypothesis. By contrast, the correlation between solar radiation and self-consumption increases sharply from 0.22 before the default to 0.73 afterwards. This indicates that the intervention increases the alignment with the relevant variation (solar radiation), but does not decrease the *unconditional* variation in the outcome.

4.4 Discussion

The treatment-group's positive, small intervention effects are of similar magnitude as other studies estimating causal effects regarding energy-saving behavior (e.g., (Imbens and Wooldridge 2009), (Weigert et al. 2022), (Bager and Mundaca 2017), (Brown et al. 2013), (Schleich et al. 2022), (Myers and Souza 2020)). We did expect our results to be at the lower end of the effect spectrum in the literature on behavioral interventions due to the publication bias and lack of causal effect methods in other studies. At the same time, the larger effects for the active EV-group even range between the few available studies with EVs (e.g., (van der Kam et al. 2019; Huber and Weinhardt 2018; Huber et al. 2019b)) and model-based studies optimizing self-consumption under optimal conditions (e.g., (Higashitani et al. 2021; Kern et al. 2022)). In summary, we show that the tested interventions for feedback and benchmarking are suitable for increasing self-consumption by changing the described choice options. Additionally, the charging default increases self-consumption effectively by re-structuring the choice task. In the following, we provide a methodological reflection, position the results, and suggest subjects for further research.

Estimating causal effects with smart-meter-data requires careful consideration of the identification strategy to extract the relevant variation from the overall noise, which our results demonstrate. We provide treatment effects using a conservative TWFE specification of the broader DiD estimation, which applies microeconomic methods in this interdisciplinary setting. In the process, we showcase the difficulty of assessing treatment effects from real-life settings: the bulk of the variation in the smart-meter-data stems from general differences across households and time. Interventions on (self-)consumption behavior cannot change the external conditions, leaving a limited margin for optimization because much of the variation is "pre-determined". However, the third intervention also indicates strong opportunities for new behavioral routines (EV-charging) that are *aligned* with exogenous variation (solar radiation).

Our employed model is a strong improvement relative to pooled ordinary least-squares, but it is not a panacea for all confounders. The fixed-effects strategy rests on the assumption that within-household behavior is constant over time and can therefore be partialled out (see [42]). This strategy does not address time-variant confounders such as newly added assets. This is most critical for intervention 3, which begins during heating season. We ensure that heatpump ownership is balanced across all four sub-groups. However, we cannot completely rule out this potential confounder (e.g., different operation across households). This is similar to the battery-storage-systems, which are operated all year long but more intensively during the summer period.

Similarly, time fixed-effects absorb factors like solar radiation common to all households on a given day, but the treatment effect is the average effect across all households. Essentially, we take the assumption that factors like weather and energy prices are common to the treatment and the control group on a given day. In practice, the approach assumes for energy prices that this is a common shock to all households, and that the groups respond similarly on average – not only regarding the direct price effect, but also how susceptible households are to energy-related information in the intervention. The tested interventions show limited behavioral effects relative to the ecosystem, but the *capacity* for exploiting solar radiation indirectly impacts how prosumers optimize self-consumption. In the summer, when some households are close to complete autarky-rate, there may not be room left for the intervention to increase it further. In the winter, there are days with very little radiation and potential to exploit. Hence, interpreting effect sizes across seasons deserves a note of caution. Moreover, the seasonal yield differences imply that, for the intervention design, interventions should stimulate additional consumption for the excess generation in summer and focus on shifts of existing consumption in winter.

The rise of smart-metering makes data for such estimations easily accessible. At the same time, the data quality is prone to technical and human failures, such as connection issues, which increase noise that is difficult to separate from systematic variation. If such issues cannot be fully mitigated, it is key to understand their implication on the results. For instance, for some participants, the winter break created longer disconnection times. If these disconnection times are due to absence from home, we would conclude that data is missing from a below-average consumption period. Studying such correlation between data issues and human behavior and deriving best practices for handling them are subjects for further research.

Human behavior could also impact the results due to social desirability. Participants were aware of being part of an experiment and, thus, may intentionally pay special attention. However, showing social desirability in everyday life over a time span of 1.5 years appears difficult (Allcott and Taubinsky 2015). In addition, the event study did not show differences over time. Thus, we believe that social desirability did not affect the results (largely). Studies examining long-term effects of behavioral interventions may consider and assess this in more detail.

Self-selection in our sample creates limitations regarding the external validity of our results. With the highly motivated prosumers and their sizable asset portfolio to optimize over (see supplementary-material 1.2), the sample does not represent the German population. At the same time, it shows typical characteristics of early adopters of rooftop-PV and EVs (Wesche and Dütschke 2021; Plötz et al. 2014), who are the current target group for this kind of intervention. Learnings from this group give insights into how to support other households at the later stages of the diffusion curve (Sarfarazi et al. 2020; van der Stelt et al. 2018). The increasing diffusion is expected to lead to greater household-dependent variations and an elevated need to tailor interventions to household conditions. Thus, our work lays a basis for further research.

Remarkably, even our self-selected sample takes up the interventions only to a limited extent. In particular, the efficacy of the charging default is weakened since only half of the EV-group activated the feature. While no significant effect for the overall EV-group is found, a comparison of the non- and activated participants shows a 15-17 percent increase in self-consumption for activated prosumers. Acknowledging the risk of low uptake, we recommend designing interventions with only a minimum amount of required interaction. In our case, we believe a charging default without the need for an initial activation would likely be more effective.

Such low uptake of interventions demonstrates limitations, which policymakers may face when upscaling behavioral interventions as policy measures. In this sense, the main results for the entire sample are a more accurate projection for policy measures since they measure the effect for the ones that were assigned to the treatment (intention-to-treat) and not the sub-group that was certainly exposed to the treatment. The uptake is likely to decrease further when the interventions are rolled out to the - likely less motivated - German population. At the same time, since the German population is younger than the sample, a rollout would target more digital natives, which may increase the chances for an uptake.

The results of the feedback and benchmark interventions confirm the efficacy of their common design aspects, i.e., condensed information presented in an appealing manner for describing choice options. Although we recognize an incremental improvement when a benchmark is added as a second intervention, both effects are not significantly different. Consequently, no conclusions can be derived from the distinctive design aspects that come with describing choice options (i.e., whether signaling colors are a more effective stimulus than benchmarking).

The effects are driven by the sub-group with controllable EVs. The increased effect size emphasizes the opportunity for technology-specific intervention designs that align with the strong exogenous drivers of the outcome of interest.. The stronger results for the EV-group in interventions 1 and 2 (compared to the non-EV group) suggest that there is potential for implementing interventions while EVs and other electrified residential technologies are still emerging and new routines around them are created. From a different angle, the large intra-day effects in intervention 3 fit with this interpretation, albeit conditional on active utilization. Since these emerging technologies are already equipped with digital interfaces, behavioral interventions could also be integrated at a low cost. However, in our study, the additional interface for the EV-group does not allow us to clearly distinguish between the impact of the technology and the interface. Future research could disentangle both factors. Furthermore, it could test the effect on other flexible technologies (e.g., heatpumps) and on households who are not yet prosumers, further assessing the heterogeneity and context-specificity of behavioral interventions. Thereby, other aspects of behavioral interventions from the literature could be further examined, e.g., (i) the relation of applied interventions to normativity (Carlsson et al. 2019), (ii) their link to economic incentives (Congiu and Moscati 2022), and (iii) their focus on the individual's or the society's welfare (Schubert 2017).

4.6 Conclusion

This paper has studied the effectiveness of three behavioral interventions within the same field experiment using a more rigorous estimation framework than much of the previous literature. We find small, positive effects for interventions through feedback and benchmarking, both in absolute self-consumption and in relative terms (autarky-rate). Sub-group analysis shows that the EV-group mainly drives the average effects. The default intervention stands out as different from the others: it increases self-consumption substantially but is ineffective for autarky-rate as total consumption increases simultaneously. We are able to show that the low uptake of the intervention explains the weak average effect. By contrast, the prosumers adopting the smart-charging-mode can increase self-consumption by 16-17 percent. As a subject for further research, we suggest exploring how behavioral interventions interact with the households' charging routine.

Overall, we contribute novel evidence on stimulating prosumers to optimize self-consumption, which is a previously understudied use case of behavioral interventions with growing potential in the energy transition and consumption shifts. The study extracts intervention effects from a real-life field experiment, which reveals that behavioral interventions target a relatively small component within the ecosystem of household energy consumption.

The uptake is likely to deteriorate for other, less dedicated prosumers. Also, the prosumers' level of energy literacy is likely to be lower, which makes interventions that change the described choice options (e.g., feedback) less attractive than interventions that re-structure the choice task (e.g., default). Future applied work could explore specifically how intervention design can be better embedded in the ecosystem.

Subtle interventions require supporting regulatory, technical, and digital conditions. The other way around, restrictive self-consumption regulation, unappealing digital interfaces, and mal-functioning flexible technologies can easily overrule the small, positive treatment effects. At the same time, if behavioral interventions are thoughtfully aligned to these conditions, they can unlock hard-to-reach flexibility potential. Orchestrating a grid-friendly operation of large consumption technologies, such as EVs and heatpumps, is a promising future case for behavioral interventions in light of emerging flexibility markets, digitalization, and other grid regulations.

5 Balancing conflicting needs of households in the governance design: Modeling tradeoffs for smart charging services[9]

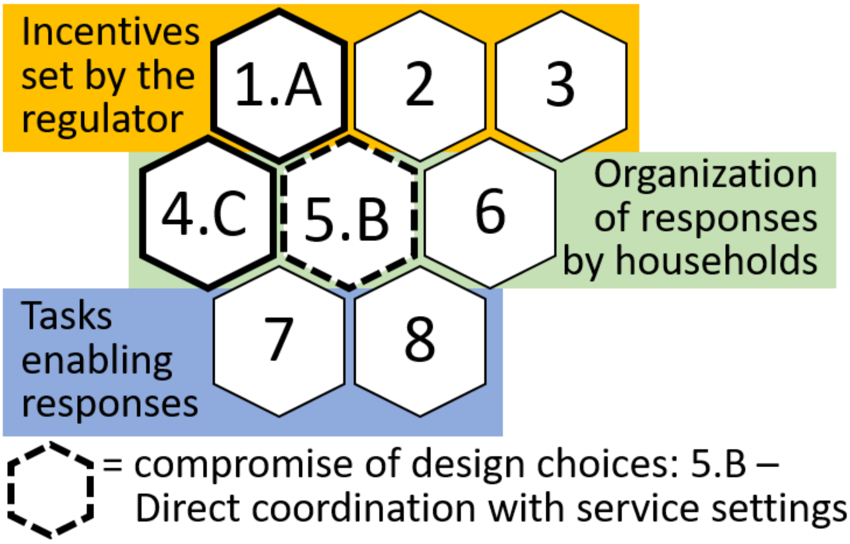

Figure 5-1: Graphical summary based on the design choices for SRQ 4

EV users who aim to become flexibility providers face a tradeoff between staying in control of charging and minimizing their electricity costs. A common practice is to charge immediately after plugging in more electricity than is necessary. Changing this can increase the EV's flexibility potential and reduce electricity costs. Our extended electricity cost optimization model systematically examines how different changes to this practice influence electricity costs. Based on prospect theory and substantiated by empirical data, the model captures EV users' tradeoff between relinquishing control and reducing charging costs.

Reducing the need to control charging results in disproportionately large savings in electricity costs. This finding incentivizes EV users to relinquish even more control over charging. We analyze changes to two charging settings that express the need for control. The modeling results reveal that comfort-driven charging offsets the energy cost savings, even if households attempt to realize savings by adjusting one of the setting parameters. However, energy cost savings are only realized if both setting parameters are adjusted. Widely documented behavioral aspects, such as rebound effects and inertia, support this finding and underline the fit of our model extension for capturing different charging behaviors. Our findings suggest that service providers should convince EV users to relinquish control of both settings.

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[9] This paper is published as Pelka S., Bosch A., Chappin E., Kühnbach M., de Vries L., To charge or not to charge? - Using Prospect Theory to model the tradeoffs of electric vehicle users, Sustainability Science, 2024

5.1 Introduction

Electric vehicle (EV) users can become flexibility providers if they adapt their charging behavior to electricity market price signals. Charging can be shifted across the time parked, providing the vehicle is charged sufficiently by the time of departure. Instead of EV-users shifting charging manually, providers of smart charging services can facilitate this activity with an optimized charging pattern.

Smart charging services based on price signals follow a charging pattern that differs from most EV-users. EV-users charge earlier and more electricity than necessary because of uncertainty (e.g., unpredictable trips), competing interests (e.g., the comfort of not having to plan ahead), and other biases (e.g., range anxiety) (Libertson 2022b).

Two parameters of smart charging services allow EV-users to control charging according to their needs. The targeted state of charge (SOC) determines the requested amount of electricity during the charging session. The level of direct load control (DLC) defines the degree of freedom with which the service provider determines the timing of the charging (Gschwendtner et al. 2021; Lehmann et al. 2022). While the target-SOC can be adapted on a daily basis depending on the scheduled trips, the decision about the level of DLC is more fundamental. It is usually made when selecting a smart charging service and is expressed as the right to overrule an optimized charging schedule or immediately charge up to a minimum SOC (Gschwendtner et al. 2021, Schmalfuß et al. 2015).

Both parameter choices, target-SOC and DLC-level, are based on the EV-users' tradeoff between minimizing the charging costs and retaining control. How the control parameters correspond to charging cost savings depends on the interplay between charging and price signals. For instance, a request for immediate charging would comply with an optimized charging pattern during periods with high renewable supply.

Successful smart charging services must consider the EV-users need for control while ensuring certain degrees of freedom for optimizing charging. It is the service provider's challenge to balance these two aspects and gain the EV-user's trust so they relinquish more control (Sloot et al. 2022). This balancing act gives rise to the following research question: "How to balance the need of EV-users to control charging with minimizing their charging costs?"

To answer this question, we tested different control parameters, which reflect the heterogeneous needs for control of EV-users, and analyzed the resulting impact on the charging costs. This was done in three steps: I) Implementing both parameters in the electricity cost optimization to represent the EV-users' needs for control, II) Analyzing the correlation between different control needs and charging costs if both control parameters are adapted consistently (i.e., ranging from a low target-SOC and high DLC to a high target-SOC and low DLC), III) Analyzing the correlation if only one parameter is adapted. The accepted levels of DLC are based on a vignette survey on smart charging services in Germany (n=1,116) (Pelka et al. 2024b). The target-SOCs were taken from a field experiment with German prosumers (n=39) (Gabriel et al. 2022). For step III, this field experiment also provided data about the reduction in the target-SOCs over time due to the service provider's influence. Since no data were available for the change of the other parameter, we combined reversed levels of DLC with the given target-SOCs in a hypothetical scenario.

Answering the above research question bridges the gap between empirical research on acceptable control parameters and energy system models calculating the flexibility potential of cost-optimal charging. We extend the electricity cost optimization of an existing agent-based model (ABM) by adding discomfort costs for relinquishing control over charging. For the latter, we apply the prospect theory (PT) of Kahneman and Tversky (1979) to capture EV users' urge to charge immediately and for longer than is needed.

The following literature section (Section 5.2) provides an overview of the control parameters of EV-users and their biases, as well as how charging is implemented in ABM (with and without PT). Section 5.3 describes how we applied PT to the electricity cost optimization problem in the existing ABM and the underlying data for the model extension. The results section (Section 5.4) presents the changes in the households' charging cost depending on different combinations of the two control parameters. A sensitivity analysis of the other parameters to test the robustness of the results can be found in Appendix J. The results are discussed, and conclusions are drawn in Sections 5.5 and 5.6.

5.2 Modeling charging behavior

This section describes the literature on charging behavior, including biases and the existing implementations of such behavior in energy system models.

5.2.1 Charging behavior and biases

The literature on EV charging behavior has expanded rapidly over the last few years. The adoption of EVs by new user groups indicates how, where, and when people charge them and may evolve further. After an initial focus on technical charging aspects, empirical insights into behavioral aspects are now also available (Sovacool et al. 2018; Krueger and Cruden 2020). The lack of alternative charging points, such as public charging stations, has resulted in EV-users primarily charging at home. The reported stress due to the lack of charging alternatives has resulted in the widespread practice of always fully charging the battery (Delmonte et al. 2020; Libertson 2022b).

Most users charge their EVs when arriving home in the evening (Morrissey et al. 2016). Charging shifts are most acceptable at night (Lehmann et al. 2022). While some research has explored the acceptance of self-executed shifts based on variable tariffs (Delmonte et al. 2020), most studies have examined smart charging services controlled by third parties (García-Villalobos et al. 2014). Constraints set for controlled charging mainly involve technical dimensions of the battery (volume, capacity), the conditions when the EV is plugged in (connection duration, start-SOC), and the requirements for departure (departure time, target-SOC) (Schmalfuß et al. 2015).

Control by third parties requires measures to guarantee that EV-users retain control of their charging and ensure that their mobility needs are covered. A minimum-SOC that needs to be reached after plugging in the EV is often stated as a key prerequisite for joining smart charging services (Bailey and Axsen 2015; Geske and Schumann 2018; Schmalfuß et al. 2015). The largest class in the survey of Bailey and Axsen (2015) (33 % of the participants) not only refuses a deviation from this minimum-SOC but is willing to pay more for a higher SOC. Willingness to pay for additional driving range (35 to 75 USD per mile) and faster charging (425 to 3250 USD per hour) was also detected by Hidrue et al. (2011). The participants of the field experiment by Schmalfuß et al. (2015) accepted a minimum SOC of 30 and 45 % of the battery volume. Other empirical research has highlighted an overriding option for the charging shifts (Yilmaz et al. 2021) or an immediate charge button as key features for a smart charging service (Gschwendtner et al. 2021).

Common charging practice 1: Charging immediately after plugging in to achieve a certain SOC

These features are in partial conflict with the provision of flexibility. This concerns the general participation in smart charging services and choosing more ambitious control parameters if they participate (e.g., a lower minimum or departure SOC) (Axsen et al. 2017; Sovacool et al. 2018). Even though EV-users were significantly motivated to contribute to grid stability and renewable integration, the survey evaluation of Will and Schuller (2016) ranked safeguarding flexible mobility needs as equally important. Having to plan ahead, and plug in their EVs more frequently, as well as being more dependent and less flexible when driving, creates discomfort (Gschwendtner et al. 2021; Schmalfuß et al. 2015). Despite larger battery volumes, range anxiety and unexpected trips remain the main concerns (Noel et al. 2019; Gschwendtner et al. 2021). EV-users argue that they can decide to share control but not the flexibility they provide since this depends on external factors, such as their working patterns, financial resources, and access to charging stations (Libertson 2022b).

Common charging practice 2: Charging more than needed and maintaining a certain SOC due to uncertainty or comfort

5.2.2 Prospect theory and its implementations of charging behavior

Charging immediately and more than needed creates a feeling of comfort. Charging less restricts mobility needs and creates discomfort. PT provides a basis for modeling this non-linear relation between charging and the perceived (dis-)comfort. Following a brief introduction to PT, this section describes how charging behavior and other cases of residential load shifting are modeled with and without PT.

PT and its sloped value function by Kahneman and Tversky (1979) express a diminishing marginal value as subject to deviations from a neutral reference point on which the function is centered. Two parameters shape the marginal value. First, the coefficient lambda λ expresses the asymmetric value assignment of negative (losses) and positive deviations (gains) from the reference point. A loss aversion implies that the discomfort created by a negative deviation is stronger (2 to 2.5 times in the literature) than the comfort of a positive deviation. Referring to common charging practice 1, EV-users with stronger loss aversion charge more electricity immediately than those with lower loss aversion.

Second, the risk attitude exponent alpha α determines the slope of the curve. Alpha values close to 0 express a strong change in the perceived value, corresponding to strongly provoked feelings. Referring to common charging practice 2, these more erratic EV-users require higher electricity prices to accept discharging and offset their strong feelings of discomfort. Alpha values close to 1 represent more even-tempered users and express a more linear relation between the perceived value and the reference point change. This is associated with so-called rational behavior and is more frequently applied in the literature (Klein and Deissenroth 2017; Kahneman and Tversky 2019a, 2019b, 1979).

In the literature on households' load-shifting decisions, a popular, simplified approach to consider such values is to include a fixed discomfort cost parameter in the optimization function. This reflects the effort of enforcing load-shifting measures of flexible appliances (Reis et al. 2019; Gonçalves et al. 2019) or deviations from a desirable state (e.g., lower thermal comfort due to shifted heat pumps) (Tiwari and Pindoriya 2021; Nguyen and Le 2014; Javadi et al. 2021). Yan et al. (2021), Esmaili et al. (2018), and Mao et al. (2018) determine this desirable state concerning EV users' SOC. If the SOC is too low for the upcoming trips, the discomfort costs incite sufficient and foresighted charging. The discomfort costs are implemented in a binary way, i.e., they occur only in the case of uncovered trips. We propose to implement a diminishing marginal value of charged electricity since the uncertainty of unexpected trips does not provide an exact threshold for needed and not needed charged electricity.

In residential energy research, PT is often applied to reflect uncertainty in the availability of resources, such as limited charging infrastructure, weather-dependent renewable supply, and price risks in the energy market. The strategies implemented to handle such uncertainties involve purchasing hedging products of service providers (Bruninx 2021; Yao et al. 2020), using resources earlier under less financially attractive conditions (Liu et al. 2014; Hu et al.; Wang and Saad 2015; Mediwaththe and Smith 2018) or placing more conservative pricing bids (Shuai 2022; Barabadi and Yaghmaee 2019). Charging applications of PT represent risk preferences towards fluctuating prices, range anxiety, and limited charging infrastructure. Despite its fit, PT has not been used so far to examine the common practices of charging immediately and maintaining a certain SOC level.

We investigate this research gap based on a mixture of recently collected empirical data on charging behavior and well-established PT parameters. For instance, Klein and Deissenroth (2017) found that German household PV investments are driven by total revenue and relative change due to regulatory uncertainty.

5.3 Materials and methods

This section describes the experiment' design, its methods and materials. The latter comprises the existing ABM model with its electricity cost-minimization (Section 5.3.2.1) and our discomfort cost extension based on PT (Section 5.3.2.2), as well as the underlying data (Section 5.3.3).

