Behavioral and Structural Drivers of Energy Demand Flexibility

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Abstract

The climate crisis and ambitious national greenhouse gas reduction targets are driving a profound transformation of the energy system. On the supply side, renewable electricity generation is expanding. At the same time, heating, mobility, and industrial processes are increasingly electrified on the demand side. While essential for decarbonization, these developments increase the challenges of balancing supply and demand in a weather-dependent electricity system. This shift contributes to a setting in which demand increasingly follows supply, thereby elevating the importance of demand-side flexibility.

The residential and industrial sectors account for 71% of electricity demand in Germany and hold considerable potential for demand-side flexibility. Whether this potential is realized, however, depends critically on the acceptability of flexibility measures and the preferences and constraints of the affected actors. Despite the growing relevance of demand-side flexibility, empirical evidence on consumer acceptance, behavior, and structural constraints remains limited. This thesis examines the behavioral and structural drivers of demand-side flexibility from a consumer and decision-maker perspective across the residential and industrial sectors and combines four studies on, (i) incentivized residential energy-saving and flexibility behavior in a real-world living-lab setting, (ii) household preferences for incentivized load shedding via controlled electricity interruptions, (iii) perceived barriers and enablers of industrial process flexibility based on expert interviews, and (iv) the theoretical future flexibility potential of energy-intensive industrial processes.

The results identify a range of behavioral and structural drivers that shape the acceptability of and engagement with demand-side flexibility across sectors. In the residential sector, flexible behavior can be activated under complex incentive schemes, and households are willing to accept controlled electricity interruptions when appropriate compensation, transparency regarding frequency and duration, and advance notice are provided. However, such incentive schemes are not universally attractive and must be tailored to diverse consumer preferences. In the industrial sector, compensation and profitability concerns likewise emerge as central drivers, while acceptability is additionally shaped by organizational routines, internal communication, technological constraints, and regulatory conditions. Key enablers include well-designed program types, sufficient advance notice, and supportive regulatory frameworks. Modeling results indicate that industrial decarbonization could unlock load reduction potentials amounting to two-thirds of today's European pumped hydro storage capacity, with particularly high contributions from ammonia electrolysis, electric arc furnaces, and food processing technologies. Overall, the findings confirm that demand-side flexibility cannot be mobilized through uniform policy instruments. Instead, effective flexibility schemes should account for heterogeneous preferences and sector-specific constraints.

List of included articles

Paper A Scharnhorst, L.; Sandmeier, T.; Kleinebrahm, M.; Fichtner, W. (2025): Household carbon caps and tariffs: A living lab experiment. *Energy Research & Social Science*, 127, Article 104294. DOI: 10.1016/j.erss.2025.104294.

Paper B Scharnhorst, L.; Kreuter, L.; Sandmeier, T.; Sloot, D.; Kleinebrahm, M.; Fichtner, W. (2025): Understanding household preferences for the security of energy supply: Insights from a choice experiment in Germany. Submitted to a scientific journal.

Paper C Scharnhorst, L.; Sloot, D.; Lehmann, N.; Ardone, A.; Fichtner, W. (2024): Barriers to demand response in the commercial and industrial sectors – An empirical investigation. *Renewable and Sustainable Energy Reviews*, 190, Article 114067. DOI: 10.1016/j.rser.2023.114067.

Paper D Scharnhorst, L.; Xie, X.; Kleinebrahm, M.; Fichtner, W. (2024): Techno-economic analysis of future process-specific demand response in European industries. In: *20th International Conference on the European Energy Market (EEM 2024)*, p. 10. DOI: 10.1109/EEM60825.2024.10608488.

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Part I

Framework, Foundations, and Implications

1 Introduction

The Paris Agreement establishes a global commitment to limit global warming and explicitly states that achieving its goals demands profound economic and social transformation, guided by scientific evidence (UNFCCC 2015). Building on this international mandate, the European Green Deal operationalizes the objective of reaching climate neutrality by 2050, while Germany has the even more ambitious goal of reaching net-zero greenhouse gas emissions by 2045 (Bundesregierung 2022). The climate targets place unprecedented demands on the transformation of both the energy system and the demand sectors that rely on the energy system. Achieving these goals requires not only a rapid expansion of renewable energy sources but also a profound restructuring of energy consumption across all demand sectors.

In Germany, the residential and industrial sectors together accounted for 57% of final energy demand in 2022 (AGEB 2025b). Their contributions to national greenhouse gas emissions resulted in 23% for households and 34% for industry and underscore their central role in the transition toward climate neutrality (RWI 2023; BAFA 2022). Both sectors are undergoing substantial electrification. Conventional cars are being replaced by electric vehicles, heat pumps are increasingly being installed in new and existing buildings, and industrial production processes that were formerly fueled by coal and natural gas are being substituted by electricity. As a result, electricity is becoming the backbone of the energy transition, simultaneously decarbonizing the supply side by the expansion of renewables and driving transformation on the demand side. This dual transformation places growing stress on the electricity grid. Rising consumption coincides with a generation landscape that is becoming more intermittent and decentralized. Consequently, maintaining system stability will depend increasingly on demand-side flexibility, i.e., the ability of electricity consumers to shift or temporarily shed load in response to signals (e.g., prices). Demand-side flexibility can help to mitigate grid congestion, reduce peak load, and support security of supply in a decarbonized electricity system.

This transformation increases the exposure of the residential sector to system conditions and, at the same time, creates new opportunities for households to contribute flexibility. Heat pumps, electric vehicles, and smart appliances create new options for shifting electricity consumption in ways that support system balancing. In this sense, households contribute to the energy transition through two channels: by decarbonizing their energy use via electrification and efficiency measures, and by adapting their electricity demand to system conditions. German regulation has begun to lay the groundwork for unlocking this flexibility. Although the smart-meter roll out progressed slowly initially, it is now accelerating, and since 2025, electricity suppliers are required to offer dynamic tariffs to all consumers equipped with a smart meter (BMWE 2025). In parallel, the regulatory framework for controlled consumption devices has undergone fundamental reform. Since 1 January 2024, distribution system operators may no longer refuse or delay the connection of high-load devices such as heat pumps, air-conditioning units, stationary storage systems, or private EV chargers due to local grid constraints (BNetzA 2024b). Instead, in acute congestion situations, distribution system operators can temporarily reduce their power draw to a minimum supply of 4.2 kW (BNetzA 2024b). In return, consumers benefit from reduced grid fees. This shift underscores the expected dependence of grid stability on residential flexibility and highlights the need to understand how consumers perceive and respond to such interventions.

Yet, despite the increasing availability of dynamic tariffs and controllable-load regulation, little is known about how households perceive such interventions, what motivates or discourages participation, and how consumers balance financial incentives, convenience, and supply reliability. This knowledge gap becomes even more relevant when flexibility measures extend beyond large appliances to everyday household devices, or, in extreme cases, to the entire household supply. Understanding these behavioral dimensions is crucial for designing acceptable and effective flexibility products. Papers A and B of this thesis address this gap by examining household responses to incentives for energy-saving behavior, and by analyzing the acceptability of incentivized load shifting and load shedding in the residential sector.

The industrial sector has historically been the largest provider of demand response in Germany, adjusting the electricity use of energy-intensive processes across multiple flexibility channels, such as participating in day-ahead and intraday spot markets as well as reserve markets and interruptible-load schemes (BNetzA 2024c; Ranaboldo et al. 2024). During the period when the regulation for interruptible loads (AbLaV) was in place[1], energy-intensive processes such as aluminum electrolysis participated in system balancing, demonstrating that process-specific flexibility is technically and practically feasible under the right conditions (Jordanova-Duda 2020). However, with the expiration of the AbLaV and no fully comparable national instrument yet in force, transparency around industrial participation has diminished and actual flexibility provision remains far below the sector's technical potential (Weiss et al. 2025). Meanwhile, regulatory signals are beginning to shift: the Federal Grid Agency has proposed reforms to grid-fee structures that would reward large consumers who modulate their load in response to system conditions, signaling a shift from purely supply-side paradigms toward demand-side flexibility frameworks (BNetzA 2024a).

At the same time, new structural changes are reshaping flexibility opportunities. The rapid electrification of production routes for industrial process heat, such as heat pumps, electric arc furnaces or electrode boilers, combined with increasing digitization, could both lead to a substantial rise in flexibility potential and impose new operational constraints (Rehfeldt et al. 2024). Recent analyses estimate that, with targeted policy reforms, German industry could more than double its currently activated flexibility by 2030 (Weiss et al. 2025). However, how companies weigh profitability, process stability, organizational capacities, and regulatory complexity in their decision to engage in demand-side flexibility remains

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[1] Until July 2022 (BNetzA 2024c).

insufficiently understood. Papers C and D of this thesis address these gaps by examining (i) the barriers and enablers shaping industrial demand-side flexibility acceptance and implementation, and (ii) the future techno-economic potential of process-specific flexibility in an industrial landscape that strives for decarbonization.

A central challenge for the energy transition is that technical flexibility is only valuable if it is actually provided. System operators and policymakers need reliable insights into how households and industrial firms respond to incentives, how acceptable different forms of demand-side flexibility are, which barriers impede participation, and how flexibility potentials evolve as energy-intensive processes are defossilized. While there is research on individual aspects of these questions, existing studies often focus either on behavioral responses or on technical and economic potential. As a result, there remains limited integrated evidence on how real consumers, across both the residential and industrial sectors, perceive, organize, and ultimately provide flexibility under emerging policy frameworks.

This thesis addresses this gap by combining a multi-method approach of behavioral experiments, stated-preference methods, expert interviews, and bottom-up modeling. By applying these complementary lenses to both households and industry, the thesis generates a more comprehensive understanding of how German electricity consumers can contribute to emission reduction and flexibility provision, and under which policy, technological, and organizational conditions this contribution may become feasible.

The overarching goal of this thesis is to examine the preferences, acceptability, and participation of German residential and industrial electricity consumers in demand-side flexibility provision. The thesis comprises four research papers, each addressing a complementary aspect by stating the following research questions:

- RQ1 (Paper A): How do households interact with incentives for energy-saving behavior and demand-side flexibility?
- RQ2 (Paper B): What is the acceptability of controlled electricity interruptions in the residential sector, and how should tariffs be designed to incentivize participation?
- RQ3 (Paper C): What barriers impede the adoption of process-specific flexibility in industry?
- RQ4 (Paper D): Which industrial production processes could provide flexibility in the future, and how will their techno-economic flexibility potential evolve under deep decarbonization?

In scientific literature, demand-side flexibility is commonly discussed in terms of different layers of potential (Gils 2014). The technical potential describes the maximum flexibility that could be provided given existing technologies and processes, abstracting from economic, regulatory, and behavioral constraints (Weber et al. 2022, pp. 24–26). Accepted potential refers to the subset of this flexibility that users are, in principle, willing to provide under existing institutional and social conditions. Practical potential, finally, captures what is actually realized in everyday operation, once market access, incentives, technologies, and behavioral frictions interact. Following Gils (2014), practical potential can be understood

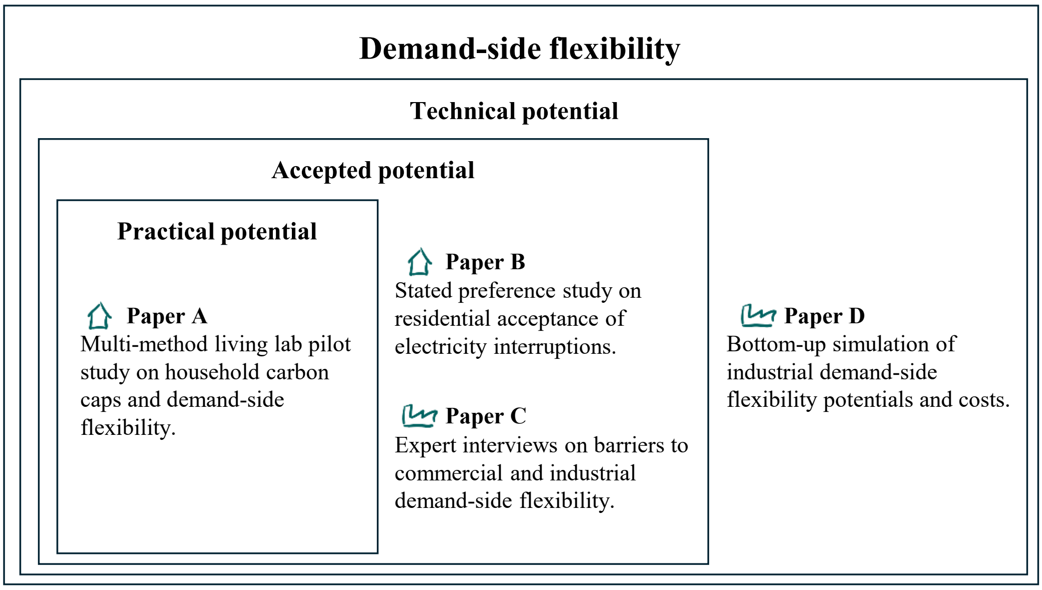

Figure 1.1: Positioning of the four dissertation papers within the conceptual hierarchy of demand-side flexibility, distinguishing technical, accepted, and practical potential. Household- and industry-focused studies are indicated by house and factory symbols, respectively. In the renewable energy literature, realizable potential is commonly treated as a subset of economic potential, implicitly incorporating acceptance and implementation constraints (Weber et al. 2022, p. 25). In the context of demand-side flexibility, however, acceptance and realization are often examined separately, as acceptance is frequently assessed ex ante, prior to market design and implementation, while realization reflects flexibility provision in operation. The figure therefore disaggregates realizable potential into accepted and practical components (Gils 2014). Economic potential is not shown as a separate layer, as none of the dissertation papers isolate economic feasibility in a system-optimal or profitability-based sense.

as the effectively usable intersection of economic feasibility and accepted use. Distinguishing between these layers is essential, because large technical flexibility potentials do not automatically translate into real-world system contributions. Figure 1.1 situates the four papers within a unified conceptual hierarchy of demand-side flexibility potential, spanning households and industry. Paper A captures near-real-world flexibility behavior at the level of practical potential in a living-lab setting. It thus reflects near-real-world flexibility provision under controlled conditions. Paper B addresses accepted potential by eliciting household preferences for electricity interruptions. Paper C examines acceptance-related barriers to industrial flexibility. Paper D quantifies upper-bound technical flexibility potentials under deep decarbonization, as it abstracts from detailed operational limitations.

This thesis comprises two parts. Part I develops the conceptual framework for the four papers. Part II contains the manuscript versions of Papers A-D. Part I is structured as follows: Chapter 2 provides an overview of the historical, current, and prospective developments in the residential and industrial sectors, focusing on sectoral characteristics, electrification trends, and consumer behavior. Chapter 3 presents the methods used across the thesis, including living lab experiments, choice experiments, expert interviews, and industrial energy-demand modeling. It highlights the methodological contributions of this work. Chapter 4 synthesizes the four research papers and discusses their key findings. Chapter 5 critically examines the methodological limitations of the thesis and outlines directions for future research. Chapter 6 summarizes the main contributions of this work and draws conclusions for policy, practice, and further academic inquiry.

2 Background

As the energy transition drives demand-side electrification and raises the share of intermittent renewable generation in the electricity mix, the role of demand-side flexibility in maintaining system stability is becoming increasingly important across all demand sectors. This chapter first introduces the conceptual foundations of demand-side flexibility, demand-side management, and demand response in Section 2.1. Further, the present state and future transformation of the residential and industrial energy demand structure, the rationales for demand-side flexibility, and the derived research needs are discussed in Section 2.2. Section 2.3 provides an overview about the behavioral drivers investigated in this thesis. More specifically, the behavioral theories, the concepts of the value of lost load and the willingness to accept electricity interruptions are presented, followed by information on nudging, incentives, and decision biases.

2.1 Demand-side flexibility

In both the academic and policy literature, the terms demand-side flexibility, demand-side management, and demand response are often used interchangeably, despite referring to analytically distinct concepts. Demand-side flexibility denotes the general capacity of electricity demand to be adjusted over time, that is, the ability of users to reduce, increase, or shift their electricity consumption relative to a baseline. This concept does not yet imply any specific policy instrument or market design. Rather, it describes a technical and behavioral potential that can, in principle, be activated through different mechanisms. In most contemporary definitions, demand-side flexibility is understood as the capacity of end-use consumers to alter their electricity usage away from normal or current consumption patterns in response to external signals such as prices or incentives (El Gohary 2024).

The broader policy framework within which demand-side flexibility is embedded is that of demand-side management. Demand-side management refers to all deliberate interventions that aim to modify either the level or the temporal pattern of electricity consumption (Williams et al. 2023). With the liberalization of electricity markets, demand-side management has evolved into two analytically distinct categories, (i) energy efficiency, which reduces the energy required to provide a given service or product, and (ii) demand response, which mobilizes adjustments in electricity demand (Morales-España et al. 2022). Demand response is the operational foundation through which demand-side flexibility is activated. Regulatory authorities define it as a change in electricity consumption by end-use customers in response to market signals, such as time-varying electricity prices or incentive payments, to increase, decrease, or shift the timing of their electricity consumption, either

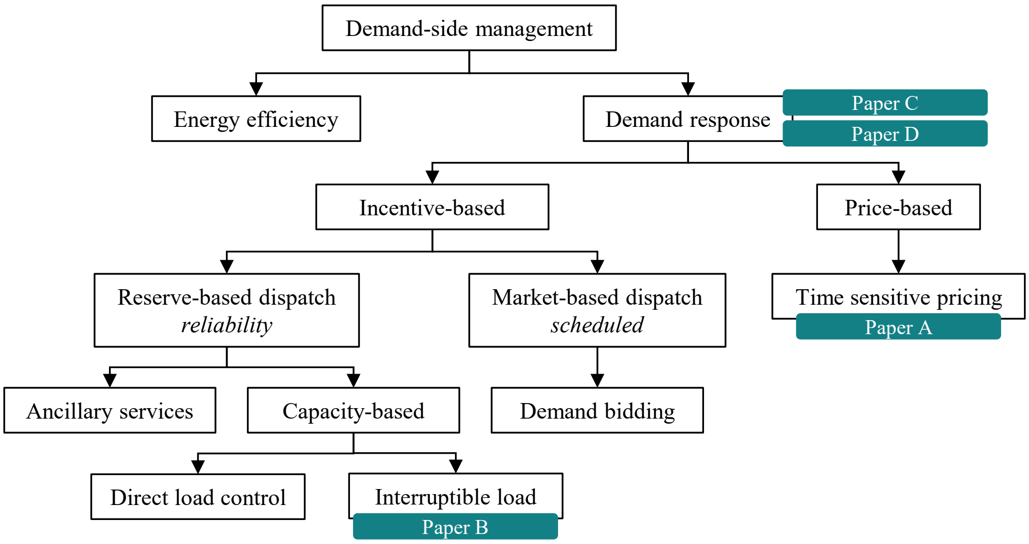

Figure 2.1: Conceptual structure of demand-side management and its decomposition into energy efficiency and demand response programs, adapted from Albadi and El-Saadany (2008) and Morales-España et al. (2022). The four dissertation papers are positioned within this framework according to their focus on demand-side flexibility.

individually or collectively (ACER 2025; CEER 2025). In this sense, demand-side flexibility characterizes the potential, while demand response describes its actual deployment in various programs. A further key distinction concerns the nature of the signal that initiates demand adjustments. Signals can be price-based, including time-of-use tariffs, critical peak pricing, or real-time pricing (Albadi and El-Saadany 2008). Alternatively, they can be incentive-based, relying on contractual agreements that remunerate participation in specific load-control, reserve, or curtailment programs through direct payments (El Gohary 2024).

Figure 2.1 summarizes these relationships by situating demand response within the broader demand-side management framework and by distinguishing price-based and incentive-based demand response instruments following Albadi and El-Saadany (2008) and Morales-España et al. (2022). For a detailed description of the classification and programs, see Albadi and El-Saadany (2008) and Morales-España et al. (2022). The figure further positions the four papers of this dissertation within this conceptual structure according to their respective focus on demand-side flexibility activation.

Within this framework, the four papers of this dissertation address distinct but complementary aspects of demand-side flexibility provision. Paper A is positioned within price-based demand response, as it analyzes household behavior in a living lab setting in which participants are assigned weekly emission caps. These caps are partially combined with the opportunity to maximize self-consumption of electricity from photovoltaic generation, as well as with additional incentives for adhering to power limitations during predefined time intervals. The latter are framed either as economic or non-economic incentives. Flexibility provision in this context is entirely voluntary and not based on contractual obligations. Paper B focuses on incentive-based, capacity-oriented demand response by investigating household acceptability and preferences with regard to externally induced electricity interruptions. Papers C and D are located at a more general level of industrial demand response and flexibility provision. Paper C provides a high-level empirical analysis of the organizational, economic, technological, and regulatory barriers to the adoption of process-specific demand response in industry, without restricting the analysis to a specific demand response program. Paper D complements this perspective by conducting a techno-economic assessment of future process flexibility potentials under alternative decarbonization pathways. Together, the four papers thus span price-based flexibility provision in households, incentive-based residential curtailment, and the broader structural conditions and future potentials of industrial demand-side flexibility.

2.2 Sectoral energy demand, emissions, and flexibility

The household and industry sector together account for the majority of final energy demand, with 29% and 28%, respectively, in Germany 2022 (see Figure 2.2). Albeit both sectors share a similar amount of energy demand, they differentiate notably in the composition of energy carrier consumption. The household sector relies mainly on gas (10%), electricity (6%), oil (5%), and biomass (5%). The industry sector features a similar consumption of gas (10%), but a higher one in electricity (9%), and still relies on coal (5%). The majority of energy consumption in households accounts for space heating (67%), followed by domestic hot water (16%), process heat (e.g., cooking appliances) (7%), and process cold (freezers) (5%) (RWI 2023). The energy consumption in the industry sector mainly falls to process heat (68%), mechanical energy (21%), and space heating (6%) (Rohde and Arnold-Keifer 2023).

The household sector was responsible for 23% and the industry sector for 34% in greenhouse gas emissions in Germany (UBA 2024). The main use of fossil fuels falls into the categories space heating and provision of domestic hot water in the residential sector, while process heat and mechanical energy share the largest part of industrial greenhouse gas emissions (see Figure 2.2).

2.2.1 Residential sector

2.2.1.1 Household energy demand and emissions

With an overall final energy demand of 632 TWh in 2023, the household sector reduced its energy demand by 3.5% compared to 1990 (UBA 2025b). The energy related greenhouse gas emissions however decreased by 40% in this timeframe, mainly due to phasing out coal, a reduction in oil consumption (-44%), and a significant increase in biomass consumption (+818%)[1] (Statista 2025; UBA 2025b). While electricity demand rose moderately (11%), the greenhouse gas emission intensity of the German electricity mix declined by 52% from 1990 to 2020 due to the expansion of renewables, most notably wind and photovoltaic,

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[1] In 2018, around one million residential units were equipped with wood-fired central heating systems in Germany. About six million residential units used various types of firewood for heat generation, mainly in individual room heaters (fireplace, room stove). (Jochem et al. 2023)

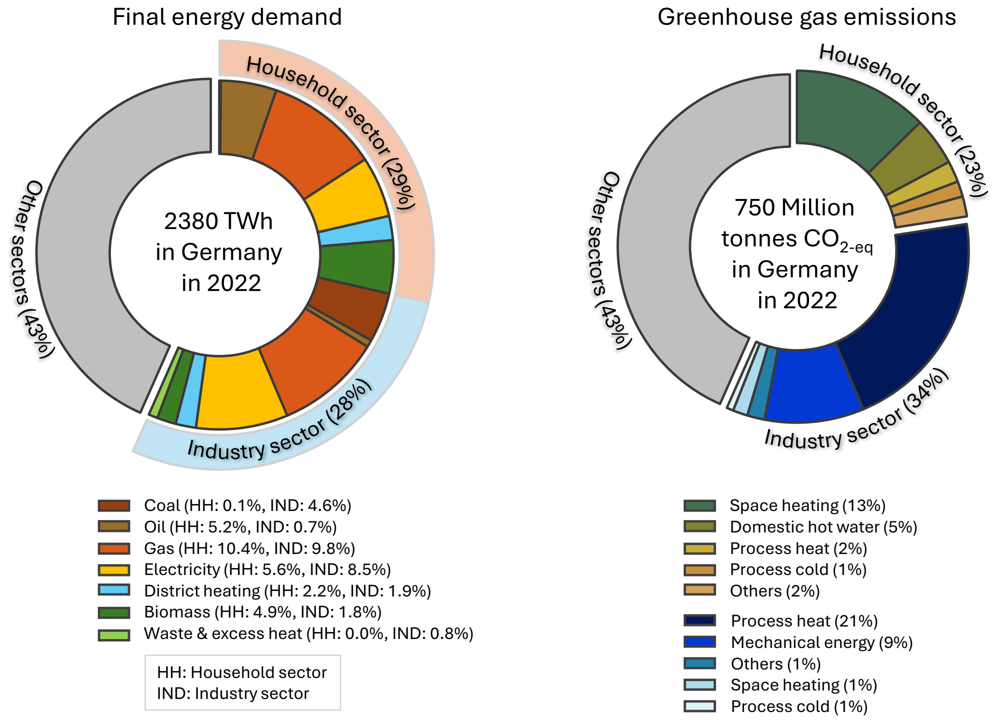

Figure 2.2: Composition of final energy consumption differentiated by energy carriers and greenhouse gas emissions by energy service application per sector in Germany 2022. Own visualization, based on own calculations with data from AGEB (2025a), RWI (2023), BAFA (2022), UBA (2023), and Rohde and Arnold-Keifer (2023).

and the structural reduction of coal-fired power generation (UBA 2023). As presented in Figure 2.2, the about two thirds of final energy is consumed by space heating, presently utilizing mainly gas and oil (RWI 2023). With the trend towards more households, bigger living areas, and less people per household, energy demand rises. However, higher energy efficiency standards for new buildings and retrofit of old buildings counters this development, effectively reducing the specific final energy demand per living space for space heating by 20% since 2008 (UBA 2025b). Electricity consumption dominates the provision of process heat (e.g., oven, dishwasher, tumble dryer) (31%) and process cold (cooling, freezing) (23%) in 2023. Those are followed by information and communication technologies (17%), warm water provision (11%), and lighting (8%) (RWI 2023).

The German Climate Protection Act postulates the goal of reducing greenhouse gas emissions by 65% by 2030, by 88% by 2040 and achieving greenhouse gas neutrality by 2045 (Bundesregierung 2022). With the update of the Climate Change Act in 2024, the annually allowed sectoral emissions are substituted by a cross-sector annual total emissions volume. With 649 million tonnes CO_2 equivalents, the overall emissions in 2024 lay below the permitted annual emissions for 693 million tonnes CO_2 equivalents (UBA 2025d).

In scenarios in line with German Climate Protection Act the final energy demand for space heating needs to be reduced by 14% by 2030 and 34% by 2045 compared to 2025 (Agora 2024a; BMWE 2024b). Energetic retrofit measures are a central energy efficiency measure and must rise from 1.1% in 2015, to 1.5-1.7% by 2030, and 1.3-2.1% by 2045 (Prognos 2022; BDI 2021; Agora 2024a; SKN et al. 2022). The overall electrification in the household sector combined with the rising energy efficiency of buildings and applications could lead to a slight increase in electricity consumption from 2025-2030 by 3% and to an increase of 11% by 2045 (Agora 2024a). Heat pumps are estimated to be the main source of space heating, increasing from one million in 2020 to four to six million in 2030, and 9-15 million 2045 (Agora 2024a; BMWE 2024b; SKN et al. 2022; BDI 2021). District heating covers most of the remaining energy demand for space heating, with 28% of the building usable floor space (Agora 2024a). Future biomass plays a minor role, only in buildings without pipe infrastructure (Prognos 2022).