5.3.1 Experiment design and scenarios

We examine the research question "How to balance the need of EV-users to control charging with minimizing their charging costs?" in three steps: I) Implementing both parameters in the electricity cost optimization to represent the EV-users' control needs, II) Analyzing the correlation between different control needs and charging costs if both control parameters are adapted consistently, III) Analyzing the correlation if only one parameter is adapted.

To validate whether the resulting charging pattern of the discomfort cost extension imitates the common charging practices identified in the literature (Section 5.2.1, Step I), we compared one scenario without (*reference* scenario, see Table 5-1) and one with the discomfort cost extension (*need for control* scenario). In Step II, we compare the differences between the household groups in the *need for control* scenario to examine the impact of varying needs to retain control on the charging costs.

For Step III, we adapt one control parameter of the *need for control* scenario to examine its impact on the charging costs. One control parameter, the target SOC, was adapted based on empirical app data from a field experiment (*lowered target SOC* scenario) (Pelka et al. 2024a). Since the data for the other control parameter, DLC-level, does not involve changes over time, we analyzed its impact in an explorative manner by reversely exchanging its values among the groups (*reverse* scenario). For instance, a high DLC-level is (counterintuitively) assigned to households with high control needs.

Table 5-1: Scenario overview

Scenario name	Elements of the cost-minimization function		Control parameters differentiated for the groups	
	Electricity cost	*Discomfort cost*	*Target SOC*	*DLC-level*
1) Reference (electricity cost only)	Applied	Not applied	-	-
2) Need for control (electricity and discomfort costs)	Applied	Applied	Initial target SOC	*DLC-level*
3.a) Lowered target SOC, moderate (based on need for control)	Applied	Applied	Lowered target SOC, moderate	*DLC-level*
3.b) Lowered target SOC, moderate (based on need for control)	Applied	Applied	Lowered target SOC, extreme	*DLC-level*
4) Reverse (based on need for need for control)	Applied	Applied	Initial target SOC	*DLC-level* reverse

In each step, the main outcome variable, charging costs per household, is compared between two scenarios or between household groups that differ with regard to their need to control charging. As another outcome variable, we analyze the charging pattern of their EVs to explain cost differences. The outcome variables are calculated using the ABM described in Section 5.3.2. In the ABM, the electricity cost-minimization function is extended by the discomfort cost of having a low SOC. In real life, households control this discomfort level by setting a target-SOC and DLC-level in their smart charging app. We capture their different needs to retain control by integrating both settings as control parameters in the discomfort cost extension.

5.3.2 Model

The modeling is based on an ABM developed by Kühnbach et al. (2022). It consists of a cost-minimization for prosuming agents that are embedded in a simulated German electricity market. To answer our research question, the cost-minimization was extended by the discomfort cost of having a low SOC based on the assumption that EV-users are only willing to pay for the electricity charged if the discomfort of having a low SOC is higher than the electricity costs. The discomfort costs diminish with a higher SOC. Thereby, the two common charging practices from Section 5.2.1, charging immediately and more than needed, are captured in the model. We apply PT to express the diminishing marginal discomfort costs.

Before describing the discomfort cost extension, we outline the relevant parts of the existing cost-minimization model - in particular, the cost-minimization function and the constraints for charging the EV. Further information on the model can be found in Kühnbach et al. (2022). An overview of the variables and parameters is given in Table Annex 13-1.

5.3.2.1 Existing electricity cost-minimization function

For each prosumer k, a mixed integer linear optimization (MILP) is set up to optimize their electricity consumption given the price signal from the electricity market (p_t^{buying}, $p_t^{selling}$) and their technical constraints. The objective function, as shown in Equation (5.1), minimizes the electricity cost incurred over the optimization period of one day. This includes the cost of purchasing electricity and the revenue of selling electricity to the market.

$$\begin{aligned} min\ C_{tot}^{k} = \sum_{t=h_{min}}^{t=h_{max}} & \left(P_t^{k,grid \to EV} + P_t^{k,grid \to EVflex} + P_t^{k,grid \to hh} + P_t^{k,grid \to bat}\right) \cdot p_t^{buying} \\ & - \left(P_t^{k,EVflex \to grid} + P_t^{k,pv \to grid} + P_t^{k,bat \to grid}\right) \cdot p_t^{selling} \end{aligned} \quad (5.1)$$

The EV-battery is divided into a flexible and an inflexible fraction to meet the constraints of covering the user's mobility demand and enabling demand response. The inflexible fraction of the EV-battery, called EV, is operated to cover the EV-user's inflexible hourly charging profile $P_{EV_{total},t}^{k}$, which ensures a sufficient SOC on time to cover the upcoming trips (see Equation (5.2)).

$$P_{EV_{total},t}^{k} = P_t^{k,grid \to EV} + P_t^{k,pv \to EV} + P_t^{k,bat \to EV} + P_t^{kEVflex \to EV} \quad (5.2)$$

The flexible fraction, called EV-flex, is modeled as a storage unit. This can shift charging to periods of low prices of p_t^{buying} and discharging to periods of high prices of $p_t^{selling}$. The electricity stored in EV-flex can be used to cover the inflexible charging profile and household energy demand or sold to the market. The stored electricity in time t equals the SOC of the previous hour SOC_{t-1}^{k} plus all power inflows and minus all power outflows, see Equation (5.3).

$$SOC_t^k = SOC_{t-1}^k + (P_t^{k,grid\rightarrow EVflex} + P_t^{k,pv\rightarrow EVflex} + P_t^{k,bat\rightarrow EVflex}) \cdot \vartheta_{EVflex,in} - \left(P_t^{k,EVflex\rightarrow grid} + P_t^{k,EVflex\rightarrow hh} + P_t^{k,EVflex\rightarrow bat}\right) \cdot \vartheta_{EVflex,out} - P_t^{k,EVflex\rightarrow EV} - P_0^{k,unexpected} \tag{5.3}$$

In addition to planned trips expressed by the inflexible charging profile, we implement additional unexpected ones at the level of 20% of the initial SOC. This amount of electricity $P_0^{k,unexpected}$ is deducted from SOC_t^k in the first hour of the day.

The storage capacity of EV-flex is constrained by Equation (5.4):

$$SFL_{min}^{k,EVflex} \leq SOC_t^k \leq SFL_{max}^{k,EVflex} \tag{5.4}$$

The usage of both combined battery fractions is constrained by the maximum charging power $P^{k,evMax}$ and discharging power as well as the availability of the EV at the home location in hour t ($vsh_{conn,t}^k$), as depicted in Equations (5.5) and (5.6).

$$P_t^{k,grid\rightarrow EV} + P_t^{k,grid\rightarrow EVflex} + P_t^{k,pv\rightarrow EV} + P_t^{k,pv\rightarrow EVflex} + P_t^{k,bat\rightarrow EV} + P_t^{k,bat\rightarrow EVflex} \leq P^{k,evMax} \cdot vsh_{t,conn}^k \tag{5.5}$$

$$P_t^{k,EVflex\rightarrow grid} + P_t^{k,EVflex\rightarrow hh} + P_t^{k,EVflex\rightarrow bat} \leq P^{k,evMax} \cdot vsh_{t,conn}^k \tag{5.6}$$

50 % of the EV-battery capacity is used as a flexible fraction. The target-SOC in the following model extension expresses whether EV-users keep a further share of the flexible fraction permanently charged (e.g., for unexpected trips).

5.3.2.2 Discomfort cost extension of the cost-minimization function

The marginal value of the charged electricity depends on its contribution to meeting the target-SOC. It diminishes with an increasing SOC. This means that charging an empty EV-battery creates a higher added value than charging an almost full EV-battery. The sloped value function of PT in Kahneman and Tversky (1979) expresses this diminishing marginal value. In our case, the value function as subject to the SOC is centered on the target-SOC (SOC_{Ref}^k) of the EV-user k as the neutral reference point. If SOC_t^k is lower than SOC_{Ref}^k, the EV-user perceives discomfort costs at the level of the SOC delta, captured by the discomfort notion. If SOC_t^k is higher than SOC_{Ref}^k, the EV-user has an increased comfort level, captured by the comfort notion. We extend the cost-minimization function with these two notions in Equation (5.7):

$$\min C_{tot}^{k} = \sum_{t=h_{min}}^{t=h_{max}} [(P_t^{k,grid\to EV} + P_t^{k,grid\to EVflex} + P_t^{k,grid\to hh} + P_t^{k,grid\to bat}) \cdot p_t^{buying} - (P_t^{k,EVflex\to grid} + P_t^{k,pv\to grid} + P_t^{k,bat\to grid}) \cdot p_t^{selling}] \cdot (1-\theta^k) - \theta^k \cdot mV_t^k \cdot \begin{cases} (SOC_t^k - SOC_{Ref}^k)^{\alpha} \cdot vsh_{conn_t^k} & if\ SOC_t^k \geq SOC_{Ref}^k \\ -\lambda \cdot (SOC_{Ref}^k - SOC_t^k)^{\alpha} \cdot vsh_{conn_t^k} & if\ SOC_t^k < SOC_{Ref}^k \end{cases} \quad (5.7)$$

θ^k is the weight assigned to the discomfort cost in relation to the electricity cost for EV-user k. In other words, how willing the EV-user is to compromise on her control need for the benefit of more electricity cost savings. The weight parameter expresses the level of accepted DLC in a reverse manner. A higher weight on the discomfort cost expresses a lower level of accepted DLC (i.e., lower willingness to relinquish control). mV_t^k describes the monetary value, which is assigned to the delta between SOC_t^k and SOC_{Ref}^k. The parameterization is presented in Section 5.3.3.

The non-linear relation between the charged electricity and discomfort costs is expressed as a mixed-integer non-linear problem (MINLP), consisting of two if-conditions for the comfort and discomfort notions. We decompose the MINLP into optimization constraints based on the Big-M method (Cococcioni and Fiaschi 2021), see G. The large value of Big M combined with a slack variable δ_t expresses the two if-conditions (i.e., whether SOC_t^k is equal to, larger or smaller than SOC_{Ref}^k, see constraints (B.2) and (B.3)) and the impact of this SOC delta on the discomfort costs (called $utility_t^k$, see constraints (B.4) – (B.7)).

The relation between the two cost elements in the combined cost-minimization function determines the charging and discharging of the EV-battery. We illustrate this mechanism based on two stylized examples in H.

5.3.3 Assumptions and data

This section describes how we parameterize the extended cost-minimization using empirical data. Four household groups are distinguished by varying the two control parameters for our comparative analysis, the target-SOC and DLC-level, which capture a household's need to retain control of charging (Section 5.3.3.3). The other parameters of the households' technical equipment (Section 5.3.3.1) and the shape of the diminishing marginal value (Section 5.3.3.2) are the same for all four groups to ensure the comparability of the results.

We base the evaluation on a scenario of the German electricity market in 2030, which was developed and validated by the previous work with this model (Kühnbach et al. 2022). We adopted the individual profiles used here for the inflexible household demand and the configuration of the prosumer's PV and battery systems. From the original 480 prosuming agents implemented by Kühnbach et al. (2022), we selected 80 with EV, PV, and stationary batteries as the target group of this analysis. We applied the same profiles for the inflexible EV and household demand across all groups for comparability. According to the empirical data on control needs in Section 5.3.3.3, the smallest group comprises 9 % of households. Therefore, we created a set of seven different profile combinations, which we applied several times for larger groups.

5.3.3.1 Parameters of the households' technical equipment

The assumptions concerning technical charging aspects were taken from the study by Kühnbach et al. (2022). It is assumed that EVs are only charged at their home location (Scherrer et al. 2019). The average charging power at residential locations is assumed to be 6.2 kW (Gnann and Speth 2021). Assuming an EV-battery of 62 kWh, as in Kühnbach et al. (2022), we assigned half of the maximum storage level to the flexible fraction of the EV-battery (31 kWh). The installed PV capacity of each prosumer is set to 8.1 kWp. A battery of 7.8 kWh and a charging power of 7.8 kW are assumed for the stationary storage.

5.3.3.2 Parameters influencing the diminishing marginal value

Parameters influencing the diminishing marginal value are alpha and lambda, as well as the monetary value of being able to drive. Alpha and lambda are set to well-established values (see Table 5-2) proposed by Kahneman and Tversky (1979) and confirmed by other scholars, such as Klein and Deissenroth (2017).

Since empirical evidence is missing for the monetary value, we randomly assigned electricity market prices based on the assumption that EV-users are willing to pay these prices for charging and that they reflect the monetary value of being able to drive. The randomization expresses the time-dependent value of being able to drive, ranging from urgent (e.g., need to go to the hospital) to flexible trips (e.g., grocery shopping).

5.3.3.3 Parameters expressing the need to retain control of charging

We varied the parameters expressing the need to retain control of charging among the four household groups. We used the empirical data collected from German EV-users in a field experiment (n=111) of the Horizon 2020 project NUDGE (H2020 NUDGE 2023) for the target-SOC and data from a vignette survey (n=1.116) of a German research project for the DLC-level. We applied the data set with the larger sample, the vignette survey, for the assignment of the 80 model agents into the four household groups.

The vignette survey asked 1,116 current or prospective owners of flexible technologies (in particular, EVs, heat pumps, or stationary batteries) to rate the likelihood of using four services facilitating the optimization of their flexible technologies on a 5-point Likert scale. We conducted a linear regression based on the likelihood of using a service that forces them to relinquish control with the need to retain control as a regressor. The β-coefficient of the need to stay in control ($\beta = 0.221$) combined with the 5-point Likert scale for usage likelihood (excluding the middle response) creates the DLC-level for the four groups (see Table 5-2).

For the assignment to the four household groups, two smaller groups (9% respectively) represented the extreme need for control and extreme indifference to control based on the sample that responded “very unlikely to use” or “very likely to use”. The two more moderate household groups correspond to the 19 % who were unlikely to use it and the 35 % who were likely to use it (also excluding the middle response). Further information on the vignette survey is provided in (Pelka et al. 2024b).

In the Horizon 2020 project NUDGE field experiment, 39 out of the 111 prosuming participants own a controllable EV and use a smart charging app that automatically optimizes their charging based on the target-SOC and other parameters. Information on the charging optimization is displayed in the app to encourage users to set a lower target-SOC (Gabriel et al. 2022). Other studies based on this field experiment have shown that such information led to a significant reduction in electricity costs (Pelka et al. 2024a; Burkhardt et al. 2022).

However, only a small sub-group of eight participants frequently interacted with the app and adapted their target-SOC. We focused on this group to extract the initial target-SOC, its average, and extreme reduction. The quantiles of the minimum target-SOCs were applied as an extreme case. For the moderate case, we deducted the standard deviation of 17 % of the values from the initial target-SOCs. Appendix I explains how the target-SOCs of the field experiment were transformed into model parameters.

Matching the resulting parameters in Table 5-2 with the scenarios in Section 5.3.1, we combined the DLC-level and initial target-SOC in the *need for control* scenario. For the scenarios testing the adaptation of one parameter, we replaced the initial SOC with the lowered target-SOC or the DLC-level with its reversed version.

Table 5-2: Behavioral parameters for calculating the discomfort cost

Group (sorted from EV-users with the lowest need for need for control to one with the highest)	***Group size***	***Parameters influencing the diminishing marginal value (Identical for the groups)***			***Parameters expressing the need to retain control of charging (Differentiated for the groups)***				
		Alpha	***Lambda***	***Monetary value***	***DLC level***	***Initial target SOC***	***Lowered target SOC, moderate***	***Lowered target SOC, extreme***	***DLC level reverse***
	#	*-*	*-*	*[EUR/kWh]*	*-*	*[kWh]*	*[kWh]*	*[kWh]*	*-*
G1	7	0.88	2.25	Random assignment based on electricity prices	0.211	9.3	7.7	0	0.844
G2	27	0.88	2.25		0.422	17.2	14.2	0	0.633
G3	39	0.88	2.25		0.633	26.7	22.1	1.9	0.422
G4	7	0.88	2.25		0.844	31	25.7	18.6	0.211

5.4 Changes in the households' charging costs due to their charging practices

The results section is structured by the three steps taken to answer the research question "How to balance the need of EV-users to control charging with minimizing their charging costs?". Section 5.4.1 compares the *reference* (assuming EV-users optimize based only on electricity cost) with the *need for control* scenario (also including discomfort costs). It shows whether including discomfort costs capture the common charging practices of charging immediately and for longer than needed (Step I). Section 4.2 compares the four household groups of the' *need for control* scenario and analyzes how their varying need to retain control influences their charging cost (Step II). The two control parameters are set consistently to represent the group's high or low need for control. Subsequently, we change one control parameter of the *control need* scenario to explore its individual impact (Step III). Section 5.4.3 shows how changes to the target-SOC influence charging costs, and Section 5.4.4 shows how changes to the DLC-level influence these costs.

For all steps, we first report the interplay between price signals, control needs and charging patterns. Second, we examine the resulting charging costs and pay particular attention to the weighted average prices during charging and discharging and the average SOC.

5.4.1 Capturing common charging practices in the charging optimization control parameter

The *reference* scenario demonstrates an optimized charging pattern based purely on electricity costs: The early morning hours with low prices are used to charge the EV-battery with electricity from the market (Figure 5-2). As the price peaks for the first time in the day, electricity is sold to the market. During the daytime, self-consumption from the PV-system is maximized, and electricity from the grid is used to fill the remaining EV and stationary battery capacity in expectation of a high price period in the evening. In the evening, both the stationary battery and the EV-battery cover the electricity demand as far as possible, avoiding purchasing expensive electricity from the market.

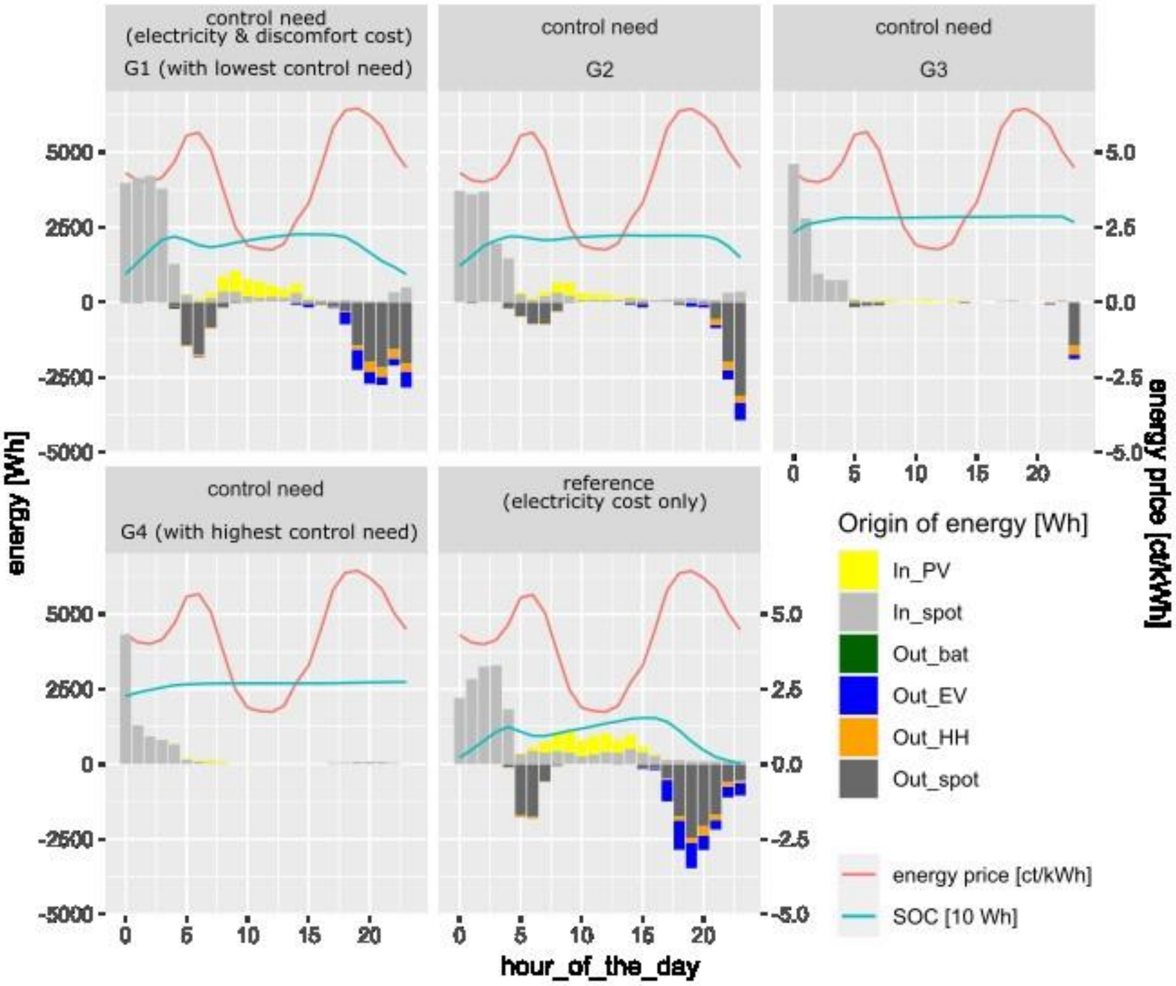
In contrast, the *need for control* scenario shows how the discomfort cost extension distorts the optimized charging pattern and captures the common charging practice: EV-users charge earlier (common charging practice 1), realize a higher SOC, and maintain this during the day (common charging practice 2) (Figure 5-2).

5.4.2 Effects of different needs to control the charging

Comparing the household groups with different needs for control in the *need for control* scenario reveals how an increased need restricts their response to electricity price signals and the local electricity demand. Conversely, a lower need for control offers households financial benefits since this leads to disproportionally large cost savings. We elaborate on these findings, referring to the four household groups, which range from group 1 (G1) with the lowest control needs (i.e., low target-SOC and high DLC) to group 4 (G4) with the highest control needs (i.e., high target-SOC and low DLC).