Furthermore, the electrification of transport transforms the electricity demand in the residential sector. At the end of 2024, 1.6 million battery electric vehicles were registered in Germany (Agora 2025). Projections estimate 8-21 million battery electric vehicles in 2030 and 32-51 million in 2045 in line with the German emission targets (Agora 2024a; Agora 2024b; SKN et al. 2022). This would lead to a significant increase of electricity consumption, that may range from 35-55 TWh by 2030 and 105-125 TWh in 2045, (BEE 2024). The latter would make 80-94% of today's electricity demand of the residential sector (AGEB 2025b).

To summarize, achieving the German climate targets requires a structural transformation of household energy systems along three main pillars: (1) decarbonizing heat supply through a rapid scale-up of heat pumps and district heating, (2) electrifying passenger transport via battery-electric vehicles, and (3) increasing building efficiency supported by retrofit policies and efficiency standards (Agora 2024a).

Taken together, these trends make electricity a pivotal element of residential decarbonization. While the necessary technologies are available, every forward-looking scenario highlights that meeting climate targets requires a far faster diffusion of heat pumps, retrofits, and electric mobility than observed today (Roth and Schill 2025). Such acceleration hinges on household willingness to adopt new technologies, to invest in low-carbon heating, and to adjust daily energy practices. This places behavioral responses at the center of the transition and raises the question of which policy instruments can effectively support and guide these choices.

Since 2021, an increasingly important price signal for household energy use is the national CO_2 price on fossil fuels. Under the German Fuel Emission Allowance Trading Act (BEHG), CO_2 emissions from fuel oils, natural gas, gas oils, liquefied gases, and petrol are priced at a fixed rate that rises annually (BMUV 2020). Introduced at 25 EUR/t_{CO_2} in 2021, the price increased to 55 EUR/t_{CO_2} in 2025 and will move into a price corridor of 55-65 EUR/t_{CO_2} from 2026 onward, before transitioning to market-based pricing (Hakenes 2025). By comparison, the European emissions trading system price fluctuated between roughly 37 and 90 EUR/t_{CO_2} in 2023-2024, highlighting the substantially higher carbon prices observed in other sectors (Hakenes 2025). While no explicit CO_2 price is levied on electricity consumption or biomass fuels such as pellets or wood chips, emissions trading system compliance costs are indirectly passed through into electricity prices since the electricity sector is part of the emissions trading system. For households relying on gas or oil, by contrast, the CO_2 price already constitutes a visible and explicit component of the heating bill. In 2025, the CO_2 price accounts for about 26% of taxes and levies on the gas price and roughly 8% of the final retail gas price[2] (BDEW 2025). As CO_2 pricing rises and fossil fuels become more expensive, households are increasingly incentivized to reduce energy use, operate heating systems more efficiently, or transition to renewable alternatives. At the same time, the current CO_2 price remains only indirectly visible to end users. Many households are unaware of the exact price level, its calculation, or the extent to which it is reflected in their energy bills. On average, households tend to overestimate the costs imposed by the current CO_2 price, while underestimating the future costs associated with rising CO_2 prices (IMK 2024). This lack of salience persists despite consistently high environmental concern. In 2024, 54%[3] of respondents of a study representative of the German population rated environmental and climate protection as very important and another 34% as somewhat important (UBA 2025c).

Alongside price-based incentives, the digital transformation of the energy sector increases the potential for more informed and flexible consumption (BNetzA 2023). Smart meters record household electricity consumption at high temporal resolution. When equipped with a smart meter gateway, standardized 15-minute consumption values can be transmitted by the metering point operator via the smart metering system, enabling automated meter readings and replacing annual manual meter readings (BSI 2024). This technological shift allows electricity providers to offer dynamic tariffs whose prices reflect wholesale market developments or grid congestion (BMWK 2024). For households with electricity intensive devices such as heat pumps, or electric vehicles, but also prosumers, who can increase their self-consumption from rooftop photovoltaics and battery energy storage systems, such tariffs can create opportunities to shift consumption in time, reduce costs, and provide system-level flexibility (Freier and Loessl 2022). Studies indicate that, under dynamic tariffs, households can lower their electricity bills by adjusting consumption patterns or automating flexible loads (Stute et al. 2024; Lorenz et al. 2026). These developments mark a broader transition from opaque, static billing schemes to a system of greater transparency, feedback, and dynamic incentives, underscoring that effective decarbonization requires not only technological availability but also active consumer engagement, understanding, and acceptance.

2.2.1.2 Discussion and research needs for personal carbon trading

A striking feature of the current climate policy debate is that it largely centers on two instruments: carbon taxes and upstream emissions trading systems in which compliance obligations lie with companies or sectors (Regeringskansliet 2018). While several European countries apply explicit carbon taxes, Germany relies on upstream emissions trading schemes with administratively set prices as part of its mitigation strategy (UBA 2025a).

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[2] Based on calculations for a single-family home with an annual consumption of 20,000 kWh and a multi-family building (six units) with an annual consumption of 80,000 kWh. The results are identical for both example households (BDEW 2025).

[3] While this value peaked in 2020 with 65%, it is now back to the level of 2016 (53%) (UBA 2025c).

However, both instruments share the common characteristic that carbon prices reach households only indirectly. The resulting price signal communicates the total fuel costs to individuals without transparently presenting the share of the carbon price. Subsequently, consumers tend to overestimate the costs from the present CO_2 price and acceptance of this policy is low (IMK 2024). What is largely absent from public debate, despite recurring discussion in the academic literature, is the idea of a downstream emissions trading system in which emissions are priced at the consumer level and individuals trade allowances. These approaches are commonly subsumed under the term Personal Carbon Trading (PCT) (Fuso Nerini et al. 2021).

PCT proposes that individuals receive a personal emissions budget for carbon-intensive activities, such as household energy use or private transport. Allowances can be traded, creating a market in which low emitters may sell unused units, whereas higher emitters must buy additional allowances. Proponents argue that such systems bring several advantages over conventional carbon pricing instruments. First, PCT provides a direct economic incentive to reduce emissions, similar to a carbon tax, but combined with an explicit budget constraint that may strengthen perceived personal responsibility. Second, the allocation of equal per-capita or household allowances introduces a redistributive dimension (Howell 2012). Households with low consumption, often lower income groups, may become net beneficiaries. Third, PCT directly enhances carbon literacy and awareness by making personal emissions visible and by linking consumption decisions to a clear, comprehensible metric (Burgess 2016; Fawcett 2010). Empirical studies suggest that, beyond the economic signal, the visibility of emissions, the comparison with others, and perceived social norms can foster behavioral change on psychological and social levels (Parag and Fawcett 2014).

Despite these potential benefits, PCT has so far been implemented only in small-scale voluntary trials, for example, in the United Kingdom, Finland, China, and Australia (Howell 2012; Kuokkanen et al. 2020; Tan et al. 2019; Webb 2018). No country has introduced a binding national scheme. Previous assessments, including those conducted in Germany, concluded in the late 2000s that administrative complexity, data availability, and public acceptability posed substantial barriers (Duscha 2014; Bothner 2021). Notably, however, more recent evidence indicates that participants in trials often view PCT more favorably than alternative consumption based carbon prices (Bristow et al. 2010; Duscha 2014). This suggests that the earlier negative assessments may need to be revisited.

Furthermore, recent advances in digitization fundamentally change the feasibility landscape. Smart meters and digital billing systems increasingly allow for real-time measurement of electricity and heating consumption. User-friendly energy apps can visualize consumption and associated emissions, and automated data flows may substantially lower administrative costs (Richter and Jetzke 2016; Fuso Nerini et al. 2021). These developments imply that several of the technological barriers highlighted in earlier assessments are becoming less restrictive. Digital infrastructures that are currently being deployed in the household sector could therefore serve as enablers for more transparent, targeted, and user-friendly PCT implementations. The integration of smart electricity, gas, and heat meters, data platforms, and personalized carbon dashboards could open new possibilities for PCT schemes that would have been difficult to realize a decade ago.

At the same time, the introduction of PCT would inevitably entail new rights and obligations for all participating actors (Richter and Jetzke 2016). The legal and governance implications have received surprisingly little attention in the literature to date (Parag and Fawcett 2014). Issues such as data protection, allowance allocation, market oversight, and interactions with existing carbon pricing frameworks require careful consideration (Fuso Nerini et al. 2021). This highlights the need for updated analyses that reflect the significantly changed technological context and contemporary expectations for consumer rights and digital services.

These developments give rise to several concrete research needs. First, given the limited and partly outdated empirical evidence, qualitative research involving experts, regulators, consumer associations, and technology providers would help reassess the feasibility and desirability of PCT in a digitalized system environment (Richter and Jetzke 2016). Second, the potential integration of PCT with smart meter-based consumption data warrants systematic investigation, including the technological, behavioral, and regulatory dimensions. Third, international experiences with voluntary PCT variants should be synthesized to assess which design features foster acceptance, learning, and durable behavioral change. Finally, the legal implications of downstream carbon trading, particularly regarding data governance, rights of recourse, and the compatibility with EU energy and climate law, remain insufficiently explored and represent a critical area for further research. In sum, while PCT has long been viewed as a concept ahead of its time, the ongoing digital transformation of household energy systems, combined with increasing demands for transparency and fairness in climate policy, suggests that a renewed examination of its potential is both timely and warranted.

While these research needs span a broad range of disciplinary perspectives, the present dissertation focuses primarily on the second aspect, namely, the interaction between PCT concepts, smart meter-based consumption data, and the technological, behavioral, psychological, and financial implications for households. Other research needs highlighted above lie beyond the scope of this work but provide important directions for future investigation.

2.2.1.3 Household demand-side flexibility

Beyond decarbonizing the residential sector via efficiency gains and electrified end-uses, households are increasingly expected to provide flexibility by adjusting the timing and level of electricity consumption in response to price-based incentives and contractual arrangements, thereby contributing to system balancing and congestion management. Different approaches exist to address the growing challenges that the rise in volatile electricity generation and increasing electricity demand pose to the electricity grid. Expanding the grid and storage capacities can counteract grid congestion. These measures are tied to large investments and can be economically inefficient, time, and resource consuming, notably, when peak loads occur rarely (Heilmann et al. 2020). In addition to grid expansion, flexible energy demand can be used for grid balancing or congestion management (Stawska et al. 2021).

Residential electricity demand follows pronounced daily and seasonal patterns shaped by occupants' routines, appliance use, and solar irradiance. Morning and especially early-evening demand peaks coincide with low photovoltaic availability and high wholesale market prices. As heating and mobility electrify further, these evening peaks are expected to intensify, particularly on cold winter days when heat pump operation and electric vehicle charging may coincide (SKN et al. 2022; Kühnbach et al. 2020). Without demand-side flexibility, such simultaneity risks increasing the frequency of local grid congestion and raising system-wide balancing costs.

While balancing markets and ancillary services for the transmission grid are already well established in Germany (BNetzA 2025b), regional or distribution-level flexibility markets that actively involve residential consumers remain at an early stage of experimentation (Scrocca et al. 2026). Yet the role of households is set to grow substantially, with the diffusion of electric vehicles and heat pumps, which not only raise household electricity demand but also provide controllable loads. As outlined in Section 2.2.1.1, these developments expose households more directly to system conditions while simultaneously creating new opportunities for flexible demand.

Direct load control of home batteries, heat pumps, or charging of battery electric vehicles could help relieve local congestion, support grid stability, and reduce system costs (ENTSO-E 2021). In Germany, this potential has recently been formalized in regulation, in the § 14a of the German Energy Industry Act (BNetzA 2024b). Since 1 January 2024, distribution system operators are required to connect devices such as heat pumps and private charging stations for battery electric vehicles. During congestion events, they may temporarily curtail the power draw of these devices to 4.2 kW, with participating households receiving reduced grid fees as compensation (BNetzA 2024b). Furthermore, from 2025 onwards, all electricity suppliers must offer dynamic electricity tariffs to consumers equipped with smart meters (BMWE 2025). Dynamic electricity tariffs comprise real-time pricing, critical peak pricing, peak-time rebates, variable peak pricing, and direct load control, all of which link retail prices to wholesale market conditions or system constraints (Parrish et al. 2019; Hao et al. 2024).

However, the adoption of dynamic electricity tariffs relies on the implementation of smart meters that measure the electricity demand with high temporal granularity. Germany is lagging behind its targets for the smart meter roll-out. At the beginning of 2025, only 2% of German households were equipped with a smart meter, far behind countries such as Sweden, Norway, and Finland with almost a 100%, and France and Spain of 90% coverage (Bakkenbüll 2025). As a result, access to dynamic tariffs and related flexibility options remains uneven across households. Beyond the roll-out delays, structural conditions such as home ownership, the implementation or access to large electricity loads (heat pumps, electric vehicles), as well as economic capital comprise opportunities for providing flexible loads (Bender et al. 2024). Household that lack these prerequisites have few opportunities to provide flexibility and may fall into what has been termed flexibility poverty, meaning a lack of capital, capacity, time, and space to act on willingness to provide flexibility (Domenig et al. 2024; Fjellså et al. 2021; White and Sintov 2020). Though individual renters with low economic capital (e.g., students) exhibit willingness and ability to provide flexible consumption behavior, collectively, the flexibility potential can be limited and "locked-in" due to daily practices and schedules, other people co-existing in the same household, socio-material factors, such as housing, life situation, as well as limited flexibility capital (Fjellså et al. 2021; Fell 2020). Thus, energy policy and innovations should consider the implications of flexibility poverty and distributional bias in public support for demand-side flexibility measures.

Household flexibility arises from several categories of flexible load and distributed energy resources. Importantly, these categories are not mutually exclusive: many devices can provide flexibility through more than one mechanism, depending on the available control options and user preferences. (1) Shiftable loads are appliances such as wet appliances (washing machines, dryer, dishwashers), battery electric vehicle charging that can be delayed without loss of service (Afzalan and Jazizadeh 2019; D'hulst et al. 2015). (2) Heat pumps, electric vehicle chargers, and stationary batteries are devices that can be modulated or scheduled and fall into the category of controllable loads (BNetzA 2024b; Kohlhepp et al. 2019). (3) Thermal inertia in buildings and hot water tanks allows short-term decoupling of energy conversion and service delivery (Kohlhepp et al. 2019). (4) Prosumption flexibility referring to households that both consume and produce electricity, for instance via rooftop photovoltaic systems, allowing them to shift consumption to periods of high on-site generation or to charge private battery storage systems (Rahman et al. 2025; Kubli et al. 2018). (5) Curtailable loads designating temporary reductions in electricity use, that can involve controlled interruptions of appliances such as tumble dryer, dishwasher, or electric oven (Harold et al. 2021; Ladenburg et al. 2022) or the whole household (Motz 2021; Scharnhorst et al. 2023).

2.2.1.4 Research needs for residential flexibility provision

Despite growing regulatory and technological momentum for activating household-level demand response, substantial evidence gaps remain regarding how residential consumers perceive flexibility measures, evaluate trade-offs between reliability and incentives, and respond to different forms of intervention. These gaps are particularly salient as flexibility options become more intrusive, ranging from automated scheduling of high-load devices to controlled curtailment or even temporary power interruptions.

Early studies on dynamic electricity tariffs found limited trust in their perceived benefits, particularly with respect to their contribution to demand-side management and the integration of renewable energy sources. Respondents also expressed skepticism regarding potential individual benefits, such as reducing electricity expenditures, saving energy, or increasing awareness of electricity consumption, with the majority of households preferring conventional electricity tariffs (Dütschke and Paetz 2013). Even about ten years later, survey evidence confirms this persistent information deficit. Months before the mandatory introduction of dynamic tariffs in 2025, 53% of respondents in Germany had never heard of such tariffs, 26% had heard of it but could not explain them, and 81% felt poorly informed about them (VZBV 2024). Thus, several studies call for awareness campaigns to inform the overall public about dynamic electricity tariffs and the benefits of flexibility provision (VZBV 2024; Kubli et al. 2018).

Pilot studies, however, show that when households gain practical experience, flexible consumption behavior can emerge and even gain acceptance over time (Dütschke and Paetz 2013; Srivastava et al. 2019; Scharnhorst et al. 2021). Furthermore, while there is general support for demand-side flexibility for the residential heating sector in Germany (Bender et al. 2024), several studies highlight that tariff design plays a critical role. Simplicity, price caps, override options, and clear communication strongly influence uptake (Kubli et al. 2018). Socio-demographic heterogeneity also matters. For instance, Torstensson and Wallin (2015) find that households living in detached-houses tend to respond more strongly to financial incentives, whereas apartment dwellers are more motivated by environmental considerations, implying that demand response schemes may need to differentiate between customer segments (Torstensson and Wallin 2015).

Participants generally express a preference for automated demand-response services that involve data sharing, with energy cost savings being the main driver and outweighing concerns about data privacy (Pelka et al. 2024). However, automated demand response may come with initial learning effort and energy literacy (Herrmann et al. 2018), as well as a certain amount of comfort loss (Sweetnam et al. 2019). Overall, the evidence suggests that there is no "one-size-fits-all" approach to activating residential load shifting.

Research on the acceptability[4] of residential load shedding[5] reveals considerable heterogeneity across demographic groups, dwelling types, appliance ownership, and motivations. Motz (2021) shows that compensation is most often the main driver, while interruption frequency, and outage duration also shape household preferences for controlled power interruptions. Zemo et al. (2019) and Meles et al. (2021) were the first to test and find that advance notice is an important characteristic for households in Ethiopia, with mixed results on the preference for one day or one to two week prior notification. Apart from these, existing studies rarely examine the role of advance notice, but call for its assessment (Motz 2021). Furthermore, qualitative evidence indicates that it is valued highly by participants in pilot settings (Scharnhorst et al. 2023). No representative intra-day advance notice analysis exists to date, which constitutes a significant gap given that flexibility markets increasingly require short-term responsiveness.

Taken together, the existing literature provides valuable insights but remains fragmented along several dimensions. First, while incentivized demand response schemes such as dynamic tariffs have been piloted partially in Germany and other countries, they have not yet been investigated in the context of being part of a PCT scheme, aiming at incentivizing energy saving behavior, as well as flexibility provision via photovoltaic self-consumption

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[4] Throughout this dissertation, the term *acceptability* refers to the degree to which a policy is evaluated positively before implementation, whereas *acceptance* describes actual approval once the policy is in place. Support goes beyond passive acceptance and captures active promotion of a policy (Bechthold 2021). Substantively, this thesis adopts the meaning of *acceptability*, yet uses the terms acceptability and acceptance interchangeably for stylistic reasons, in line with common practice in the literature (Motz 2021; Lehmann et al. 2022).

[5] Entailing the power interruption of devices or entire households.

and power constraints during peak load periods. Second, despite consistent calls for more research on the design elements of controlled power interruptions, particularly advance notice, representative evidence for Germany remains scarce. Third, very few studies integrate behavioral, technical, and contextual factors in a way that reflects the increasingly digital and electrified reality of German households.

This dissertation addresses these gaps through two empirical studies. Paper A examines how households adjust their energy use under carbon caps, real-time feedback on energy consumption, and load-shifting incentives in a fully instrumented living-lab environment, thereby providing behavioral evidence on demand flexibility in everyday routines. Paper B investigates how households evaluate controlled electricity interruptions, quantifying preferences for duration, frequency, compensation, and intra-day advance notice using a dual-response discrete choice experiment. Together, these studies deliver insights into residential flexibility provision and acceptability, spanning both load shifting and load shedding. They thereby provide empirical foundations for designing consumer-centered, digitally supported flexibility schemes and complement the ongoing policy shift toward greater residential participation.

2.2.2 Industrial sector

2.2.2.1 Industrial energy demand and emissions

The industrial sector in Germany accounted for 656 TWh of final energy demand in 2022, representing a reduction of about 21% compared to 1990 (AGEB 2025a; Rohde and Arnold-Keifer 2023). Over the same period, energy-related greenhouse gas emissions decreased by approximately 48%, driven by significant reductions in the consumption of hard coal (- 38%), lignite (- 81%), mineral oil (- 68%), and more modestly natural gas (- 9%) (Agora 2023; AGEB 2025a). Biomass use has increased roughly sevenfold since 1990, although it still accounts for only around 5% of industrial final energy demand today (AGEB 2025a). Efficiency improvements and process optimization contributed further to the overall decline in emissions (Wuppertal Institut 2025).

Industrial energy use in Germany is highly heterogeneous. A distinction is commonly drawn between energy-intensive and less energy-intensive sub sectors. Figure 2.3 illustrates that chemicals, iron and steel, non-ferrous metals, coke and petroleum refining, non-metallic minerals (including glass and ceramics), and the paper, pulp, and print industry jointly account for roughly 81% of total industrial final energy demand (Destatis 2025).

Around 60% of industrial greenhouse gas emissions arise from three sectors alone: iron and steel, cement, and chemicals (Agora 2024a). As shown earlier in Figure 2.2, industrial process heat is responsible for the majority of emissions (60%), predominantly supplied by natural gas (45%), coal (24%), and, to a lesser extent, district heating (9%), electricity (8%), and biomass (7%) (Rohde and Arnold-Keifer 2023; UBA 2023). Figure 2.4 disaggregates process heat demand across sub sectors and confirms that natural gas remains the dominant energy carrier, while coal is still concentrated in iron and steel and parts of the non-metallic minerals industry. The largest contributors to process heat demand are iron and steel (27%),

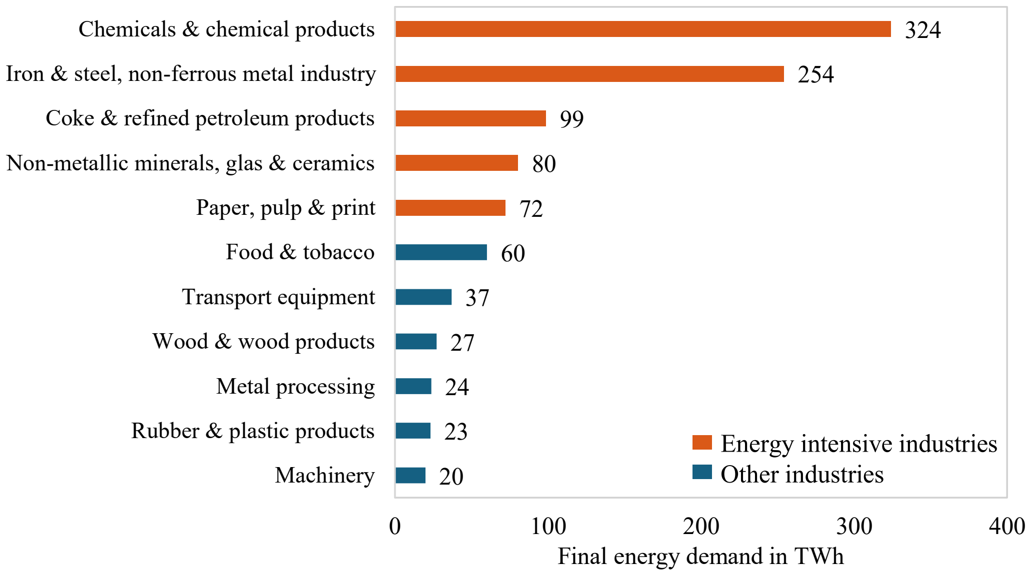

Figure 2.3: Final energy demand of the industry by sub sector in Germany 2021, differentiated between energy intensive and other industries. Only industries with > 19 TWh are accounted for in this figure. Own visualization after Destatis (2025).

basic chemicals (21%), non-metallic minerals (10%), paper and pulp (8%), and food and tobacco (8%) (Rohde and Arnold-Keifer 2023). Electricity plays a comparatively minor role across most sub sectors. Only, for the production of non-ferrous metals (43%), mining and quarrying[6] (25%), transport equipment (15%), metal processing (14%), and basic chemicals (11%), higher shares of electricity demand can be noted (Rohde and Arnold-Keifer 2023). Aside from providing process heat, electricity is used primarily for mechanical energy applications such as pumps and compressed air systems (Wuppertal Institut 2025).

Because process heat supply across nearly all industrial sub sectors remains heavily reliant on fossil fuels, electrification technologies are expected to play a central role in future mitigation strategies. Recent assessments conclude that electric process heat technologies, expected to reach market maturity by 2035, could supply up to 90% of today's non-electrified process heat demand, while already available technologies such as industrial heat pumps, electric boilers, and electric arc furnaces could cover more than 60% (Rohde and Arnold-Keifer 2023). This illustrates that a substantial share of fossil-based process heat demand could be decarbonized with technologies that are either commercially available today or expected to be deployable within the next decade.

Looking ahead, scenario projections consistent with the targets of the German Climate Protection Act estimate a decline in industrial final energy demand of 1-24% by 2030 and 8-50% by 2045 relative to 2022 levels (SKN et al. 2022; BDI 2021). At the same time, electrification is expected to raise industrial electricity consumption by 21-47% by 2030 and to roughly double it by 2045 (Agora 2024a; BDI 2021). By 2045, electricity is projected to supply 65-69% of industrial final energy demand[7], with renewable hydrogen contributing an additional 11% (Agora 2024a; BDI 2021). Electrification of low-temperature process heat

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[6] Subsumed in "Other" in Figure 2.4.

[7] Of which approximately 17% will be used for low-temperature process heat below 500°C (Agora 2024a).

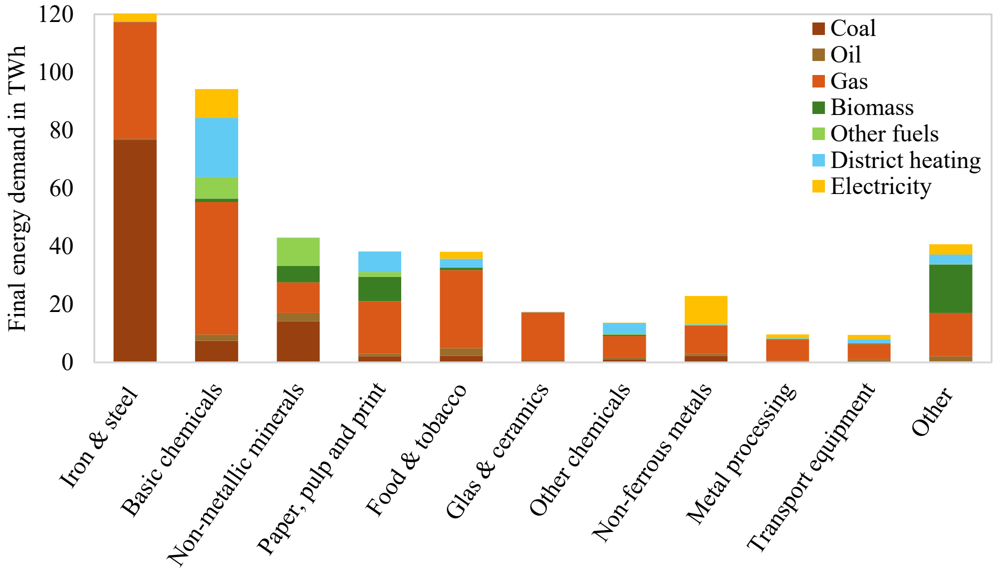

Figure 2.4: Final energy demand for process heat by industry sub sector and energy carrier in Germany 2022. Own visualization, with data from Rohde and Arnold-Keifer (2023).