EV-users' price responsiveness decreases with an increasing need to control charging. EV-users in G1 and G2 with lower control needs charge larger amounts of electricity during low-price periods and discharge more during high-price periods than G3 and G4, which have higher control needs (Figure 5-2). The lack of price responsiveness in G3 and G4 is especially apparent for charging during the first hours of the day and for discharging during the last hours of the day. These groups charge during the high price periods of the first hours to immediately reduce the discomfort of having a low SOC. Because of their already full EV-battery, they sell their self-generated electricity to the market during the midday price drop instead of consuming it themselves (Figure 5-3). During the evening price peak, they opt for increased comfort and decide to maintain the high SOC level up to the last hours of the day instead of selling the stored electricity.

For G1 and G2, they balance the discomfort of a low SOC level (such as G3 and G4) with realizing cost savings (such as the cost-optimal *reference* scenario). In particular, they decide to spread the charging over the first hours of the day and the discharging over the last hours of the day.

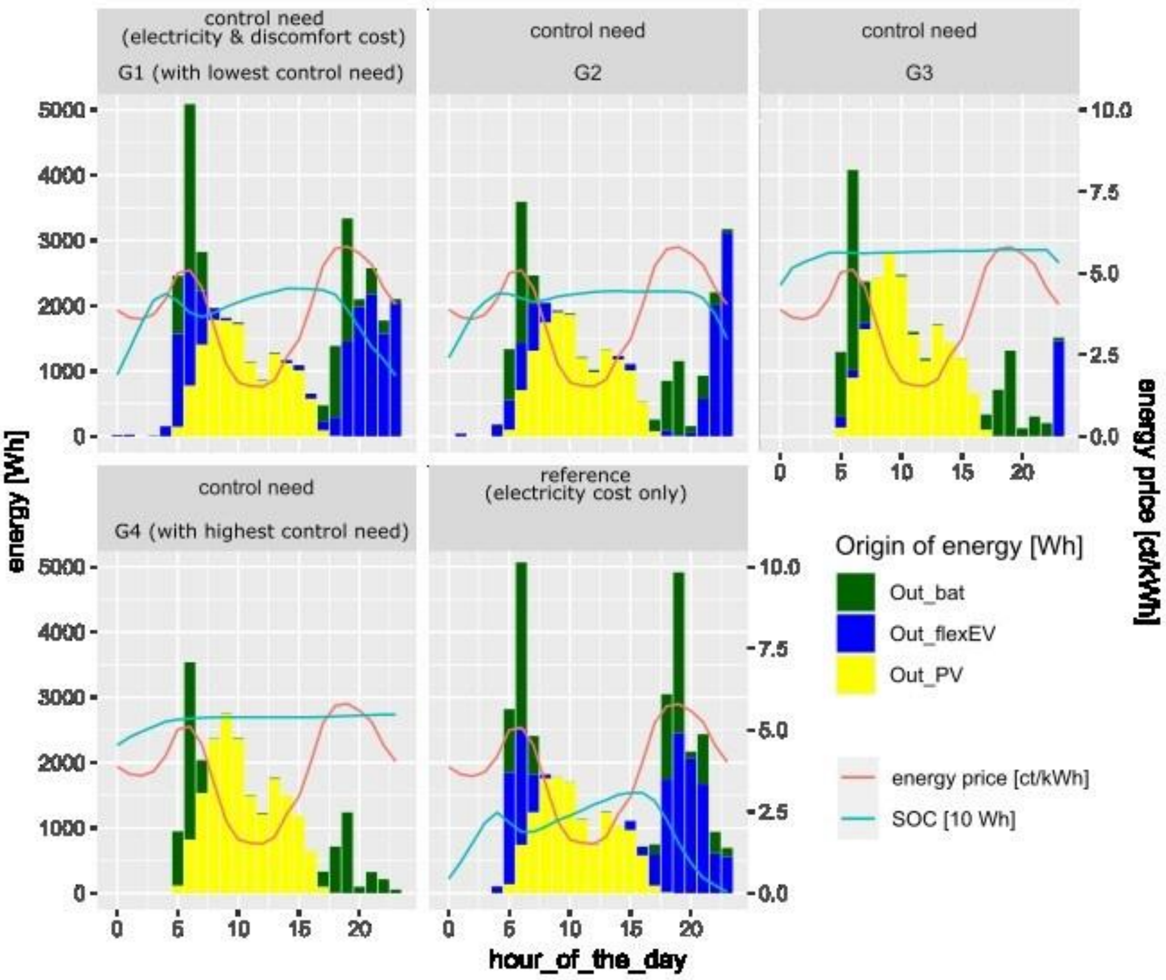


Note: Distinguished by sources (In_[...] = charged electricity from [...], Out_[...] = discharged electricity provided to [...], spot = electricity spot market, bat = stationary battery, EV = inflexible charging demand, HH = inflexible household demand), the SOC values in Wh are divided by 10 to fit the primary x-axis

Figure 5-2: Average in- and outflows of the EV battery over 24 hours for scenario *control need*

Restricting the usage of the EV-battery as a flexibility source results in a more frequent usage of the stationary battery to cover the inflexible demand during price peaks. For instance, while the stationary battery only covers 4 % of the inflexible EV demand in the cost-optimal *reference* scenario, it covers 26 - 27 % for G3 and G4.

Figure 5-3: Average market supply within 24 hours shows the cost-optimal usage of the stationary battery in the *reference* scenario. For G3 and G4, the simultaneity of inflexible demand and price peaks does not allow the stationary battery to sell its electricity during the price peaks.



Note: Distinguished by sources (bat = stationary battery, EV-flex = EV-battery, PV= PV system), the SOC values in Wh are divided by 10 to fit the primary x-axis

Figure 5-3: Average market supply within 24 hours

As illustrated in Figure 5-4, the less price-responsive charging pattern of the groups with a higher need to retain control leads to increased charging costs. The average monthly charging cost between the groups ranges between 0.45 EUR for G1 and 16.03 EUR for G4. Comparing the changes in the control parameters to changes in the charging costs reveals a disproportional development. EV-users can save on average 1.5 EUR per lowered target-SOC by switching from the control parameters of G2 to those of G1. In contrast, they only save 0.3 EUR per lowered target-SOC when switching from G4 to G3 or G3 to G2.

We can identify how the different groups realize cost savings in their weighted average prices and average SOC. Compared to G3 and G4, G1 and G2, with lower control needs, are able to exploit the price spreads and realize additional revenues when charging and discharging the EV-battery. This practice results in an average SOC above their target SOC. In contrast, the discomfort-driven charging of G3 and G4 during the morning price peak leads to high purchasing prices (up to 43.84 EUR/MWh) and a radical drop in the selling price (up to 5.63 EUR/MWh).

All in all, more relaxed control parameters result in greater charging cost savings. To what extent the low costs of G1 are due to its low target-SOC or its high DLC-level is explored in Section 5.4.4.

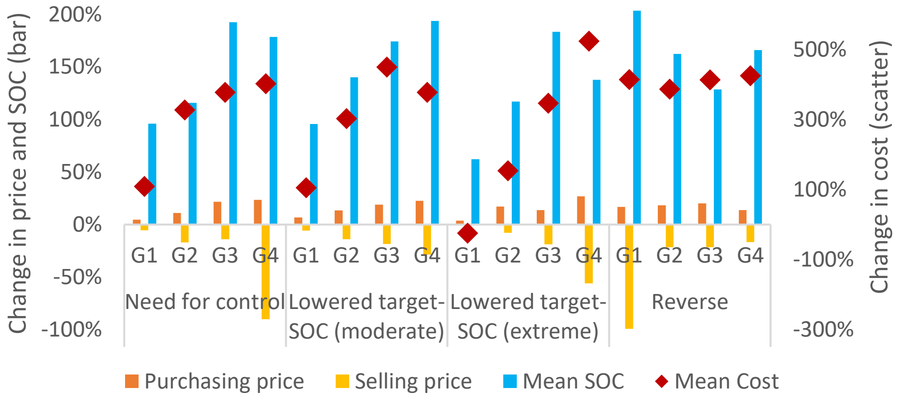
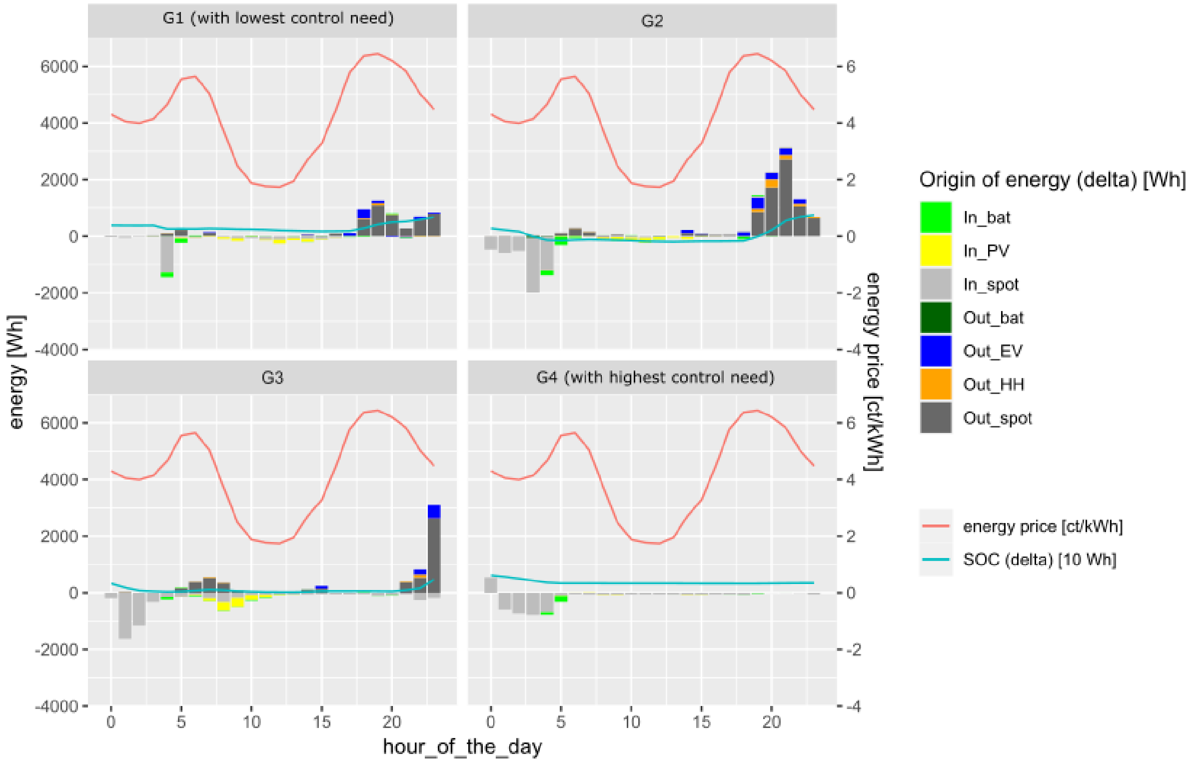


Figure 5-4: Changes in charging costs and underlying factors for all scenarios compared to the reference scenario (electricity cost only)

5.4.3 Effects of reducing the target-SOC

The following analysis tests the impact of reducing the target-SOC (compared to the *need for control* scenario) while the other control parameter, the DLC-level, remains the same. The results indicate that the highest cost savings result from a lower target-SOC combined with a high DLC-level. If a lower target-SOC is combined with a low DLC-level, the EV-user creates additional comfort (and electricity costs) by charging more than targeted. We first elaborate on the savings in the case of an extreme target-SOC reduction (i.e., a complete reduction to 0 kWh for G1 and G2, a 93% reduction for G3 and 40 % for G4), followed by a moderate target SOC reduction (i.e., 17 % per group).

G1's higher DLC-level leads to higher relative cost savings than G2. With a reduction of 7.05 EUR on their average monthly charging costs, G1 has the second-highest absolute and the highest relative savings per reduced target SOC (i.e., 0.76 EUR /target-SOC). G2, which displays the largest target-SOC reduction (17.2 kWh), has the highest absolute cost savings, a reduction of 9.22 EUR, and the second-highest relative savings (i.e., 0.54 EUR/target-SOC). The lower target-SOC allows both groups to charge more during the later morning hours with falling prices and discharge more during the evening price peak. Due to its higher DLC-level, G1 can align the discharging with the highest prices. In contrast, G2 delays discharging for a few hours to minimize the remaining time with a lower SOC (see Figure 5-5).

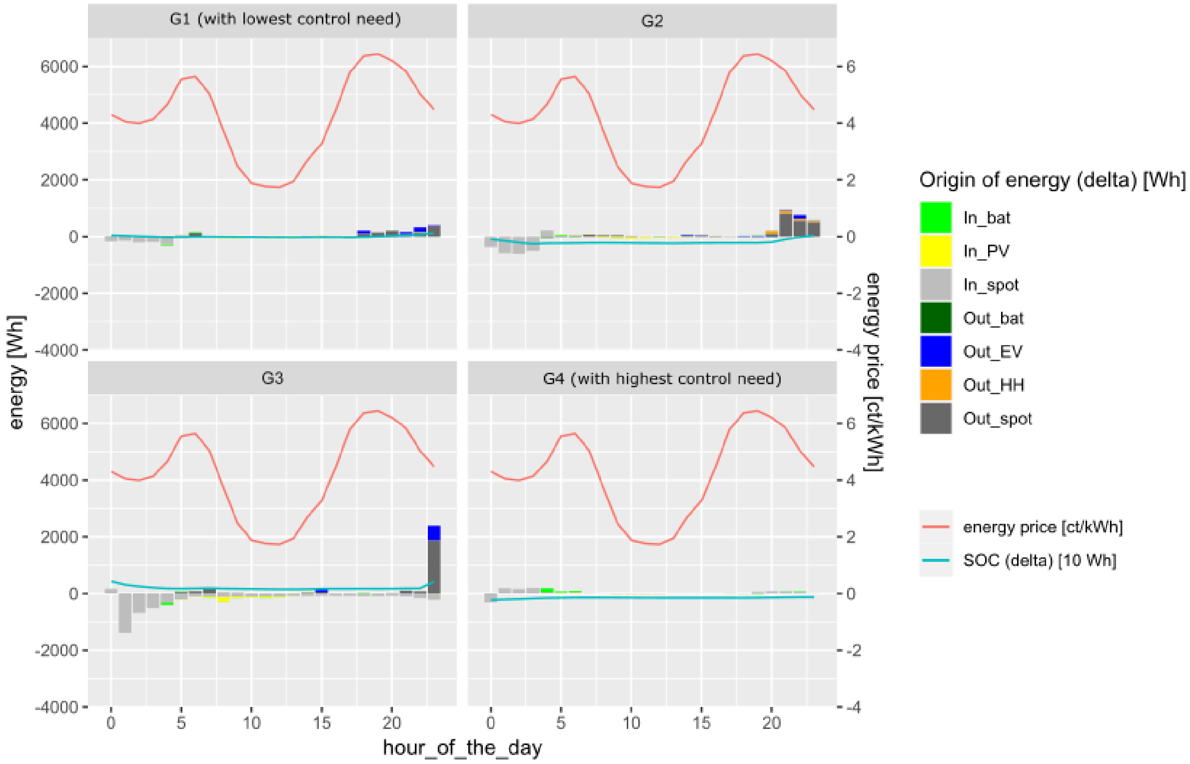


Note: Negative values correspond to higher values in need for control than in the lowered target SOC, and vice versa. The SOC values in Wh are divided by 10 to fit the primary x-axis

Figure 5-5: Delta calculation between scenarios lowered target SOC (extreme) and need for control for the in- and outflows of the flexible EV battery from different sources

Remarkably, G4's reduction of 12.4 kWh leads to an average monthly cost increase of 6.45 EUR (see Figure 5-4). Since G4 charges more electricity during the first hours of the day (see Figure 5-5) and reaches the target-SOC faster, it creates additional comfort by charging the EV-battery more than targeted. Lowering the target-SOC combined with a low DLC-level leads to (uncontrolled) surplus charging and increases costs.

The slightly increased price responsiveness due to the moderate target SOC reduction leads to minor cost savings (see Figure 5-4). The largest difference compared to the *need for control* scenario is for G3, whose monthly charging cost even increases by 3.82 EUR. G3's low DLC-level only allows the EV-battery to discharge at the end of the day. Although this charging strategy successfully decreases discomfort costs over the last hours, it requires additionally charged electricity at the beginning of the following day (see Figure 5-6). Optimization periods longer than one day are expected to reduce the particularity of discharged electricity at the end of the optimization period.



Note: Negative values correspond to higher values in need for control than in the lowered target SOC scenario, and vice versa. The SOC values in Wh are divided by 10 to fit the primary x-axis

Figure 5-6: Delta calculation between scenarios lowered target SOC (moderate) and need for control for the in- and outflows of the flexible EV battery from different sources

5.4.4 Effects of increasing the levels of direct load control

The previous section demonstrated that additional degrees of freedom for one control parameter, the target SOC, result in the greatest cost savings if they align with a similar degree of freedom in the other parameter, the DLC-level. We used a hypothetical scenario that reversed the values of both parameters to assess how varying both control parameters impacts the charging cost. We examine the difference in the charging costs if one or both parameters are switched from a restrictive value (target-SOC of 31 kWh and DLC of 0.844) to a relaxed one (target-SOC of 9.3 kWh and/or DLC of 0.211) (Table 5-3).

Table 5-3: Comparison of the extreme values of each control parameter w.r.t. the mean monthly costs, the mean SOC, the weighted average purchasing and selling price

Mean monthly charging cost [EUR]		*Target-SOC analysis*			***Mean SOC [kWh]***		*Target-SOC analysis*		
		9.3 kWh	*31 kWh*	**Diff.**			*9.3 kWh*	*31 kWh*	**Diff.**
DLC-level analysis	*0.211*	0.45	17.26	**16.80**	*DLC-level analysis*	*0.211*	18.66	25.31	**6.66**
	0.844	16.65	16.03	**-0.63**		*0.844*	28.88	26.51	**-2.37**
	Diff.	**16.20**	**-1.23**			**Diff.**	**10.22**	**1.19**	
Selling price for EV [EUR/MWh]		*Target-SOC analysis*			***Purchas. price for EV [EUR/MWh]***		*Target-SOC analysis*		
		9.3 kWh	*31 kWh*	**Diff.**			*9.3 kWh*	*31 kWh*	**Diff.**
DLC-level analysis	*0.211*	53.43	47.11	**-6.32**	*DLC-level analysis*	*0.211*	37.18	40.42	**3.24**
	0.844	0.45	5.63	**5.19**		*0.844*	41.53	43.84	**2.31**
	Diff.	**-52.98**	**-41.48**			**Diff.**	**4.35**	**3.43**	

Reading guidance for the tables

Indicator [metric]		*Target-SOC analysis*		
		Relaxed	*Restrictive*	**Diff.**
DLC-level analysis	*Relaxed*	Need for control for G1	Reverse for G4	**Diff. for relaxed DLC**
	Restrict.	Reverse for G1	Need for control for G4	**Diff. for restrictive DLC**
	Diff.	**Diff. for relaxed target-SOC**	**Diff. for restrictive target-SOC**	

The switch from a restrictive to a relaxed value results in similar charging cost savings for both control parameters. In fact, if one parameter is already defined in a relaxed manner, the switch of the other parameter creates higher savings (16.80 EUR for the target-SOC-switch or 16.20 EUR for the DLC-switch) than in the case of an already restrictively defined parameter (-0.63 EUR and 1.23 EUR).

How the two parameters affect the charging costs becomes apparent when looking at the weighted average prices and the average SOC. A relaxed DLC-level allows the service provider to select a more cost-optimal time to sell. In particular, the relaxed DLC-level of 0.211 leads to higher, more favorable selling prices (53.43 and 47.1 EUR/MWh) compared to the other combinations with a restrictive DLC-level of 0.822 (0.45 and 5.63 EUR/MWh). On the other side, a low target-SOC allows the EV-battery to be charged less fully, especially not during high-price periods, and results in lower purchasing prices (37.18 and 41.53 EUR/MWh) than the other two combinations with a high target-SOC (40.42 and 43.84 EUR/MWh, respectively).

Remarkably, combining both restrictive parameters leads to lower charging costs (16.03 EUR) than a combination with only one restrictive setting (16.80 EUR and 16.20 EUR). If only one control parameter is adapted, the other compensates for the EV-user's need for control, leading to higher charging costs. The implication is that service providers should aim for consistently chosen control parameters.

An easy-to-reach target-SOC combined with a restrictive DLC-level acts as a strong incentive to charge beyond this level for EV-users, since the restrictive DLC-level does not permit the service provider to enforce compliance with the target-SOC. This additionally charged electricity is apparent in the high average SOC of 28.88 kWh.

Conversely, a more relaxed DLC-level (i.e., lower weight of 0.211) creates fewer incentives to charge the EV-battery. As a result, it takes longer to cover the SOC delta. This inertia has a particularly strong effect when combined with a restrictive, high target-SOC. EV-users lack the incentive to meet the target-SOC and miss opportunities to optimize their charging costs by selling electricity.

In a sensitivity analysis in Appendix J, we illustrate the effect of varying other parameters from Section 5.3.3.2. Lowering the risk attitude exponent alpha $\boldsymbol{\alpha}$ has the strongest impact on charging costs. In this case, the marginal discomfort cost hardly decreases at the start of the optimization with an empty EV-battery and creates no incentive to charge electricity. We discuss the impact of the parameters affecting the diminishing marginal discomfort cost in Section 5.5.

5.5 Discussion

Our extension to the electricity cost optimization model of Kühnbach et al. (2022) allows us to systematically vary two parameters (target-SOC and DLC-level) that capture EV-users' need to retain control of charging and to explore the impact of these variations on the cost of charging in a future energy system with a higher share of renewables. If both parameters are set to provide greater degrees of freedom for the optimization, there is a disproportional increase in the additional cost savings. The prospect of additional savings incites EV-users to relinquish more control over their charging. However, if only one parameter is set to provide increased degrees of freedom, the other (constant) parameter offsets its positive impact on cost savings. Providers of smart charging services should try to incentivize that both parameters are set to maximize cost savings.

Our extended cost optimization analysis confirms expected findings but also reveals surprising particularities of EV-users' charging behavior. On the one hand, the model extension based on Prospect theory achieves its aim of reproducing common charging practices documented in the literature. It confirms that a higher need to retain control results in higher charging costs. On the other hand, the model revealed an unexpected correlation between relinquished control and cost savings (in particular, if only one parameter is adapted). In the following, we discuss how the modeling results support the interpretation of these unexpected correlations by exposing the underlying mechanism of control needs and charging cost.