(< 500°C) and high-efficiency cross-cutting technologies are expected to drive short-term emission reductions (Agora 2024a). Industrial heat pumps are projected to reach capacities of 10 GW by 2030 and 35 GW by 2045 (Agora 2024a). In the iron and steel sector, the shift to hydrogen-based direct reduction is anticipated to account for 39-55% of production in 2045, reducing the reliance on the blast furnace route by about one-third compared to 2019 (BDI 2021; SKN et al. 2022; Wuppertal Institut 2025). Secondary steel production via electric arc furnaces could increase by 50-100% by 2045, supported by improved scrap collection and recycling (BDI 2021; SKN et al. 2022; Wuppertal Institut 2025). Emerging technologies such as iron ore electrolysis are not yet deployable but may play a role in later global transitions (Wuppertal Institut 2025). Additional costs incurred from the production of "green" steel will amount to approximately 1-2% of the vehicle price (Agora 2024a; Wuppertal Institut 2025).

In the cement sector, future mitigation is expected to rely on reduced clinker ratios, improved material efficiency, a shift toward timber construction, leading to a reduction of up to 25% in cement demand, and, critically, the deployment of carbon capture and storage to address unavoidable process emissions (Agora 2024a). The chemical sector is projected to transform its feedstock usage from the utilization of oil to recycled plastics. At the same time, rising imports of green ammonia are expected, while Germany retains domestic production capacity to safeguard fertilizer supply and food production (Agora 2024a).

The literature converges on four principal drivers of industrial decarbonization: (1) decarbonization of process heat through electrification, biomass, renewable gases, district heating, and industrial heat pumps (BDI 2021; Agora 2024a; Wuppertal Institut 2025); (2) fundamental process-route changes in energy-intensive industries, including hydrogen-based steelmaking, ammonia, and methanol production, electrification of steam crackers, and substitution of fossil feedstocks with synthetic or biogenic alternatives (BDI 2021;

Agora 2024a; Wuppertal Institut 2025); implementation of carbon capture and storage technologies in the cement and lime production to account for process emissions; (BDI 2021; Wuppertal Institut 2025). (3) efficiency improvements in cross-cutting technologies such as motors, pumps, and process automation (BDI 2021); and (4) enhanced material efficiency and substitution, as well as circular economy measures to reduce the use of energy-intensive primary products (Wuppertal Institut 2025).

Decarbonizing energy-intensive industrial processes requires a combination of policy measures that both strengthen incentives for emission reductions and mitigate investment risks. The gradual phase-out of free emissions trading system allowances is a key element in reinforcing the carbon price signal faced by firms. At the same time, Climate Protection Contracts (carbon contracts for difference) reduce investment risks for low-carbon industrial processes by compensating firms when the CO_2 price is below mitigation costs and requiring repayment when it exceeds them (Aydemir et al. 2024; DIW 2024; BDI 2021; Agora 2024a; Wuppertal Institut 2025). Additional measures include the creation of lead markets for green steel (Aydemir et al. 2024), the European Carbon Border Adjustment Mechanism, reforms of grid tariffs for flexible loads, targeted subsidies for industrial heat pumps, electricity tax reductions, and strengthened hydrogen and CO_2 infrastructure planning (Agora 2024a).

Finally, the structure of German industry itself may change as the energy transition progresses. Recent research suggests that energy-intensive upstream production stages such as raw iron, steel, ethylene or ammonia, are particularly sensitive to regional differences in renewable energy availability and electricity costs, creating incentives to locate these activities to renewable-rich regions (Samadi et al. 2023; Verpoort et al. 2024). In contrast, downstream manufacturing stages with higher value added and lower energy intensity are more likely to remain in countries such as Germany, where industrial capabilities, skilled labor, and infrastructure are concentrated (Wuppertal Institut 2025; Verpoort et al. 2024).

2.2.2.2 Industrial demand-side flexibility

Beyond decarbonizing industrial energy use through efficiency improvements, fuel switching, electrification, and process-route changes, the industrial sector is increasingly expected to provide operational demand-side flexibility. The manufacturing industry is the largest electricity consumer in Germany, accounting for 43% of final electricity demand, compared with 28% in the residential and 25% in the commercial and public services sectors (IEA 2024). Demand response is therefore seen as a key flexibility option alongside grid expansion, storage, sector coupling, and flexible generation (Lund et al. 2015; Brouwer et al. 2016; Papaefthymiou et al. 2018; Strbac 2008). Several studies highlight that industrial demand-side measures can provide substantial flexibility and reduce total system costs, particularly in scenarios with high variable renewable penetration (Brouwer et al. 2016; Papaefthymiou et al. 2018).

In contrast to the household sector, many industrial firms already operate energy management systems with automated metering, monitoring, and sometimes direct control of machinery (Paulus and Borggrefe 2011; Gils 2014). Some energy-intensive companies participate in balancing power markets or interruptible load schemes, yet the bulk of industrial demand response capability remains untapped (BNetzA 2024c). Existing studies estimate the technical demand-side management potential of German industry between 2 and 6 GW, depending on the assumed processes and time frames (Müller and Möst 2018; Gils 2014; Stede 2016). For comparison, the German annual peak load amounted to about 80 GW in 2021 (BNetzA 2023). To put this estimate into perspective within the broader flexibility landscape, the projected[8] residential flexible capacity could reach around 230 GW by 2029, corresponding to more than twice today's national peak demand (Agora 2024c). While the aggregate industrial flexibility potential appears modest in comparison to the rapidly growing residential flexibility capacity, industrial demand-side flexibility remains highly valuable due to its large unit sizes, high controllability, longer activation durations of several hours, and the fact that many firms already operate advanced automation and metering infrastructure (Dedecca et al. 2025; Ranaboldo et al. 2024). As a result, industrial demand-side flexibility is particularly relevant for system-wide balancing and congestion management at higher grid levels, whereas residential flexibility is more decentralized and could contribute to relieving local congestion in low-voltage distribution networks (Dedecca et al. 2025; Arboleya et al. 2022).

To structure this potential, the literature typically distinguishes technical, economic, accepted and practical demand response potentials (Gils 2014; Grein and Pehnt 2011). The technical potential comprises all loads that are, in principle, shiftable or curtailable given existing technologies, infrastructure, and process characteristics. The economic potential comprises the share that is profitable under prevailing market conditions. Finally, the accepted potential captures the share of technical flexibility that firms are, in principle, willing to offer ex ante, given risk perceptions, product quality requirements, and organizational constraints, while practical potential reflects the flexibility that is actually provided in operation once these factors interact with market access and incentives (Gils 2014).

Industrial flexibility arises from a combination of process characteristics, storage options, and production planning choices. Process-related drivers include batch versus continuous operation, availability of intermediate storage, tolerance ranges for temperature and pressure, and opportunities to pre-produce or catch up production. Compared to households, industrial systems often exhibit larger absolute flexible loads[9] and higher degrees of automation, but their flexibility is constrained by tighter quality standards, safety requirements, and complex interdependencies between upstream and downstream processes (Müller and Möst 2018; Buhl et al. 2021). The taxonomy of Buhl et al. (2021) distinguishes between *organizational* and *technical* industrial demand-side management measures. Organizational measures modify the way production is planned and scheduled without necessarily changing the underlying machinery, whereas technical measures directly intervene in operating parameters, equipment, or energy carriers. Table 2.1 summarizes central organizational flexibility measures identified in the literature.

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[8] At present, residential flexibility in Germany is largely unrealized, so available estimates necessarily rely on projected rather than observed capacity (Bender et al. 2024; Agora 2024c).

[9] From hundreds of kW to several MW per plant (Buhl et al. 2021).

Table 2.1: Overview of organizational industrial demand-side flexibility measures. Based on Buhl et al. (2021).

Organizational measure	Short description
Adaptation of staff break times	Shifting employee breaks to temporarily reduce or increase electricity use in response to price or grid signals.
Adaptation of working shifts	Aligning shift schedules with periods of low prices or high renewable generation (e.g., nights, weekends, holidays).
Adaptation of order execution sequence	Changing the sequence in which different manufacturing orders are processed, exploiting their differing load profiles.
Capacity planning adjustment	Assigning products to alternative machines with different load and timing characteristics.
Adaptation of production start	Advancing or delaying the start of production runs to better match system conditions or price signals.
Manufacturing order interruption	Temporarily interrupting an ongoing manufacturing order to reduce load for a limited period.
Adaptation of order production sequence	Changing the order of process steps for a specific product across machines with different load profiles.
Adaptation of resource allocation	Selecting machines or lines based on their resource use (e.g., gas vs. electricity) to adapt the electrical load profile.

Technical demand-side flexibility measures intervene more directly in the physical operation of industrial systems. They include, among others, adjustments of process parameters, temporary shutdowns of equipment, use of inherent or dedicated energy storage, and switching between energy carriers. Table 2.2 presents an overview.

The flexibility characteristics of these measures differ markedly. Buhl et al. (2021) characterize flexibility options using three key indicators: *flexible power* (the load change relative to a baseline), *activation duration* (time between decision and effective load change), and *active duration* (minimum and maximum period for which a measure can be sustained). Organizational measures such as adapting staff break times or working shifts generally involve comparatively long activation durations (hours to days), moderate active durations, and modest flexible power. Measures such as adapting production start, interrupting manufacturing orders, or reallocating resources can provide higher flexible power with shorter activation times. Technical measures, particularly adaptation of operation parameters and operation interruption, offer substantially higher flexible power (up to several MW in individual plants) and short activation durations, making them suitable for fast-response flexibility products. Measures based on inherent or dedicated storage often provide intermediate flexible power but can be constrained by storage capacity and charging time.

Table 2.2: Overview of technical industrial demand-side flexibility measures. Based on Buhl et al. (2021).

Technical measure	Short description
Adaptation of operation parameters	Modifying process parameters (e.g., temperature, throughput) within tolerance ranges to change the load profile.
Operation interruption	Temporarily suspending the operation of specific equipment, independent of the manufacturing order being processed.
Adaptation of the operational sequence	Changing the sequence of production tasks within a single machine to alter the temporal load pattern.
Inherent energy storage	Exploiting process-internal inertia (e.g., thermal mass, buffer tanks) to decouple energy input from production output.
Bivalent operation	Switching a system between two energy carriers (e.g., gas vs. electricity) while maintaining product quality.
Energy carrier exchange	Temporarily substituting one energy carrier with another (e.g., combined heat and power plant vs. electric boiler) without altering the process route.
Dedicated energy storage	Charging or discharging dedicated storage (e.g., thermal storage, batteries) to shift electricity draw from the grid.

From a system perspective, industrial demand-side flexibility measures can be used across several flexibility applications. Buhl et al. (2021) match flexibility options and other flexibility technologies (sector coupling, storage, thermal power plants) to three main application categories: integration of excess renewable feed-in, energy-only markets (day-ahead and intraday), and ancillary services (frequency containment and restoration reserves). Sector coupling technologies such as electrolyzers, power-to-heat, or power-to-gas are particularly well suited for integrating excess renewable feed-in due to their long active durations. Large-scale thermal storage and pumped hydro storage likewise support long-duration flexibility. For day-ahead and intraday markets, a broader set of options qualifies: large-scale batteries, thermal storage, combined heat and power units, gas turbines, and many organizational and technical demand-side flexibility measures with sufficient flexible power and activation times on the order of minutes to hours. Ancillary services impose more stringent prequalification requirements regarding response time and minimum bid size (50Hertz et al. 2022). Here, electrolyzers, large-scale batteries, some thermal power units, and a subset of technical demand-side flexibility measures (especially adaptation of operation parameters and energy carrier exchange) can qualify, whereas small-scale devices and many purely organizational measures are typically too slow or too small.

Despite these technical opportunities, the realization of industrial demand-side flexibility potential is constrained by regulatory, economic, and societal factors. The current German regulatory framework has historically provided limited incentives for flexible demand and, in some cases, even penalized it.

Energy-intensive firms can benefit from individually agreed grid fee reduction[10]. At present, around 560 such agreements exist, predominantly in the chemical industry, iron and steel, paper, glass, and food processing sectors, but also partly in data centers and other electricity-intensive activities (BNetzA 2025a). In total, these arrangements reduce industrial grid fee payments by approximately EUR1.42 billion per year (BNetzA 2025a). However, the Federal Network Agency now explicitly assesses the bandload incentive as systemically misaligned under conditions of volatile renewable generation, as it promotes inflexible consumption and can exacerbate congestion and renewable curtailment (BNetzA 2025a; SynErgie 2020; Leinauer et al. 2022). The procedure for the determination of the general network charge system for electricity proposes to replace this bandload privilege with a flexibility-oriented incentive scheme, in which future grid fee reductions would be conditional on verified market- or grid-serving load adjustments (BNetzA 2025a).

In parallel, historically reduced levies and surcharges (e.g., EEG reliefs and electricity tax reductions) have often been tied to high annual electricity consumption and specific efficiency benchmarks, which can create tensions between cost minimization, efficiency improvements, and flexibility provision (Leinauer et al. 2022; BMWE 2024a). The current regulatory reform of industrial grid charges aims to better align network tariffs with grid conditions and congestion patterns, thereby strengthening locational and temporal price signals and indirectly improving incentives for flexible load behavior (BNetzA 2025a). At present, clear market-based incentives for industrial demand-side flexibility remain limited, while complex prequalification[11] procedures for participation in balancing markets further constrain the attractiveness of flexibility provision (50Hertz et al. 2025; Buhl et al. 2021; Sauer et al. 2019).

Societal and organizational aspects play a central role for the realization of industrial demand-side flexibility. The general normative acceptance of the energy transition within German industry is relatively high and flexibility is widely perceived as a potentially important building block of decarbonization strategies. At the same time, the concrete implementation of flexibility measures is strongly embedded in firm-specific organizational cultures, strategic priorities, and monetary efficiency logics (Sauer et al. 2019). Internal investment decisions remain closely tied to short- to medium-term profitability requirements, while flexibility projects are often characterized by long planning horizons and uncertain returns. Industry actors therefore express strong expectations toward politics to provide stable, transparent, and fair framework conditions. Planning security, transparent price signals, and a coherent regulatory environment are viewed as necessary preconditions for long-term flexibility investments (Sauer et al. 2019). Furthermore, demand-side flexibility measures that affect staffing patterns, break times, or shift schedules must comply with labor

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[10] §19(2) StromNEV bandload rule, rewarding constant consumption above 10 GWh/year (BNetzA 2025a).

[11] The prequalification procedure for industrial demand-side flexibility under the German balancing markets sets strict metering, control, and documentation standards. Meeting these prerequisites may impose a substantial administrative and technical burden, particularly for firms lacking prior experience in market-based flexibility provision (50Hertz et al. 2022).

law and be acceptable to employees and works councils (Olsthoorn et al. 2015; Roth et al. 2020). Firms face internal coordination challenges when aligning production planning, maintenance, and energy management objectives. While case studies suggest that demand-side flexibility measures are generally regarded as compatible with the broader goals of the energy transition, their implementation demands careful consideration of workplace conditions, data sharing, and internal communication structures (Buhl et al. 2021).

The economic potential of industrial demand-side flexibility is only a subset of the technical potential once transaction costs, market-access costs, and production constraints are taken into account (Grein and Pehnt 2011; Gils 2014). Large industrial consumers, such as steel and aluminum mills, constitute the greatest and often also most cost-effective demand-side flexibility potential (dena 2010; Gils 2014). Making their potential accessible to the relevant markets can be a great source of low-cost flexibility (Brouwer et al. 2016; Papaefthymiou et al. 2018). At the plant level, for example, Schoepf et al. (2018) show for the paper industry that the value of process flexibility is strongly influenced by the relative prices of raw materials and electricity, as well as by product-quality requirements, implying that firms' willingness to invest in flexible technologies and practices hinges on expectations about future energy and input prices. Furthermore, demand-side flexibility competes with other flexibility options such as storage, sector coupling, and flexible generation and will only be realized at scale where market design and price signals make it attractive relative to these alternatives (Papaefthymiou et al. 2018; Buhl et al. 2021).

In sum, industrial demand-side flexibility offers significant technical potential, but the gap between technical and practically realized potential remains large. This gap is shaped not only by technological and cost factors but also by regulatory design, organizational routines, and perceptions of risk and complexity within firms. These unresolved issues motivate a closer, empirically grounded examination of barriers and enablers to industrial demand-side flexibility participation, as well as detailed, process-level assessments of future techno-economic flexibility potentials. These topics are taken up in the following subsection and in Papers C and D of this dissertation.

2.2.2.3 Discussion and research needs for present and future industrial flexibility barriers and potentials

While the technical and economic potential of industrial demand-side flexibility has been assessed by several studies, substantially less is known about how firms actually make decisions about participating in demand response (Gils 2014; Gils 2016; Sauer et al. 2019). More recent studies suggest that participation is shaped not only by financial cost-benefit considerations, but also by cultural, structural, regulatory, and behavioral factors (Leinauer et al. 2022; Cardoso et al. 2020; Parrish et al. 2020; Sloot et al. 2022). However, empirical research on industrial demand response barriers remains scarce and fragmented. Prior work often focuses on isolated barrier dimensions, specific sub sectors, or regulatory and market perspectives, without systematically capturing how organizational, behavioral, informational, and competence-related barriers interact (Olsthoorn et al. 2015; Leinauer et al. 2022; Buhl et al. 2021). This is particularly problematic given the high heterogeneity of industrial consumers with respect to production processes, automation levels, risk exposure, and regulatory environments. Moreover, comprehensive interview-based studies covering multiple sectors and associations across Germany remain rare. This gap motivates the need for an integrated, empirically grounded analysis of industrial demand-side flexibility barriers and enablers. Paper C addresses this need by developing a multidimensional barrier taxonomy and providing a systematic empirical assessment of barrier interrelations based on expert interviews across diverse commercial and industrial actors.

Beyond current participation barriers, a second major research gap concerns the future role of industrial demand-side flexibility under deep decarbonization and electrification pathways. Most existing flexibility potential estimates are based on today's production structures and energy carrier mixes, even though industrial processes are expected to undergo profound transformations through electrification, hydrogen use, and process-route changes (Gils 2014; Müller and Möst 2018). As a result, today's flexibility potentials may substantially underestimate the flexibility that could emerge in a future industrial system. To date, no other study has yet addressed future demand-side flexibility potentials at process-level in Europe. Paper D investigates this gap by quantifying the technical future process flexibility potential of energy-intensive industries under ambitious decarbonization scenarios, thereby complementing the present-oriented barrier analysis of Paper C with a forward-looking system perspective.

2.3 Behavioral drivers of energy saving and flexibility provision

The transformation of the energy system depends not only on technological change and infrastructure expansion, but also on the behavioral engagement of energy consumers (Heberlein 2012). Experience from climate and energy policy shows that even technically sound and economically efficient measures may fail if they are perceived as illegitimate, overly burdensome, or unfair. Public resistance against fuel tax increases in France in 2018 or the heated debate surrounding recent German heating regulations illustrate that acceptance is a critical precondition for effective climate policy (Mehleb et al. 2021; Haas et al. 2025).

Demand-side flexibility constitutes a particularly behavior-sensitive policy field. Unlike many supply-side measures, flexibility provision directly interferes with everyday practices, comfort levels, production routines, and perceptions of autonomy. Whether households shift loads, accept interruptions, or whether firms adapt production schedules therefore depends on how individuals and organizations perceive, evaluate, and respond to flexibility incentives. For this reason, this dissertation builds on approaches from behavioral economics and environmental psychology to analyze residential and industrial demand-side flexibility from a behavioral perspective.

2.3.1 Behavioral theories

Energy-related behavior is shaped not only by prices and technologies, but also by a range of psychological factors such as attitudes, beliefs, social norms, and values (Lorenzo Varela 2019; Will et al. 2022). These factors influence how individuals interpret information, evaluate trade-offs between comfort and savings, and respond to policy instruments or market signals. A wide range of behavioral theories has been applied to explain technology adoption and energy-related behavior, including the Theory of Reasoned Action (Fishbein 2008), the Technology Acceptance Model (Davis 1989), the Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003), Goal-Framing Theory (Lindenberg and Steg 2007), and the Value-Belief-Norm theory (Stern et al. 1999). These approaches emphasize different drivers of behavior, ranging from perceived usefulness and ease of use in the Technology Acceptance Model, social influence and facilitating conditions in the Unified Theory of Acceptance and Use of Technology, to normative goal orientations of the Goal-Framing Theory, and value-based moral motivations for the Value-Belief-Norm theory. For the analysis of demand-side flexibility as a deliberate, intention-driven behavior embedded in everyday practices, the Theory of Planned Behavior provides a particularly suitable and widely applied framework (Ajzen 1991). The Theory of Planned Behavior has been used extensively to study energy conservation, technology adoption, and climate-relevant behavior (Wittenberg et al. 2021). It assumes that behavior is primarily determined by behavioral intention and perceived behavioral control. In short, the stronger one's intention, the more likely one is to engage in the behavior. Intentions are shaped by the three core components attitude, subjective nom, and perceived behavioral control, as shown in Figure 2.5. Attitudes reflect whether individuals evaluate a behavior positively or negatively and are assumed to originate from the weighted beliefs about the costs and benefits of behavior. Subjective norms capture the perceived social expectations of important others, weighted by the individual's motivation to comply with these expectations. Behavioral control describes the perceived ability to perform the behavior, comprising factors that may hinder or enable the behavior.

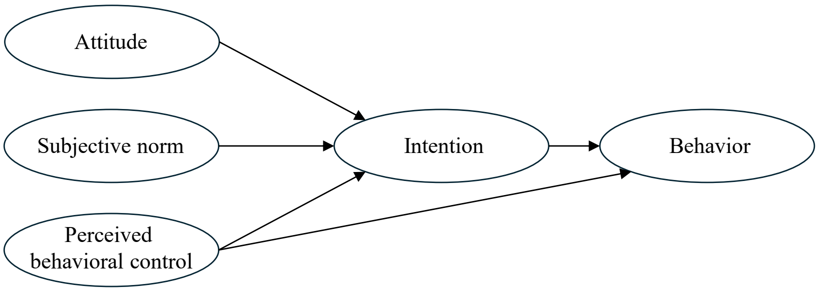

Figure 2.5: Schematic representation of the Theory of Planned Behavior according to Ajzen 1991. Own visualization, adapted from Ajzen (1991) and Steg and Nordlund (2018).

However, intention can also be a poor predictor of actual behavior change, resulting in the so called intention-behavior gap (Faries and Dudgeon 2019). With regard to pro-environmental behavior, intentions have been found to account for only approximately 30% of behavioral variance (Bamberg 2013). Established habits may counter newly adopted intentions, exhibiting a slow pace to learn a new habit which may take weeks or months of repetition in stable contexts (Walker et al. 2015). As argued by Verplanken and Orbell (2022), behavior change can precede and eventually reshape attitudes: once a new practice is enacted, for instance through structural interventions or policy, it may become habitual and thus persist independently of initial motivations, rendering attitude-based interventions alone insufficient. Legal or regulatory interventions can trigger such shifts. For example, smoking bans in public buildings, restaurants, and pubs, led to a decline in overall smoking among those who regularly visit these places (Anger et al. 2011). Furthermore, other factors, such as changing environments are effective for behavior interventions, as e.g., moving house, having a child, or changing jobs disrupt old habit cues (Carden and Wood 2018). For example, in a field experiment with over 800 households, an informational intervention to promote environmental behaviors was more effective for half of the households who had relocated within the last three months (Bamberg 2006). More information on the psychological aspects and behavioral mechanisms is detailed in Section 2.3.2.

2.3.2 Nudging, incentives, and decision biases

Classical economic theory assumes that individuals respond rationally to price signals and optimize their decisions accordingly. In this view, demand-side flexibility emerges when compensation exceeds the subjective costs of inconvenience. Behavioral economics extends this perspective by recognizing that human decision-making is not completely rational, but highly contextual (Wittenberg et al. 2021). Furthermore, experimental approaches rooted in psychology indicate that heuristics, cognitive distortion, intuition, emotions, and social impacts play significant roles in the decision making of individuals (Kahneman 2003). In the energy context, findings show that individuals often act neither according to their knowledge, values, or attitudes, nor according to their material interests as utility maximizers with regard to energy saving behavior (Frederiks et al. 2015).

In the following, a non-exhaustive list of cognitive biases and psychological mechanisms is presented that may affect energy consumption behavior.

- Cognitive and decision-related concepts and biases: bounded rationality, satisficing, status quo bias, loss aversion, risk aversion, sunk cost effect, anchoring, availability and affect heuristics.
- Habitual and comfort-related factors: routines and convenience, comfort preferences.
- Social and motivational factors: social norms, perceived trust, intrinsic and extrinsic rewards.

Bounded rationality is a concept suggesting that an individual's decision making is limited by imperfect information, cognitive constraints, and time limits (Simon 2005). Status quo bias describes the tendency of consumers to tend to stick to existing tariffs, appliance settings, and habits (Frederiks et al. 2015). Satisficing stands for the effort needed to make a satisfactory, rather than optimal decision (Simon 2005; Simon 1956). Strategies that reduce cognitive load and support effective decision-making can help to address this behavior, for example, by short and simple communication, when it comes to energy consumption feedback or incentives (Scharnhorst et al. 2021). Loss aversion refers to weighing losses more heavily than equal-sized gains, so that people perceive the disutility of losing something as far greater than the utility of gaining something of equivalent value (Kahneman et al. 1991). This is often reflected in contingent valuation studies where the willingness to accept tends to be higher than the willingness to pay (Shogren and Taylor 2008). With regard to risk aversion, people have the tendency to be more risk averse when confronted with high probability gains or low probability losses, but are more risk-seeking when it comes to certain losses or uncertain gains (Kahneman and Tversky 1979). Sunk costs are past expenditures such as time, effort, or money that continue to shape subsequent behavior. One explanation for this persistence is the overgeneralization of the “don’t waste” rule commonly learned in childhood. Purchased electrical appliances in the residential sector may be used more, even if it is not required (Frederiks et al. 2015). Daily routines and coordination with work, care, and household schedules restrict when loads such as washing, heating, or EV charging can realistically be shifted (Fjellså et al. 2021). Households may strongly value thermal comfort, which may limit willingness to save energy (Moeller and Bauer 2022). Heuristics can, for example, comprise affect heuristics, where decisions are made without a rational considerations, but purely based on emotions of affection or aversion (Slovic et al. 2007). Another heuristic is the availability heuristic, where individuals measure the probability of an event by what first comes to their mind (Tversky and Kahneman 1974). The availability heuristic may, for example, influence household responses to demand-side flexibility when individuals assess the likelihood and consequences of power outages based on salient personal experiences or media reports. In such cases, rare but vivid inconvenience experiences can disproportionately shape perceptions of risks, while the benefits of load shifting or dynamic pricing remain less cognitively accessible. Furthermore, the anchoring effect is where people rely too heavily on the first piece of information offered (the "anchor") when making decisions, so that even if arbitrary or irrelevant, the information will serve as the reference point that influences subsequent judgments, such as price negotiations or estimates (Tversky and Kahneman 1974; Li et al. 2021). Trust can be used as a simple decision-making heuristic, when assessing risk and making cost-benefit appraisals (Terwel et al. 2009). Social norms reflect that people are influenced by the attitudes and behaviors of others, tending to follow norms that reflect what is socially approved (i.e., injunctive norms that steer behavior by providing social rewards or punishment) or common (i.e., descriptive norms that motivate by giving suggestions about effective and adaptive behavior) (Cialdini et al. 1991; Frederiks et al. 2015).

People can be motivated by rewards that comprise intrinsic and extrinsic incentives. Intrinsic incentives can relate to altruism, equity, or fairness, and extrinsic to money (Stern 1999). The findings on financial incentives, however, show that using such incentives is often short-lived or inconsistent (Katzev and Johnson 1984). Extrinsic rewards may even have a negative effect, exhibiting loss of motivation, overjustification, or moral licensing effects, specifically when the person is already intrinsically motivated (Merritt et al. 2010; Deci 1971; Handgraaf et al. 2013). Furthermore, individuals may perceive various barriers when it comes to behavior change, as illustrated by Table 2.3.

Table 2.3: Perceived individual and social barriers to climate-relevant behavioral change. Based on Lorenzoni et al. (2007) and Burgess (2019).

Barrier category	Barriers
Individual barriers	• Lack of knowledge, experience, and information • Uncertainty and skepticism • Distrust in information sources • Externalization of responsibility and blame (e.g., “Governments and industry should take the lead.”) • Strong reliance on future technological solutions • Climate change perceived as a distant or abstract threat • Competing priorities in everyday life • Reluctance to change established lifestyles • Fatalism (e.g., “It’s too late to make a difference.”) • Feelings of helplessness (e.g., “My contribution does not matter.”)
Social barriers	• Perceived lack of action by government, business, and industry • Worry about free-rider behavior (unwillingness to act if others do not) • Pressure of social norms and expectations • Lack of enabling political, institutional, or infrastructural initiatives • Lack of trust in institutions and policy actors

All these concepts can influence flexibility provision decisions, but they can also guide the design of effective consumer focused interventions that incentivize energy saving and demand-side flexibility. Against this background, nudging refers to behavioral interventions that steer decisions in predictable ways without restricting options or imposing economic sanctions (Wittenberg et al. 2021). Nudges deliberately exploit well-documented deviations from fully rational decision-making to promote socially desirable behavior, such as energy conservation or demand-side flexibility. In energy contexts, several types of nudges have proven particularly relevant. Feedback and salience increase the visibility of energy use through real-time consumption information, peer comparisons, or goal tracking, thereby counteracting limited attention (Ayres et al. 2013; Scharnhorst et al. 2021). Framing influences how outcomes are interpreted, for example by presenting flexibility as avoiding losses rather than achieving gains, thereby leveraging loss aversion. Social norm nudges highlight the behavior of relevant peer groups to activate conformity motives (Frederiks et al. 2015). Closely related, social comparison can serve as a driver of sustainable behavior by showing individuals how their performance relates to that of peers (e.g. electricity consumption relative to neighbors). Laboratory evidence demonstrates that digital nudges that amplify social comparison increase engagement with sustainability objectives (Staudt et al. 2021). These findings illustrate how nudging designs can systematically leverage social constructs to influence individual decision-making. Defaults exploit status quo bias through preconfigured energy-saving settings, default enrollment in energy-related programs, strategies targeting inertia and encourage to shift from the status quo (e.g., free trial periods), or by making use of trigger points that disrupt habits (e.g., moving house) (Frederiks et al. 2015; Verplanken and Orbell 2022). Reminders and timing help bridge intention-action gaps by intervening at critical decision moments.

The living lab study (Paper A) draws on these insights. Rather than assuming rationally behaving households, it leverages real-time feedback, goal framing, salience effects, as well as reminders and timing in communicating incentives. To verify if the attitudes, motivations, and communicated behaviors, are realized by the participants, smart meter data is used to assess their communicated intentions against the actual energy saving and load shifting or shedding behavior.

2.4 Valuation of electricity supply interruptions

2.4.1 Value of lost load

The value of lost load (VoLL) is a central reliability metric in electricity system planning and market design. It represents the monetary value that consumers assign to avoiding a power outage and is commonly interpreted as society's willingness to pay (WTP) for uninterrupted electricity supply (Gorman 2022). In formal terms, the VoLL expresses the economic damage associated with unserved electricity, typically measured either per unit of time (e.g., EUR/hour of outage) or per unit of energy not supplied (e.g., EUR/kWh) (Ratha et al. 2013). The VoLL is highly heterogeneous. It depends on customer class (residential, commercial, industrial) (Leahy and Tol 2011; Röpke 2013), outage characteristics such as advance notice (Baarsma and Hop 2009; Harold et al. 2021; Ratha et al. 2013) and the outage timing (Morrissey et al. 2018; Carlsson and Martinsson 2008; Sullivan et al. 2018), as well as regional differences (Shivakumar et al. 2017; Sullivan et al. 2018; ACER 2020). Table 2.4 illustrates the diverse categories of costs that power outages impose on industrial, commercial and residential consumers. It shows that the nature and severity of impacts differ systematically across demand sectors. These differences underpin the strong variation in VoLL estimates observed across customer classes. Despite this heterogeneity at the individual and sectoral level, VoLL in the literature is typically differentiated only by broad customer class (Schröder and Kuckshinrichs 2015). In addition, outage mitigation costs arise, when consumers try to lessen the impact of the above outage costs. These measures can reduce the probability that an outage affects end-use consumption and may, during an outage, either fully supply an end consumer's electricity demand or be restricted to covering specific critical loads, such as oxygen machines in hospitals (Gorman 2022).

Table 2.4: Non-exhaustive list of potential costs that incur for the industry/commercial sector and the residential sector in the case of a power outage. Based on Shivakumar et al. (2017), Morrissey et al. (2018), Gorman (2022), Sanghvi (1982), and Munasinghe and Sanghui (1988).

Cost category	Industrial/Commercial sector	Residential sector
Direct economic costs	• Opportunity costs of idle resources • Production losses • Equipment damage • Equipment damage • Foregone revenues	• Food spoilage • Property damage • Appliance damage
Operational impacts	• Disruptions of production processes • Logistics, contractual obligations	• Restrictions on daily activities such as cooking, heating, working from home, and leisure
Health and safety impacts	• Safety risks for employees • Hazards due to uncontrolled shutdowns of machinery	• Health risks for vulnerable individuals (e.g., dependence on medical devices, air filtration, heating)
Indirect / macroeconomic costs	• Downstream businesses, consumers	• Other members of society rarely depend on an individual household's power consumption
Non-material costs	• Stress for personnel • Reputational risks • Contract penalties	• Stress • Discomfort • Fear

2.4.2 Willingness to accept compensation for electricity interruptions

Residential customers primarily demand electricity as an input into the provision of energy services, understood as immaterial outcomes, such as a heated or lighted living area (Weber et al. 2022, pp. 31–32). The economic value of electricity therefore depends on the specific end-use it serves at a given moment (Fell 2017; Kalt et al. 2019). Empirical work shows that even within the same customer class, households value different electricity services very differently (Fouquet 2014; Hunt and Ryan 2015; Morrissey et al. 2018). As a result, the welfare loss caused by a power outage varies strongly with the mix of electricity services in use at the time and during the duration of the interruption. This heterogeneity implies that consumer preferences may differ significantly with regard to demand-side flexibility schemes (Pepermans 2011).

Consumers may prefer, dislike, or remain indifferent toward flexibility schemes (Varian 2016). These preferences can be represented through utility functions, where households derive utility from energy services rather than from electricity consumption per se. While firms aim to maximize profits, households derive utility from comfort, mobility, thermal convenience, and everyday reliability, making utility highly subjective (Lai 1995). Consequently, utility is a dimensionless unit and its scale is arbitrary, i.e., statements about its magnitude or differences of utility cannot be made. The marginal rate of substitution is the rate at which a consumer is willing to trade one good for another while maintaining the same level of satisfaction or utility. Instead of goods, the marginal rate of substitution can also be applied to attributes of a product (e.g., the duration of a power interruption). Since these attributes are not always easily understood or possible to trade against other goods or attributes, the denominator is typically replaced by the price. This transforms the marginal rate of substitution into a monetary valuation, which can be interpreted as willingness to pay (WTP) or, in the case of losses, as willingness to accept (WTA) compensation. WTA therefore captures the minimum monetary compensation required for accepting controlled electricity interruptions (Varian 2016).

The discrete choice experiment in Paper B is grounded in this economic theory. Households repeatedly choose between mutually exclusive tariff alternatives that differ in interruption frequency, duration, advance notice, and compensation. From these observed choices, preference parameters and WTA measures for specific reliability attributes can be derived using econometric decision rules. Consequently, depending on the decision rule and if compensation is included as an attribute to describe the alternatives, WTA can be derived from the observed choices. The decisions rules used in Paper B are described in detail in Section 3.1.3.

3 Methodology

Section 3 gives an overview of the methodological approaches used in this thesis to answer the research questions (see Section 1). The first three research questions are assessed adopting socio-empirical methods, to analyze consumer acceptance, preferences, and behavior with regard to complex incentives for energy saving and demand-side flexibility provision. Paper A is an explorative study based on living lab interventions. Paper B uses data from choice experiments, supplemented by data on observable consumer characteristics (i.e. sociodemographic data), while Paper C deploys expert interviews with industry stakeholders, specifically interview partners from firms and national industry associations. These methodological approaches are discussed in Section 3.1. Section 3.2 presents a bottom-up industry demand simulation model that is extended in this thesis to evaluate the future process flexibility potential of the European industrial sector under an ambitious decarbonization pathway (Paper D).

3.1 Empirical methods to analyze consumer preferences and energy demand behavior

This chapter presents the set of empirical methods used to investigate consumer preferences and energy demand behavior, spanning multi-method living-lab interventions, stated-preference choice experiments, and qualitative expert interviews.

3.1.1 Living lab studies - multi-method interventions

It has been widely argued that strategies for systemic innovation should not rely solely on isolated technological solutions (e.g., smart meters, automation) designed for application across multiple contexts. Instead, such strategies should be theory-informed and context-specific, embedded in local socio-cultural conditions, and involve a broad range of stakeholders, including researchers, practitioners, technology developers, policymakers, and citizen-consumers (Colvin et al. 2014). Against this background, living labs have gained increasing relevance in both research and policy arenas. Over recent decades, European funding programs have strongly promoted living-lab activities as instruments for advancing sustainable development (Schuurman 2015). Since its foundation in 2006, the European Network of Living Labs (ENoLL) has connected more than 480 recognized living labs worldwide under a common umbrella association (ENoLL 2025). According to ENoLL, living labs are defined as “user-centred, open innovation ecosystems based on a systematic user co-creation approach, integrating research and innovation processes in real-life communities and settings” (ENoLL 2025).

The original idea of living labs was to extend traditionally controlled laboratory environments into real-life settings in order to gain deeper insights into human behavior (Stuckrath et al. 2025). Early concepts emphasized different core dimensions, such as living labs as experimentation environments (Ballon et al. 2005), as user-centred research methodologies (Eriksson et al. 2005), or as emerging public-private partnership concepts (Niitamo et al. 2006). Today, living labs are increasingly understood not only as laboratories in the classical sense, but also as living systems (Ceseracciu et al. 2023). They provide dedicated spaces for social learning and socio-technical innovation (Ceseracciu et al. 2023). Furthermore, the living-lab approach builds on practice-centred design in two key ways. First, living labs create a temporary space in which different rules apply, thereby moving beyond the design phase into real-life experimentation setting (Voytenko et al. 2016). During this period, routinized practices are deliberately interrupted to encourage participants to engage in alternative behaviors. Second, living labs represent a process rather than a fixed outcome: collaboration between citizens, research teams, implementation partners, and other stakeholders is prioritized in order to foster collective and social learning. This contrasts sharply with approaches that aim to “nudge” individuals towards predefined behavioral goals based on the premise of liberal paternalism, that is, the assumption that some authority knows best how people ought to behave (Schuurman and Desole 2025). However, literature reviews on living lab research reveal that living labs are highly heterogeneous with respect to their structures, methods, goals, and stakeholder constellations (Schuurman 2015). Reflecting this heterogeneity, living labs have been applied across a wide range of research fields, including agriculture (Sroka et al. 2025), computer science and information and communication technologies (Eriksson et al. 2005), and the energy sector (Sahakian et al. 2021). In energy research in particular, living labs have been used to experiment with living in zero-emission homes (Korsnes et al. 2018), smart heating systems (Sovacool et al. 2020), innovative electricity tariffs that promote load shifting and/or shedding (Scharnhorst et al. 2021; Scharnhorst et al. 2023; Christensen et al. 2020), as well as the reduction of overall energy use (Sahakian et al. 2021). These studies reveal novel interaction dynamics between actors engaged in energy transitions (Canzler et al. 2017). A comprehensive overview of living lab applications in the energy sector is provided by Mbatha and Musango (2022).

Despite their heterogeneity, living labs can be systematically analyzed using the three analytical levels proposed by Schuurman (2015), which are presented in Table 3.1. These levels differentiate between the macro level of the living-lab constellation, the meso level of concrete innovation projects, and the micro level of research activities and methodological instrumentation.

The living lab employed in this work is the Energy Smart Home Lab (ESHL), which is embedded within the Energy Lab at the Karlsruhe Institute of Technology (KIT) (KIT 2025). At the macro level, the ESHL is used by various projects and institutes at KIT across multiple research fields. Previous studies conducted at the ESHL have investigated, among others, the power-to-frequency dependency of residential loads (Geis-Schroer et al. 2024), optimal

Table 3.1: Three analytical levels of living labs. Own table based on Schuurman (2015).

Level	Definition	Research paradigm
Macro *Living lab constellations*	Organized stakeholders (Public-Private-People partnership)	Open innovation Knowledge transfers between organizations
Meso *Living lab projects*	Innovation projects	Open & user innovation Real-life experimentation, active user involvement, multi-method & multi-stakeholder
Micro *Research activities*	Methodology	User innovation User involvement & contribution for innovation

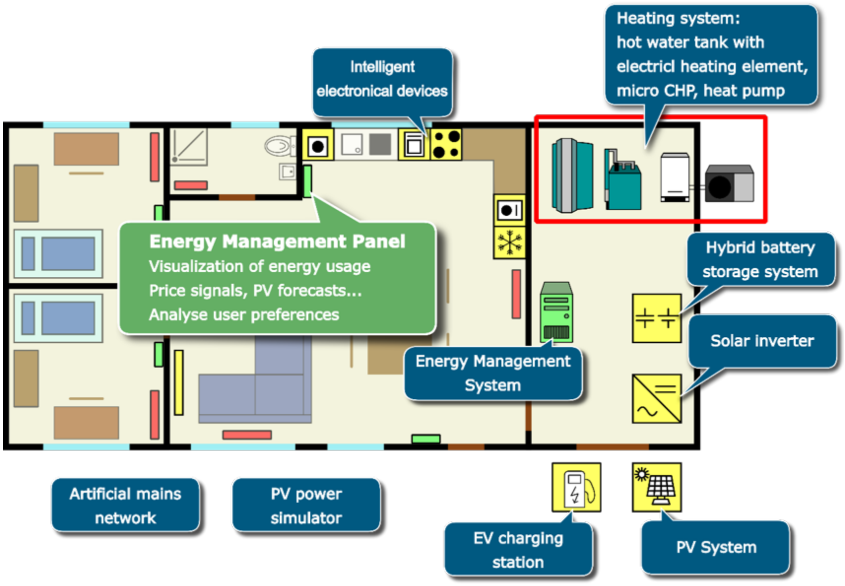

Figure 3.1: Layout of the Energy Smart Home Lab. Visualization from Scharnhorst et al. (2021).

battery operation strategies (Mueller et al. 2022), and consumer preferences for dynamic electricity pricing (Dütschke and Paetz 2013; Scharnhorst et al. 2021). At the meso level, the present work situates Paper A as a living-lab project that investigates household carbon caps and tariffs as instruments to incentivize energy savings and demand-side flexibility (Scharnhorst et al. 2025b). At the micro level, the ESHL enables instrumented socio-technical experimentation by combining high-resolution sensor-based energy measurements with behavioral and socio-cognitive observation of how households respond to carbon caps, tariffs, and demand-side incentives.

As discussed in Section 2.3.1, routinized practices can be disrupted by changes in life events, such as moving to a new dwelling. Living labs provide a methodological means to deliberately interrupt such routinized practices by creating a real-life experimental setting in which different rules apply for a limited period of time (Sahakian et al. 2021). In the ESHL, participation in the intervention requires that participants move into the lab and live there for the duration of the experiment while maintaining their ordinary daily routines. Figure 3.1 illustrates the layout and technical setup of the ESHL.

Triangulation is commonly understood as the use of multiple methods to investigate the same empirical phenomenon. Building on the classical definition by Denzin, triangulation refers to the deliberate combination of two or more theories, data sources, or research methods within a single study (Denzin 2017). More specifically, methodological triangulation is defined as the joint use of at least two methods, typically qualitative and quantitative, to address the same research problem (Kimchi et al. 1991). As emphasized by Arias Valencia (2022), the central rationale of methodological triangulation lies in combining methods whose respective strengths and weaknesses complement each other, thereby increasing the robustness and interpretability of empirical findings. Quantitative data analysis provides insights into measurable outcomes such as load profiles, setpoint modulations, and room temperatures. However, quantitative analysis alone may overlook important subjective factors, motivations, and contextual nuances that shape occupant practices. This is where qualitative data, derived, for example, from interviews and observations, can complement. Qualitative methods enable a deeper understanding of the underlying values, perceptions, social norms, and lived experiences that influence energy-related behavior (Andersen et al. 2025). At the empirical level, recent energy studies demonstrate the value of methodological triangulation in practice. For instance, Vavouris et al. (2024) discuss that limitations related to the scalability and reliability of qualitative surveys and interviews can be mitigated through the triangulation and cross-validation of qualitative and quantitative data (smart metering), thereby strengthening the accuracy and validity of their results. Similarly, März et al. (2020) combine interviews, questionnaires, and regression analysis to investigate landlord decision-making in residential energy efficiency, while Andersen et al. (2025) rely on household monitoring data (heating energy, room temperatures, and setpoints) alongside semi-structured interviews. The combination of sensor data, interviews, and survey responses thus constitutes a triangulated methodological design that enables the cross-validation of behavioral, technical, and normative findings.

A multi-method approach was applied in the living-lab intervention. Both quantitative and qualitative data were collected. Quantitative data comprise measurements and sensor-based observations of heat and electricity consumption, temperature set points, and room temperatures. Qualitative data were generated through weekly semi-structured interviews as well as a survey administered after the end of the intervention. Communication with participants happened (i) by receiving real-time feedback on device-specific electricity consumption as well as on aggregated emissions from electricity and heat in relation to the weekly emission cap and (ii) by a digital dashboard that communicated the incentives implemented during the intervention, including the emission cap, the tariff applied to emissions exceeding the cap, and load-shifting incentives. The load shifting incentives incorporated photovoltaic generation into the household energy balance as well as (non-)economic incentives for load shifting and shedding during simulated grid congestion scenarios. Accordingly, Paper A applies a triangulated multi-method design that systematically combines qualitative and quantitative data to cross-validate behavioral, technical, and normative findings.

3.1.2 Contingent valuation

Contingent valuation is a stated-preference method that elicits individuals' monetary valuations for non-market goods or hypothetical scenarios. In the context of electricity supply reliability, contingent valuation has been used to estimate households' willingness to pay for improved reliability or their willingness to accept compensation for supply disruptions (Woo et al. 2014; Schubert et al. 2013; Meles et al. 2021).

In this thesis, contingent valuation serves as a complementary approach to the discrete choice experiment employed in Paper B. While the discrete choice experiment allows for the analysis of trade-offs between multiple outage attributes, the contingent valuation framework provides a direct monetary measure of outage disutility, facilitating the interpretation of compensation requirements for electricity interruptions. Both approaches rest on the assumption that preferences for non-market reliability attributes can be meaningfully elicited in a hypothetical, yet incentive-compatible, setting. Respondents are asked to state their WTP and WTA for power interruptions of 1 h, 2 h, and 4 h duration using open-ended questions. Eliciting both WTP and WTA allows for capturing potential asymmetries in valuation arising from loss aversion and reference dependence, which are well documented in the literature on electricity outages and other non-market goods. Open-ended questions are chosen to avoid anchoring effects from predefined payment levels, while acknowledging that such formats may entail higher response variance and susceptibility to hypothetical bias (Li et al. 2021). The resulting valuation measures are therefore interpreted as indicative estimates of perceived outage disutility rather than precise welfare measures.

3.1.3 Choice experiments and preference modeling

This section gives an overview on the experimental design of choice experiments, the derived data set and the statistical models used to analyze the choice data.

3.1.3.1 Experimental design

In a choice experiment respondents repeatedly choose between hypothetical scenarios described by multiple attributes. In Paper B, this approach is implemented through a survey that was administered via an online panel in 2022 to a sample of 682 residential respondents[1], representative of the German population, using gender and age quotas. The experiment comprised 12 choice tasks per respondent, including two fixed and ten randomized choice sets. Following (Backhaus et al. 2015), this design balances information efficiency with respondent fatigue and survey cost constraints. More generally, the number of choice situations and alternatives presented to respondents can substantially affect observed choice behavior: too few choice tasks increase the risk of non-trading[2] and lexicographic[3] decision-making, whereas too many may induce inconsistent responses due to cognitive fatigue or boredom (Hess et al. 2010). Each choice set consisted of three hypothetical electricity interruption alternatives that differed with respect to key outage characteristics.

In each choice task, respondents first completed a forced choice between the presented alternatives and subsequently a free choice that allowed opting out (also called none option).

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[1] Post data cleaning.

[2] I.e., respondents consistently choose the same option without making trade-offs between attributes.

[3] I.e., choices are based on a single dominant attribute regardless of other attributes.

A forced choice hereby refers to a choice task where respondents have to choose from the set of alternatives without an opt-out option to elicit more information regarding the tradeoffs between the attributes (Allenby et al. 2013). The subsequent free choice asked respondents whether they would actually choose their preferred alternative over the none-option. This two-step structure enables the identification of both relative preferences between outage profiles and absolute acceptance or rejection of outage situations. The inclusion of a none-option in the free-choice stage allows respondents to reject all offered interruption scenarios. This accounts for the possibility that none of the proposed alternatives in the forced choice is acceptable and avoids forcing respondents into artificially positive acceptance of interruptions (Brazell et al. 2006).

The alternatives in the choice experiment were described by four core attributes: interruption frequency, interruption duration, advance notice, and monetary compensation. Attribute selection was guided by the outage valuation literature, practical grid-operation considerations, and evidence from a prior field study indicating that households strongly prioritize advance notice over other outage characteristics (Scharnhorst et al. 2023). Designs with more than four alternatives are possible, but they impose greater cognitive demands on respondents and may therefore reduce the quality of their responses (Louviere et al. 2011). Monetary compensation was individualized relative to respondents' monthly electricity expenditure to ensure that compensation levels were meaningful and proportional to household budgets. The scaling was anchored to the grid-fee component of German residential electricity prices, in line with the regulatory framework for controllable loads, under which flexibility provision is compensated through reduced or dynamic grid fees (BNetzA 2024b). This approach supports the interpretability of stated preferences in hypothetical outage scenarios (Hensher et al. 2015).

Figure 3.2 provides an illustrative example of a choice task as presented to respondents. The choice set visualization added icons for the respective attributes and levels so that respondents received visual stimuli and kept cognitive load to a minimum (Backhaus et al. 2015; Kabaya et al. 2025; Netusil et al. 2023). Furthermore, the choice tasks included mouse-over elements with information about the attributes. Detailed information on the experimental design is provided in Paper B (see Part II of this thesis).

3.1.3.2 Statistical models to analyze discrete choice data

Random Utility Theory
The random utility theory builds the basis for discrete choice modeling and assumes that the decision maker selects the option with the highest utility from all available alternatives (McFadden 1974). The theory of consumer behavior stipulates that the utility of an alternative comes from its attributes (characteristics) and their levels (Lancaster 1966). It is assumed that the decision maker n from a sample of N individuals derives a certain level of utility $U_{n,j,t}$ from an alternative j in a choice task t. But since utility cannot be fully observed by the researcher, it is modeled as consisting of a systematic (observable) and a stochastic (unobservable) component (McFadden 1974; Train 2002):

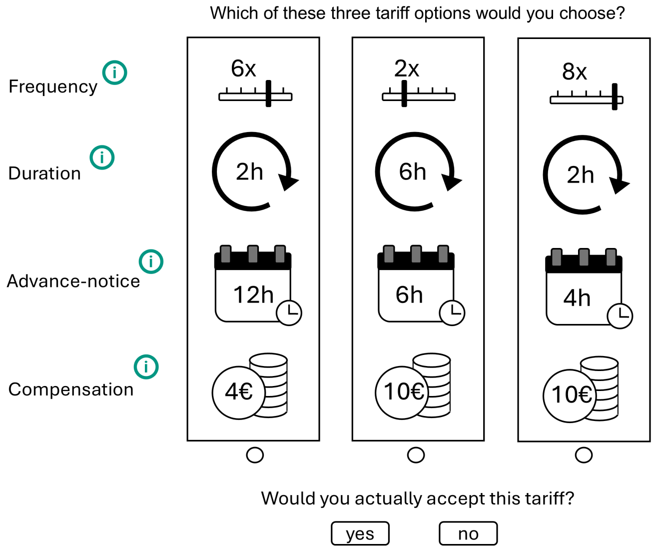

Figure 3.2: Visual presentation of an exemplary choice set presenting the four attributes frequency, duration, advance-notice, and compensation and three alternatives in the forced choice and the subsequent free choice. Own visualization, published in Scharnhorst et al. (2025a).

$$U_{n,j,t} = V_{n,j,t} + \varepsilon_{n,j,t} = \beta_n{}' X_{n,j,t} + \varepsilon_{n,j,t}, \tag{3.1}$$

$V_{n,j,t}$ represents the deterministic component of utility expressed as a function of observed variables $X_{n,j,t}$ and preference parameters β_n, and $\varepsilon_{n,j,t}$ is a random error term. X can not only comprise attributes X_A (e.g., compensation), but also observable respondent characteristics X_Z (e.g., sociodemographic data). Different assumptions about the distribution of ε_{ni} give rise to different discrete choice models, such as the Multinomial Logit, Mixed Logit, and Latent Class specifications (Train 2002; Hensher et al. 2005).

Multinomial Logit model

The Multinomial Logit (MNL) model is the most fundamental model used in discrete choice analysis, often used to begin the analysis to gain initial insights of the choice data (Mariel et al. 2025). MNL models assume homogeneous preferences, with fixed utility coefficients β across respondents ($V_{n,j} = f(\beta, X_{n,j})$). Under this assumption, the probability that respondent n chooses alternative j from a number of alternatives J in choice situation t, conditional on β, is

$$P_{n,j,t}(\beta) = \frac{e^{V_{n,j,t}}}{\sum_{j=1}^{J} e^{V_{n,j,t}}} = \frac{e^{f(\beta, X_{n,j,t})}}{\sum_{j=1}^{J} e^{f(\beta, X_{n,j,t})}} \tag{3.2}$$

While computationally efficient, this model is limited in its ability to capture unobserved preference heterogeneity (Mariel et al. 2025).