The comparison of the household groups with different needs to retain control demonstrates that changes in the control parameters result only in additional cost savings of the same magnitude if parameters are aligned. If EV-users decide to switch to more relaxed control parameters, the average cost savings are larger for those who already have relaxed parameters than for those with more restrictive ones. The group with the lowest needs for control realizes an almost cost-optimal level of charging costs. A scale-free variation of parameters over a larger range would help to explore the correlation between control needs and costs. Our finding of disproportionally large savings should be subjected to further research.

Changing only one parameter demonstrates behavioral peculiarities (rebound effects and inertia) that are known from other social science studies of residential energy. If the target-SOC is reduced, but service providers are not allowed to ensure compliance (=low DLC), then EV-users are inclined to charge beyond the target-SOC for the comfort of having a higher SOC. Since a lower target-SOC achieves cost savings by reducing the urge to purchase a large amount of electricity during high-price periods, the additional charging offsets any potential cost savings. Conversely, if service providers are allowed to control the charging (=high DLC) but are faced with a high target-SOC, their focus on optimizing charging costs leads to a high SOC delta for an extensive period. The discomfort cost of a high SOC delta distorts the optimization. This is counterproductive, as the higher DLC-level is supposed to create cost savings by selecting a more cost-optimal time to sell electricity. Both findings demonstrate that the properties of the sloped PT value function are a good fit for capturing different behavioral peculiarities. How different slopes and their diminishing marginal discomfort costs affect these peculiarities is a subject for further research.

The empirically substantiated implementation of diminishing discomfort costs that drive EV-users' charging decisions captures common charging practices. It allows us to explore the interaction between EV-users and the electricity market systematically and based on empirical evidence. Nevertheless, we recommend caution with interpreting these findings for a future electricity market for two reasons. First, current EV-users' need to retain control might change in the context of our reference electricity system in 2030. Second, the composition of the EV-user group is likely to change with a more widespread adoption of EVs. Future EV-users are less likely to own private charging infrastructure and to relinquish more control of charging (Pelka et al. 2024b). These changes need to be examined in the future using updated empirical data or in countries where smart charging services are already more widely established.

Updating and extending the existing empirical data basis would increase the robustness of the results. Future research should seek to substantiate the monetary value of being able to drive by collecting subject- and time-dependent values. For instance, if they are ill, EV-users in remote areas may be willing to pay more for a sufficient SOC to drive to the hospital than healthy urban EV-users.

Apart from improving the empirical data basis of the model input, we propose two model adaptations to capture charging behavior more realistically. On the one hand, EV-users are expected to adapt the control parameters depending on their mobility experiences. If EV-users are unable to make planned trips, high discomfort costs occur, and they will select their control parameters more restrictively as a result. We recommend implementing a learning algorithm based on these experiences and a more targeted occurrence of unexpected trips (so far, only randomly implemented for different distances and points in time). On the other hand, EV-users are expected to optimize their charging over a longer time period. Participants of the field experiment described in Section 5.3.3.3 reported charging their EV every three days on average (Gabriel et al. 2022). Longer periods to optimize the charging process are likely to augment the differences between EV-users with varying control needs. As a future model adaptation, such longer charging periods could be implemented as longer, rolling optimization horizons.

For policymakers and service providers, our extended cost optimization reveals which changes in the control parameters have the biggest impact on saving charging costs and providing flexibility. Our recommendation to encourage equal relaxation of both control parameters might be in conflict with EV users' charging practices. In the field experiment described in Section 5.3.3.3, participants changed their target-SOC more frequently than their DLC-level. A possible explanation for this discrepancy is that the DLC-level is associated with greater uncertainties and other biases (e.g., concern about having to make unexpected trips), while the electricity needed to cover planned trips is easier to predict on a daily basis. Empirical research needs to identify EV users' preferences and conditions for accepting the transfer of control over both charging aspects.

5.6 Conclusion

We investigated how EV-users' need to retain control of charging affects them becoming flexibility providers for the electricity system. Our results suggest providers of smart charging services should encourage EV-users to transfer a greater degree of control of charging. Ideally, any relaxation of control should equally apply to both assessed control parameters, the target-SOC and the DLC-level, as they are mutually dependent. We arrived at these results by modeling EV-users' tradeoff between minimizing the discomfort of relinquishing control and minimizing the charging costs by implementing two cost elements in one cost-minimization function. This novel approach extends the current state-of-the-art in modeling smart charging. It allows us to consider the EV-users' need for more nuanced estimations of the flexibility potential and to make recommendations for the design of smart charging services.

Our results show that the charging cost savings for EV-users increase disproportionally if they lower their need to retain control of the charging. The prospect of additional savings incites EV-users to relinquish further control. We find that both control parameters, the level of DLC and the target-SOC of the EV-battery, are equally important for realizing electricity cost savings. While lowering the target SOC reduces the purchasing price and the amount of charged electricity, higher degrees of freedom when choosing the (dis-)charging timing (i.e., higher DLC) have a significant impact on the selling price.

We therefore encourage service providers to convince EV-users to transfer a greater degree of control for both parameters equally. If only one parameter is changed, the other (constant) parameter offsets the positive impact on cost savings. For instance, if the target SOC is reduced, but the service provider is not allowed to ensure its compliance via a high level of DLC, EV users are inclined to charge beyond the target SOC for the comfort of having a higher SOC. In real life, this inconsistent setting of control parameters is likely to lead to erratic, additional charging activities.

How households charge their EVs is strongly but not exclusively driven by electricity costs. Limited time, lack of perfect information (e.g., unscheduled trips), and competing needs (e.g., comfort of not planning ahead) strongly influence their decision-making. We successfully combine these cost- and comfort-driven aspects in our model extension and recommend further exploiting the synergies between empirical and model-based research. As a next step, empirical research is required to determine whether EV-users would be willing to transfer control over both control parameters equally in light of the potential charging cost savings.

6 Discussion

6.1 Role of consumer governance and its design challenge

How households consume and produce energy is affected by a set of arrangements that form what is known as *consumer governance*. These arrangements consist of formal rules set by policymakers and services offered by intermediaries. Policymakers (or regulators on their behalf) determine the formal rules by considering policy objectives, market developments, and stakeholder interests. The main stakeholder groups are households and the intermediaries who support them in adapting their energy use. Based on the formal rules set by policymakers, both stakeholder groups negotiate services to facilitate household participation. Usually, the services are settled in a contract between the household and the intermediary, which is often a commercial market actor. Examples of such actors that may take on the role of intermediaries are retailers, service providers, and aggregators. The intermediary provides a specific service to households, such as optimizing their EV operations with smart charging services or their distributed energy assets and battery storage with energy management services. In contrast to the formal rules, households can individually choose a service that best meets their needs. If all households choose similar services, then it becomes easier for intermediaries and policymakers to tailor all arrangements that are part of consumer governance to said services.

We frame the update of consumer governance as a design challenge to facilitate household participation, which is not possible with the current design. The consumer governance framework, presented in Chapter 2, reveals how the arrangements determine the organization of household energy use. In particular, they determine how certain *organizational functions* are performed. These functions, in turn, steer the technical functions of the energy system (i.e., generating, distributing, and consuming energy) toward both *household needs* as well as the policy objectives of a decarbonized, cost-efficient, and secure energy system. The consumer governance framework identifies eight organizational functions, which can be summarized under the following three categories (see Table 6-1):

i. Incentives set by policymakers;
ii. Organization of households' responses to the incentives;
iii. Tasks that enable the intended households' response.

The following paragraphs describe the eight functions of the framework. Then, in Section 6.2, we present recommendations for how to perform the functions.

(i) Incentives set by policymakers

The first category of organizational functions consists of incentives for households to adapt their energy use to the conditions of the energy system. The formal rules set by policymakers determine these functions. The incentives are provided through price signals and express the availability of renewable generation and grid capacity. The following three functions of consumer governance determine the character and magnitude of the incentives:

- How households receive access to price signals from the wholesale market (Function 1);
- How grid congestions are managed (Function 2);
- How taxes, levies, and other administrative price elements are allocated (Function 3).

The design choices for performing these functions range from having no price signals (resulting in a flat energy tariff) to conveying price signals from established markets and the grid to households or creating new markets for households. Table 2-2 provides more details.

(ii) Organization of households' responses to the incentives

The second category of organizational functions of consumer governance is determined by the services of intermediaries that facilitate households' responses to incentives. The services determine the following functions:

- The extent to which intermediaries preprocess the price signals before conveying them to households (Function 4);
- Whether the household or the intermediary is in charge of adapting the energy use based on price signals (Function 5);
- How investments should be coordinated if households do not already own energy assets (Function 6).

Energy use can be adapted by curtailing electricity from distributed generation assets, by shifting the consumption of flexible technologies, or by discharging battery storage.

(iii) Tasks that enable the intended response of households

The following functions fall under the third category of organizational functions of consumer governance:

- Collecting household consumption and generation data (Function 7);
- Billing the consumed energy (Function 8).

Intermediaries usually perform these two functions. However, the functions are strongly regulated by policymakers to ensure a level playing field for services that organize households' responses.

If the eight functions of the framework are performed in such a manner that the benefits of participation offset its burden (i.e., monetary and non-monetary costs, such as effort and discomfort), then households can be assumed to adapt their energy use to the conditions of the energy system.

However, the current design of these functions does not enable households to realize the benefits of adapting their energy use (see Chapter 2). Nevertheless, an advantage of the current governance design is a low burden on households. A supply contract with a flat energy tariff allows households to consume energy under the same conditions whenever they want. Nevertheless, households' uncoordinated energy use leads to the inefficient operation of generation and grid infrastructures, as well as to potentially high energy system costs. Therefore, the current consumer governance design does not take advantage of the potential of residential energy assets for decarbonizing the energy system.

Moreover, to the best of our knowledge, no coherent governance design has been proposed that determines all of the required functions for organizing household energy use. The proposals in the literature typically focus on individual functions and provide different design choices for them. Thus, we provide recommendations for a coherent governance design that facilitates household participation in the following sections.

6.2 Design choices for needs-driven consumer governance

An updated governance design should exploit the benefits of adapting household energy use while carefully considering the additional burden imposed on households. The level of benefits and burdens depends on the specific *needs* of households. The literature overview in Chapter 2 presented the range of existing household needs (see Table 2-1). The key household needs are listed as follows:

- To contribute to the decarbonization of the energy system;
- To realize energy cost savings;
- To limit operational burden;
- To safeguard data privacy;
- To have control over consumption.

Household participation in the energy system contributes to decarbonizing the energy system. This household need is implicitly fulfilled by updating the governance design. By contrast, whether the other needs are met—and to what degree—depends on *how* the functions are performed.

Where the literature proposes alternative ways of performing certain functions, they are in terms of specific subsets of recognized household needs. Here, a research gap arises as a single governance design cannot meet all household needs and their priorities are ambiguous. Through this dissertation, we contribute to the debate on consumer governance by categorizing the existing proposals into a function-based inventory, clarifying households' priorities, and identifying design choices that fit them.

Our empirical research demonstrates that a governance design should focus on enabling households to achieve energy cost savings, convincing them to participate by safeguarding their need for control, and keeping them involved by limiting their operational burden. Chapter 2 demonstrated that no single consumer governance design exists under which all identified household needs are sufficiently met.

One reason for the mismatch between designs and needs is that some needs result in design choices that are mutually exclusive. Thus, one way to arrange a function for fulfilling one need would conflict with another need. For instance, if intermediaries operate the energy assets on households' behalf (Function 5), then this choice fits with the household need to limit one's operational burden. Simultaneously, this choice conflicts with the need to retain control over one's consumption. Such mutually exclusive design choices require a tradeoff in the design.

In this dissertation, we provide recommendations for the design choice of each function in three steps. First, Chapter 2 presented recommendations for the design choices that are not mutually exclusive. They do not conflict with other household needs (e.g., different options for pricing grid congestions). Independent of which design choice is selected, none of them violate another household need, which is the case for five of the eight functions. Second, Chapters 3 and 4 identified the priorities of the conflicting household needs for two further functions. They were revealed by asking households to select one of the mutually exclusive design choices. For instance, we found that households do not mind sharing data to optimize their energy trading as long as they realize energy cost savings. Thus, energy cost savings are more important to households than data privacy. Third, Chapter 5 dealt with the last remaining function, for which we could identify no clear priorities. We modified the design to find a reasonable balance between conflicting needs. In particular, we balanced the conflicting needs for control and limited the operational burden by giving households the right to intervene in the optimization of an intermediary. The right to intervene is formalized in service settings.

We summarize the recommendations for the design choices in the following subsections, starting with recommendations for non-mutually exclusive design choices (Subsection 6.2.1); then, we continue with two recommendations based on prioritized needs (Subsections 6.2.2 and 6.2.3); and lastly, we end with a recommendation for a modified design choice to balance conflicting needs (Subsection 6.2.4). Table 6-1 presents a compact summary of the recommended design choices, including which chapter provides the underlying analysis for each recommendation. A description of each design choice can be found in Section 2.3.

Table 6-1: Recommended design choices (marked A–C) for each function (numbered 1–8)

Function category	Function	Recommended design choices (incl. those from Chapter 2 that are not mutually exclusive)	Chapter reference
(i) Incentives set by the regulator	F1. Matching electricity and flexibility	A. Aggregation	3
	F2. Congestion management	B. Congestion pricing or C. flexibility market	2
	F3. Allocation of administrative price elements	B. Capacity-based or C. fixed	2
(ii) Organization of households' response	F4. Pricing for consumers	C. Business model	4
	F5. Operation of energy assets	B. Direct coordination	5
	F6. Investment in energy assets	A. Individual investment or B. collective investment or C. investment-as-a-service	2
(iii) Tasks that enable households' response	F7. Data collection	B. High resolution and frequency of metering	2
	F8. Billing	B. Continuous billing	2

6.2.1 Design recommendations without need tradeoffs

In this subsection, we present recommendations for design choices that result from the design inventory of Chapter 2. They do not conflict with the identified household needs.

(i) Incentives set by the policymakers

Consumer governance should ensure that households have access to price signals that express the availability of renewable electricity and grid capacity. For grid-based price signals, distribution grid operators should price the usage of the limited grid capacity to manage grid congestion. However, in most countries, the implemented design choice for congestion management takes the form of distribution grid operators intervening in household energy use (design choice 2.A). Based on our research, two alternative design choices are recommended for managing congestion with grid-based price signals. Variable network tariffs integrate price signals into households' electricity tariffs (design choice 2.B). Alternatively, flexibility markets can be introduced (design choice 2.C), which build on the premise that using the grid is a right that households can trade on a market.

Furthermore, taxes, levies, and other administrative price elements should be allocated in a way that does not diminish price signals or at least as little as possible. Over the last decades, policymakers in most countries have decided to allocate them with each consumed kilowatt-hour (design choice 3.A). This choice incentivizes reductions in energy consumption. Simultaneously, it lowers the grid- and market-based portions of the retail energy price, which signals whether households overuse the grid or the generation capacity in moments of scarcity. As less distortive alternatives, we recommend allocating administrative price elements based on households' maximum capacity (design choice 3.B) or a lump sum (design choice 3.C).

(ii) Organization of households' responses to incentives

Two of the three functions of the second category are subject to conflicting household needs, as we discussed in the previous section. However, this is not the case for the function of investments in energy assets. Households have more leeway to adapt their energy use if they own energy assets, such as distributed generation assets, flexible technologies (e.g., EVs and heat pumps), and stationary battery storage. Investments by individual households (design choice 6.A) are the most common design choices for investing in energy assets. However, they require certain financial means and property ownership. If households own a house but do not have the financial means to invest in energy assets, then intermediaries can invest instead of them and offer the usage of the energy asset as a service (design choice 6.C). If households do not own a house and do not have the financial means, participation can still be arranged through collective actions, which enable households to invest smaller amounts in jointly owned energy assets (design choice 6.B). While this design choice can lead to investments in more cost-efficient, large-scale energy assets, it also requires more coordination between the investing parties. All three design choices should be part of consumer governance since they enable investments in energy assets for different household groups.

(iii) Tasks that enable households' response to incentives

To organize households' response to price signals, the intermediaries must receive consumption and generation data of a high resolution and frequency from households' smart meters (design choice 7.B). In return, they should report their performance to households more frequently in an energy bill (design choice 8.B). The current form of data collection and billing is yearly metering (design choice 7.A) and billing (design choice 8.A), which provides an insufficient data basis for planning and inciting adaptations in household energy use. For instance, without high-resolution data, distribution system operators cannot associate a solved grid congestion issue with the consumption shifts of a household and reduce network tariffs accordingly.

In summary, we provide recommendations for the functions with the least potential for conflict. Policymakers should set incentives with price signals from the grid (based on variable network tariffs or flexibility markets) without the distortions that can arise from volume-based administrative price elements. To respond to these price signals, intermediaries should facilitate different forms of investments in energy assets for households. Moreover, household energy use should be monitored and adapted based on high-frequency and -resolution smart meter data.

The three remaining functions are subject to design tradeoffs with regard to household needs. They concern the design of market-based price signals (Function 1; see Subsection 6.2.2) and the organization of the response to said signals (Functions 4 & 5, see Subsection 6.2.3). No clear priority for household needs exists for Function 5 on the operation of energy assets. Therefore, we modify the design to find a reasonable balance in the tradeoff between conflicting needs in Subsection 6.2.4.

6.2.2 Design recommendation for tradeoff 1: Identifying priorities for matching electricity and flexibility

Designing market-based price signals is more challenging than designing the other incentives in the first category of functions. Policymakers must decide between giving residential energy assets access to the existing wholesale market (design choice 1.A) and creating a specific market for households to match their energy demand and supply (design choice 1.B).

Market-based price signals indicate the equilibrium between the demand for and supply of energy in a market. Larger markets are more liquid and result in a more cost-efficient dispatch of demand and supply. Households can only benefit from the cost-efficient dispatch of the existing wholesale market if households' energy assets meet the requirements of the market access regulation. This can be realized by aggregating the energy of the energy assets (e.g., self-generated electricity and demand-side flexibility) in a virtual power plant (design choice 1.A). Nevertheless, the requirements create an additional burden and impose an obligation on households to share their smart meter data. These data are used to prequalify and register the energy assets, develop forecasts and bids, and verify the amount of traded energy. Local energy markets are an alternative to aggregation with lower requirements for market access and data sharing (design choice 1.B). However, the dispatch is less cost-efficient due to the limited market size.

The results from Chapter 3 reveal that the most critical priority for households when choosing a service is to effectively and efficiently realize energy cost savings. They will be willing to share their data if they realize cost savings. Their prioritization of energy cost savings leads to our recommendation for aggregating and trading their energy on the wholesale market (design choice 1.A).

6.2.3 Design recommendation for tradeoff 2: Identifying priorities for pricing for consumers and the operation of their energy assets

The design choices for organizing households' response create a dilemma for them. When selecting a design choice, households must prioritize between retaining control over consumption and limiting the operational burden. If intermediaries preprocess the price signals to variable tariffs (design choice 4.A), then they put households in a position to adapt their energy use self-sufficiently (design choice 5.A); thus, they retain control over it. Alternatively, if intermediaries adapt the energy use on households' behalf (design choice 5.B), then they limit the operational burden on households. Instead of being exposed to price signals and controlling their energy consumption, they receive the energy cost savings as a lump sum at the end of the settlement period (design choice 4.C).

The results of this dissertation reveal that households' priorities vary between the participation stages (i.e., when selecting a service that supports household participation and when operating the service). Retaining control over consumption is the second-most critical priority after realizing energy cost savings when selecting a service (see Chapter 3). Households do not prioritize limiting the operational burden at the selection stage; rather, this need emerges during the operation stage. The field trial from Chapter 4 demonstrated that the self-dependent responses of households (design choices 4.A & 5.A) are less effective at realizing cost savings than the responses by the intermediary (design choices 4.C & 5.B). In the case of intermediary responses, household needs for limiting the operational burden and realizing energy cost savings are met. However, since households were allowed to overrule the response of the intermediary in the field trial, they also retained control over their consumption to some extent.

Unsurprisingly, priorities vary between the participation stages because households become more knowledgeable and different areas of their lives are affected (Sloot et al. 2023). Households may reassess their priorities based on emerging needs and experience with the service. A risk exists that needs that emerge in the short term (i.e., when operating the service) override households' intention to realize energy cost savings in the long term (i.e., when choosing the service).

We refine the tradeoff for organizing the households' response in the sense that its design choice should ensure a balance between short- and long-term needs. This notion of present bias is well known from intertemporal decisions such as pension savings and healthy food choices. Still, it has received little attention in governance questions for energy behavior (O'Donoghue and Rabin 2015). Intermediaries are likely better positioned than households to anticipate emerging needs due to their experience with the services. They should emphasize the burden of self-dependent responses of households (design choices 4.A & 5.A) and prioritize responses by themselves in their service portfolio (design choices 4.C & 5.B). They support households in making more informed and balanced decisions when choosing a service.

Nevertheless, the needs were found to be less heterogeneous among the household groups than we originally hypothesized. Our empirical research confirms variations in needs over the participation stages but not between household groups. Chapter 3 demonstrated that the needs do not appear to vary systematically depending on which flexible technology the households have (i.e., EVs or heat pumps) or whether they own or only intend to purchase the technology. The common priorities of cost savings and control form an argument for a unified service design across technologies and adoption levels.

Overall, if intermediaries adapt the operation of energy assets on households' behalf (design choices 4.C and 5.B), then households realize energy cost savings relatively more effectively and efficiently. These design choices imply a low operational burden for households but also a loss of control over consumption. The field trial in Chapter 4 demonstrated that the design choices can be modified to allow households to retain some control. In the following subsection, we examine how a modified design balances household needs for control and energy cost savings.

6.2.4 Design recommendation for tradeoff 3: A modified design for balancing ambiguous priorities for the operation of energy assets

If intermediaries respond to price signals on households' behalf (design choices 4.C & 5.B), then they meet the need for realizing energy cost savings with low operational effort. The field trial in Chapter 4 demonstrated that these design choices can meet the need to retain control to some extent if intermediaries give households the right to intervene in their optimization. This right can be formalized in service settings. Their design ensures a balance between the conflicting short-term needs (i.e., low operational burden and control) and long-term needs (i.e., realizing energy cost savings).