Mixed Logit model

Models that allow preferences to vary across choice sets (intra-individual heterogeneity) and respondents (inter-individual heterogeneity), or both, comprise, among others, the random parameter Mixed Logit (MIXL) model, the Latent Class (LC) model, or the LC-MIXL model (Hess and Train 2011; Hensher and Greene 2003; Hess and Daly 2014, pp. 311–330).

The MIXL model in particular has gained momentum and popularity in the recent past and is widely used to analyze choice data (Lehmann et al. 2022; Huster et al. 2024; Guetlein et al. 2025). Several benefits are related to the MIXL model (Lehmann 2023). While the MNL model assumes homogeneous preferences across individuals, the Mixed Logit (MIXL) model relaxes this restriction by allowing utility coefficients β_n to vary across respondents and explicitly captures unobserved preference heterogeneity (Train 2002; Hensher and Greene 2003). Furthermore, parametric distributions such as normal, lognormal, or triangular distributions can be assigned to the utility coefficients, coefficients can be fixed or random across respondents, and the choice of distribution can be chosen by the researcher (Hensher and Greene 2003). The model further accommodates rich correlation structures in the unobserved utility components by allowing random coefficients to be correlated across attributes. This enables the MIXL framework to capture complex substitution patterns between alternatives that arise from shared unobserved factors, such as similarity in technologies, contexts, or decision strategies. As a result, the restrictive Independence of Irrelevant Alternatives (IIA) property inherent to the MNL model is relaxed (Hess and Train 2017). As a result, MIXL models often achieve improved model fit and prediction accuracy compared to MNL models, and can be easily extended to incorporate additional covariates (e.g., sociodemographic variables) (Hensher and Greene 2003; Abou-Zeid and Ben-Akiva 2014). At the same time, the absence of prior information on appropriate distributional assumptions, may require the estimation of numerous alternative model specifications (Lehmann 2023).

In the MIXL framework, the individual-specific utility parameters are assumed to be random draws from a continuous distribution, $\beta_n \sim g(\beta \mid \Omega)$, where $g(\beta \mid \Omega)$ denotes a parametric density (e.g., normal, lognormal, uniform, triangular) characterized by the parameter vector Ω. The unconditional choice probability $P_{n,j,t}$ is obtained by integrating the standard MNL probability over the distribution of random coefficients (Hess and Daly 2014, p. 313):

$$P_{n,j,t}(\Omega) = \int_{\beta} P_{n,j,t}(\beta)\, g(\beta \mid \Omega)\, d\beta = \int_{\beta} \frac{e^{V_{n,j,t}}}{\sum_{j=1}^{J} e^{V_{n,j,t}}}\, g(\beta \mid \Omega)\, d\beta. \tag{3.3}$$

Since this integral has no closed-form solution in general, estimation is performed using simulation-based maximum likelihood methods (Train 2002; Molloy et al. 2021; Hess and Daly 2014). For panel data with T_n observations per respondent and the actually chosen alternative j_n^t, the individual likelihood is given by

$$L_n(\Omega) = \int_{\beta} \left[\prod_{t=1}^{T_n} P_{n,j_n^t,t}(\beta)\, g(\beta \mid \Omega) \right] d\beta, \tag{3.4}$$

and the overall likelihood function is constructed as the product over all respondents.

In this thesis, the MIXL model is used to analyze individual trade-offs and heterogeneity in preferences in Paper B.

Latent Class model

The Latent Class (LC) model offers an alternative way of representing heterogeneity in discrete choice data by assuming that the population consists of a finite number of unobserved (latent) classes, each with distinct preference parameters (Greene and Hensher 2003; Sfeir et al. 2021). Instead of assuming a continuous distribution of tastes across individuals (as in Mixed Logit), the LC model treats heterogeneity as discrete: each respondent belongs to one latent class $c = 1, \dots, C$, and within each class the utility coefficients β_c are homogeneous. Formally, for individual n considering alternative j in choice situation t, conditional on class c, utility is specified as

$$U_{n,j,t|c} = \beta_c' X_{n,j,t} + \varepsilon_{n,j,t}. \tag{3.5}$$

The overall choice probability is a weighted sum over classes

$$P_{n,j,t} = \sum_{c=1}^{C} \left[s_{n,c} \cdot \frac{e^{\beta_c' X_{n,j,t}}}{\sum_{j=1}^{J} e^{\beta_c' X_{n,j,t}}} \right], \tag{3.6}$$

where $s_{n,c}$ is the probability that individual n belongs to class c, estimated jointly with the class-specific parameters (Hess and Daly 2014, pp. 314–315). LC models are particularly useful for identifying groups of respondents whose preferences follow qualitatively different patterns (e.g., cost-sensitive, quality-focused, risk-averse classes). This makes interpretation more intuitive and supports segmentation analyses, targeted policy or marketing recommendations, and investigation of socio-demographic or attitudinal correlates of choice behavior (Greene and Hensher 2003; Sfeir et al. 2021). Compared with continuous-random-parameter approaches (like Mixed Logit), LC models

- do not require strong distributional assumptions over coefficients, as the discrete mixture is non-parametric in nature (Greene and Hensher 2003).
- facilitate straightforward segmentation and posterior assignment of respondents to classes (Greene and Hensher 2003; Araghi et al. 2016).
- are often more parsimonious and interpretable (Greene and Hensher 2003; Sorgente et al. 2025).

However, they also require the researcher to choose the number of classes, which may lead to extensive model testing. Additionally, they may oversimplify heterogeneity by forcing individuals into one of a few fixed classes rather than modeling a continuum of tastes. To complement the MIXL model, a LC model was estimated in Paper B to identify distinct preference segments within the choice data.

3.1.4 Expert interviews

To assess the acceptability of demand-side flexibility and to identify implementation barriers in the manufacturing and commercial sectors, semi-structured expert interviews were conducted. Semi-structured interviews are particularly suitable for expert studies, as they combine predefined thematic structures and guiding questions with the flexibility to follow up on emerging aspects during the conversation (Soest 2023; Tansey 2007). This format enables both comparability across interviews and sensitivity to sector- and firm-specific contexts.

Following the classic understanding by Dexter (2006), an expert is defined as a person who possesses specialized information on, or has been directly involved in, the political, economic, or organizational processes under investigation. Experts may include academics, practitioners, political elites, managers, or other individuals with specialized knowledge and experience (Atkeson and Alvarez 2018). Expert interviews are particularly valuable in research contexts where central processes are not directly observable, systematically documented, or publicly accessible (Soest 2023). This is especially the case for industrial decision-making regarding demand-side flexibility, which is shaped by firm-internal strategies, operational constraints, and institutional conditions that cannot be captured through experiments or quantitative models alone.

As a research instrument for tracing causal mechanisms, expert interviews offer several advantages. First, they complement experimental and quantitative studies by providing contextualized insights into micro-level decision-making processes and organizational practices (Fu and Simmons 2021). In this way, qualitative expert knowledge supports the interpretation of correlational findings and can strengthen causal inference (Glynn and Ichino 2015). Second, expert interviews are well suited for research questions that involve complex, system-level developments and small numbers of observations, where experts can aggregate and weigh different pieces of information (Soest 2023). Third, expert interviews enable the analytical linkage between micro-level operational decisions within firms and macro-level institutional and regulatory frameworks (Balcells and Justino 2014; Shesterinina 2016). At the same time, qualitative expert interviews pose methodological challenges. According to Soest (2023), typical problems include the often unsystematic selection of experts, selection of elites rather than experts, insufficient reflection on experts' personal biases, and the lack of standardized evidence collection. These shortcomings can severely limit the ability of expert interviews to trace causal mechanisms if they are not addressed explicitly through careful research design. Following Soest (2023), this study adopts a broad and inclusive understanding of expertise and integrates both inside and outside experts within a shared analytical framework. Inside experts are understood as interview partners directly involved in firm-level decision-making processes, while outside experts possess sectoral and institutional oversight without being directly responsible for operational decisions. In this study, inside experts include energy managers, lead process engineers, and managers at different hierarchical levels within firms, while outside experts are represented by industry association officials. This intentional diversity of expert roles allowed the study to capture a wide range of perspectives, experiences, and strategic assessments of demand-side flexibility (Scharnhorst et al. 2024a).

Expert selection followed a non-probability, network-based sampling strategy (Goldstein 2002), combined with snowball sampling (Heckathorn and Cameron 2017; Shesterinina 2016). Initial contacts were established through industry associations, which forwarded the interview invitation to potentially relevant member firms. Participation was thus based on voluntary self-selection. This approach is particularly appropriate for hard-to-survey populations (Tourangeau et al. 2014), such as manufacturing companies, where access barriers, confidentiality concerns, and limited participation incentives often constrain large-scale survey-based data collection. As emphasized by George and Bennett (2005), the inclusion of both higher-level decision-makers and lower-level operational experts enhances the reconstruction of organizational processes, as lower-level experts often possess more detailed knowledge of everyday decision-making and operational constraints. With regard to the analytical purpose of expert interviews, Soest (2023) distinguishes four central applications: assessment, aggregation, anticipation, and affirmation. The present study primarily follows the assessment logic, as the interviews aim to reconstruct decision-making processes, perceived barriers, and strategic considerations surrounding industrial and commercial demand-side flexibility (Tansey 2007; Bennett and Checkel 2015).

The expert-interview study presented in Paper C complements the existing literature on industrial demand response and flexibility. Existing participation in demand response programs is still largely concentrated in energy-intensive industries such as paper manufacturing and aluminum electrolysis (Gils 2016). In contrast, many other industrial and commercial sectors have received little empirical attention so far (Wohlfarth et al. 2019), despite flexibility potentials identified in modeling studies (Gils 2014). Further studies indicate demand response potentials for space heating, ventilation (Kirkerud et al. 2021), and air conditioning in commercial buildings (Tina et al. 2022). At the same time, most empirical demand response research still focuses on the residential sector (Sloot et al. 2022; Parrish et al. 2020). A recent review of demand response enablers and barriers confirms that commercial and industrial sectors remain largely underrepresented in empirical studies (Parrish et al. 2020). While firms are often assumed to evaluate demand response participation primarily based on economic cost-benefit considerations, the role of additional cultural, regulatory, structural, organizational, and awareness-related barriers remains insufficiently understood (Leinauer et al. 2022). To the best of our knowledge, no previous study has conducted a nationwide interview-based investigation with both commercial and industrial firms and industry associations in Germany that systematically identifies demand response barriers and explicitly considers interrelations between barrier dimensions. The categorization of demand response barriers as well as the combined deductive-inductive coding procedure applied to the interview material are developed and documented in full detail in Paper C. The present section therefore focuses on the methodological rationale of expert interviews and their role within the overall empirical design of the thesis.

3.2 Modeling of industrial energy demand and process flexibility

Industrial energy demand modeling plays a central role in the quantitative assessment of decarbonization pathways and the evaluation of future technology deployment. Existing modeling approaches can broadly be distinguished into top-down, bottom-up, and hybrid frameworks. Top-down models derive industrial energy demand from macroeconomic data, and aggregated sectoral indicators, while bottom-up models represent production processes, technology stocks, and efficiency measures in a detailed manner. Hybrid models combine both perspectives in order to capture system-wide interactions while preserving technological detail.

Large-scale energy system models typically provide only aggregated sectoral resolution, instead of process related granularity (Victoria et al. 2022; Pedersen et al. 2022). A wide range of industrial energy demand models exists at the European level. Prominent examples include energy system optimization models such as TIMES PanEU (Kuder 2014), TEMOA (Lerede et al. 2024), and PRIMES (E3Modelling 2018), as well as more detailed sectoral and industry-focused simulation models such as FORECAST (Rehfeldt et al. 2018), WISEE-EDM (Kemmler et al. 2020), SmInd (Hübner 2020), and recent bottom-up industry models focusing on specific transformation pathways such as hydrogen-based steel and basic chemical production (Neuwirth et al. 2024a). These models are widely used to project future industrial energy demand, technology diffusion, and mitigation pathways under alternative climate policy scenarios. In addition, highly detailed techno-economic models are increasingly applied to single industries such as the steel sector (Schneider 2022; Schoepf et al. 2018), to assess electrification, hydrogen use, and process-integrated emission reduction options.

Modeling industrial energy demand and decarbonization pathways poses distinct methodological challenges due to the sector's pronounced heterogeneity, long technology lifetimes, and high capital intensity of production assets (Wesseling et al. 2017). Existing modeling approaches address these challenges in different ways. Large-scale energy system models such as PRIMES, TIMES, and TEMOA incorporate bottom-up representations of industrial technologies and processes, but implement investment and production decisions at the level of representative sectors and regions (Wesseling et al. 2017). As a result, technology diffusion and production pathways are resolved in an aggregated manner, often driven by system-wide constraints and scenario assumptions, which limits insights into process-level dynamics and heterogeneous investment behavior (Victoria et al. 2022; Johannsen et al. 2023). More detailed bottom-up and sectoral industry models offer higher technological resolution, but often impose technology diffusion through exogenous rates, stylized stock turnover assumptions, or statistical trend extrapolations rather than modeling endogenous adoption decisions (Rehfeldt et al. 2020; Mathiesen et al. 2023). Across much of the literature, spatial resolution below the national level remains limited, and plant-specific characteristics such as age structure, reinvestment cycles, and local infrastructure constraints are rarely represented explicitly (Neuwirth et al. 2024a). Consequently, estimates of diffusion speed and flexibility deployment remain sensitive to modeling assumptions, e.g., when future production volumes are assumed to be fixed (Moya et al. 2020; Neuwirth et al. 2024a). While recent studies have begun to explore site-specific and georeferenced approaches for selected industries, most notably for hydrogen-based steel and basic chemical production, these efforts remain sector-specific and are only just emerging (Lieberwirth and Hobbie 2023; Neuwirth et al. 2024a). Moreover, the majority of established industrial energy demand models are not fully open access[4], with transparent and reproducible implementations becoming available only very recently, such as the approaches from Neuwirth et al. (2024b) and Lerede et al. (2024). While the availability of openly accessible, technology-specific data on European industrial production has improved in recent years, for example for selected sectors such as steel, cement, and basic chemicals, comprehensive and consistently structured process-level data remain scarce across some industries (GEM 2025a; GEM 2025b). As a result, purely bottom-up representations are often infeasible at the European scale, whereas fully top-down approaches abstract from technological detail that is crucial for assessing process-level flexibility and decarbonization options (Neuwirth et al. 2022). Against this background, hybrid modeling approaches provide a compromise by combining bottom-up process representations where open and reliable data permit with top-down representations where data availability remains limited (Guminski 2021).

The industry simulation model used as the basis for Paper D is a hybrid model that represents energy-intensive production processes across key industrial sectors at the European level. Figure 3.3 illustrates the model structure and the linkage between top-down and bottom-up components via an application balance derived from the literature.

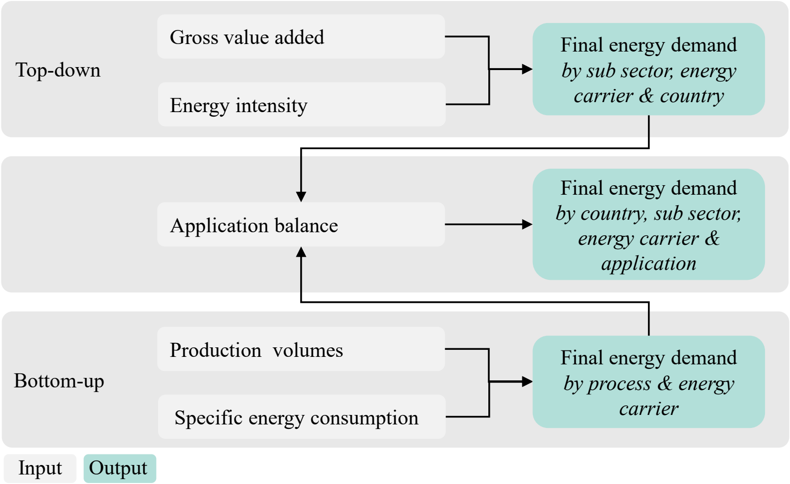

Figure 3.3: Illustration of the top-down and bottom-up structure in the industry demand simulation model used in Paper D. Own visualization.

As presented by 3.4, the bottom-up approach accounts for a share of the total final energy demand of 88% in the iron and steel sector, 47% for the production of (petro-)chemicals, 94% of non-metallic minerals, 83% of pulp, paper, and print, 53% of food, beverages, and

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[4] Or only partially documented, providing publications on results and methods, but not the full model code (Kuder 2014; Hübner 2020; Rehfeldt et al. 2018).

tobacco, and 36% of the non-ferrous metals production. The geographical scope covers the EU27 plus Norway, Iceland, and the United Kingdom. The model includes 13 industrial sub sectors (top-down), 16 reference processes (bottom-up), and 13 applications, including industrial process heat and cold at different temperature intervals, and cross-sectional technologies. The 16 reference processes represent the industry technologies in the starting year of the model, while additional processes can be introduced endogenously to account for the diffusion of innovative technologies. This is illustrated in Figure 3.5 for aluminum production, where the primary and secondary routes dominate initially and are gradually complemented or replaced by new technologies such as Hall-Héroult with inert anodes, kaolinitic reduction, and carbothermic reduction. Scenario computation[5] follows the modeling approach of the sectoral industry model SmInd (Hübner 2020; Guminski 2021) .

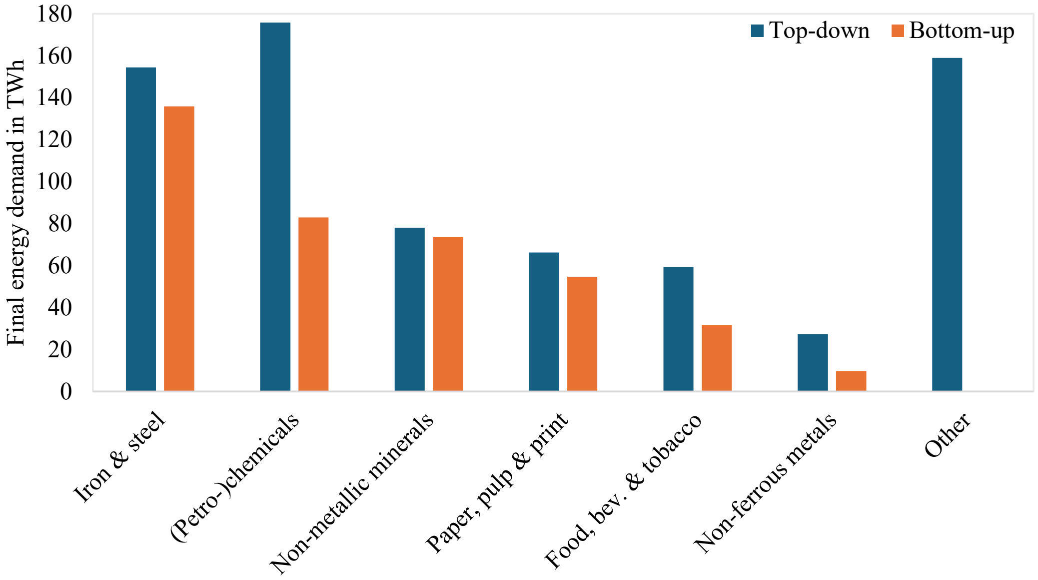

Figure 3.4: Top-down and bottom-up final energy demand covered by the industry demand simulation model by sub-sector in Germany 2019. Own visualization.

The decarbonization scenario underlying Paper D implements six overarching strategies: reduction of material demand, material efficiency, circular economy and industrial waste, energy efficiency, electrification and fuel switch, and carbon capture and storage. In total, the scenario currently comprises 127 measures implemented at the process and application level. The modeling of process flexibility potentials in Paper D builds on the simulated hourly electricity demand profiles. A techno-economic evaluation is subsequently applied to estimate the costs of flexibility provision. The detailed modeling framework, assumptions, and computational procedures are documented in the methods section of Paper D (see Section 4.4).

Flexibility potentials in industry have been addressed to varying extents in the literature (Boßmann and Eser 2016). Shoreh et al. (2016) provide an overview of process-level flexibility options and identify barriers to large-scale implementation. Several studies

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[5] See Hübner (2020) for a comprehensive overview of measure computations.

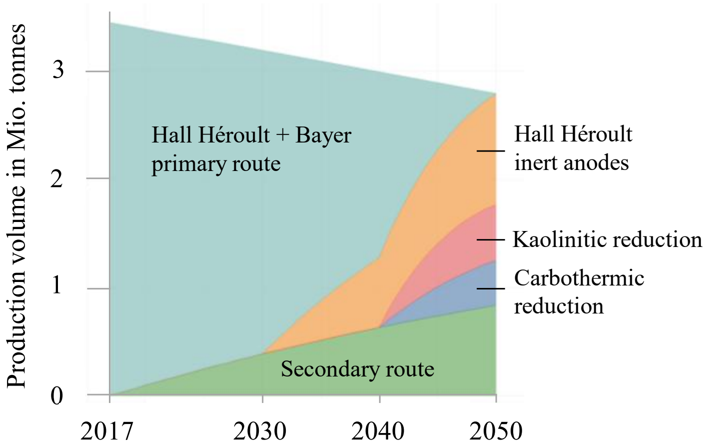

Figure 3.5: Technology diffusion in the aluminum production route in the ambitious decarbonization scenario. Published in Scharnhorst et al. (2024b).

adopt bottom-up approaches to derive regional flexibility potentials from process-specific parameters and cross-cutting technologies. For Germany, Gruber et al. (2013) and Ausfelder et al. (2018), for instance, quantify flexibility potentials of energy-intensive processes such as cement and steel at plant and regional level (Gruber et al. 2014; Ausfelder et al. 2018). Gils (2014) extends this approach to Europe and reports flexibility potentials at NUTS-3[6] resolution.

Based on a Germany-specific implementation of the TIMES model (TIMES-D-DSM), Haasz (2017) analyzed the endogenous deployment of industrial demand-side management until 2050 for selected energy-intensive processes such as aluminum, copper and chlor-alkali electrolysis, electric steel production, and pulp processing. Nebel et al. (2020) investigate the system-level impact of flexibilizing aluminum electrolysis in comparison to other flexibility options, including electricity storage, district heat storage, electric vehicle charging, and hydrogen buffer storage, using an hourly dispatch model for a future renewable-based power system. They find that while the relative contribution of aluminum flexibility to cost and curtailment reduction is high, its absolute impact remains limited due to the small number of available processes.

Schnaars et al. (2022) conduct a techno-economic simulation of industrial demand-side management for Germany and China in aluminum and chlor-alkali electrolysis, cement and raw mills, and the full paper production chain for scenarios up to 2030 and 2035. Mayer et al. (2024) apply an optimization framework to a net-zero Swiss energy system, using a generic, process-agnostic representation of industrial demand-side management and product storage to quantify the contribution of industrial flexibility at the system level. More recently, Luciani et al. (2024) provide a detailed review-based assessment of flexibility potentials in selected EU energy-intensive industries, including steel, paper, cement, polymers, bio fuels, pharmaceuticals, and the automotive industry, identifying manageable loads, working cycles, time constraints, and idle capacities, but without explicit modeling of future

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[6] NUTS-3 represents small regions in the Eurostat nomenclature of territorial units for statistics (Eurostat 2021).

technology diffusion. Dedecca et al. (2025) further highlight the importance of specialized industrial demand response aggregators as intermediaries that bundle flexibility across sites and enable collective market participation, illustrated by case studies from the food industry in Spain, printable products manufacturing in Germany, and multi-temperature warehousing in England.

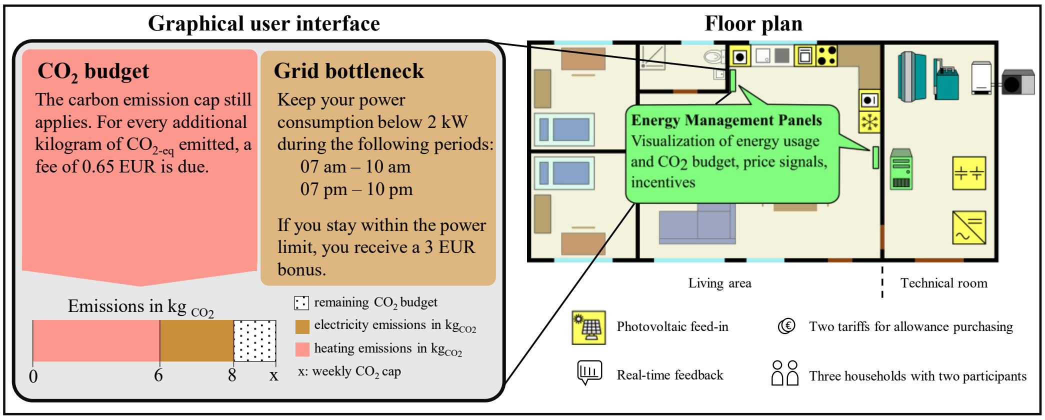
While numerous studies have investigated process-specific demand response and flexibility potentials, their scope remains limited in several respects. Existing work either focuses on the present technical potentials or addresses economic potentials in isolation. Only Haasz (2017) has assessed the economic potential for different industry processes, however did not account for potential technology diffusion in a future decarbonized industry and only accounted for Germany. Many studies remain restricted to individual countries, single sectors or specific process technologies, or highly aggregated representations of industry-wide flexibility. A systematic techno-economic assessment of future process-specific flexibility potentials across European industry under ambitious decarbonization pathways is still missing. Against this background, Paper D presents a techno-economic assessment of future industrial process flexibility potentials in Europe until 2050.

4 Summary of papers and main findings

This chapter provides a summary of each of the four papers in this cumulative dissertation. First, the study context and the scientific contribution are presented, followed by the results and their discussion. The corresponding research papers are included in Part II of the dissertation.

4.1 Paper A: Household carbon caps and tariffs: a living lab experiment

This section refers to the article "Household carbon caps and tariffs: A living lab experiment", co-authored with Thorben Sandmeier, Max Kleinebrahm, and Wolf Fichtner. The article was published in the journal *Energy Research & Social science* and is cited in this thesis as Scharnhorst et al. (2025b). The graphical abstract is presented in Figure 4.1.



The carbon emission cap still applies. For every additional kilogram of $CO_{2\text{-eq}}$ emitted, a fee of 0.65 EUR is due.

Keep your power consumption below 2 kW during the following periods:
07 am – 10 am
07 pm – 10 pm

If you stay within the power limit, you receive a 3 EUR bonus.

Visualization of energy usage and CO_2 budget, price signals, incentives

Figure 4.1: Visualization of the floor plan, the main information of the graphical user interface, and details of the experimental setup. Own visualization, based on the figures in the publication Scharnhorst et al. (2025b).