The settings should be designed such that households are guided in making conscious decisions on the tradeoff between short- and long-term needs. If households adjust the settings to express their consumption needs, then they may intervene in the optimization that is supposed to realize energy cost savings. Such short-term needs should be safeguarded.

To this end, intermediaries should design settings for automated services through the following three steps: First, they must identify suitable settings that capture household consumption needs; second, they must choose reasonable default values that balance short- and long-term needs and avoid excessive overriding by households; and third, if households adjust the default values, just-in-time prompts should be used to warn them about how the adjustment will affect their energy cost savings.

We examined these steps for households with EVs and smart charging services in Chapters 4 and 5. Referring to the first step, if households activate a smart charging mode to optimize the charging process, then they can express their mobility needs based on two setting parameters—namely the targeted state of charge and restrictions on charging timing. For the second step, we set a smart charging mode as the default and tested its impact in the field trial presented in Chapter 4. As outlined in the previous chapters, having smart charging as the default mode leads to significant cost savings for households.

The third step involves adjusting the setting parameters. A common charging practice of households is to charge immediately and for longer than required. Households tend to determine the setting parameters of smart charging services in line with this charging practice, thereby safeguarding their mobility needs. When households adjust the setting parameters by lowering the targeted state of charge and not intervening in the optimized schedule, this conflicts with the aforementioned common practice but reduces their charging costs. By adjusting the setting parameters, households express their tradeoff between these long- and short-term needs. In Chapter 5, we captured both needs in an agent-based model and tested whether adjustments to setting parameters resulted in a reasonable balance for the tradeoff.

The modeling results revealed that comfort-driven charging offsets energy cost savings, even if households attempt to realize savings by adjusting one of the setting parameters. However, energy cost savings are only realized if both setting parameters are adjusted. The comfort-driven charging that offsets the savings exhibits common behavioral particularities, which are known from empirical research. For instance, lowering the targeted state of charge leads to rebound effects if households do not comply with the optimized charging schedule. They are inclined to charge beyond the targeted state for the comfort of having a fully charged EV (Jing Liang et al. 2022; Gschwendtner et al. 2021). Moreover, compliance with the optimized schedule with a high targeted state of charge provides little leeway for minimizing charging costs (Schmalfuss et al. 2015).

The setting design should guide households in making conscious tradeoffs between comfort-driven and cost-optimal consumption. In the case of smart charging services, just-in-time prompts could notify households about their unbalanced parameter adjustments and their impact on charging costs. Based on this information, households can decide to lower both parameters for cost savings or prioritize the comfort of a fully charged vehicle. Thus, the setting design would avoid frustration along the path of becoming an active participant of the energy system.

6.3 Scientific contributions

The design process, on which this dissertation is based, identifies and solves tensions between the design choices based on a multi-method approach. The starting point was a literature-based inventory of design choices. The design steps based on empirical and model-based research generated new insights for the design choices. In particular, the vignette study (see Chapter 3) and the field trial (see Chapter 4) identified households' priorities in different participation stages and revealed conflicts between the stages. In Chapter 5, our agent-based model captured the conflicting needs and tested which design choices resulted in a reasonable balance between them. Thus, after each design step, the design for consumer governance could be further specified. Thereby, the contributions of this dissertation cover both content-related (Subsection 6.3.1) and methodological aspects (Subsection 6.3.2).

6.3.1 Content-related contributions

This dissertation provides advice for designing governance that incites more participatory interactions between households and the energy system. It assimilates the point of view of the individuals, the energy system, and the intermediaries who coordinate between them. The content-related contributions are part of the transition from the problem into the design space of consumer governance. They encompass the identification of household dilemmas in the problem space, the application of transaction cost theory as the theoretical foundation of the design space, and the development of a coherent governance design. The latter also refines the role of intermediaries. The research presented in Chapters 2–5 contributed equally to the following four content-related contributions:

Revealing the dilemmas of participation with a broader perspective on household needs: The conflict potential of intertemporal changes in household needs can only be identified if research covers different stages of participation. The potential reasons for changes in needs are manifold. The most important factors identified in this dissertation are as (i) the accumulation of information over time; (ii) stages that affect different areas of life; and (iii) an intention–action gap. Said gap could be driven by overly ambitious intentions (e.g., due to socially desirable responses) or behavioral biases during the action (e.g., immediate gratification bias). For instance, the comfort of having a fully charged vehicle may outweigh the objective of saving on charging costs. The combination of a vignette survey on stated needs and a field trial on revealed needs revealed the conflicts between the stages.

Applying transaction cost economics to household participation in the energy system: To the best of our knowledge, this dissertation represents the first application of transaction cost determinants in the case of household participation in the energy system. We confirm the fit of the determinants for examining the viability of a consumer governance design. Thus, transaction cost economics builds links between common research activities in the field of household participation. On the one hand, it expands the cost notions of neoclassical economics, which is the basis of most energy cost optimization models. On the other hand, the tradeoff between transaction costs and benefits captures household needs that are examined in social science.

Designing coherent, needs-driven consumer governance: We have demonstrated that existing proposals for consumer governance do not define all of the functions required for organizing household energy use. The consumer governance design framework and its inventory of functions and design choices reveal the common and distinctive design choices of the proposals and which household needs they target. Based on this inventory, we have identified gaps in the design, clarified priorities for conflicting household needs, and provided design choices that meet them.

Refining intermediaries' role in facilitating interaction between households and the energy system: Finding a reasonable degree of involvement and interaction is a core issue for household participation, particularly how intermediaries should preprocess price signals for households and how households should communicate their consumption needs to intermediaries that coordinate their energy use with the energy system. The research scope of consumer governance has allowed us to examine these questions at the joint interfaces between households, intermediaries, and policymakers. We advise intermediaries to respond to price signals on households' behalf as much as possible. By offering households the right to override the response, intermediaries will gain their trust. The services offered by intermediaries should include default settings that allow them to respond and optimize household energy use despite household inertia. Moreover, they should inform households of the consequences of overriding their response and make conscious decisions about it.

6.3.2 Methodological contributions and strengths

We placed a special emphasis on methods that ensure coherence in the governance design, identify changes in household needs during the participation stages and between household groups, and capture these needs in an agent-based model to test its impact on the energy system. Chapters 2 and 5 contributed to the newly developed framework and the integration of behavior in energy system models. As a strength of this dissertation, the empirical research in Chapters 3 and 4 combined existing methods and developed them further for new research challenges.

Developing a design framework for consumer governance: The framework developed in Chapter 2 ensures that existing proposals for consumer governance fulfill the required functions for organizing household energy use. It enhances the coherence between design and household needs in research. In particular, scholars who conduct research in the problem or design space of consumer governance will be able to expand it to the space that has been uncovered. On the one hand, if scholars detect changing household needs in the future, they will be able to derive recommendations for consumer governance design. On the other hand, they can more easily link upcoming developments in consumer governance to the needs they aim to address.

Moreover, the framework and its inventory of functions and design choices provide a basis for future design iterations if needs change in the future. Experience in taking on an active role, the involvement of household groups other than those represented in this dissertation, technological innovations, and price developments may all be reasons why households require change. These trends were not covered in the empirical work of this dissertation. For instance, households whose conditions do not allow them to invest individually in energy assets are only partly represented. Collective investments in energy communities could enable them to participate actively. Identifying design choices for the operation of collectively owned energy assets is a subject for further research.

Examining heterogeneity in household needs: We examined heterogeneity in household needs in sub-group analyses. The analyses were enabled through the development of a survey design in Chapter 3 that was both concrete (to ensure that the households can relate to it) and generic (to be applicable to different sub-groups of households). Furthermore, our empirical data provided sufficient analytical power for the sub-group analyses. The vignette survey involved 962 German households that owned or intended to own different flexible technologies. The field trial presented in Chapter 4, which lasted 1.5 years and involved 111 German households, created a rich panel data set for a technology-specific analysis.

Comparing causal effects between different nudging interventions in one field trial: The effect size of nudging interventions in the literature varies strongly between the kind of nudge and the context of the experiment. Following the testing of three nudges in one randomized controlled trial, Chapter 4 presented the causal effects that allowed the interventions to be compared. The experiment design accounted for households' learning effects by accumulating the nudging interventions over time and testing only the incremental changes of the newly added nudge. The experiment design, combined with state-of-the-art methods for causal effects, effectively managed confounding factors such as price shocks and weather changes.

Modeling behavioral aspects of charging: The agent-based model developed in Chapter 5 determined the impact of design choices on the tradeoff between conflicting needs. The case of smart charging demonstrated the risk that emerging needs in the short term (e.g., comfort-driven consumption) override long-term needs (e.g., cost-minimizing consumption). We extended an agent-based model with behavioral charging aspects that were captured by Kahneman's prospect theory and supported by empirical data. This extension made it possible to iterate through a set of modified designs without collecting new empirical data and also to identify the ones that result in a reasonable balance between the conflicting needs.

7 Conclusion

7.1 Overview

In its current design, the governance of household energy use does not facilitate their participation in the energy system. Households' conflicting needs with respect to their participation complicate the selection of a new design based on the multiple proposals available in the literature. By answering the following research question, this dissertation provides advice regarding a new consumer governance design:

> **How can one design governance that facilitates household participation in the energy system?**

Our empirical research demonstrates that a governance design should focus on enabling households to achieve energy cost savings, convincing them to participate by safeguarding their need for control, and keeping them involved by limiting their operational burden. A governance design, such as virtual power plants offered by aggregators, matches most priorities of households: It effectively and efficiently realizes energy cost savings by aggregating household energy for trading. Its automated response to price signals on households' behalf limits their burden of participation. However, three pitfalls exist that need to be incorporated into the design.

First, the comfort of consuming whenever one wants and having a low operational burden are latent household needs that emerge during operation. Such short-term needs jeopardize the fulfillment of long-term needs, such as energy cost savings. Chapters 3 and 4 illustrated this dilemma. When choosing a service to facilitate household participation, the most popular choice facilitates it by responding to price signals on behalf of households. The second most popular choice empowers households to respond by themselves by sending price signals. The results from the operation of these services indicate that the self-dependent responses of households lead to lower energy cost savings than automated responses made on their behalf. Anticipating this dilemma and incorporating upcoming needs early in the design are key challenges for consumer governance.

Second, well-designed settings for automated responses enable households to express their consumption needs and balance them with other conflicting needs. The dilemma of short-term needs that offset long-term ones remains with the design of the settings. Just-in-time prompts should avoid frustration for households if some setting adjustments do not lead to the desired energy cost savings. In the case of smart charging, Chapter 5 demonstrated that adjusting only one setting parameter favors impulsive, comfort-driven charging and offsets the desired cost savings. Smart charging services only realize energy cost savings if all setting parameters are adjusted equally. Well-designed services notify households about their unbalanced adjustment and encourage them to decide consciously between the comfort of having a fully charged EV and saving energy costs.

Third, formal rules must ensure households access to price signals and smart metering infrastructure. Policymakers are in charge of providing reliable conditions, based on which intermediaries create innovative, needs-driven services for households. A sound interplay between the formal rules of policymakers and the services of intermediaries constitutes a viable consumer governance design.

If households require change in the future, the developed consumer governance design framework and its inventory of design choices presented in Chapter 2 provide a basis for future iterations of the design process.

7.2 Research outcomes

This dissertation answered the main research question by performing a complete design process for consumer governance. The design steps involved empirically identifying household needs, choosing a design that matches them, and examining its impact on the household and the energy system. The design steps formed the following four SRQs:

1. Which governance designs are proposed in the literature for facilitating household participation in the energy system?
2. Which needs do households prioritize when deciding to participate?
3. Which needs do households prioritize while participating?
4. How can conflicting household needs be balanced in the governance design?

In response to SRQ 1, an inventory of the designs proposed in the literature was created. The research for SRQs 2 and 3 examined household needs as design requirements at different participation stages (i.e., when choosing a service to participate in the energy system and when operating it). Based on the design inventory, designs that match the identified needs were proposed. The research for SRQ 4 tested the impact of the proposed design on households and the energy system and proposed adjustments to balance conflicting household needs. The following four subsections discuss the research outcomes for each SRQ.

7.2.1 SRQ 1: Which governance designs are proposed in the literature for facilitating household participation in the energy system?

In the literature, multiple proposals have been presented for governance designs that facilitate household participation in the energy system. Chapter 2 summarized them under four distinctive governance designs—namely variable tariffs, virtual power plants, local energy markets, and energy communities. The four designs perform the functions required for organizing household energy use in different ways. The functions concern the incentives to participate, the means for households to respond to them, and the underlying tasks for enabling responses.

None of the design proposals performs all of the required functions: Energy communities coordinate collective investments in energy assets but do not define how to operate them, while the other proposals focus on the operation of the assets without specifying the coordination of their investments.

The design proposals are distinguished by how they organize market access for households, the extent to which households respond to price signals by themselves, and who coordinates the investments in energy assets. Energy communities are characterized by the latter, while the distinction between the others focuses on market access and response coordination. Local energy markets create their own markets for trading household energy. Virtual power plants aggregate and trade the energy on existing markets, performing the response to price signals on behalf of households. By contrast, variable tariffs enable households to respond self-suffciently.

Furthermore, each design proposal addresses different household needs. Virtual power plants effectively and efficiently realize energy cost savings and limit the operational burden for households; variable tariffs allow households to retain control of their consumption; local energy markets safeguard their data privacy and accelerate local value creation; and energy communities enable collective investments for households whose conditions do not allow them to invest individually in energy assets.

Moreover, conflicting household needs impede the convergence into one viable, coherent governance design that facilitates household participation in the energy system. Households face tradeoffs between contrasting designs that only fulfill one need or the other.

7.2.2 SRQ 2: Which needs do households prioritize when deciding to participate?

As part of consumer governance, households prefer data-driven, automated services when selecting a service for organizing demand response. They prefer them to other services since they effectively and efficiently realize energy cost savings. This prioritized need outweighs other needs, such as the need to safeguard data privacy. As the second most important need that the service should fulfill, households claim the right to retain control over their consumption.

Chapter 3 presented these results based on a vignette survey of German households (n = 962). The participants owned or intended to purchase a flexible technology, such as an EV, heat pump, or stationary battery. The vignette survey put them in the position of choosing between conflicting service designs for optimizing the consumption of their flexible technologies.

The needs were found to be less heterogeneous among the household groups than expected. The preferences did not fundamentally differ between the type of flexible technology and the adoption level. Contrary to our expectations, EV owners had no stronger control needs than households with other flexible technologies. Moreover, no stronger comfort needs were found for households that do not yet own flexible technologies than were found for their present owners. Common preferences speak for a unified design across technologies and adoption levels.

7.2.3 SRQ 3: Which needs do households prioritize while participating?

While households do not prioritize limiting the operational burden when selecting a service, they do exhibit a clear need to limit it when operating the service. The field trial (n = 111; Chapter 4) demonstrated that services with automated consumption adjustments realize energy cost savings more effectively than services that request households to adjust their consumption by themselves. The field trial tested different ways in which households adjust their consumption to increase the share of self-consumed electricity from their rooftop photovoltaic panels. Through increasing their self-consumption, households claim to realize energy cost savings.

The design choices for consumption adjustments can limit the operational burden or safeguard households' control needs. The field trial tests which of both needs were more compatible with households' priorities for energy cost savings. Therefore, the participants received three interventions on their digital devices. In the first two interventions, two sets of information—one with simple feedback and one with a historical comparison—enabled them to adjust their consumption self-sufficiently. By contrast, the third intervention changed how the participants' EVs were charged. Specifically, a default was introduced to charge the vehicles exclusively with self-generated electricity. The default realized energy cost savings more effectively and efficiently than the interventions that required self-dependent adjustments by households. While the latter led to a small increase in self-consumption (3–4%), the default led to a 16% increase for active participants. Such automated adjustments limit the operational burden for households and are in line with their main priority of energy cost savings.

7.2.4 SRQ 4: How can conflicting household needs be balanced in the governance design?

Adjustable settings for automated responses are one option for allowing households to express their consumption needs. As illustrated in the field trial (Chapter 4), this option is especially suitable for smart charging since the consumption needs can be expressed based on a limited set of parameters (e.g., the targeted state of charge at the time of departure) and are based on predictable routines (e.g., daily rides to work).

Chapter 4 demonstrated that if households' inertia leads to no setting adjustment, then system-friendly default settings will effectively ensure energy cost savings. Thus, the settings balance households' control needs while limiting the operational burden.

Moreover, if households adjust the settings to express other consumption needs than the default, then they will intervene in the optimization that realizes energy cost savings. Consumer governance can guide households to make conscious decisions on the tradeoff between short-term consumption needs and their long-term priority of energy cost savings. Such guidance is especially relevant when households charge immediately and longer than necessary to cover their mobility needs for comfort. When setting charging parameters in this manner, households with cost-saving intentions should be notified.

In Chapter 5, we tested the impact of adjustable smart charging settings. Smart charging services optimize households' charging processes given two settings—namely the targeted state of charge and restrictions on its timing. Lowering the targeted state of charge and not intervening in the optimized schedule may affect households' mobility needs but reduce their charging costs. We examined the impact on charging costs of different levels for both settings in an agent-based model with EV users who optimize the charging cost and comfort of a fully charged EV.

The modeling results revealed that comfort-driven charging offsets the energy cost savings, which households aim to realize by adjusting the settings. This was the case when only one setting parameter was adjusted (i.e., a lower targeted state of charge or fewer time restrictions). The other setting parameter favors comfort-driven charging and offsets the intended cost savings. Unbalanced setting adjustments are ambiguous regarding whether households prioritize cost savings or comfort-driven charging. Services must clarify this ambiguity to avoid causing frustration and undermining households' intentions to optimize their charging.

The comfort-driven charging in the model expresses common behavioral particularities that are known from empirical research. For instance, lowering the targeted state of charge leads to rebound effects if households do not comply with the optimized charging schedule. They would be inclined to charge beyond the targeted state for the comfort of having a fully charged EV. Moreover, compliance with the optimized schedule with a high targeted state of charge provides little leeway for minimizing charging costs.

The setting design should guide households in making conscious decisions regarding their ambiguous priorities for comfort-driven and cost-optimal consumption. In the case of smart charging services, just-in-time prompts can be used to notify households about their unbalanced setting adjustment and its impact on charging costs. Based on this information, households can decide to reduce both settings for cost savings or prioritize the comfort of a fully charged EV. Thus, the setting design will avoid frustration along households' path to becoming an active participant in the energy system.

7.3 Recommendations for intermediaries & policy implications

Consumer governance ensures that household energy use is organized so that the needs of households and the energy system are met. If household energy use follows the price signals of the energy system, then costs are saved for households and the energy system simultaneously. Households' comfort-driven energy consumption sometimes contradicts cost minimization on both sides. Thus, more coordination is required to balance these conflicting needs.

Moreover, consumer governance consists of voluntary contracts between intermediaries and households and the formal rules of policymakers (or regulators on their behalf). Formal rules set the conditions for intermediaries and households to form arrangements. If they are unsuitable for creating innovative arrangements, then intermediaries have the means to stress the need to revise them (e.g., lobbying). Policymakers and intermediaries perform different functions of consumer governance: While policymakers are in charge of setting incentives, intermediaries organize households' responses to them. In this dissertation, our empirical and model-based research focused on the design of the latter, assuming that the incentives are set. In this section, after summarizing our recommendations for intermediaries, we present implications and recommendations for policymakers.

Intermediaries should attract households with energy cost savings, convince them to participate by safeguarding their control needs, and keep them involved by limiting their operational burden. Automating households' responses to price signals and aggregating their energy for trading help to effectively and efficiently realize energy cost savings. How automation eases operation must be explained to households since they underestimate its added value when selecting a service to support their participation.

Moreover, intermediaries should implement system-friendly default settings and just-in-time prompts. These are key elements of automated services that balance household needs for comfort-driven consumption and energy cost savings. If households' inertia leads to no setting adjustment at all, then system-friendly default settings will ensure energy cost savings. The set value must align with households' consumption needs to avoid excessive adjustments. Just-in-time prompts should warn households how the setting adjustments affect their energy cost savings.

Furthermore, intermediaries should avoid using resources to differentiate demand response services for households' types of flexible technologies and their adoption levels. Rather, they should focus on households' common priorities when choosing a demand response service. Thus, services should safeguard the control needs of all households (and not primarily of those with EVs, as assumed in the literature). This is also the case for the main driver of demand response, namely the realization of energy cost savings. However, the need for such savings is expected to increase if larger parts of the population participate in demand response services.

Notably, our recommendations for intermediaries rely on certain regulatory framework conditions. Therefore, the following paragraphs present additional recommendations for policymakers based on insights from the research field.

Regulators should ensure that distribution system operators provide grid access for energy assets and interoperable smart metering infrastructure. Participation in the energy system requires households to monitor their energy use and remotely control their energy assets. The widespread availability of smart meters avoids service-specific investments by households for these functionalities, which reduces the risk of being locked in by one intermediary. Thus, regulators will ensure a level playing field for intermediaries.

Moreover, policymakers should guarantee households access to real-time pricing and the freedom to choose between tariff designs. While real-time pricing enables the most efficient optimization of energy use, it increases the burden for households. Intermediaries are expected to reduce said burden by translating it into a simpler tariff scheme, consumption advice, or automated adjustments. Households' freedom of choice incites intermediaries to create supportive services that make real-time pricing more attractive than flat tariffs. The obligation to offer real-time pricing may first be introduced for supply contracts for flexible technologies, which are the most viable cases for demand response. If real-time pricing and the corresponding services become popular among households, then the obligation should be expanded.

Furthermore, policymakers should mandate intermediaries to offer risk mitigation measures for countering the adverse effects of real-time pricing, such as price risk during moments of scarcity. One proposal from the field is capacity subscriptions, where by paying a subscription for backup capacity, households hedge their consumption during times of scarcity. Social security services should cover a minimum capacity subscription for vulnerable consumers.