4.1.1 Study context and contributions

When it comes to reaching carbon neutrality in the domestic sector, households are expected to either follow electrification (e.g., heat pumps) or react to indirect policy mechanisms such as carbon taxes for fossil fuels. As the latter has had mixed results in the past, PCT could offer an alternative, as a policy approach that makes household emissions from energy consumption visible (Guzman and Clapp 2017; Lin and Li 2011; Fuso Nerini et al. 2021). Albeit this policy approach has been discussed in scientific literature repeatedly, few pilot studies investigated the direct implications on households living with such a policy. This paper introduces and evaluates a carbon cap and tariff approach that allocates emission budgets to households. Building on a real-world living lab experiment, the study empirically examines how such a PCT scheme shapes household energy behavior. In particular, it investigates (1) how carbon caps affect energy demand, (2) how automated allowance pricing mechanisms influence consumption patterns, and (3) how participants respond to additional incentive signals for load shifting or shedding under grid congestion. By integrating behavioral and system-level dimensions, the study contributes to evidence-based design of direct and transparent carbon policies at the household scale.

4.1.2 Objective and significance

Over the past two decades, PCT has been discussed as a promising policy approach in several countries, exploring its potential integration into existing environmental strategies and its contribution to national carbon reduction goals. While this literature highlights the value of PCT schemes in enhancing individuals' awareness of personal emissions, it also consistently raises concerns regarding public acceptability and implementation costs (Niemeier et al. 2008; DEFRA 2008). Consequently, PCT has often been described as a concept ahead of its time, yet one that warrants empirical validation through real-world pilot studies (Duscha 2014; Fleming 2007). To date, only three such pilots have been conducted. Community based one with multiply communities participating independently of each other in the UK, one on Norfolk Island (Australia), both focusing on household energy use and personal transport, and a third in Finland targeting urban mobility. Of these, only the Finnish pilot integrated real-time feedback, and all suffered from substantial participant attrition. This scarcity of robust empirical evidence underscores the need for controlled experimental research that adds to the present data.

Against this backdrop, our study contributes by implementing a living lab intervention involving three households within a smart home environment equipped with extensive sensory and data measurement infrastructure. The experiment tests a combined carbon cap-tariff scheme that blends economic and psychological mechanisms to influence energy behavior. Specifically, the intervention integrates:

- real-time feedback on household emissions,
- transparent allocation and conversion of carbon allowances,
- high allowance prices and automated purchasing upon cap exceedance,
- two differentiated tariffs for allowance purchasing,
- inclusion of photovoltaic generation in the household carbon balance, and
- (non-)economic incentives for load shifting and shedding under grid congestion.

By testing this multifaceted design, the study aims to shed light on how complex incentives can be structured to effectively reduce energy consumption and manage load within everyday household contexts, thereby expanding the empirical foundation for engaging household-level carbon policies.

4.1.3 Methodology

The study was conducted in the Energy Smart Home Lab at Karlsruhe Institute of Technology, a fully instrumented living lab simulating a modern apartment equipped with photovoltaic panels, a heat pump, programmable appliances, and a comprehensive monitoring and control infrastructure (Scharnhorst et al. 2021). Three sequential household interventions (each seven to nine weeks) were carried out between March 2023 and June 2024 to test the carbon cap and tariffs scheme under real-world conditions. Each household received a weekly carbon cap for electricity and heating-related emissions, derived from measured energy use and German average emission factors, with real-time feedback of the cap and energy emissions displayed on a digital dashboard. When the cap was exceeded, participants automatically purchased additional carbon allowances through one of two tariff mechanisms: (1) a linear per-kilogram fee or (2) a bulk-purchase option. Additional incentives for load shifting and shedding simulated grid congestion events, encouraging participants to temporarily limit power consumption during pre-defined hours that target the participants peak demand intervals throughout the day. Data collection combined high-frequency energy and emissions monitoring with weekly semi-structured interviews and a survey to capture behavioral, perceptual, and technical responses. Despite the small sample size, the design ensured strong experimental control, enabling a detailed analysis of how households interacted with combined carbon pricing, and grid-management incentives within a smart-home environment.

4.1.4 Main findings and discussion

The study demonstrates that carbon caps and tariffs can effectively reduce households emissions while revealing the behavioral complexity underlying such policy instruments. Across the three households, emissions declined substantially, by 73%, 33%, and 48% relative to baseline levels, showing that all participants actively adapted their routines to remain within their carbon budgets. The observed behavioral responses were shaped by a combination of economic, psychological, and social mechanisms, with the latter two proving most influential. Economic incentives, such as the differentiated carbon tariffs and modest rewards for grid load shifting, served primarily as structural or symbolic signals rather than decisive motivators, echoing prior findings that monetary penalties alone have limited behavioral leverage. In contrast, psychological mechanisms, including real-time feedback and visualizing the carbon budget and emissions, substantially increased participants' carbon literacy and self-regulation, enabling them to experiment with energy use and develop more sustainable habits, such as shifting appliance operation to peak solar hours. Emotional engagement, ranging from stress under stringent caps to satisfaction from meeting targets, further shaped the persistence of behavioral change. Finally, social and normative motivations often outweighed financial considerations: participants viewed the carbon caps as personal challenges aligned with their environmental values, though comfort needs and social contexts occasionally overrode these commitments. Overall, these findings highlight the potential of carbon caps and tariffs as a policy approach that integrates psychological, social, and economic dimensions, demonstrating how complex incentive schemes can foster low-carbon lifestyles within digitalized household environments.

4.2 Paper B: Understanding household preferences for the security of energy supply: insights from a choice experiment in Germany

This section refers to the article "Understanding household preferences for the security of energy supply: insights from a choice experiment in Germany", co-authored with Lisa Kreuter, Thorben Sandmeier, Daniel Sloot, Max Kleinebrahm, and Wolf Fichtner. The article was submitted to the journal *Energy Policy* and is cited in this thesis as Scharnhorst et al. (2025a).

4.2.1 Study context and contributions

While Germany's electricity supply continues to be highly reliable, growing electrification across demand sectors and the increasing share of intermittent renewables already now challenge the management of the electricity grid. Instances of grid congestion and supply imbalances become more frequent, highlighting the urgency of developing effective demand-side flexibility. In this context, understanding how private households perceive and accept controlled electricity interruptions as a potential load-shedding measure gains importance. Previous studies have explored this issue through a range of experimental designs, yet the evidence remains fragmented and often limited by strong status quo bias, with respondents predominantly favoring uninterrupted supply. This study extends existing research by conducting a choice experiment with 682 German residential consumers to examine their willingness to accept targeted electricity interruptions under varying tariff conditions. By explicitly addressing status quo bias through a dual-response design, this study offers new insights into household preferences and the conditions under which flexibility measures may gain broader public acceptance.

4.2.2 Objective and significance

Ensuring a reliable electricity supply is becoming increasingly complex as power systems transition toward higher shares of variable renewable generation and electrification of demand sectors. Temporary or controlled electricity interruptions are therefore gaining attention as potential measures to enhance system flexibility, yet their implementation depends on social acceptability and adequate compensation schemes. Understanding how households value reliability, specifically, their willingness to accept (WTA) or pay (WTP) for controlled interruptions, is central to designing feasible demand-response measures.

Existing studies have approached this issue through production function methods, contingent valuation, and discrete choice experiments. While production function models provide macro-level estimates of the value of lost load, they overlook behavioral and contextual heterogeneity. In contrast, stated preference methods, particularly discrete choice experiments, allow a more nuanced analysis of household preferences by incorporating multiple attributes such as duration and frequency of an outage. However, the current evidence base remains fragmented. Few studies have examined the role of advance notice time, a critical factor of household preparedness, as a pilot study found (Scharnhorst et al. 2023). Furthermore, no previous studies, to the best of our knowledge, have applied a dual-response choice experiment design to differentiate between the respondents' preferences and status quo bias. On the contrary, most studies have reported a strong status quo bias. Addressing these gaps, our study combines a representative sample of 682 German households with a survey that combines contingent valuation and a discrete choice experiment that accounts for the attributes frequency, duration, and advance-notice of an electricity interruption, as well as the expected compensation, and deploys a dual response choice design.

4.2.3 Methodology

We conducted the survey in December 2022 via an online panel that accounted for the German age and gender quotas. After accounting for programmed attention and straightlining checks, as well as ex-post speeding the survey yielded a final analytical sample of 682 respondents. The survey consisted of (1) a section asking about demographic characteristics, living conditions, and blackout experience, (2) the contingency valuation asking a self-assessment on WTA and WTP for different outage durations, and (3) the choice experiment with 12 choice tasks. Each choice task comprised first a forced choice among three unlabeled interruption tariffs, immediately followed by a free choice between the selected tariff and a None option. Alternatives varied along four attributes: (1) interruption frequency (2, 4, 8 times per month), duration (1 h, 2 h, 4 h), advance notice (15 mimn, 1 h, 6 h, 24 h), and a monthly compensation. The compensation was respondent-specific, set as a fraction of the reported electricity bill or imputed from household-size averages if respondents did not know their bill, thereby anchoring the payments to realistic magnitudes that oriented themselves around the share of the grid tariff that is a part of the German residential electricity costs. Extreme values were winsorized at the 98th percentile (60 EUR) (Thomas and Ward 2006). To capture systematic heterogeneity, we collected sociodemographics (age, gender, education, income, homeownership, region), living conditions (home office use, electric heating, electric hot water), and blackout experience, and considered parsimonious interactions with attributes and opt-out behavior. To analyze the consumer preferences, we used two models: First, a joint mixed logistics model (MIXL) estimated via hierarchical Bayes, that captured continuous taste heterogeneity with random coefficients, alternative-specific constants, covariate interactions, and a scale factor for the free choice. Second, a latent class model (LCM) with log-likelihood estimation identified discrete segments with class-specific utilities and covariate-based class membership probabilities, as well as scale parameters for the forced and free choice. Both models used the sample consisting of 8,184 observations for both the forced and free choice stages (Hess and Train 2011). The models were built and estimated in R (version 4.4.2 for Windows) with the "apollo" package version 0.3.5 (Hess and Palma 2019). Multiple models were tested and assessed using the Akaike Information Criterion and Bayesian Information Criterion to balance model fit and parsimony (Temme 2007; Backhaus et al. 2015).

4.2.4 Main findings and discussion

The findings of this study show that residential consumers are, in principle, willing to trade electricity reliability for compensation. In the free-choice stage, respondents accepted their previously chosen tariff in about two-thirds of tasks, thus rejecting our hypothesis, that respondents would prefer the status quo. In addition, more frequent and longer electricity interruptions reduce utility, while longer advance notice and higher compensation increases it. The highest gains in utility for advance notice are shown between 15 min. and 1 h, and 1 h and 6 h. The attribute importances confirm compensation as the main driver, followed by frequency and duration, with advance notice least important overall. Both the joint MIXL and the LCM reveal substantial heterogeneity. With the LCM, three classes emerge: (1) the likely adopters responsive to compensation, (2) convenience-oriented participants who value predictability, and (3) non-participants largely unmoved by incentives and attributes. Older respondents are more likely to accept tariffs, respondents with higher education value increased advance notice, and home owners dislike longer durations. Interestingly, respondents with previous blackout experience were more likely to opt-out, while respondents who frequently work from home were more likely to accept a tariff.

The findings suggest that differentiated tariff schemes could be more effective than a one-size-fits-all approach for policy design. Utilities could offer tiered tariff options that trade off reliability and compensation in transparent steps. For example, lower payments for rare and short interruptions, and higher payments for more frequent or longer ones. This would allow households to self-select into the level of flexibility that best fits their routines and risk tolerance, improving participation while keeping costs predictable. Similarly, performance-contingent payments, where compensation is tied to actual interruption events rather than fixed monthly bonuses, could limit unnecessary expenditure and link rewards more closely to system needs. Finally, targeted communication strategies could strengthen engagement by emphasizing predictability and control for convenience oriented consumers, highlighting financial rewards for price sensitive adopters, and assuring reliability safeguards for more skeptical consumers. While these approaches cannot ensure universal acceptance, the findings suggest that a majority of consumers may welcome compensation for tolerating occasional, well-communicated power interruptions. Furthermore, not all households would need to participate in such programs to be effective. If even a moderate share of consumers provide flexibility, controlled demand-side measures could relieve peak stress periods and reduce the need to expand grid capacity to the very last percentage point, thereby contributing to overall system cost efficiency. Future research could test the real-world acceptance and performance of such tariffs in pilot studies, as well as explore how consumer preferences vary across countries with different reliability norms, electricity costs, and institutional settings. In addition, studying long-term acceptance and preference dynamics would be valuable, as perceptions of security of supply are likely to evolve with increasing electrification, renewable integration, and the challenges these will bring to maintaining security of supply.

4.3 Paper C: Barriers to demand response in the commercial and industrial sectors: an empirical investigation

This section refers to the article "Barriers to demand response in the commercial and industrial sectors - An empirical investigation", co-authored with Daniel Sloot, Nico Lehmann, Armin Ardone, and Wolf Fichtner. The article was published in the journal *Renewable and Sustainable Energy Reviews* and is cited in this thesis as Scharnhorst et al. (2024a).

4.3.1 Study context and contributions

Existing participation in demand response programs within the industrial sector shows that flexibility is technically feasible, but much of the process-specific potential in both industrial and commercial (C&I) settings is still far from being fully leveraged. In practice, demand response participation in these sectors is still concentrated in a few energy-intensive industries, whereas other branches show little engagement, indicating the presence of significant non-technical barriers. This study addresses this gap by examining the barriers that impede demand response adoption in the German C&I sectors. Drawing on twenty semi-structured expert interviews with firms and national industry associations, we identify and assess the perceived obstacles to demand response participation and propose a new taxonomy of barrier dimensions. Our analysis not only highlights the most salient constraints, but also uncovers interrelations between technical, organizational, economic, and informational barriers that have so far been treated as independent by other barrier frameworks in scientific literature. By extending the empirical basis beyond single-sector perspectives and integrating the views of both industrial and commercial actors, this research provides a more comprehensive understanding of why demand response adoption remains limited and offers guidance for policy and industry initiatives to enhance flexibility participation.

4.3.2 Objective and significance

The objective of this study is to advance the empirical understanding of the factors constraining demand response participation in the C&I sectors, where substantial process-specific flexibility potentials remain largely unrealized. Although parts of the industrial sector already contribute to established demand response schemes, uptake across the broader C&I landscape continues to fall short of technical assessments, and the barriers underpinning this gap are insufficiently captured in the existing literature. Prior research has predominantly adopted technical, system-level, or utility-oriented perspectives, while empirical work focusing directly on C&I consumers remains sparse, often restricted to single sectors, predefined barrier typologies, or analyses that treat economic, technological, organizational, and regulatory factors as independent domains. This study addresses these limitations by conducting twenty semi-structured interviews with firms and national industry associations in Germany and by developing an integrated taxonomy of demand response barrier dimensions grounded in both prior literature and inductive analysis. By identifying sixteen barriers and systematically tracing their interrelations across economic, technological, policy, and organizational domains, the study contributes a more comprehensive and conceptually coherent account of the impediments to demand response participation in heterogeneous C&I environments. In doing so, it extends the empirical basis for understanding adoption constraints, refines the theoretical categorization of demand response barriers, and provides insights to inform the design of incentive structures and regulatory frameworks aimed at fostering greater engagement in flexibility provision.

4.3.3 Methodology

Given the limited empirical evidence on how C&I actors themselves perceive barriers to demand response participation, a qualitative approach was adopted, drawing on semi-structured interviews with experts from German companies and national industry associations. Participants were recruited via sectoral associations and represent eight C&I segments as defined by the German statistical office, including firms both with and without demand response experience (Destatis 2008). Interviews were conducted via video conference, lasted 30-60 minutes, were recorded with consent, and followed a three-part guideline covering (1) organizational roles and the companies/sectors energy use, (2) the discussion of processes and technologies which may exhibit flexibility potentials, and (3) perceived constraints with regard to economic, political, and organizational hurdles. The recordings were transcribed in the software *f4transkript* and analyzed using a hybrid deductive-inductive content analysis (Schreier 2014). In the deductive stage, a theoretically derived coding framework comprising the four overarching barrier dimensions of *economic, technological, policy*, and *organizational* barriers served as the initial analytic structure, thus guiding the first cycle of coding and ensuring consistency with the established literature. The inductive stage then involved systematically identifying new, specific barriers emerging from the interview material and adding them as subcodes within, or, when necessary, across, these dimensions (Kuckartz 2012). This allowed the analysis to remain anchored in an previously determined conceptual framework while still capturing unanticipated themes and context-specific nuances. All transcripts were coded line by line, and the resulting categories were subsequently examined to document the prevalence of individual barriers and to trace interrelations between dimensions, thereby generating an integrated account of the multifaceted constraints shaping demand response participation in heterogeneous C&I contexts.

4.3.4 Main findings and discussion

The interviews revealed a complex set of sixteen barriers that impede demand response participation in German commercial and industrial sectors, cutting across economic, technological, organizational, and policy domains and exhibiting substantial interdependencies. Profitability concerns were mainly driven by revenue uncertainty, hidden costs, and competitive pressure and emerged as the most critical barrier, followed by fears of compromising product quality, challenges in personnel planning, general organizational reluctance to alter established routines, and technical interdependencies between upstream and downstream processes. Several regulatory issues, including restrictive rules and administrative complexity, further intensified these constraints. Less frequently mentioned but still consequential barriers concerned supply-contract obligations, autonomy over production processes, and space or storage limitations. Across sectors, the perceived barriers varied in emphasis but not in kind, reflecting shared structural tensions despite heterogeneity in processes and technologies. Interviewees also identified a range of enabling activities. These comprised most notably selecting suitable demand response program types, ensuring sufficient advance notice, and improving internal communication. These enablers could mitigate several barriers, though many enabling measures require supportive regulatory conditions. Taken together, the findings underscore that addressing demand response barriers in the C&I sectors will require both organizational adjustments within firms and changes to external incentive and regulatory frameworks. Future research should examine sector-specific differences in greater detail, explore cross-country variability in light of divergent regulatory regimes, and place greater emphasis on identifying effective enabling measures to translate technical demand response potential into practicable, widely adopted flexibility.

4.4 Paper D: Techno-economic analysis of future process-specific demand response in European industries

This section refers to the article "Techno-economic analysis of future process-specific demand response in European industries", co-authored with Xinyi Xie, Max Kleinebrahm, and Wolf Fichtner. The article was published in the proceedings of *IEEE - 20th International Conference on the European Energy Market (EEM 2024)* and is cited in this thesis as Scharnhorst et al. (2024b).

4.4.1 Study context and contributions

The European energy transition towards a decentralized, renewables-based electricity system is intensifying the need for flexibility on the demand side (Koolen et al. 2022). The manufacturing industry, one of the largest electricity consumers in Europe and historically an important demand response (DR) provider, is expected to gain further importance as production process electrification and net-zero industrial strategies progress (Boldrini et al.

2024; European Commission 2023). While previous studies have quantified technical or economic demand response potentials for selected sectors, countries, or aggregated industries, there is still limited evidence on process-specific techno-economic demand response potentials in a consistent European framework and the potential future industrial landscape (Gils 2014; Heitkoetter et al. 2022; Müller and Möst 2018). This study addresses this gap by developing a bottom-up assessment of future demand response potentials for energy-intensive industrial processes in Europe up to 2050. It links process-level decarbonisation pathways with load shifting and shedding options and provides a first estimate of how decarbonization measures such as electrification and fuel switching may reshape both the magnitude and composition of industrial demand response potential across countries and technologies.

4.4.2 Objective and significance

The central objective of this paper is to quantify the future techno-economic potential of process-specific industrial demand response in Europe and to examine how this potential evolves under different decarbonization pathways. Specifically, the study aims to (i) derive technology- and process-specific hourly demand response potentials regarding potential load reduction and load increase for energy-intensive industries in EU27 + UK, Norway, and Iceland up to 2050, and (ii) estimate the associated capital and operating costs of enabling and providing demand response at process level. By embedding demand response potential estimation within a bottom-up industry demand simulation model, the analysis demonstrates how measures such as electrification, hydrogen-based process routes, efficiency improvements, and other structural changes in production can both create and reduce demand response opportunities. The results are relevant for system planning and decision makers as they highlight which industries and countries may become key flexibility providers.

4.4.3 Methodology

The study builds on an existing industry demand simulation model that computes bottom-up energy and emissions balances for energy-intensive processes and applications under two scenarios: a reference scenario, which continues current trends such as energy efficiency measures but does not account for process-specific decarbonisation (Capros et al. 2014; Fleiter et al. 2017). The target scenario assumes ambitious uptake of a broad set of decarbonisation measures on process and application level (Lerede et al. 2021; Guminski 2021). Across EU27 + Norway, Iceland, and the UK, 127 decarbonisation measures are modelled for 16 processes, 13 applications, and 13 sub sectors, accounting for energy carrier substitution, circular economy measures, increase in material efficiency, and process route changes. The annual process-level electricity demand is translated into hourly load profiles using synthetic, process-specific profiles derived from open data, scientific literature, and industrial reports and have been synthetized with regard to typical days and holiday dates annually, on country level (Seim et al. 2021; Dock et al. 2020; Starke et al. 2013). Technical demand response potentials are calculated for load reduction or shedding and load increase based on production capacities and accounting for revision downtime, utilisation levels, and process-specific flexibility factors derived from the literature (Gils 2014). Hourly demand response costs are then derived by combining capital expenditures for information and communication technology, as well as control infrastructure, and operating expenditures that comprise fixed costs, variable activation costs, and provision costs (Steurer 2017; Gruber 2017). The variable costs differentiate between load shifting and shedding due to higher production losses during load shedding. Provision costs occur only when load flexibility is provided and account for e.g., plant operation under suboptimal conditions or maintaining increased inventory (Langrock et al. 2015). The resulting technical demand response potentials are therefore based on the assumed technologies, scenarios, and cost parameters. However, they do not yet account for operational constraints such as required minimum durations for reduced or increased load states or limits on how frequently demand response interventions can occur for a given process.

4.4.4 Main findings and discussion

The model results indicate that the future industrial demand response potentials in Europe are substantial, but also strongly scenario-dependent. Overall, average hourly positive (load reduction) and negative (load increase) demand response potentials are estimated at roughly 17 GW and 8 GW, respectively, in 2020, rising to about 29 GW and 11 GW in 2050 under the target scenario. In the reference scenario, by contrast, positive demand response potential reaches only around 13 GW and negative demand response potential around 6 GW in 2050, amounting to less than half of the flexibility available in the target scenario. Furthermore, the load reduction potential of the target scenario in 2050 corresponds to around two-thirds of today's European pumped hydro capacity, underscoring the potential strategic role of industrial demand response (Statista 2024). Germany exhibits the highest demand response potentials, followed by France, reflecting their already substantial energy-intensive industrial production capacities. At the process level, ambitious decarbonisation substantially reshapes the demand response landscape: ammonia electrolysis, meat, and milk production emerge as the processes with the highest future load flexibility potentials, with secondary steel production via the electric arc furnace adding considerable load-decrease potential. Food processing (meat, milk, baked goods) offers considerable sheddable and shiftable loads but faces comparatively high variable costs for shedding, suggesting a stronger suitability for load shifting rather than outright shedding. In some existing processes, such as paper or conventional glass production, the flexibility potential declines with efficiency gains or process substitution. The analysis highlights that deep industrial decarbonization can increase overall demand response potential, but in a highly heterogeneous manner across processes and countries. At the same time, the study acknowledges limitations related to parameter uncertainty, the use of synthetic rather than metered load profiles, and the omission of detailed process-specific operational constraints, motivating future work to validate these potentials and examine their economic value in electricity market models.

5 Critical reflection

Despite considerable effort and methodological rigor across the living lab intervention, stated-preference surveys, expert interviews, and techno-economic modeling, this thesis is subject to a range of limitations. These concern internal and external validity, measurement and data constraints, model assumptions, and ethical as well as normative dimensions of behavioral energy research. This chapter critically reflects on these limitations and outlines implications for future research. More detailed study-specific limitations are provided in the discussion sections of the individual papers in Part II of this thesis.

5.1 Internal validity

Selection bias and reactivity in living labs
The Energy Smart Home Lab (Paper A) provides high internal validity due to its controlled experimental conditions and sophisticated technical infrastructure. At the same time, participation was voluntary and highly selective. Individuals willing to live for several weeks in a monitored smart home tend to be more technology-affine, sustainability-oriented, less privacy-sensitive, and more open to experimentation than the general population. This induces a clear self-selection bias, well documented in environmental psychology and behavioral economics. Moreover, several forms of reactivity are likely. A novelty effect is particularly relevant: in the first weeks, participants often exhibit heightened engagement, stronger pro-technology attitudes, and increased responsiveness to feedback and incentives. While this effect has been noticed in longer living lab interventions (> 3 months, up to several years) with mixed feedback in the context of energy saving incentives, the here conducted interventions lastet only a few months, so that the novelty effect may not have had time in most cases to wear off. In addition, Hawthorne effects may have influenced behavior: participants were aware of being observed and may have engaged in impression management, over-reporting pro-environmental intentions and compliance (Levitt 2007). The artificiality of the setting further limits internal behavioral realism. Although the apartment resembles a real home, it is not the participants' own home. Environmental psychology emphasizes that "home" is deeply tied to identity, emotional attachment, and long-term habit formation (Verplanken and Orbell 2022). With intervention durations of seven to nine weeks, routines could stabilize but deep habit change is unlikely, as habit discontinuity research suggests that longer periods in familiar environments are required (Verplanken and Orbell 2022). Finally, dyadic living arrangements introduced social interaction effects. Two-person households involve negotiation processes, conformity or divergence, and social contagion, creating unobserved intra-household dynamics that cannot be disentangled with the available sample size (Sringeswara et al. 2025).

Hypothetical bias in choice experiments

Paper B relies on stated-preference data and is therefore subject to hypothetical bias. In hypothetical contexts, respondents have no real economic incentives to reveal true preferences, which may lead to overstatement of willingness to accept controlled power shutdowns or participation in flexibility tariffs. Hypothetical bias is a well-known challenge in stated-preference research (Hensher 2010). While extensive survey design measures were applied (introductory texts, graphics, videos, simple language), hypothetical bias cannot be directly measured ex post. As a result, estimated compensation requirements and participation rates likely represent upper bounds of real-world engagement.

Positionality and bias in expert interviews

Expert interviews (Paper C) are intrinsically shaped by the positionality of respondents. As purposeful communication, expert interviews reflect interests, institutional roles, strategic incentives, and cognitive framing (George and Bennett 2005; Soest 2023). Bias may arise through purposeful misrepresentation, unintentional distortion, selective recall, or limited knowledge (Berry 2002). Furthermore, all interviews were conducted online due to COVID-19 restrictions, as travel was drastically inhibited, whether within one's country or abroad (Mwambari et al. 2022; Keen et al. 2022). While video conferencing has proven a viable alternative, when both interviewers and interviewees feel comfortable with the technology (Archibald et al. 2019; Lo Iacono et al. 2016), online formats complicate trust-building, non-verbal cue interpretation, and rapport, particularly with high-level decision-makers (Mwambari et al. 2022; Baalen 2018). At the same time, digital interviews reduced costs and enabled geographically broad coverage (Soest 2023).

5.2 External validity and transferability

Across all four Papers, external validity is constrained. Living lab findings originate from a highly controlled pilot with a very small, selective sample. Their behavioral insights are analytically rich but not statistically representative. The choice experiment captures preferences at a single point in time and for specific German electricity products. Transferring these results to other demand response designs, peer-to-peer markets, or other countries is connected with high uncertainty. Expert interviews focus on Germany and emphasize selected energy-intensive and commercial sectors. Major manufacturing branches such as automotive, machinery, rubber and plastics, and food processing industries are not covered. These sectors may exhibit fundamentally different flexibility constraints. The simulation model (Paper D) is European in scope but remains scenario-dependent. External validity depends on the plausibility of future assumptions on, e.g., technology costs, fuel prices, and policy instruments. Consequently, results should be interpreted as conditional projections rather than predictions.