In addition, regulators should remove intermediaries' obligation to supply households based on a standardized load profile. Alternative load profiles based on smart metering would create a baseline to verify households' load shifts. Currently, deviations from the standardized load profile are penalized in most countries, even if they provide flexibility.

Moreover, policymakers should introduce incentives for the grid-friendly operation of residential energy assets. In particular, they should mandate distribution grid operators to price the usage of the limited grid capacity to manage grid congestion. The usage can be priced in two ways, namely by using variable network tariffs to integrate price signals into households' retail tariffs or by introducing flexible markets, which assume that using the grid is a right of households and that they can trade in the market.

In addition, policymakers need to adjust the participation requirements for redispatch and balancing markets to seize the potential of residential flexibility. For instance, a special approach for aggregated flexibility pools would facilitate their prequalification for these system services.

Finally, as long as the trading of households' self-generated electricity and flexibility is not possible, policymakers should expand the incentives of self-consumption to energy sharing. This expansion would stimulate investments in distributed generation assets and flexible technologies by wider parts of the population. Currently, mainly house owners can avoid paying levies and taxes by consuming self-generated electricity. If a broader definition of self-consumption in the sense of energy sharing is established, then wider parts of the population would profit from these incentives.

7.4 Suggestions for future research

A key challenge for household participation is to balance households' conscious long-term and latent short-term needs. If households' priorities are ambiguous, then the governance design must encourage them to consciously decide between them. Adjustable settings represent one strategy for creating these decision moments. Conscious decisions ensure that the operation is aligned with household needs; however, they also create cognitive effort for households. If households' decisions form a recurring pattern, then the need to double-check their priorities would no longer exist; thus, the pattern could be directly incorporated into the governance design.

A direction for further research is to design settings for automated services that clarify ambiguous household needs. This dissertation has exemplified the following three design steps for the case of smart charging services: First, suitable service settings that capture households' consumption needs must be identified; second, one must choose reasonable default values for the settings that balance the needs of households and the energy system; and third, if households adjust the default values, then just-in-time prompts should warn them against new conflicts of needs. Future research should follow these steps to design the service settings of other flexible technologies, such as heat pumps.

Noteworthily, further testing is required for the proposed smart charging settings that balance household needs for cost savings, safeguard mobility needs, and limit the operational burden. Referring to the second design step, an acceptable level of default settings depends on households' perceived mobility needs. Future research should investigate which internal (e.g., risk aversion) and external factors (e.g., distance of daily rides, availability of public charging, and vehicle characteristics) determine this level. Referring to the third step, agent-based modeling demonstrated that the unbalanced adjustment of settings jeopardizes cost savings. Therefore, the relevance of the case of unbalanced adjustments in real life must be tested in field trials.

Clarified priorities for conflicting needs simplify the governance design. This dissertation does not provide final conclusions on households' tradeoff between control needs and operational burden. If the vignette survey is repeated in the future, participants' judgments regarding the operational effort will be based on further experiences with flexible technologies; therefore, they will be more robust. Moreover, examining the usage patterns of digital devices for energy management would provide insights into their tradeoff.

The developed consumer governance design framework and its inventory of design choices provide a basis for future design iterations if changes are required. For instance, the transposition of the European Union's second Renewable Energy Directive into national law enables collective investments to be made in energy assets for households that would not be able to invest individually. External incentives are likely to drive the participation of these households even more than those represented in this dissertation. Thus, future research should investigate how to design consumer governance that meets the needs of these newcomers.

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9 Appendix A: Descriptive statistics of vignette study & additional tests

9.1 Appendix A.1: Descriptives

Mean (Standard Deviation) - if not specified alternatively	Owning only HP	Owning only EV	Owning only stationary battery	Owning more than one flexible technology	With purchase intention
Acceptance of control loss	3.45 (0.67)	3.18 (0.67)	3.21 (0.69)	3.46 (0.73)	3.35 (0.70)
Acceptance of effort	3.56 (0.73)	3.25 (0.66)	3.60 (0.75)	3.94 (0.65)	3.60 (0.74)
Importance of data privacy	3.04 (1.06)	3.08 (1.02)	3.15 (1.03)	3.06 (1.04)	2.92 (1.07)
Importance of cost savings	4.13 (0.68)	3.93 (0.68)	4.10 (0.62)	3.91 (0.78)	4.31 (0.60)
Environmental awareness	3.56 (0.81)	3.57 (0.75)	3.64 (0.80)	3.92 (0.76)	3.62 (0.76)
Technology openness	3.60 (0.96)	3.90 (0.69)	3.76 (0.86)	4.28 (0.77)	3.71 (0.92)
Social norm	3.55 (0.76)	3.32 (0.69)	3.35 (0.77)	3.61 (0.84)	3.62 (0.77)
Electricity tariff change in 2022	4.02 (0.76)	3.68 (0.88)	3.63 (0.79)	3.85 (0.86)	3.94 (0.79)
Age	45.91 (12.94)	53.65 (13.00)	52.52 (14.71)	47.91 (12.09)	53.50 (13.75)
Gender (share of males)	44.80%	80.20%	55.80%	82.00%	51.20%
Tenure (share of owners)	97.40%	77.20%	86.50%	96.60%	92.80%
Education (share of higher education)	58.30%	67.30%	59.60%	80.00%	58.20%
Income (share above 3,000 EUR/month)	80.20%	71.90%	65.40%	84.70%	58.70%

Table Annex 9-1: Socio-demographic and psychological variables for each household group

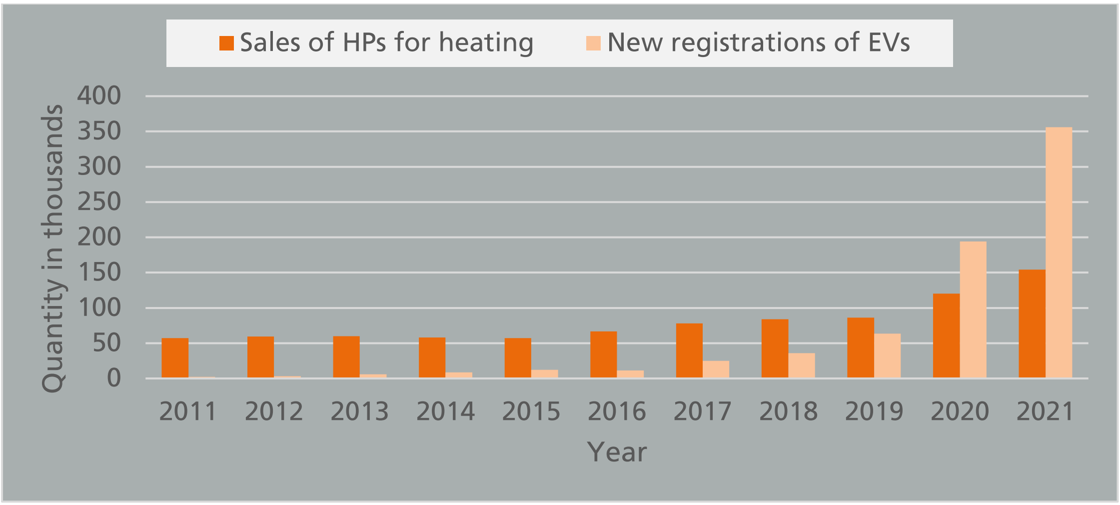


Figure Annex 9-1: Yearly sales of HPs and new registration of EVs from 2011 to 2021 in Germany based on (Statista 2022a) and (Statista 2022c)

9.2 Appendix A.2: Further analysis for hypothesis testing

	Ref. to H1	Ref. to H1	Ref. to H2	Ref. to H3	Ref. to all
	Importance of data privacy	Importance of cost savings	Acceptance of control loss	Acceptance of effort	Technology openness
Asymp. sig. for Kruskal -Wallis –Test (n = 962)					
Household groups	.140	.000***	.006**	.000**	.000***
Significance adjusted for Bonferroni corrections - pairwise comparison based on Kruskal -Wallis –tests					
only HP vs. only interested	-	.123	1	1	1
only HP vs. only EV	-	.005**	.04*	.003**	.060
only HP vs. multiple	-	.192	1	.000***	.000***
only interested vs. only EV.	-	.001**	0.255	.000***	.487
only interested vs. multiple	-	.000***	1	.000***	.000***
only EV vs. multiple	-	.703	.014*	.000***	.003**
*** p < .001, ** p < .01;*[1] p <.0083, **[1] p <.0017, ***[1] p <.0002; n = 910 if not stated differently; For pairwise comparison, owners of BSS only were excluded from these analyses due to a small subgroup size and power issues.					

Table Annex 9-2: Results of Kruskal-Wallis-test testing differences between the household groups on the general, psychological measurements

#	DR service	t	Effect size d	P-value for sig. (2-tailed)	Relevant aspects to test Hyp. 1: Lower usage likelihood for DR service with...	Result
1	1 vs. 2	-2.06	.066	.040	-	-
2	1 vs. 3	-5.31	.172	.000***	less control than more data sharing (preference for DRS 3)	supported
3	1 vs. 4	5.33	.172	.000***	less control loss than less energy cost savings (preference for DRS 1)	not supported
4	2 vs. 3	-3.49	.112	.001**	more effort than more data sharing (preference for DRS 3)	supported
5	2 vs. 4	8.34	.269	.000***	more effort than less energy cost savings (preference for DRS 2)	not supported
6	3 vs. 4	11.61	.374	.000***	-	-

Adj. p-value based on Bonferroni Correction: p-value / 6;

* p <.0083, ** p <.0017, *** p <.0002

Table Annex 9-3: Testing Hypothesis 1 - Paired t-tests showing the same result pattern as the Wilcoxon signed-ranked tests

To test Hypothesis 2, we also conducted a one-way ANOVA with planned contrast (only EV-owners coded as 1, all other groups coded as -0.25). The ANOVA as well as the contrast for Hypothesis 2 were non-significant, $F(957, 4) = 0.59$, $p = .667$, contrast $t(957) = -1.30$, $p = .195$. However, the hypothesis was descriptively supported when assessing the mean of adoption likelihood for DRS 1 for each group (see TableAnnex 4). Thus, this analysis provides the same pattern of results as the more robust, non-parametric analysis of the Kruskal-Wallis test.

Household group	Likelihood to adopt DRS 1 Mean (SD)	Likelihood to adopt DRS 2 Mean (SD)	Likelihood to adopt DRS 3 Mean (SD)	Likelihood to adopt DRS 4 Mean (SD)
Only HP (n = 192)	3.18 (1.06)	3.08 (1.09)	3.31 (1.04)	2.82 (1.06)
Only EV (n = 101)	3.07 (1.27)	3.29 (1.16)	3.56 (1.13)	2.88 (1.10)
Only BSS (n = 52)	3.35 (1.08)	2.85 (1.07)	3.27 (1.07)	2.69 (1.20)
Multiple flexible technologies (n = 261)	3.17 (1.21)	3.51 (1.15)	3.65 (1.14)	3.17 (1.20)
Only interested (n = 356)	3.21 (1.06)	3.28 (1.04)	3.33 (1.06)	2.83 (1.08)

Table Annex 9-4: Testing Hypotheses 2 and 3 – means from the adoption likelihood for DRS 1 and 2 following two one-factorial ANOVAs with planned contrasts

To test Hypothesis 3, we also performed a one-way ANOVA with planned contrast (only interested households coded as 1, all other groups coded as -0.25). The ANOVA revealed significant differences between the groups for likelihood adoption of DRS 2, $F(957, 4) = 6.58$, $p < .001$. However, the planned contrast was not significant, $t(494.18) = 1.31$, $p = .190$, indicating that the subgroup of only interested households does not differ significantly from the other subgroups regarding DRS 2. For descriptive statistics are presented TableAnnex 4). In contrast, when conducting non-parametric Mann-Whitney U-tests for pairwise comparisons, we receive the same results as reported in Table 5 (with and without Bonferroni correction). In summary, for Hypothesis 3, the results with the planned contrast differ (slightly) from the non-parametric Kruskal-Wallis test reported in the main text (see Table 5), however, since we applied conservative Bonferroni corrections to the paired comparison in the main text, we prefer to report the more conservative non-parametric Kruskal-Wallis test in the main text (compared to the one-way ANOVA with planned contrast).

9.3 Appendix A.3: Further analysis for explorative analysis

DRS 1	Model 1: Service specifications		Model 2: Technology ownership		Model 3: Other psychological aspects		Model 4: Socio-demographics	
	Coefficient [a]	p-value	Coefficient [a]	p-value	Coefficient [a]	p-value	Coefficient [a]	p-value
Acceptance of control loss	0.196	0.000***	0.195	0.000***	0.169	0.000***	0.166	0.000***
Acceptance of effort	-0.009	0.775	-0.013	0.699	-0.068	0.098	-0.068	0.104
Importance of data privacy	-0.087	0.006 ***	-0.089	0.006 ***	-0.090	0.005 ***	-0.090	0.006 ***

Importance of cost savings	0.019	0.545	0.015	0.655	-0.023	0.511	-0.025	0.488
Owning only HP (1= yes, 0= no)			-0.004	0.924	-0.016	0.729	-0.027	0.574
Owning only EV (1= yes, 0= no)			-0.046	0.269	-0.069	0.107	-0.070	0.116
Owning only stationary battery (1= yes, 0= no)			0.044	0.243	0.035	0.351	0.030	0.432
Purchase intention (but not owning) (1= yes, 0= no)			0.001	0.983	-0.012	0.823	-0.021	0.715
Environmental awareness					0.096	0.005 ***	0.102	0.004 ***
Technology openness					0.042	0.272	0.040	0.305
Social norm					0.057	0.140	0.060	0.126
Electricity tariff change in 2022					0.050	0.118	0.048	0.141
Age							-0.019	0.584
Gender (=male, =female)							0.031	0.374
Tenure							0.031	0.350
Education							-0.015	0.661
Income							-0.015	0.668
Adjusted R^2	0.043 ***		0.040		0.038		0.051 ***	
a. standardised beta coefficient, * p < .05, ** p < .01, *** p < .001. n=962								

Table Annex 9-5: Results of hierarchical linear regression on usage likelihood of DRS 1 with less control

DRS 2	Model 1: Service specifications		Model 2: Technology ownership		Model 3: Other psychological aspects		Model 4: Socio-demographics	
	Coefficient [a]	p-value	Coefficient [a]	p-value	Coefficient [a]	p-value	Coefficient [a]	p-value
Acceptance of control loss	0.124	0.000 ***	0.129	0.000 ***	0.108	0.001 ***	0.109	0.001 ***
Acceptance of effort	0.237	0.000 ***	0.223	0.000 ***	0.126	0.002 ***	0.134	0.001 ***
Importance of data privacy	0.022	0.489	0.022	0.472	0.021	0.499	0.022	0.474
Importance of cost savings	0.018	0.566	0.038	0.248	-0.003	0.929	-0.011	0.744
Owning only HP (1= yes, 0= no)			0.022	0.618	0.014	0.745	0.020	0.666
Owning only EV (1= yes, 0= no)			0.162	0.000 ***	0.118	0.004 ***	0.149	0.001 ***
Owning only stationary battery (1= yes, 0= no)			0.006	0.880	-0.004	0.921	0.004	0.909
Purchase intention (but not owning) (1= yes, 0= no)			0.112	0.039	0.100	0.063 *	0.111	0.041 **
Environmental awareness					0.073	0.028 **	0.080	0.018 **
Technology openness					0.144	0.000 ***	0.157	0.000 ***
Social norm					0.049	0.187	0.036	0.339
Electricity tariff change in 2022					0.035	0.264	0.032	0.312
Age							-0.014	0.687
Gender (=male, =female)							-0.078	0.022 **
Tenure							-0.020	0.535
Education							-0.055	0.101
Income							-0.004	0.910

Adjusted R^2	0.085 ***		0.083		0.100 ***		0.124 ***	
a. standardised beta coefficient, * p < .05, ** p < .01, *** p < .001. n=962								

Table Annex 9-6: Results of hierarchical linear regression on usage likelihood of DRS 2 with more effort

DRS 4	Model 1: Service specifications		Model 2: Technology ownership		Model 3: Other psychological aspects		Model 4: Socio-demographics	
	Coefficient [a]	p-value	Coefficient [a]	p-value	Coefficient [a]	p-value	Coefficient [a]	p-value
Acceptance of control loss	0.078	0.018	0.074	0.024	0.053	0.114	0.047	0.166
Acceptance of effort	0.187	0.000 ***	0.166	0.000 ***	0.079	0.054	0.067	0.106
Importance of data privacy	0.107	0.001 ***	0.102	0.001 ***	0.114	0.000 ***	0.114	0.000 ***
Importance of cost savings	-0.078	0.015	-0.056	0.096	-0.088	0.011	-0.079	0.023
Owning only HP (1= yes, 0= no)			0.091	0.042	0.082	0.065	0.050	0.284
Owning only EV (1= yes, 0= no)			0.106	0.011*	0.089	0.036*	0.096	0.029*
Owning only stationary battery (1= yes, 0= no)			0.025*	0.505	0.023*	0.539	0.016	0.679
Purchase intention (but not owning) (1= yes, 0= no)			0.096	0.080	0.084	0.126	0.087	0.117
Environmental awareness					-0.008	0.823	0.016	0.646
Technology openness					0.095	0.012	0.096	0.012
Social norm					0.112	0.004	0.108	0.005
Electricity tariff change in 2022					0.047	0.136	0.033	0.299
Age							-0.131	0.000 ***

Gender (=male, =female)							0.011	0.752
Tenure							0.015	0.644
Education							0.027	0.435
Income							-0.037	0.300
Adjusted R^2	0.052 ***		0.064 **		0.068		0.081 ***	
a. standardised beta coefficient, * p < .05, ** p < .01, *** p < .001. n=962								

Table Annex 9-7: Results of hierarchical linear regression on usage likelihood of DRS 4 with less cost savings

9.4 Appendix A.4: Ridge regression

Negatively specified attribute	Coefficient (p-values if applicable)				
	Linear regression with attributes as one categorical variable & ranging reference attributes				Ridge regression with attributes as binary variables
Control of shifts	(reference)	-.114* (0.153)	-.249*** (.000)	.253*** (.000)	-.026
Effort of performing shifts	.114* (.015)	(reference)	-.135** (.004)	.366*** (.000)	.085
Consump-tion data sharing	.249*** (.000)	.135** (.004)	(reference)	.502*** (.000)	.22
Electricity cost savings	-.253*** (.000)	-.366*** (.000)	-.502*** (.000)	(reference)	-.27
Adjusted R^2	.0263				-
Pseudo-R^2	-	-	-	-	.9998
Lamda	-	-	-	-	.049
Standardised beta coefficient, * p < .05, ** p < .01, *** p < .001. n=962					

Table Annex 9-8: Results of linear regression and ridge regression on usage likelihood of all services

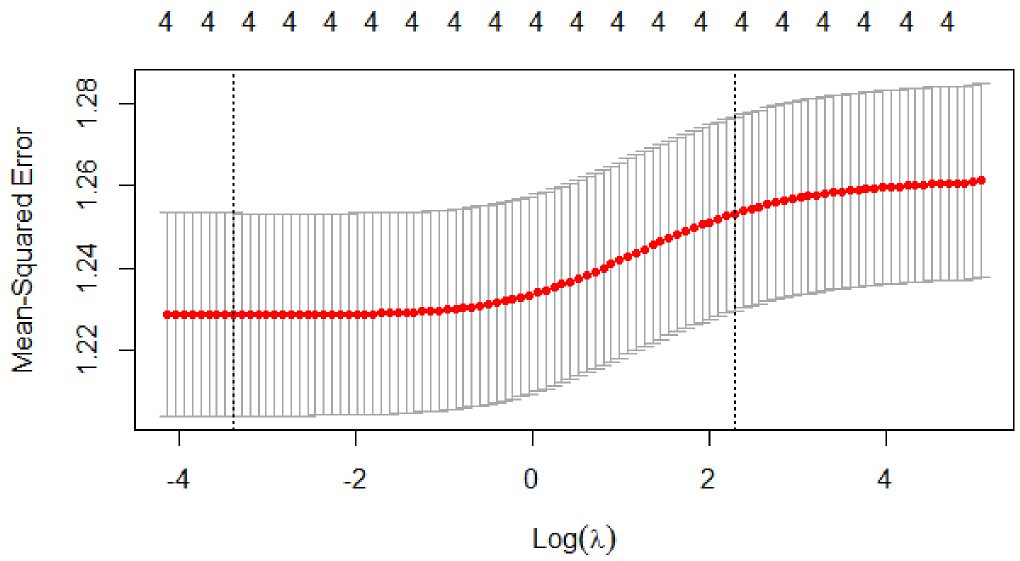


Figure Annex 9-2: Cross-validation curve showing the mean-squared error as subject to different penalty terms (Lambda)

Note: We determine the optimal value for the penalty term (Lambda) in the context of the bias-variance-tradeoff based on cross-validation. The left of the two vertical, dotted lines presents the optimal value for the penalty term, which minimizes the mean cross-validated error (applied to determine the coefficients in TableAnnex 8). The right line provides the upper bound for the penalty term, which is the value within one standard error of the minimum. The cv.glmnet function in R is used.

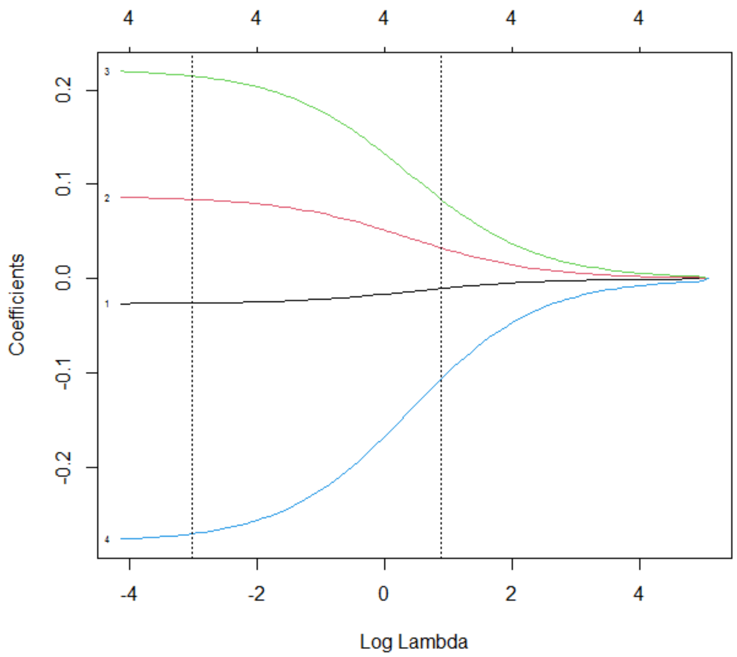


Figure Annex 9-3: Ridge Trace plot showing how different weights in the penalty term (Lambda) shrink the coefficients. The green line represents the coefficients for data, red for effort, black for control, blue for cost

Note: The left of the two vertical, dotted lines presents the optimal value for the penalty term, which minimizes the mean cross-validated error (applied to determine the coefficients in TableAnnex 8). The right line provides the upper bound for the penalty term, which is the value within one standard error of the minimum. Both lines indicate the viable range of penalty terms. Within this range, the order of the coefficients remains the same, confirming the findings of the hypothesis testing.