Method triangulation

A key strength of this thesis lies in its triangulation of methods across behavioral experiments, surveys, and expert interviews. This reduces the risk of systematic bias inherent to any single method. Nevertheless, triangulation remains asymmetric across papers. Paper C relies exclusively on expert interviews. Soest (2023) argues that combining expert interviews with complementary methods such as surveys or list experiments is crucial for reducing social desirability bias and increasing robustness. In this thesis, expert insights were triangulated primarily at a secondary level through comparison with other empirical studies rather than through direct multi-method integration. Future work should explicitly combine interviews and standardized surveys within the same study.

Data and measurement limitations

Smart meter and sensor data in the living lab offered unprecedented resolution but at the cost of extremely small sample size and limited scalability. At larger scales, household device heterogeneity, privacy restrictions, and lower data granularity would significantly constrain measurement precision. Web surveys suffer from sample-quality uncertainty, limited control over respondents' environments, and self-selection biases (Mariel et al. 2025). Expert interviews rely on interpretive judgment and organizational filtering. Industrial data opacity further constrains Paper D: many firm-level process details are unavailable, forcing reliance on aggregated sectoral assumptions that propagate into long-term projections. The simulation framework in Paper D relies on exogenous scenario narratives. Techno-economic analyses abstract from socio-technical realities such as organizational inertia, risk perception, learning dynamics, and political resistance. Energy systems, however, are socio-technical systems embedded in institutional, cultural, and behavioral contexts (Miller et al. 2015).

Fairness

Personal carbon caps and targeted demand-response schemes raise ethical concerns regarding potential regressive effects and the risk of deepening energy poverty. These fairness and distributional considerations are not addressed in the empirical analyses of this thesis and are therefore discussed here as a normative limitation. Earlier UK and German studies identified distributional fairness as a central barrier to the acceptability of personal carbon trading (DEFRA 2008; Duscha 2014). Research highlights that vulnerable households may face disproportionate burdens due to structural factors such as housing inefficiency, limited mobility alternatives, or higher essential energy needs, reinforcing the importance of designing PCT schemes with explicit equity safeguards (Parag and Fawcett 2014; Pitkänen et al. 2022).

Researcher influence

Small qualitative samples are particularly prone to analyst confirmation bias and narrative overfitting. Intervention design, framing of survey attributes, and scenario construction necessarily reflect researcher choices. Sequencing effects may have taken place during the living lab interventions, as the research team learned with each intervention (getting better at running the study, which subtly changes the intervention). Maintenance and state of the living lab may drift. This creates non-stationarity and the experiment subtly evolves while running. Although triangulation mitigates these risks, it cannot eliminate them. In choice data analysis, Bayesian estimation adds further subjectivity through the definition of priors and model structure (Akinc and Vandebroek 2018).

6 Summary, conclusion, and outlook

This thesis investigates behavioral and structural drivers of demand-side flexibility in both the residential and the industrial sector by combining stated and revealed preference methods with techno-economic analysis. Against the backdrop of increasing electrification, renewable integration, and rising system volatility, understanding how households and firms respond to dynamic incentives and flexibility requirements becomes a central challenge for the design of future energy systems.

To address this challenge, the thesis applies empirical methods from behavioral economics and environmental psychology to analyze how consumer acceptance, preferences, and everyday practices shape the effectiveness of incentive-based instruments for energy saving and demand-side flexibility. The analysis combines a residential living lab intervention on household carbon caps and tariffs (Paper A), a choice experiment on the acceptability and preferences regarding controlled power interruptions (Paper B), and expert interviews with stakeholders from the commercial and industrial sectors (Paper C). These insights are complemented by a bottom-up techno-economic assessment of future industrial process flexibility at the European level (Paper D). Together, the four studies provide an integrated perspective on micro-level behavioral responses, meso-level organizational and regulatory barriers, and macro-level system potentials for demand-side flexibility.

Household carbon caps and tariffs represent a novel behavioral instrument for governing residential emissions and demand-side flexibility, and their practical feasibility and effects are demonstrated through a real-world living lab experiment.

Across three consecutive household interventions in a highly controlled smart home environment, participating households achieved substantial emission reductions, ranging from around 30% to over 70% relative to their respective baselines. These results indicate a high effectiveness of the combined incentive scheme in inducing immediate behavioral change. The observed adaptations were shaped by a combination of economic, psychological, and social mechanisms. While carbon tariffs and financial load-shifting incentives were acknowledged, participants consistently reported that price signals alone were not the dominant driver of behavior. Instead, psychological mechanisms proved particularly influential: real-time feedback and visualized carbon budgets fostered carbon literacy, self-monitoring, and strategic experimentation with everyday energy use, such as shifting appliance operation toward periods of high photovoltaic generation. Emotional responses, ranging from stress under strict carbon constraints to satisfaction when achieving targets, played a central role in shaping compliance and engagement. Social and normative motivations, including environmental values and personal commitment to the carbon budget, often outweighed monetary considerations, although comfort needs and social obligations occasionally overrode carbon-oriented intentions. With respect to demand-side flexibility, load shifting into sunny hours was successful, leading to noticeable increases in electricity use during periods of high photovoltaic electricity generation when corresponding information was communicated via the dashboard. In contrast, incentives to shift load outside peak load intervals were not consistently followed, as households had to balance incentive compliance with health, social routines, and attentiveness to the interface. This highlights both the potential of targeted reminder systems (e.g., real-time smartphone notifications) and the practical limits of sustained flexibility provision in everyday life, especially given the deliberately high frequency of load-shift events tested in the experiment. Overall, the study demonstrates that a digitally implemented, household-level variant of personal carbon trading can induce substantial emission reductions under real-world conditions and provides transferable insights for the design of larger-scale pilots and complementary survey-based research.

To overcome the shortcomings of previous approaches that aim to assess consumer preferences with regard to electricity interruptions in the residential sector, a dual-response choice experiment designed was implemented to be able in a) assess consumer preferences for different attributes of the tariff (frequency, duration, advance-notice, and compensation of an interruption) and b) then ask whether participants would actually accept the chosen tariff. While previous approaches had either a none or status quo option within the choice task with the actual tariff options or no none or status quo option at all, the proposed approach is thus able to reveal consumer preferences with regard to the tariff attributes, as well as status quo bias (in a second step) and thus foregoes the problem of heavy status quo bias and a loss of information on the tariff attribute preferences in the previous approaches. The findings indicate that consumer preferences for power interruption tariffs are primarily driven by financial compensation, followed by the frequency and duration of interruptions, while advance notice plays a comparatively smaller role. Overall acceptance is high: in the free-choice stage, respondents accepted the selected tariff in around two thirds of cases, indicating that, under transparent conditions and adequate compensation, a substantial share of households is willing to participate in controlled, time-limited interruptions rather than remain with the status quo. Consumers generally prefer short and infrequent interruptions, and the utility of longer advance notice increases with diminishing returns beyond roughly 12 hours. While most respondents value compensation positively, a non-trivial share is either relatively insensitive to monetary incentives or requires very high payments. The latent class analysis reveals three groups: likely adopters who respond strongly to compensation, convenience-oriented participants valuing predictability and short events, and reluctant non-participants who remain largely unresponsive to financial incentives. Sociodemographic effects further highlight that homeowners dislike longer durations more, higher incomes dampen compensation sensitivity, and prior blackout experience increases the likelihood of opting out. These findings imply that compensation is effective, but only up to a point. Rather than applying uniform high payments, utilities could implement differentiated, performance-based schemes that align with heterogeneous preferences, for example, higher rewards for longer and more frequent interruptions, and lower compensation combined with longer advance notice for short and rare events. Targeted communication strategies addressing predictability, financial benefits, and reliability concerns across consumer groups appear more promising than standardized program designs. This suggests that well-designed interruption schemes could complement traditional reliability strategies, alleviate periods of system stress, support renewable integration, reduce reliance on costly short-term balancing options, and provide financial benefits to participating households. Future research should test these insights in real-world pilots with dynamic compensation, examine learning and fatigue over repeated events, and assess how acceptance evolves with actual interruption experience and growing system stress.

Conducting expert interviews provides a systematic empirical assessment of demand response barriers in the German commercial and industrial sector based on 20 expert interviews with firms and industry associations. Sixteen interrelated barriers were identified and structured along organizational, economic, policy, and technological dimensions, revealing strong interdependencies, particularly between economic and technological constraints, and between policy barriers and all other dimensions. Five barriers emerged as especially critical: lacking profitability, concerns over product quality, implications for personnel planning, missing organizational acceptance, and technical interdependencies within production chains. In parallel, thirteen enabling activities were identified, most prominently suitable demand response program design, adequate advance notice, and expectation management within firms. The findings highlight that while some constraints can be addressed internally through information, awareness-raising, and organizational learning, the broader diffusion of demand response in the commercial and industry sector crucially depends on regulatory clarity, consistent incentive structures, and the reduction of institutional complexity. In this vein, increasing transparency about prequalification procedures and operational safeguards may help to alleviate persistent fears regarding quality and process stability. Beyond its immediate empirical contribution, the study demonstrates that demand response adoption is not primarily limited by technical feasibility but by a complex interaction of economic risks, organizational routines, and regulatory uncertainty. Future research should therefore place greater emphasis on sector-specific barrier constellations, cross-country comparisons of regulatory environments, and the systematic evaluation of enablers rather than obstacles alone, in order to support more targeted and effective demand response policy design.

Understanding how much flexibility energy-intensive industry can realistically provide is crucial for system planning under ambitious decarbonization pathways. Eighteen processes were evaluated with respect to their hourly load shifting and load shedding capabilities, offering detailed insights into how industrial flexibility potentials may evolve in the future. At the aggregated European level, the average hourly DR potential for load reduction amounts to approximately 16-17 GW in 2020 and increases to 13-29 GW in 2050 across the reference and target scenarios. In parallel, load increase potentials range from about 7-8 GW in 2020 to 6-11 GW in 2050. These results highlight the growing strategic relevance of industrial flexibility in a deeply decarbonized energy system, particularly in conjunction with increasing process electrification and the large-scale deployment of green hydrogen. The highest future load increase potentials are identified in ammonia electrolysis as well as in meat and milk production, while load shedding potentials are primarily associated with ammonia electrolysis, electric arc furnaces, and food processing. From an economic perspective, however, load shedding, especially in the food sector, is characterized by comparatively high variable costs, suggesting that these processes are generally better suited for load shifting rather than absolute load reduction. Moreover, several processes that appear attractive from a flexibility perspective in the near term, such as cement production or direct reduced iron with electric arc furnaces, may lose relevance in the long term due to fundamental changes in production routes and energy carrier substitution. In the case of cement, this points to the need for further research on future-oriented production pathways such as belite cement and autoclaved aerated concrete. Finally, the study reveals pronounced regional differences in flexibility potentials across Europe, closely reflecting the spatial distribution of energy-intensive industries. Accordingly, Germany, characterized by the highest industrial electricity demand, also exhibits the largest industrial flexibility potential in the European context.

While the proposed studies and methodologies provide important results, there is still opportunity for methodological extension. The living lab approach in Paper A demonstrated the feasibility of combining complex emission reduction and flexibility incentives under real-world conditions. Future studies should build on this proof of concept by extending such interventions to larger and more diverse samples, covering a broader range of sociodemographic characteristics and housing contexts. In addition, future research should pay greater attention to intra-household decision-making processes, as energy-related decisions are typically negotiated within households rather than made by isolated individuals. A further extension would be to introduce an actual trading component into household carbon cap schemes would allow testing the full mechanics of personal carbon trading under realistic market conditions. Furthermore, with disruptive geopolitical events, such as the war in Ukraine and the diffusion of digital infrastructure, a new window of opportunity emerges to investigate the acceptability of personal carbon trading with surveys that are representative for the German population and which may shed more light whether public acceptability has shifted in recent years. For Paper B, future work could further integrate unobserved variables, such as consumer value orientations into the statistical models to better capture latent motivational drivers behind flexibility-related decisions. Longitudinal stated-preference designs would be particularly valuable to capture how household preferences, risk perceptions, and acceptance of demand-side flexibility evolve over time in response to changing price environments, policy signals, and lived experience with flexibility programs. With regard to Paper C, the expert interview approach could be expanded both methodologically and sectorally. Several important industrial branches, such as automotive manufacturing, machinery, food processing, and rubber and plastics production, remain underrepresented. Complementing qualitative interviews with large-scale firm surveys, as already piloted in first projects such as the Synergie initiative, would enable systematic quantification of barrier prevalence and inter-sectoral contrasts across the German and European industry landscape (SynErgie 2022). Finally, Paper D relies on multiple assumptions regarding, i.e., technology diffusion, process electrification, and projections on energy carrier prices and production volumes, when quantifying long-term industrial flexibility potentials. Future modeling work should therefore move toward integration of process-specific ramping constraints and maximum activation durations, as well as the explicit inclusion of cross-sectional technologies, which are likely to exhibit particularly high flexibility value. Moreover, extending the techno-economic assessment to explicitly compare alternative market-based flexibility remuneration schemes would allow a more policy-relevant evaluation of economic deployment potentials beyond purely technical bounds.

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Part II

Research Papers

Paper A

Household carbon caps and tariffs: A living lab experiment

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Original research article

Household carbon caps and tariffs: A living lab experiment

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ABSTRACT

Transnational efforts to combat climate change are intensifying, with Germany targeting net-zero emissions by 2045. The residential sector is a significant CO_2 emitter but lacks direct mitigation strategies, such as personal carbon budgeting and trading, which are common in industry. Although theoretical research on personal carbon trading exists, real-world household-level studies are scarce. This study addresses that gap by examining the implementation of household carbon caps and tariffs in a living lab experiment. Conducted in the Energy Smart Home Lab, the experiment involved three households under weekly carbon caps, with the option to purchase additional allowances under two different tariffs. In two households, photovoltaic feed-in was accounted for to incentivize load shifting and maximize self-consumption. Additionally, participants were encouraged through economic and non-economic incentives to adhere to a 2 kW power limit during simulated grid congestion. Real-time energy consumption monitoring and weekly interviews provided insights into how participants responded to the imposed carbon limits and power restrictions. Essential household activities, such as cooking and heating, occasionally took precedence over economic motivations, leading to breaches of the power limit. As weekly carbon emission caps were reduced by 45 % to 75 % by the end of the intervention, participants faced substantial challenges, compounded by unmodifiable appliance emissions and external pressures like exams. Although limited in sample size, this study is the first to combine carbon caps, tariffs, real-time feedback, and photovoltaic-based incentives in a living lab setting.

1. Introduction

Despite adopting multiple climate policies, most countries in the European Union still lack behind the ambitions to reach net-zero emissions by 2050 [1]. In 2023, the global average surface temperature already reached about 1.2 °C above pre-industrial levels, however, net zero targets may still be achieved, as more and more countries implement clean energy policies [2]. Carbon pricing remains a key mitigation strategy. The EU Emission Trading Scheme (EU-ETS), launched in 2005, covers the energy, manufacturing, and aviation sectors, accounting for 40 % of overall emissions [3]. The EU-ETS2 coming in 2027 will extend coverage to buildings, road transport and small industries [4].

While central to climate policy, instruments like the EU-ETS and carbon taxes often fail to engage individuals directly in emission reduction efforts [5]. The inclusion of buildings and transport in the EU-ETS2 brings it closer to the individual level, yet its upstream, market-based mechanisms remains abstract [5]. Carbon taxes impact consumer behavior directly by increasing the cost of fossil fuel-based goods and services but show mixed results in the residential sector. In countries with high tax rates, such as Sweden and Finland, household emissions dropped significantly [6]. In other countries, e.g., Canada, the emissions reduction was not that high [5]. The carbon tax, is often hidden within the price, thus limiting consumers' awareness of the carbon price [5]. Moreover, carbon taxes lack a specific carbon cap, and their social acceptability remains contested, particularly if revenues are not redistributed to protect low-income households that bear a disproportionate burden [7–9]. Many consumers remain unaware of the carbon pricing embedded in costs, weakening their motivational effect [5].

To engage individuals more transparently, personal carbon trading (PCT) schemes offer a more tangible approach by directly linking individual actions to emissions [10]. Scientific literature suggests that direct and visible incentives can support behavioral changes to reduce carbon emissions [11,12]. Parag et al. [13] argue that PCT schemes combine economic, psychological, and social mechanisms that create synergies to foster low-carbon behavior. Carbon prices become more visible, carbon budgeting fosters awareness, and shared emissions targets can cultivate

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collective norms [5,10,13]. PCTs also promise greater fairness: low-income households tend to emit less and could financially benefit from trading surplus allowances [14–17]. However, higher income households may be able to pay off their high emission lifestyle, therefore, a trading limit is suggested [16]. Considering these conceptual foundations and existing policy limitations, our study aims to empirically explore how households respond to a digital PCT scheme applied to residential energy use. Specifically, we examine (1) the effects of carbon caps on energy demand behavior, (2) the influence of automated allowance pricing mechanisms, and (3) how participants engage with additional incentive signals for load shifting or shedding in response to grid congestion.

While PCTs have been discussed since the early 2000s, early policy efforts (e.g., in the UK) were abandoned due to concerns over public acceptability[1], technological hurdles, high implementation costs, and complexity [13,19–21]. A 2014 German study echoed these concerns, citing fragmented policy landscapes and challenges in accounting for indirect emissions [22]. Yet, with increasing climate urgency, interest in PCTs is resurfacing [10,23–27]. Alongside political commitments, public support for ambitious climate action has grown, as seen by the global rise of youth-led initiatives like the Fridays for Future movement and climate strikes [28]. The COVID-19 pandemic also revealed a surprising willingness to accept personal restrictions and digital tracking for collective benefit [10]. Moreover, the pandemic accelerated acceptance of contact tracing apps introduced in multiple countries, which could inform the design of applications for tracking personal carbon emissions [10,29,30]. Current policies like the EU-ETS present additional complexities, potentially leading to double-pricing of emissions when overlaid with PCT schemes [11,22]. Nevertheless, the integration of diverse policy instruments to address environmental challenges is a well-established practice, though incorporating a radical, untested policy like PCT into existing frameworks remains risky and challenging for policymakers [10,31,32]. Furthermore, recent advances in digitalization and AI promise to reduce administrative costs associated with PCTs, while improving personalized feedback, information, and user engagement [33–35].

Since not much is known about the impact of PCT schemes on household energy demand behavior, we conducted three consecutive interventions in a living lab in Karlsruhe, Germany, from spring 2023 to summer 2024. In this setting, we tested a PCT scheme that we called household carbon caps and tariffs (HCCT) that allocated weekly free allowances as a weekly decreasing carbon cap to a household of two participants, accounting for heating and residential electricity consumption. With this in mind, we formulated our first research question:

RQ1. What are the potential impacts of HCCT schemes on energy demand behavior when implemented in a residential setting?

The HCCT scheme included an automated purchase option for additional allowances once the weekly cap was exceeded, allowing us to test two different purchase tariffs and address our second research question:

RQ2. How do allowance allocation and trading mechanisms influence household behavior towards energy usage?

Given that future low-carbon energy systems may combine carbon price signals with incentives to respond to critical grid states, such as grid congestion, we also incorporated these incentives to better understand the interdependencies between multiple signals. This approach allowed us to examine our third research question:

RQ3. How do participants interact with incentives to offer load shifting or shedding behavior, while also accounting for the PCT scheme?

While prior pilots such as CRAGs in the UK, NICHE in Australia, and CitiCAP in Finland laid important groundwork for personal carbon trading, they also faced key limitations that our study seeks to address. CRAGs relied on manual tracking and self-reported data, with little automation [36]. NICHE lacked real-time feedback, limiting participant responsiveness [37]. CitiCAP focused on urban mobility and did not extend their scope to residential energy use [38].

Our HCCT scheme addresses these limitations by targeting residential electricity and heating, using continuous real-time feedback and digital carbon budgeting. Participants received weekly caps, real-time updates, and automatic allowance purchases if caps were exceeded. Instead of full trading, we tested two fixed pricing schemes to assess behavioral responses. The inclusion of photovoltaic (PV) generation and dynamic incentives for grid congestion enables a nuanced analysis of how households navigate complex incentive structures. By answering the three research questions, this study offers new insights into the behavioral and technical feasibility of PCT-like schemes in everyday residential settings.

The remainder of this study is structured as follows: Section 2 presents the theoretical background, followed by the methodological approach in Section 3. The results are detailed in Section 4, and discussed in Section 5. A conclusion and outlook are given in Section 6.

2. Theoretical background

The following provides a more detailed overview of PCT concepts, variations, and real-world pilots to frame the theoretical foundations of the HCCT approach used in this study. Personal Carbon Trading (PCT) refers to downstream cap-and-trade approaches that assign individuals a carbon allowance for activities like household energy use and personal travel, linking personal behavior to national climate goals [39]. First introduced as “Domestic Tradable Quotas” in the 1990s, PCT has also been referred to using terms such as tradable energy quotas, personal carbon allocation, personal carbon budget, CO_2 budgets, carbon budgets, emission allowances, and emission trading [10,17,40–47]. Despite the variety of terms used to describe PCT, the literature broadly agrees on several core characteristics. Emissions caps, surrender of allowances for carbon-intensive actions, and optional trading mechanisms within a declining emissions cap [39,48].

There is no single definition of PCT. Designs vary in population coverage and emissions scope, ranging from household energy use to personal travel or consumption products. Schemes also differ in the rules for allocating, surrendering, and trading allowances, and in how actively individuals are expected to engage with the system. Some proposals stress mandatory participation as a requirement for effectiveness, while others allow for voluntary engagement or a choice between PCT and carbon taxation [39]. This diversity suggests that PCT is best understood as a conceptual family of carbon accountability tools rather than a single policy model.

While related tools like carbon labelling or personal carbon allowances focus on awareness or fixed caps without trading, PCT uniquely combines capping, allowance allocation, and the option to trade surplus units, making it a more comprehensive market-based approach to individual carbon accountability [44].

The HCCT scheme used in this study shares key elements with PCT, namely emissions caps and pricing signals, but applies them at the household level without trading. Instead of a trading mechanism, it incorporates a two-tiered tariff system for cap exceedance alongside incentives for energy demand flexibility. As such, HCCT can be viewed as a foundational or early-stage implementation aligned with the broader principles of PCT.

Over the past two decades, PCT schemes have been explored as viable policy proposals in various countries, examining their potential to integrate with existing environmental strategies and their impact on national carbon reduction goals. A complete overview of historical PCT policy proposals and design variants can be found in Appendix A

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[1] Here, the term “acceptability” is used instead of “acceptance” because the discussion about PCT is still a theoretical one [18].

(Table A1). Despite most of these policy proposals underlining the fostering of visibility and greater awareness on personal carbon emissions by PCTs, most raise concerns about public acceptability [49] and the costs of implementation [22], or in general describe PCT as a concept ahead of its time [50]. However, most also call for pilots to test PCTs in real-world interventions [5,10,22,41,50].

The first policy investigations related to personal carbon accountability to have departed the theoretical stage have emerged in China and other countries (see Table 1). While these initiatives do not represent full implementations of PCT as defined above, they mark a departure from purely theoretical discussions by operationalizing core elements of individual-level carbon responsibility. Most of these initiatives are better classified as carbon labelling or personal carbon allowance models. They do not impose hard carbon caps or require allowance surrender and thus fall outside a strict definition of PCT. However, they embody key mechanisms such as carbon tracking, visibility of individual emissions, and behavior-oriented incentives, making them important early steps in the broader development of downstream carbon accountability tools. From this perspective, they can be seen as foundational or precursor models that align with the broader conceptual scope of PCT. A smaller number of pilot studies, shown in the second half of Table 1, move closer to full PCT schemes by incorporating baseline emissions measurements and defined reduction targets. These studies vary in their experimental design, such as the details of the PCT scheme, the duration, the sample size, as well as where they have been deployed.

The first early volunteer scheme was established by Carbon Rationing Action Groups (CRAGs) in the UK, which counted 21 groups in 2010 [48], with most having since ended [24]. The Norfolk Island Carbon and Health Evaluation (NICHE) pilot in Australia, introduced a voluntary PCT scheme, starting with baseline surveys in 2012 [51,52], followed by 15-month trial period from April 2013 to June 2014, with 218 participating households (486 people) [37]. For the NICHE study, real-time data transmission of the participants' emissions was not possible due to poor internet connection on the island, so that banking and trading of allowances were waived [52].

These pilot programs illustrate both the promise and the practical challenges of operationalizing individual carbon accountability. For instance, the Norfolk Island Carbon and Health Evaluation (NICHE) in Australia faced infrastructure limitations that prevented real-time feedback or trading of emission allowances [37]. Both pilots, NICHE and CitiCAP saw significant reduction in participants, mainly due to economic downturn and the COVID-19 pandemic, respectively [37,62]. Despite these issues, these pilots provide valuable groundwork and highlight the importance of testing different configurations of incentives, data transparency, and engagement strategies. More detailed information on the design frameworks, baseline conditions, and emission reduction targets of these pilots is provided in Table A2 in Appendix A.

Building on these precedents, our study introduces a highly controlled experimental design to directly address key research questions concerning the implementation and effectiveness of PCT schemes in residential settings. Our research aims to clarify the potential impacts of PCT schemes on household energy demand behavior (RQ1), investigate the influence of allowance allocation and trading mechanisms on

Table 1
Characteristics of the first pilots investigating or implementing personal carbon accountability schemes.

Project	Year	Country	Scope	Addressees	Communication with participants	Sample size	Real-time feedback	Emission data	Ref.
Real-world personal carbon accountability schemes									
Carbon Generalized System of Preferences	2015-now	China	Consumption-related goods and services such as clothing, food, water conservation, household energy, and travel	Per capita	App-based	Large (Multiple cities and provinces)	Yes	Financial transactions	[24,53]
Credit card	2011-now	South Korea	Consumption products, household energy, transport	Per capita	App-based	15 million credit cards (55 % of the economic active population)	Yes	Financial transactions	[54–56]
Doconomy Credit card	2018	Sweden	Carbon emission purchase tracking	Per capita	App-based	No information disclosed	Yes	Financial transactions	[57–59]
Commons app	2019	California, US	Carbon emission purchase tracking	Per capita	App-based		Yes	Financial transactions	[60,61]
Pilot studies on PCT schemes									
Carbon Rationing Action Groups (CRAGs)	2000–2010	UK	Household energy, personal travel	Per capita (50 %)	Offline and self-assessed	21 groups with 8–12 people; overall approximately 200–300 people	No	Own computations, agreed conversion factors, or one person per group	[48]
Norfolk Island Carbon and Health Evaluation (NICHE)	2012–2014	Australia	Household energy, personal transport	Household	Website (fuel purchases), e-mail (household energy consumption) every 3 months	486 people (218 households)	No	NICHE carbon card (fuel); utilities (energy consumption)	[37,51,52]
CitiCAP	2018–2021	Finland	Urban mobility	Per capita	App-based	350 at the beginning, 47 final surveys	Yes	Mobility traced by phone acceleration sensor	[38]
Energy Smart Home Lab	2023–2024	Germany	Household energy	Household	Tablet	3 households (6 people)	Yes	Real-time energy measurements	This study

household energy use (RQ2), and analyze the interaction between participants and multiple incentive structures within a PCT framework, including critical responses to grid congestion (RQ3). The study investigates how households engage with a scheme that integrates both economic and psychological mechanisms to influence energy behavior

- real-time feedback on emissions,
- transparent allocation and conversion of carbon allowances,
- high allowance prices,
- alongside automated purchasing for cap exceedance,
- two different tariffs for allowance purchasing,
- the inclusion of PV generation into the households' energy balance,
- and (non-)economic incentives for load shifting and shedding during grid congestion

and thus, offers fresh perspectives on the adaptability and behavioral response to complex incentive schemes. These elements are crucial for understanding how multi-faceted incentives can be structured to effectively reduce energy consumption and manage load within a smart home environment, providing valuable data on the feasibility of scaling PCT systems in the residential sector. The highly controlled environment of the Energy Smart Home Lab allows for a detailed examination of these dynamics, ensuring precise measurement of energy use and participant behavior in response to the PCT scheme. This study contributes new evidence on the behavioral, technical, and economic feasibility of adapting PCT principles to everyday household settings, with an emphasis on how complex incentive structures can shape energy use in real time.