9.5 Appendix A.5: Analyses with ranked usage likelihood

#	DR service	Asymp. Sig. (2-tailed)	Relevant aspects to test Hyp. 1: Lower usage likelihood for DR service with...	Result	Difference to rated usage likelihood
1	1 vs. 2	2.2e-16***	-	-	
2	1 vs. 3	2.337e-09 ***	less control than more data sharing	supported	consistent
3	1 vs. 4	.05927	less control loss than less energy cost savings	not supported	inconsistent since insignificant for ranking
4	2 vs. 3	. 0.198	more effort than more data sharing	not supported	inconsistent since insignificant for ranking
5	2 vs. 4	2.2e-16***	more effort than less energy cost savings	supported	consistent
6	3 vs. 4	2.2e-16***	-	-	

Adj. p-value based on Bonferroni Correction: p-value / 6;

* p <.0083, ** p <.0017, *** p <.0002

Table Annex 9-9: Sign test for hypothesis 1 based on ranked usage likelihood

	DRS 1 with less control	DRS 2 with more effort	DRS 3 with more data sharing	DRS 4 with fewer cost savings
Asymp. sig. for Kruskal -Wallis –Test (n = 962)				
Household groups	3.703e-05***	.813	.02221*	.7801
Significance adjusted for Bonferroni corrections - pairwise comparison based on Kruskal -Wallis –tests (effect size r for significant outcomes)				
only HP vs. only interested	1	-	1	-
only HP vs. only EV	1	-	1	-
only HP vs. multiple	.00436**	-	.038*	-
only interested vs. only EV.	1	-	1	-
only interested vs. multiple	.00573**	-	.519	-
only EV vs. multiple	1	-	1	-
Differences to rated usage likelihood	different since ranking significant	different since ranking insignificant	different since only interested vs. multiple insignificant	different since ranking insignificant

*** p < .001, ** p < .01;*[1] p <.0083, **[1] p <.0017, ***[1] p <.0002; n = 910 if not stated differently - For pairwise comparison, owners of BSS only were excluded from these analyses due to a small subgroup size and power issues.

Table Annex 9-10: Kruskal-Wallis test for hypotheses 2 and 3 based on ranked usage likelihood

	Coefficient for rated dependent variable (5= most likely to use)	Odds for ranked dependent variable (1= most likely to use)	Differences to rated dependent variable
Acceptance of control loss	.156***	.77*	Lower significance level
Acceptance of effort	0.069	1.11	
Importance of data privacy	-.242***	1.72***	
Importance of cost savings	.069*	1.48	Not significant
Owning only HP (1 = yes, 0 = no)	-0.058	.75	
Owning only EV (1 = yes, 0 = no)	0.074	0.89	

Owning only stationary battery (1 = yes, 0 = no)	-0.01	.72	
Purchase intention (but not owning) (1 = yes, 0 = no)	-0.071	.86	
Environmental awareness	-0.031	.00	
Technology openness	.120**	.86*	
Social norm	.082*	.84*	
Electricity tariff change in 2022	.008	.77	
Age	-0.047	.73	
Gender (1=male, 0=female)	.100**	.66*	
Tenure	-0.009	.81	
Education	0.024	1.09	
Income	0	.47	
Adjusted R^2	.189***	-	
Residual Deviance	-	2766.52	

Table Annex 9-11: Logistic regression for explorative analysis with DRS 3 based on ranked usage likelihood

9.6 Appendix A.6: Vignette description

German original	English translation
<u>Optimal automatisierter</u> Strom-Tarif <u>ohne</u> Eingriffsmöglichkeiten und <u>ohne</u> Datenweitergabe Bei diesem Strom-Tarif wird der Verbrauch Ihrer Wärmepumpe automatisiert zeitlich verschoben, ohne dass Sie aktiv werden müssen. Sie können nicht eingreifen, um der Verschiebung zu widersprechen. Dadurch ist eine durchschnittliche Reduktion Ihrer Stromrechnung um 10-15 % zu erwarten.	**<u>Optimally automated</u> electricity tariff <u>without</u> opt-out and <u>without</u> data transfer** With this electricity tariff, the consumption of your heat pump is automatically shifted in time without you having the need to take action. You cannot intervene to object to the postponement. This results in an average reduction in your electricity bill of 10-15 % can be expected.
<u>Variabler</u> Strom-Tarif mit <u>selbstständiger</u> Umsetzung und <u>ohne</u> Datenweitergabe	**<u>Variable</u> electricity tariff with <u>independent</u> implementation and <u>without</u> data transfer**

Ein variabler Strom-Tarif hat im Gegensatz zu einem Einheitstarif (von z.B. 30 ct/kWh) zusätzlich höhere und niedrigere Preisstufen, die sich stündlich ändern können. Sie erhalten über eine App Informationen zur aktuellen Preisstufe. Daraufhin können Sie manuell den Verbrauch Ihrer Wärmepumpe in die günstigen Nachtstunden verschieben. Bei einer regelmäßigen Verlagerung ist eine Reduktion Ihrer Stromrechnung um 10-15 % zu erwarten.	In contrast to a standard tariff (e.g. 30 ct/kWh), a variable electricity tariff also has higher and lower price levels that can change hourly. You receive information on the current price level via an app. You can then you can manually shift the consumption of your heat pump to the cheaper night-time hours. With a regular shifting, you can expect a reduction in your electricity bill of 10-15 %.
Optimal automatisierter Strom-Tarif mit Eingriffsmöglichkeiten und mit Datenweitergabe Bei diesem Strom-Tarif setzt eine App die Verbrauchsverschiebung Ihrer Wärmepumpe automatisiert um. Sie können mit der App eingreifen, um der Verschiebung zu widersprechen. Für eine optimale Berechnung der Verschiebung werden Ihre Stromverbrauchs-Daten mit dem Anbieter geteilt. Dadurch ist eine durchschnittliche Reduktion Ihrer Stromrechnung um 10-15 % zu erwarten.	**Optimally automated electricity tariff with opt-out and with data transfer** With this electricity tariff, an app automatically implements the consumption shift of your heat pump. You can intervene with the app to object to the shift. For an optimal calculation of the shift, your electricity consumption data is shared with the provider. As a result, you can expect an average reduction in your electricity bill of 10-15 % can be expected.
Semi-optimal automatisierter Strom-Tarif mit Eingriffsmöglichkeiten und ohne Datenweitergabe Bei diesem Strom-Tarif setzt eine App die Verbrauchsverschiebung Ihrer Wärmepumpe automatisiert um. Sie können mit der App eingreifen, um der Verschiebung zu widersprechen. Die Verschiebung wird lokal auf Ihrem Endgerät (z.B. Handy oder Tablet) berechnet. Es werden keine Stromverbrauchs-Daten mit dem Anbieter geteilt. Dadurch ist eine durchschnittliche Reduktion Ihrer Stromrechnung um 1-5 % zu erwarten.	**Semi-optimally automated electricity tariff with opt-out and without data transfer** With this electricity tariff, an app automatically shifts the consumption of your heat pump. You can intervene with the app to object to the shift. The shift is calculated locally on your end device (e.g. cell phone or tablet). No electricity consumption data is shared with the provider. This is expected to reduce your electricity bill by 1-5% on average.

Table Annex 9-12: Vignette description in the chronological order (i.e., DRS 1, DRS 2, DRS 3, DRS 4), illustrated for heat pump owners, the technology is adjusted depending on which technologies does the household own or is interested in purchasing

10 Appendix B: Design of the Interventions for the Smart-Charging-App (intervention 1 and 2) and the Monthly Report Download (intervention 3)

A description of the interventions can be found in the supplementary-material of the corresponding journal paper.

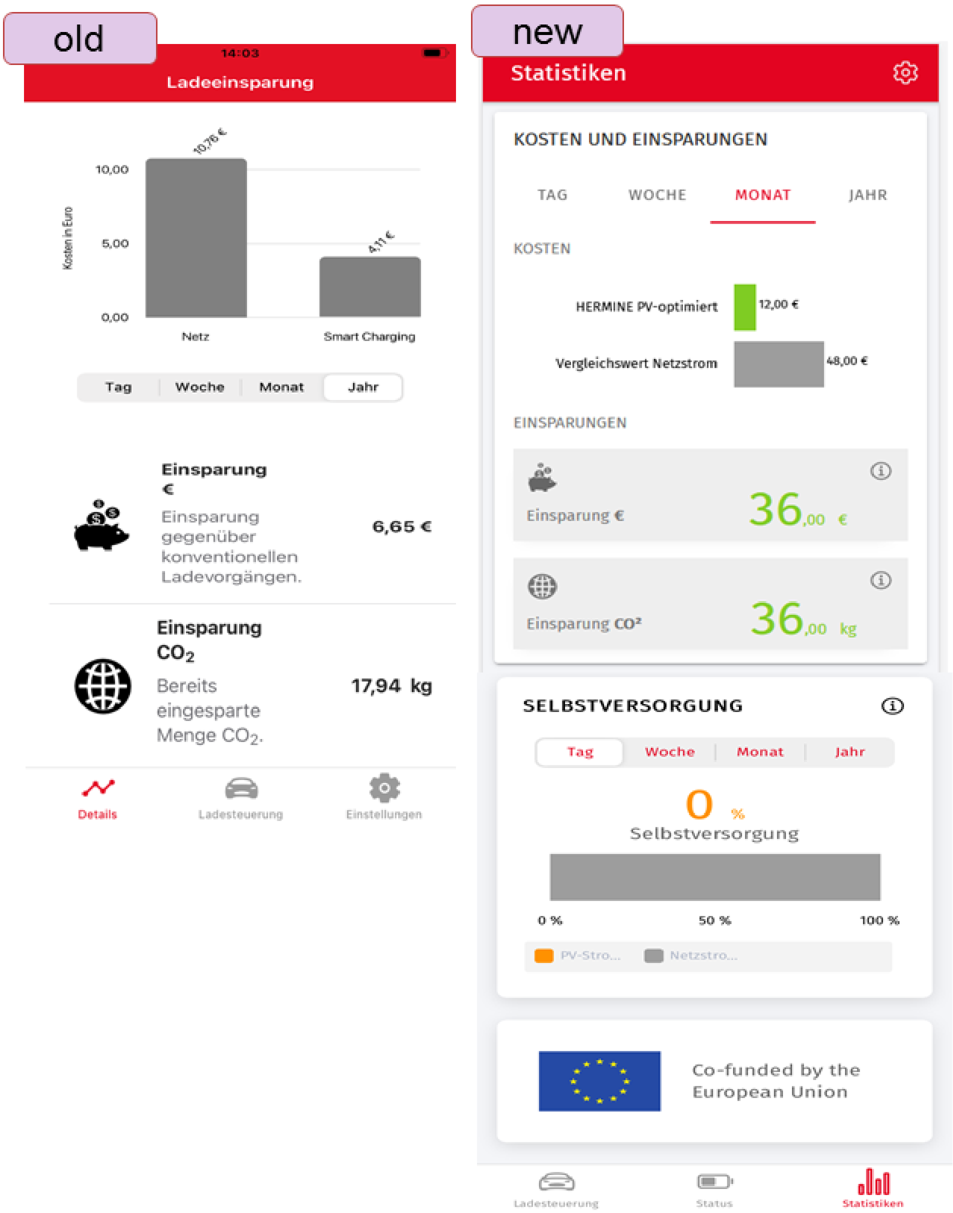


Figure Annex 10-1: Intervention 1 for the EV-group providing simple indicators in signaling color

Figure Annex 10-2: Intervention 2 for the EV-group providing benchmarks of previous and current self-consumption of charging and upcoming optimized charging process

Figure Annex 10-3: Intervention 3 for both groups providing aggregated information on past self-consumption in form of energy reports

11 Appendix C: List of robustness checks

We conducted an extensive set of additional tests and ensure that our main results are robust to these adaptations. The results are omitted due to space constraints, but output and code are available upon request.

Outliers

- General outlier elimination based on 1.5 times interquartile range (IQR)
- Observations with Autarky rate under 0.05 or above 0.95
- Eliminating households with high within variation (based on IQR)

Excluding households with exogenous changes to consumption

- Households with construction, additional people, new EVs based on survey data
- Technical problems with a specific Wallbox type during Nudge 1 and 2
- Households with heatpumps

Accounting for time-variant changes

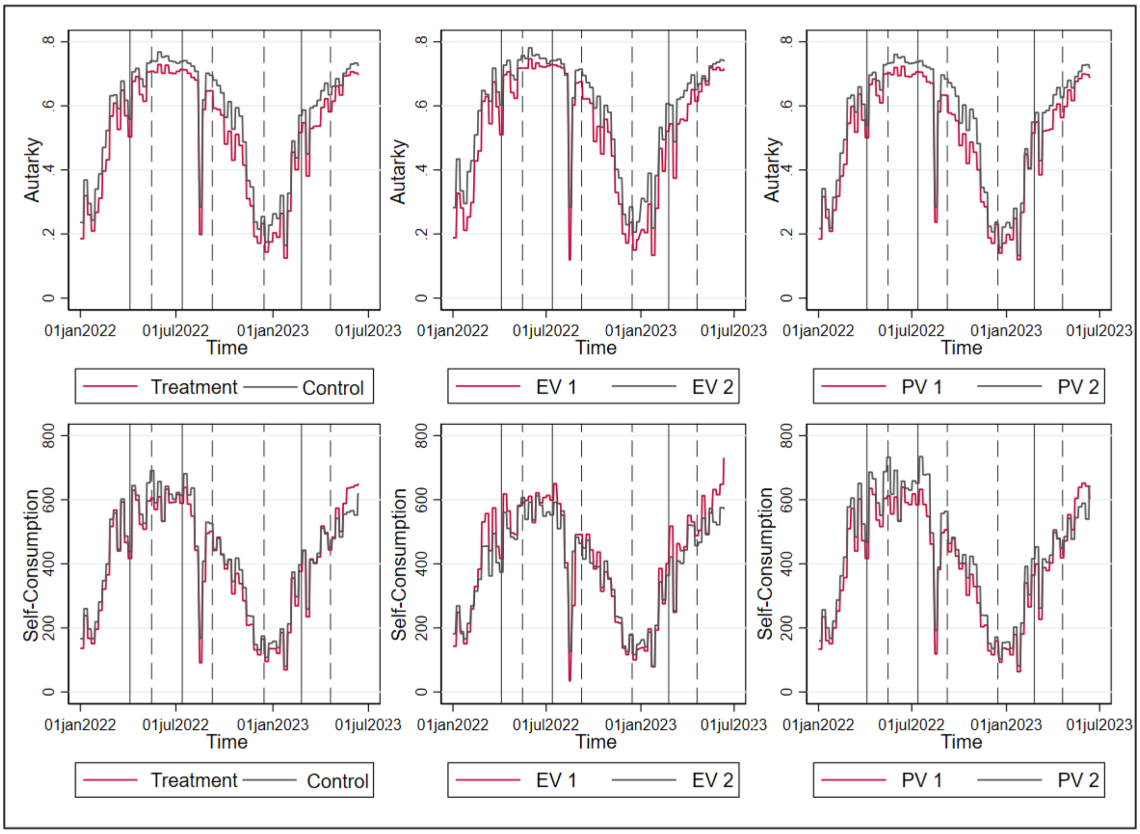
- Aggregation at weekly level to reduce noise
- Restriction to first 10 days of nudge to test for fatigue

App data usage

- Different definition variable "Active" as an absorbing state
- Specifications with different fixed-effects structure

Figure Annex 11-1: List of robustness checks

12 Appendix E: Descriptive Development between EV and PV-group over Time



Notes: Left panel refers to full sample, middle panel to EV group, right panel to PV group. Index 1 refers to sub-sample of treatment-group, index 2 to control-group. Aggregated to weekly means for exposition.

FigureAnnex 13-1: Outcomes by sub-group over time at weekly aggregation

13 Appendix F: Variables and parameters used for the prosumer modeling

Table Annex 13-1: Variables and parameters used for the prosumer modeling

Variables and parameters used for the prosumer modeling in the original minimization of energy costs from Kühnbach et al. (2022)	
$t \in T$	Hours per optimization interval
k	Prosumer k
$p_t^{selling}$	Price for selling electricity to the market in hour t
p_t^{buying}	Price for buying electricity from the market in hour t
$P_{EV_{total},t}^{k}$	Total EV charging load in hour t
$P^{k,evMax}$	Minimum and maximum charging power of the EV
$\vartheta_{EVflex,in}$	Efficiency of EV-battery when charging/discharging
$SFL_{min}^{k,EVflex}$, $SFL_{max}^{k,EVflex}$	Minimum and maximum storage fill level of the EV storage (i.e., the share of the EV-battery available for demand response) Parameters declaring if an EV is connected at home or mobile in t
$P^{k,evMin}$, $P^{k,evMax}$	Minimum and maximum charging power of the EV PV generation in hour t
$P_t^{k,grid\rightarrow hh}$	Electricity flow from the market to the prosumer
$P_t^{k,grid\rightarrow bat}$	Electricity flow from the market to the home storage system
$P_t^{k,bat\rightarrow grid}$	Electricity flow from the home storage system to the market
$P_t^{k,pv\rightarrow grid}$	Electricity from the PV unit sold to the market
$P_t^{k,pv\rightarrow EV}$	Electricity generated by the prosumer's own PV unit to charge the EV-battery
$P_t^{k,bat\rightarrow EV}$	Electricity flow from the home storage system to the EV-battery Energy content of the home storage system in kWh Power flow from spot market to the DR-ready fraction of the EV-battery
$P_t^{k,grid\rightarrow EV}$	Power flow from spot market to the mobility fraction of the EV-battery
$P_t^{k,EVflex\rightarrow EV}$	Power flow from the DR-ready fraction of the EV-battery to the mobility fraction of the EV-battery Energy content of the (virtual) DR-fraction of the EV-battery in kWh Power flow from PV to the demand response fraction of the EV-battery
$P_t^{k,bat\rightarrow EVflex}$	Power flow from home storage system to the demand response fraction of the EV-battery

$P_0^{k,unexpected}$	Power of unexpected trips deducted from SOC_t^k in the first hour of the day
$vsh_{conn_t^k}$,	Binary parameter indicating whether the EV is connected [1] or disconnected from the grid [0]

Variables and parameters used for the prosumer modeling in the extended minimization of discomfort costs

θ^k	Weighting parameter, which indicates how much importance prosumer k assigns to the discomfort cost in relation to energy cost
SOC_{Ref}^k	Target-SOC that is indicated by prosumer k as needed state of charge to cover her mobility needs
mV_t^k	Monetary value, which is assigned to the delta between SOC_t^k and SOC_{Ref}^k
λ	Coefficient expressing the loss aversion
α	Exponent expressing the risk attitude

14 Appendix G: Implementation of MINLP based on Big M Method

This MINLP is implemented with the big-M method (Cococcioni and Fiaschi 2021).

$$\min C_{tot}^{k} = \sum_{t=h_{min}}^{t=h_{max}} [(P_t^{k,grid\rightarrow EV} + P_t^{k,grid\rightarrow EVflex} + P_t^{k,grid\rightarrow hh} + P_t^{k,grid\rightarrow bat}) \cdot p_t^{buying} - (P_t^{k,EVflex\rightarrow grid} + P_t^{k,pv\rightarrow grid} + P_t^{k,bat\rightarrow grid}) \cdot p_t^{selling}] \cdot (1-\theta_t^k) \quad - \theta_t^k \cdot mV_t^k \cdot \; -\lambda \cdot utility_t^k \cdot vsh_{conn_t^k} \tag{B.1}$$

$$SOC_t^k \geq SOC_{Ref}^k - bigM \cdot (1-\delta_t) \tag{B.2}$$

$$SOC_t^k \leq SOC_{Ref}^k + bigM \cdot \delta_t \tag{B.3}$$

$$utility_t^k \geq (SOC_t^k - SOC_{Ref}^k)^{\alpha} - bigM \cdot (1-\delta_t) \tag{B.4}$$

$$utility_t^k \leq (SOC_t^k - SOC_{Ref}^k)^{\alpha} + bigM \cdot (1-\delta_t) \tag{B.5}$$

$$utility_t^k \geq (SOC_{Ref}^k - SOC_t^k)^{\beta} - bigM \cdot \delta_t \tag{B.6}$$

$$utility_t^k \leq (SOC_{Ref}^k - SOC_t^k)^{\beta} + bigM \cdot \delta_t \tag{B.7}$$

In order to assess the risk of finding local optima rather than global ones, we implement a linear transformation of our MINLP with an exemplary set of parameters. After comparing both approaches, we recognize no significant differences and assess the risk of distortions due to local optima as small.

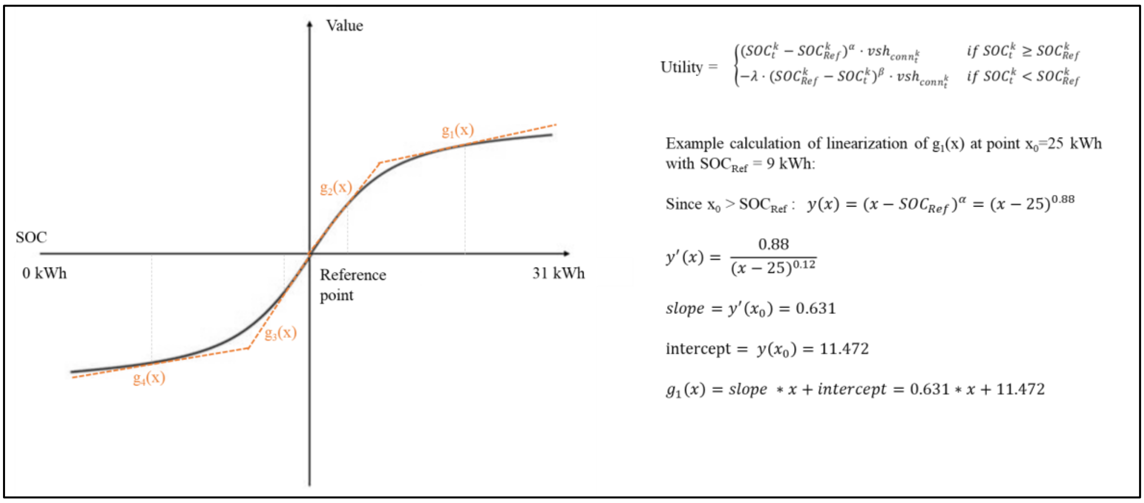


Figure Annex 15-1: Linear approximation of MINLP

Due to risk of local optima, the results of the MINLP were compared with those of the linear approximation approach. As an example, Figure Annex 15-1 depicts the results of both approaches for the EV-battery SOC and for the prosumer utility. The results are based on one data from a test run: both approaches were run for one prosumer for one month, and the resulting SOCs and utility values were used. As Figure Annex 15-2 and 15-3 show, both approaches produce the same results except for minimal deviations.

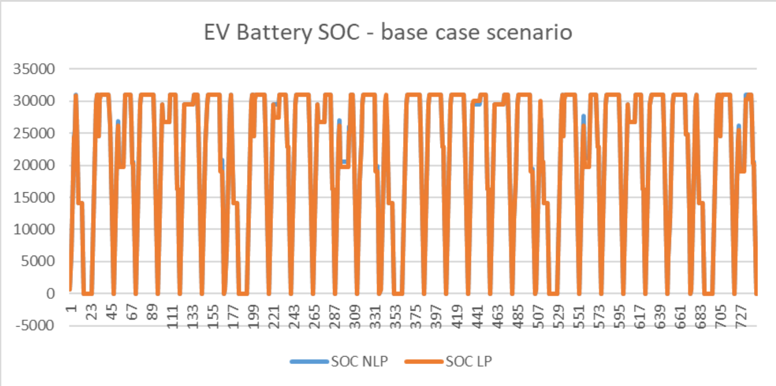


Figure Annex 15-2: Comparison of MINLP and linearized approach for the SOC of the EV-battery

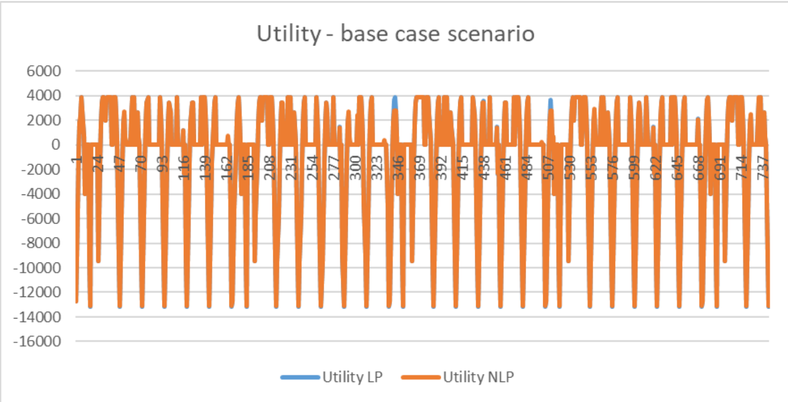


Figure Annex 15-3: Comparison of MINLP and linearized approach for the utility

15 Appendix H: Stylized examples for the relation between both cost elements in the combined cost-minimization function

We illustrate how the relation between the charging and discomfort cost determines the charging and discharging of the EV-battery by two stylized examples of SOCs for the four groups. In Figure Annex 16-1 and 16-2, the four curves represent the value function of each prosumer group as subject to the quantity of charged electricity. The red line represents the electricity costs. The EV-users are willing to pay for the charged electricity, as long as the electricity costs are below the discomfort costs of having a low SOC. The willingness to pay for the charged electricity decreases with a higher SOC. We illustrate this based on empty EV-batteries (Figure Annex 16-1) and EV-batteries that reached half of the target-SOC of the four groups (Figure Annex 16-2).

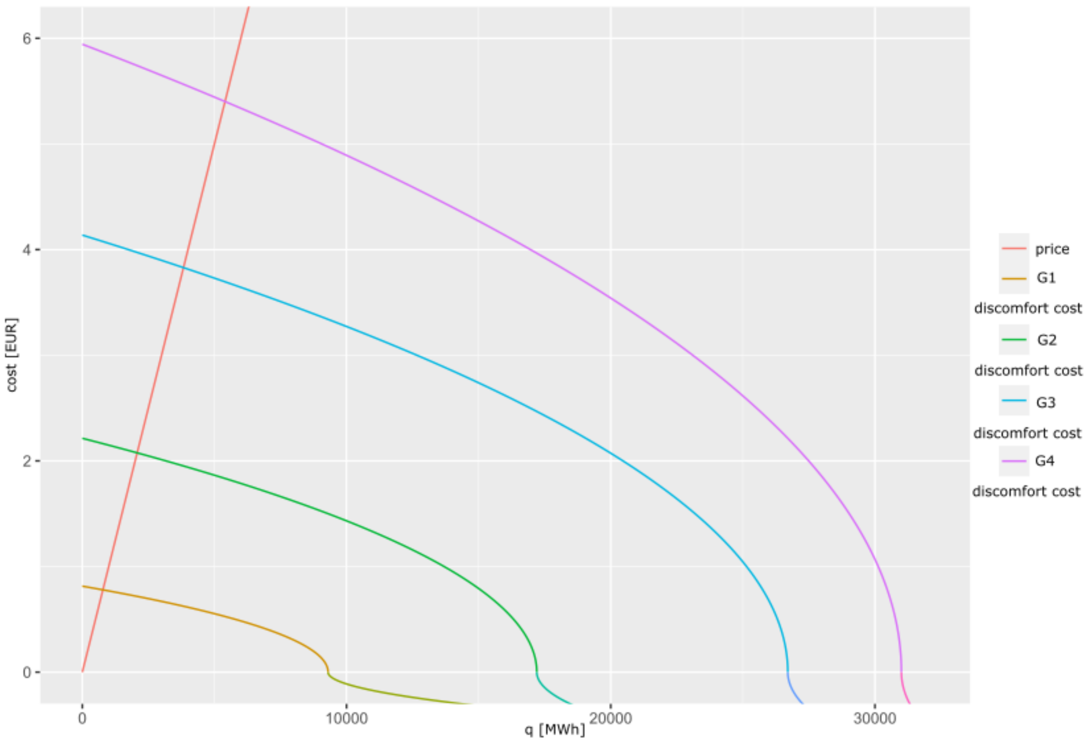


Figure Annex 16-1: Simplified illustration of the cost mechanism, which determines the amount of charged electricity based on the electricity price and the discomfort cost, when the EV-battery is empty

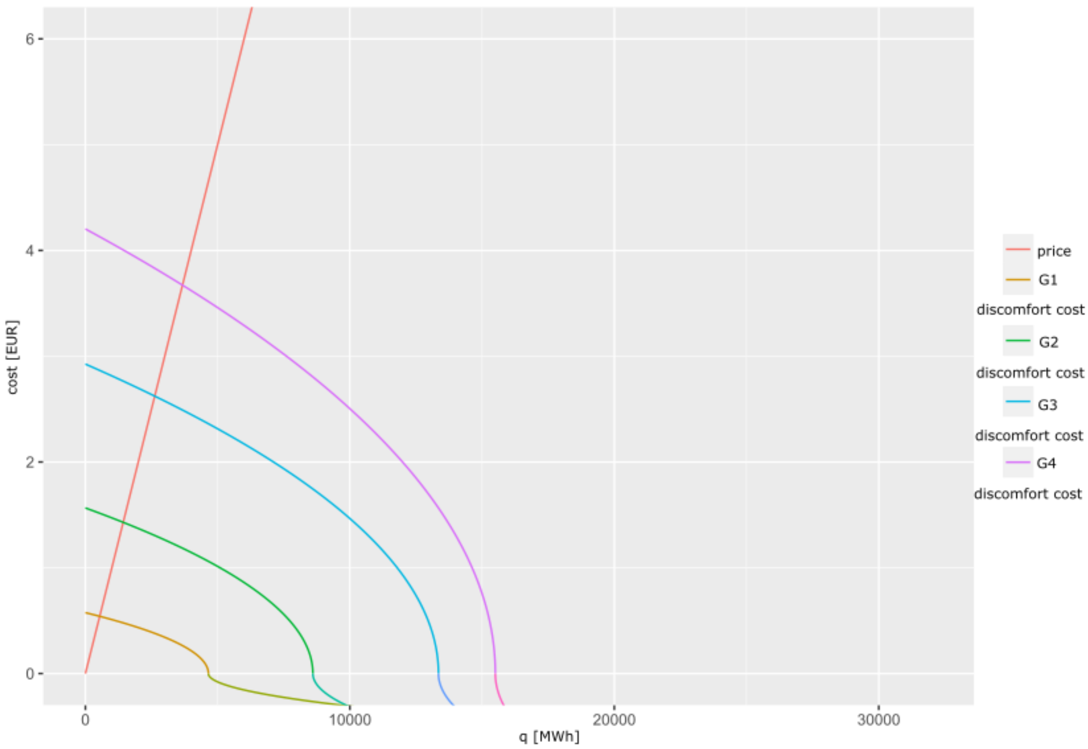


Figure Annex 16-2: Simplified illustration of the cost mechanism, which determines the amount of charged electricity based on the electricity price and the discomfort cost, when the EV-battery reached half of the target-SOC

16 Appendix I: Transforming the lowered target-SOC in the field experiment into model parameters for the EV-battery

The minimum of target-SOC of eight responsive participants ranged between 25 and 80 % of their EV-battery volume. The average standard deviation accounted for 17 %. We use the standard deviation as a moderate scenario with a medium target-SOC and the quartiles of the minimum target-SOC as an extreme scenario for the adjusted mobility needs due to smart charging services. The target-SOC in % is applied to the standard battery volume of the model (62 kWh). Additionally, 50 % of the EV-battery volume, which is withheld for its inflexible fraction, are deducted. For the scenario with a minimum target-SOC, this implies that no fraction of the flexible battery is withheld as safety buffer for group 1 and 2, since the first (35 %) and second quartile (45 %) is below this threshold.

17 Appendix J: Sensitivity analysis of other behavioral parameters

We presented in Section 5.4 how changes in the target-SOC and the DLC-level parameter influence the electricity cost savings. In the following, we test how a change of the other behavioral parameters, particularly the alpha, lambda, and monetary value, influence the results. Since the values for lambda and alpha are already at the higher end of their range, we reduce them (alpha from 0.88 to 0.5, lambda from 2.25 to 1.125). Furthermore, we test a higher spread of the monetary values (2x its standard deviation), as well as its overall reduction (0.5x its mean). We use the control need scenario as the basis for the sensitivity analysis.

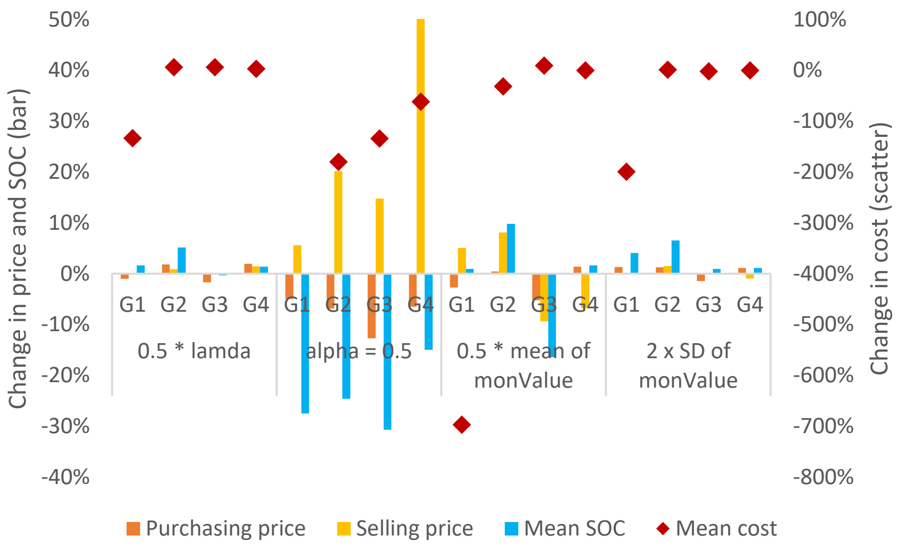


Figure Annex 18-1: Changes in electricity costs and underlying factors for the sensitivity analysis compared to the scenario control need. Since the costs are close to 0 (0.36 EUR) for G1 in the control need scenario, relative changes result in extreme values on the secondary y-axis (e.g., see for 0.5 * mean of monValue). For G1 in alpha = 0.5, the change in cost is not even displayed (from 0.36 EUR to -8.64 EUR). The same applies for the 9 times higher selling price (from 5.63 EUR/MWh to 54.81 EUR/MWh)

As illustrated in Figure Annex 18-1, the greatest changes are recognized for the lowered alpha. It entails that the slope of the discomfort cost curve increases around the target-SOC and shows saturation at the outer side of the curve. The initially empty EV-battery combined with this lower alpha leads to almost constant discomfort costs, independently of the change in SOC. These minor incentives to increase the SOC are overruled by the price signals. Consequently, they charge their EV more cost optimally (see Figure Annex 18-2).

The given implementation of PT successfully captures the tradeoff on the amount of charged electricity when a high alpha is applied. For the application of smaller alphas, another formulation of the SOC delta or a higher initial SOC needs to be defined.

The decrease of the discomfort costs in all other parameter variations leads to a more cost-optimal charging behavior of G1. For the other groups with a higher DLC-level and target-SOC, the decrease does not substantially change the tradeoff between minimizing charging and discomfort costs. We expect this result since G1's low target-SOC results in high marginal discomfort costs. Its relative decrease has a stronger effect on G1 than the other groups.

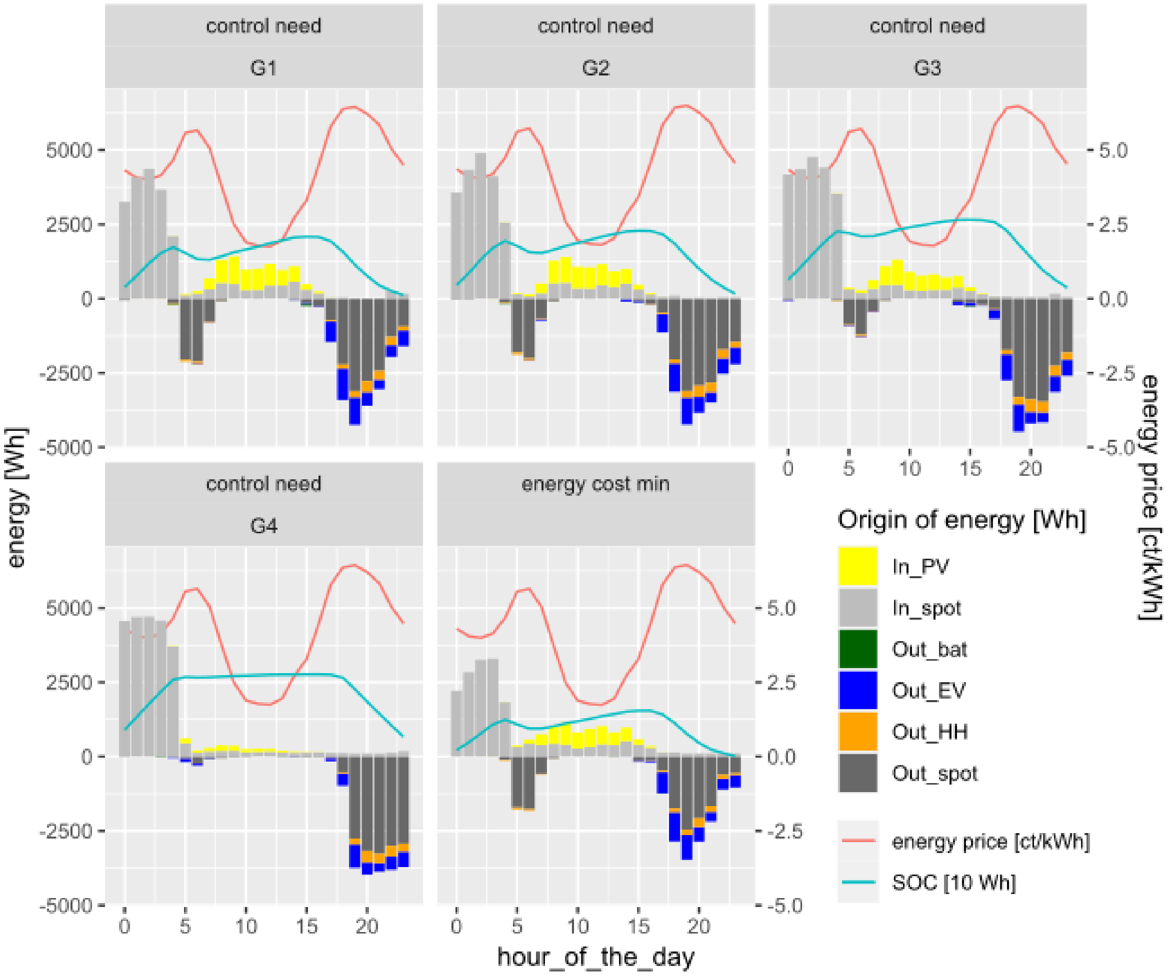


Figure Annex 18-2: Average in- and outflows of the EV-battery within 24 hours for a lowered alpha of 0.5, distinguished by sources (In_[...] = charged electricity from [...], Out_[...] = discharged electricity provided to [...], spot = electricity spot market, bat = stationary battery, EV = inflexible charging demand, HH = inflexible household demand)

18 List of Publications

Articles in scientific journals that form the basis of this dissertation
(including CRediT author statement)

Pelka S., Chappin E., Klobasa M., De Vries L., Participation of active consumers in the electricity system: Design choices for consumer governance, Energy Strategy Review, 2022

> *Sabine Pelka: Conceptualization, Methodology, Investigation, Visualization, Writing - Original Draft, Review & Editing. Emile Chappin: Conceptualization, Methodology, Writing – Review & Editing, Supervision. Marian Klobasa: Writing - Review & Editing, Supervision. Laurens de Vries: Conceptualization, Methodology, Writing – Review & Editing, Supervision.*

Pelka S., Preuß S., Chappin E., de Vries L., One service fits all? Insights on demand response dilemmas of differently equipped households in Germany, Energy Research Social Science, 2024

> *Sabine Pelka: Conceptualization, Methodology, Formal Analysis, Investigation, Writing – Original Draft, Writing – Review & Editing, Visualization. Sabine Preuß: Conceptualization, Methodology, Investigation, Writing – Review & Editing, Supervision. Judith Stute: Conceptualization, Investigation, Writing – Review & Editing, Visualization. Emile Chappin: Writing – Review & Editing, Supervision, Laurens de Vries: Writing – Review & Editing, Supervision.*

Pelka S., Kesselring A., Preuß S., Chappin E., de Vries L., Can nudging optimize self-consumption? Evidence from a field experiment with prosumers in Germany, Smart Energy, 2024

> *Sabine Pelka: Conceptualization, Methodology, Formal Analysis, Investigation, Writing - Original Draft - Anne Kesselring: Methodology, Formal Analysis, Software, Writing - Original Draft - Sabine Preuß: Conceptualization, Methodology, Investigation, Writing - Review & Editing - Emile Chappin: Writing - Review & Editing - Laurens de Vries: Writing - Review & Editing*

Pelka S., Bosch A., Chappin E., Kühnbach M., de Vries L., To charge or not to charge? - Using Prospect Theory to model the tradeoffs of electric vehicle users, Sustainability Science, 2024

> *Sabine Pelka: Conceptualization, Methodology, Formal analysis, Investigation, Software, Data curation, Writing - original draft preparation, Writing - review and editing. Antonia Bosch: Methodology, Investigation, Software, Data curation, Writing - review and editing. Emile Chappin: Conceptualization, Writing - review and editing, Supervision. Fabian Liesenhoff: Software, Writing - review and editing. Matthias Kühnbach: Software, Writing - review and editing. Laurens de Vries: Writing - review and editing, Supervision.*

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19 Curriculum Vitae

Sabine Pelka (M. Sc.) studied Systems Engineering, Policy Analysis and Management at the Technical University Delft (NL) and Comillas Pontifical University (ESP) with the track specialization on the energy sector. The design and evaluation of interventions in socio-technical systems, as well as the energy sector, constitute the core of her studies. She applied these competencies, e.g., for her master thesis about the impact of extreme weather conditions on the energy sector in cooperation with the German Aerospace Center. Before her master studies, she used to work for three years for EnBW Energie Baden-Württemberg AG in the energy economics and policy department. Thereby, she evaluated the market environment and developments in a qualitative and quantitative way for the annual group-wide strategy process. Furthermore, she managed the internal positioning process for relevant political topics conveyed the results in form of policy briefings and at association work on the national and EU-wide levels. She focused especially on new energy services, smart meter, and smart grid topics. Since September 2018, she is a scientific researcher at the Fraunhofer Institute for Systems and Innovation Research in the Competence Center Energy Technology and Energy Systems. In her research, she identifies the drivers and barriers of household integration, evaluates business models supporting households, and conducts impact assessments of the corresponding regulatory framework. Thereby, she combines techno-economic analyses with quantitative social science methods. She was the internal project coordinator at Fraunhofer ISI for the Horizon 2020 Project NUDGE and led two working packages at the national project Dima Grids, funded by the Federal Minister for Economic Affairs and Climate Action of Germany.