3. Method

This chapter details the experimental setup, the design of the interventions, and the methods to assess participant interaction with the implemented carbon budgets and grid congestion scenarios in the Energy Smart Home Lab.

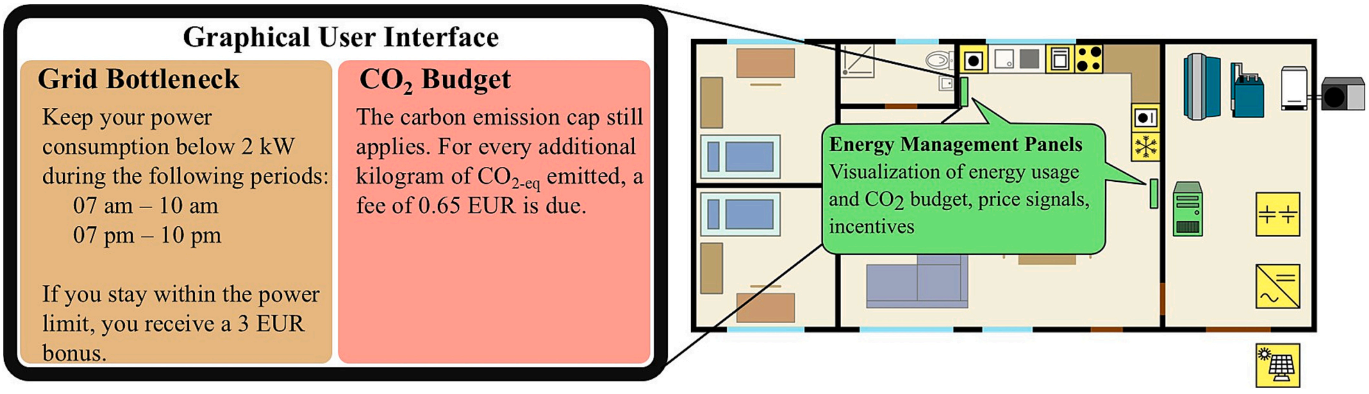
3.1. The Energy Smart Home Lab

The Energy Smart Home Lab, established in 2010 at the Campus South of the Karlsruhe Institute of Technology, blends the elements of a modern apartment and a smart home within a living lab environment. Equipped with programmable appliances such as oven and dishwasher, and a real-time energy monitoring panel, the Energy Smart Home Lab features advanced energy technologies including a 4.7 kW peak PV panel, a heat pump, and a comprehensive sensor and measurement system for detailed electricity and heat monitoring, as presented in Fig. 1. Furthermore, Fig. 1 illustrates the physical layout of the living lab alongside a zoom-in of the graphical user interface illustrating exemplary two incentive mechanisms: a carbon budget with financial penalties for excess emissions, and a grid bottleneck alert encouraging reduced electricity use during specific time windows. The visualization provided participants with immediate insights into their performance, helping them align daily routines (e.g., cooking, heating) with both CO_2 caps and grid signals.

Two persons can live in the Energy Smart Home Lab for multiple weeks up to three months, interacting with various incentives via a tablet with web-interface that provides real-time data on energy use and feedback on energy-saving incentives. Although its small sample size limits demographic representation, the lab is ideal for pioneering and testing early-stage household carbon caps and tariffs (HCCT) schemes and other innovative concepts in a controlled setting. Further details about the Energy Smart Home Lab are available in references [35,63].

Due to the complexity of the intervention and the infrastructure of the Energy Smart Home Lab, the study was limited to a sample of three households. The smart home can accommodate one household (with up to two tenants) at a time. Each intervention requires a full technical setup and participant onboarding. As such, interventions must be conducted sequentially, therefore, only one to two studies can realistically be scheduled per year. Table 2 provides an overview of key socio-demographic characteristics and pre-existing relationships within the participating households. The participants of HH1 did not know each other beforehand but were introduced prior to confirming their participation in the intervention.

While the small sample limits generalizability, the Living Lab provides a highly controlled environment with continuous real-time monitoring and detailed behavioral tracking. This allows for in-depth analysis of participant responses to the HCCT scheme and offers valuable insights into its design and feasibility in residential settings. This study is therefore framed as an exploratory pilot that prioritizes behavioral depth and experimental control over sample size, with the



Keep your power consumption below 2 kW during the following periods:
07 am – 10 am
07 pm – 10 pm

If you stay within the power limit, you receive a 3 EUR bonus.

The carbon emission cap still applies. For every additional kilogram of $CO_{2\text{-eq}}$ emitted, a fee of 0.65 EUR is due.

Energy Management Panels
Visualization of energy usage and CO_2 budget, price signals, incentives

Fig. 1. Layout of the Energy Smart Home Lab and zoom into the graphical user interface.

Table 2
Household characteristics.

Household	Age	Occupation	Relationship	Smart technology experience
HH1	25–35	Student, employee	Acquaintances	No information
HH2	25–35	Student, student	Friends	No, yes
HH3	25–35	Employee, employee	Couple	Yes

aim of testing the feasibility and conceptual design of the HCCT scheme under real-world conditions. This approach aligns with previous small-N living lab studies in energy research, which have likewise employed highly instrumented environments to investigate early-stage behavioral responses to innovative electricity tariffs and energy policies [63–65]. More information about participant recruitment and selection, as well as their socio-demographic characteristics can be found in Appendix B and Appendix C.

3.2. Intervention setup

The study was divided into interventions with three households, each designed to evaluate the impacts of HCCT within a household setting from March 2023 to June 2024. Participants were provided accommodation free of charge and were not university employees. All signed data privacy agreements to ensure confidentiality.

The interventions involved carbon emission caps, grid congestion scenarios, weekly semi-structured interviews, and a final survey to assess participants' responses to the HCCT scheme, as outlined in Table 3. The interviews were conducted to gather qualitative feedback on participants' experiences, challenges, and behavioral adaptations to the HCCT scheme [66]. A survey at the end of the intervention was conducted to capture final feedback from the participants. More information on the interview and survey methods can be found in Appendix D. See Appendix H–Appendix K for the interview and survey protocols.

Carbon caps targeted household heating and electricity demand, excluding personal travel. Further information why we chose household allocation instead of per capita allocation is detailed in Appendix F. When the cap was exceeded, the system prompted the purchase of additional allowances, with a dashboard providing weekly budget updates and real-time feedback on carbon emissions. Fig. 2 presents how the weekly cap and the real-time feedback on emitted $CO_{2\text{-eq}}$ by electricity and heat consumption was visualized on the dashboard.

Up to two grid congestion scenarios per week were communicated through the dashboard, with updates loaded at midnight for planning the next day. The study aimed to understand participant behavior under these combined carbon pricing and grid management scenarios. Appendix E details how we measured and cleaned the energy consumption data for further analysis.

3.3. Household carbon caps and tariffs schemes

The study explored HCCT schemes through a reference week to measure participants' standard energy use, followed by testing monetary penalties for exceeding caps. The overall emissions $\mathrm{EM}_{\mathrm{CO}_2}$ in $\mathrm{kg}_{\mathrm{CO2\text{-}eq}}$ were computed based on the thermal and electricity consumption E_{th} and E_{el} multiplied with their respective emission factors, as Eq. (1) shows.

$$\mathrm{EM}_{\mathrm{CO}_2} = E_{\mathrm{el}} * \mathrm{EMF}_{\mathrm{el,DE}} + E_{\mathrm{th}} * \mathrm{EMF}_{\mathrm{th,DE}} \quad (1)$$

$\mathrm{EM}_{\mathrm{CO}_2}$ Total emissions in $\mathrm{kg}_{\mathrm{CO2\text{-}eq}}$

E_{el} Electricity consumption in $\mathrm{kWh}_{\mathrm{el}}$

E_{th} Thermal energy consumption $\mathrm{kWh}_{\mathrm{th}}$

$\mathrm{EMF}_{\mathrm{el,DE}}$ Emission factor for electricity consumption in $\mathrm{kg}_{\mathrm{CO2\text{-}eq}}/\mathrm{kWh}_{\mathrm{el}}$

$\mathrm{EMF}_{\mathrm{th,DE}}$ Emission factor for thermal energy consumption $\mathrm{kg}_{\mathrm{CO2\text{-}eq}}/\mathrm{kWh}_{\mathrm{th}}$

The electricity consumption was obtained by accounting for the household's overall electricity consumption, which was tracked by an electricity meter. The electricity consumption E_{el} was then multiplied with an emission factor $\mathrm{EMF}_{\mathrm{el,DE}}$ (0.485 $\mathrm{kg}_{\mathrm{CO2\text{-}eq}}$ per $\mathrm{kWh}_{\mathrm{el}}$ - average emission factor of the German electricity mix in 2021 [67]) to get the caused carbon emission equivalents. For the thermal energy demand, we must distinguish between heating and cooling. For the heating demand, we measured the thermal energy E_{th} produced by the heat source with a heat meter and calculated the emissions with an emission factor $\mathrm{EMF}_{\mathrm{th,DE}}$ that represents the German heating average with 0.25 $\mathrm{kg}_{\mathrm{CO2\text{-}eq}}$ per $\mathrm{kWh}_{\mathrm{th}}$ which is still dominated by gas and oil heating systems [68]. In week 4 to 5 of HH1, a correction factor of 0.6 was added because we registered tremendous heat losses from the warm water storage which resulted in a high heating demand that the participants had no influence on. The emissions for the cooling demand were calculated by considering the electricity consumption of the air conditioning and the same emissions factor as for the electricity demand.

Based on findings by Niemeier et al. [49], that receiving money does not change behavior as much as penalties, we did not provide monetary rewards to under-emitters but instead tested two monetary penalties. After a reference week, participants received a carbon budget with no monetary incentives, allowing them to adjust to monitoring their emissions, testing whether the budget itself encouraged them to act, while still providing a buffer for a positive initial experience. All tenants received a 30 EUR credit at the beginning of the incentive intervention, so that the tariffs would not be subtracted from private finances. Depending on their interaction with the cap and the grid congestion scenarios, they could earn compensation or would have to pay a respective fee, thus adding or subtracting from their bonus. In the following weeks, we tested two monetary incentives. The first one included a fee (0.65 $\mathrm{EUR}/\mathrm{kg}_{\mathrm{CO2\text{-}eq}}$) for emissions exceeding the weekly cap. The second, a bulk tariff, automatically purchased an additional five kilograms of carbon allowances for 3.25 EUR if the cap was exceeded. The tariffs were determined by multiplying the EU-ETS average price by a factor of ten to ensure a tangible behavioral incentive, following recommendations in the literature [69]. No separate pilot testing or participant feedback was used to set the tariffs. Values were chosen to align with similar personal carbon trading schemes and social cost of carbon estimates reported in prior studies [38,70]. More information on how we deducted the carbon price is detailed in Appendix G.

Fig. 3 displays the weekly carbon budgets and incentives for all households. Each household started with one reference week without incentives to acclimate participants to the environment. HH2 included two reference weeks due to initially high energy consumption, which did not repeat in the second week, leading to a slightly higher but stable

Table 3
Process of the interventions, showing the scheduling of caps, congestion scenarios, interviews and the survey.

Household	Intervention method	Week								
		1	2	3	4	5	6	7	8	9
1	Cap in $\mathrm{kg}_{\mathrm{CO2\text{-}eq}}$	Ref.	60	40	40	25	20	15	No cap	10
	# Congestion scenarios			1	1			1	1	
2	Cap in $\mathrm{kg}_{\mathrm{CO2\text{-}eq}}$	Ref.		55	50	40	No cap	30	30	
	# Congestion scenarios							2	2	
3	Cap in $\mathrm{kg}_{\mathrm{CO2\text{-}eq}}$	Ref.	55	30	40	30	15	15		
	# Congestion scenarios				2	2	2	2		
	Interviews	Short interviews once a week							In-depth interview	
	Survey								After the experiment	

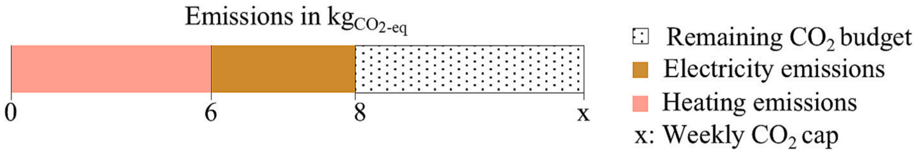


Fig. 2. Visualization of the weekly cap, as well as real-time feedback of the cumulative electricity and heating emissions over the course of the week.

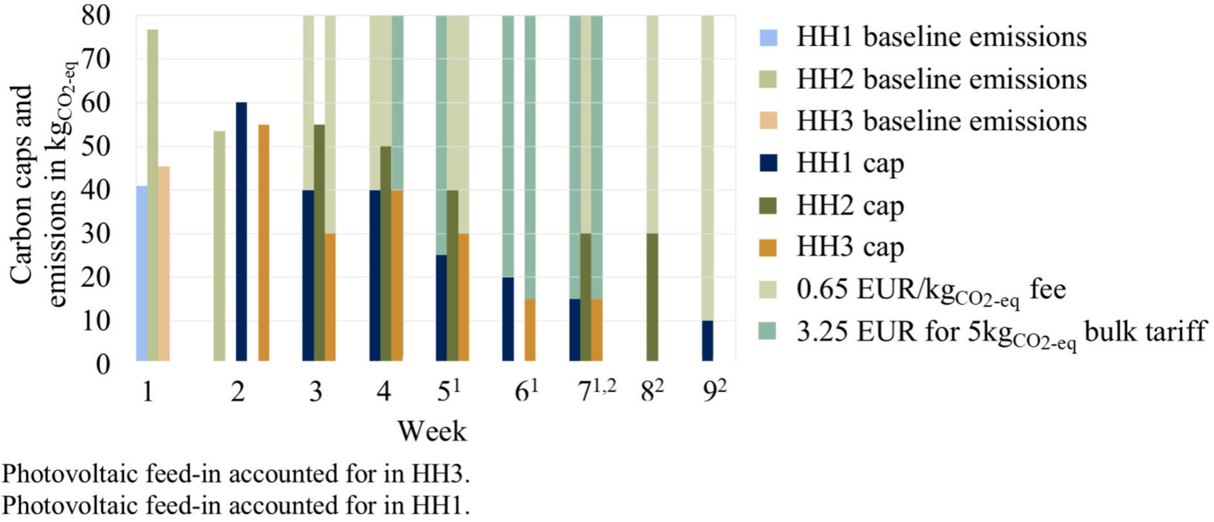


Fig. 3. Carbon caps and cap exceedance tariffs.

consumption level that set the baseline for subsequent carbon budget allocations. Therefore, the carbon budgets for HH2 were consistently higher than in other households.

In our study, the weekly cap generally decreased, starting from an initial high to encourage early success. Since the 60 $kg_{CO2\text{-}eq}$ cap had been set very generously in HH1, this cap was followed in the following week by a significant reduction of about 33 % to 40 $kg_{CO2\text{-}eq}$. To contextualize the carbon cap levels used in this study, it is important to note that the average German household emits approximately 2.9 $tons_{CO_2\text{-}eq}$ per year for electricity and heating (as of 2023) [71]. The reference-week emissions measured in our study households and scaled to one year were lower than the average: 2.1 $tons_{CO_2\text{-}eq}$ for HH1, 2.8 $tons_{CO_2\text{-}eq}$ for HH2, and 2.4 $tons_{CO_2\text{-}eq}$ for HH3, based on actual measured consumption at the household level. These values served as the basis for determining carbon budgets. In the case of HH1, for example, the weekly emissions in the reference week were around 40 $kg_{CO_2\text{-}eq}$, yet the initial cap was set to 60 $kg_{CO_2\text{-}eq,}$ a deliberately generous buffer intended to ease participants into the system and ensure a positive early experience. The subsequent 33 % reduction to 40 $kg_{CO_2\text{-}eq}$ in week 2 appears large numerically, but functionally, it simply brought the cap back in line with participants' actual baseline consumption. This adjustment was therefore not intended as a challenge, but rather a return to a realistic starting point for testing price responsiveness and feedback effects.

A linear decrease in the cap wasn't a priority in our experiment because we tested multiple factors, including PV feed-in that enabled load shifting. In this case the electricity consumption was obtained by subtracting the PV feed-in from the demand for each time-interval of the measurement and this needed to be accounted for by adjusting the cap. For example, in HH3, the introduction of air conditioning required raising the cap by 10 $kg_{CO2\text{-}eq}$ to accommodate the additional usage.

3.4. Grid congestion scenarios

Considering that future low-carbon energy systems might integrate carbon pricing with incentives to manage grid congestion, we introduced similar incentives in our study to examine how they interact. Utilizing our experiences from earlier experiments in the Energy Smart Home Lab [35,63], we simulated grid congestion scenarios during the interventions to evaluate participants' willingness to adjust their electricity consumption.

During these scenarios, participants were incentivized to limit their power consumption to no more than 2 kW over a three-hour interval. Scenarios were scheduled during typical peak household consumption periods, such as morning hours (7–10 am) and evening hours (7–10 pm), or, where applicable, during individually identified household peak usage times (e.g., 12–3 pm or 9 pm–12 am). These periods were selected based on consumption patterns observed during the reference weeks and supported by prior findings [34], as they represent times when participants were least flexible due to daily routines like preparing meals or using household appliances [34]. The specific days on which grid congestion events occurred were randomized to prevent predictability and anticipatory behavioral adjustments by participants. Each household encountered up to two congestion scenarios per week, balancing the need for a sufficient number of intervention data points with the goal of minimizing participant burden. A detailed description of the congestion setup and the derivation of the monetary incentive (3 EUR per day for compliance or non-compliance) can be found in [35].

4. Results

The participants' final bonuses varied significantly across the three households: those in HH1 achieved an increase in bonus to 33.80 EUR, the ones in HH3 14.00 EUR, and the participants in HH2 finished with 8.80 EUR. These variations reflect the differing levels of engagement and success in adhering to carbon budgets and grid congestion scenarios across the households, which will be detailed in the following sections.

4.1. Interaction with carbon budgets

Each household was assigned a progressively decreasing carbon budget, requiring them to actively manage their electricity and heating consumption to stay within the limits. The results reveal distinct household-specific responses to the carbon caps, ranging from highly engaged strategies that prioritized strict adherence to budgetary limits to more flexible approaches where external circumstances, convenience, and comfort played a larger role. HH1 exceeded three out of seven carbon budgets, HH2 exceeded two out of five carbon budgets, and HH3 exceeded two out of six carbon budgets, as Fig. 4 presents.

As shown in Fig. 4, HH1 successfully stayed below the cap when the bulk tariff applied, HH2 maintained relatively stable performance with minor deviations, and HH3 exhibited a more fluctuating consumption pattern with both close compliance and two overages towards the end of the intervention. Since each household consisted of two participants, we also calculated per capita emissions to enable a more meaningful comparison to literature. Dividing the total household emissions by two, HH1 achieved a final per capita carbon footprint of approximately 0.29 tons$_{CO_2\text{-eq}}$, HH2 of 1.13 tons$_{CO_2\text{-eq}}$, and HH3 of 0.64 tons$_{CO_2\text{-eq}}$, extrapolated to an annual basis. These per capita results are discussed in more detail in Section 5.1. in comparison to national averages and previous studies.

Behavioral adaptation was observed in all three households, but to varying degrees: HH1 actively sought to optimize their energy usage within budget constraints, HH2 displayed a strong initial commitment but later faced external challenges that influenced their motivation, while HH3 strategically managed their energy use but encountered constraints in their ability to reduce further. The following sections provide a detailed breakdown of each household's experience, including their strategies, successes, and challenges in adhering to the carbon budgets.

4.1.1. *Household 1: engaging with the challenge*

HH1 exceeded three out of seven carbon budgets, but showed consistent efforts to reduce emissions over the nine-week period, ultimately reaching a reduction of 73 % compared to their baseline emissions. It is notable that they reached all carbon budgets paired with the bulk tariff in week five to seven. Their behavioral adaptations included small but impactful choices, such as replacing oven use with the microwave:

> *"[The bulk tariff] definitely influenced me. I opted for the microwave over the oven for cheese toast to save energy, which wasn't great for the taste. [Laughs.]"*
>
> (participant A, translated from German)

Participant B agreed to this, following with:

> "*I liked the gradual approach best because it felt like the penalty was minor if you didn't meet the target. Buying the extra 5 kg$_{CO2\text{-eq}}$ seemed pointless because if we exceeded, it was always by a minimal amount that wouldn't benefit us.*"
>
> (participant B, translated from German)

HH1's response to the bulk tariff was shaped less by convenience and more by a desire to avoid perceived overpayment. Participants often anticipated that they would exceed their weekly cap by only a small margin (e.g., 1–2 kg$_{CO_2\text{-eq}}$), making the flat purchase of an additional 5 kg feel excessive and inefficient. This mismatch between need and cost heightened their motivation to stay within the cap. From a behavioral perspective, this may reflect a form of loss aversion: participants were reluctant to incur a fixed penalty that felt disproportionate to their actual emissions overage, particularly when avoiding it seemed achievable.

In week 7, the participants took extreme measures on the last day, including not cooking, using candlelight, not showering, not using the kettle, and charging devices outside the home, to avoid exceeding the budget:

> "We could see that we would make it barely, therefore we were motivated to not exceed the budget."
>
> (participant A, translated from German)

Without a carbon cap in week 8, more relaxed behaviors among participants were notable, showing a slight rebound effect with a 15 % increase in emissions compared to the previous week. However, total emissions remained at 42 % of the baseline, indicating that many low-carbon habits persisted. The rebound appeared to stem from small comfort-driven behaviors, such as making coffee at home which participant A reported, rather than deferred 'pent-up' demand.

Participant B maintained certain routines, like checking the weather to optimize the use of appliances in sync with solar energy availability. This aligns with literature indicating that rebound may be muted when participants retain internalized behavior patterns and may be driven more by comfort or habit than by overt moral licensing [72,73].

The participants viewed the carbon budget more as a personal challenge than a commitment to broader environmental or social goals. Overall, participants A and B found it challenging to balance comfort with strict energy restrictions. Participant B particularly felt a psychological strain, aware of their above-average energy efficiency yet experiencing it as a form of self-denial:

> "And at the same time with my awareness that we are quite good [in comparison to the] average in Germany anyway. I would then have the feeling that it was a bit of self-mortification."
>
> (participant B, translated from German)

4.1.2. *Household 2: The impact of external motivations*

HH2 exceeded two out of five carbon budgets and reduced their

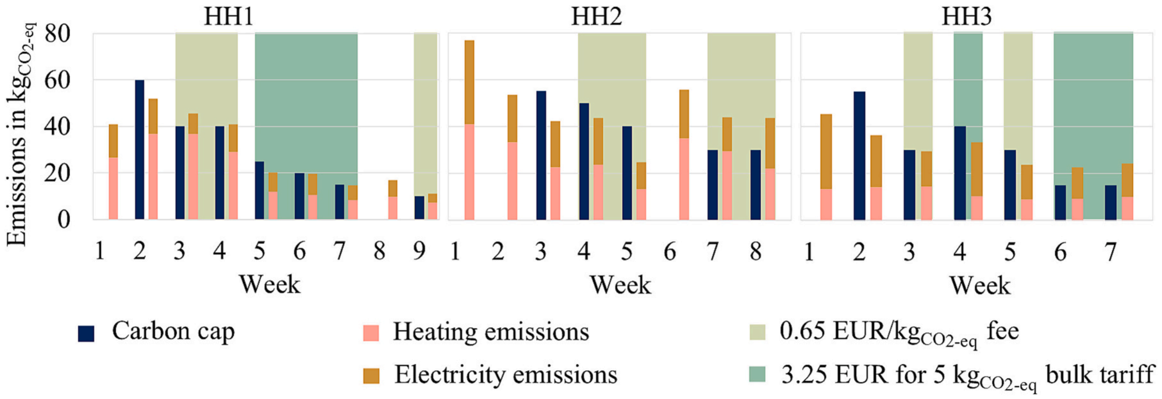


Fig. 4. Carbon budgets over time and the participants electricity and heat consumption for HH1, HH2, and HH3 (no caps in week 1 and 8 for HH1, week 1,2, and 6 for HH2, and week 1 for HH3).

overall emissions by 33 %. They displayed a high level of initial motivation, stating in the first week with a carbon emission cap that they extremely cut back in their energy consumption to try to keep within the given budget.

Fig. 4 shows that indeed, their overall emissions dropped well below the budget that was set similar to the emissions of the previous reference week.

> "[…] the dryer uses a lot, we won't use it, we won't use the washing machine for now and we'll see. So yes, we used very little at the beginning."
>
> (participant D, translated from German)

Participant C reduced the heating temperature early in the study to conserve energy and monitored their consumption closely to maintain a buffer for later weeks. They also optimized energy use by showering at sports facilities, reducing the oven pre-heating time, and charging devices on campus or at friends' homes. Even though there was no financial incentive in this first week, the participants agreed that they wanted to achieve the challenge and see if they were able to keep below the 55 $kg_{CO2\text{-}eq}$ cap. They mentioned knowing one participant from HH1, which motivated them to perform better, so some normative incentive did exist here.

By week four, the familiar cap levels allowed them to comfortably manage their consumption, strategically using high-energy appliances like the tumble dryer later in the week to ensure budget compliance. Similar strategies continued into week five, with extensive use of campus facilities and minimal home heating, though comfort was compromised, prompting a temperature increase and rebound effect in week six. In contrast to HH1, HH2 showed a more pronounced rebound effect, with emissions increasing by 125 % compared to the previous week, reaching 85 % of their baseline emissions. Interview responses indicate that this rebound was driven by pent-up demand as participants expressed relief at finally being able to cook more energy-intensive meals and restore room temperatures that had previously been lowered for savings. Participant D stated:

> *"I was looking forward to finally cooking some meals I had been putting off."*
>
> (participant D, translated from German)

And participant C added:

> *"I turned the heat back up. It had been colder in my room last week, and that was fine until I actually had to spend time in the room."*
>
> (participant C, translated from German)

Unlike HH1, HH2 lacked access to PV generation, which made behavioral alternatives like load shifting less available, amplifying the intensity of their rebound once constraints were lifted.

In week seven, a dislodged thermostat led to unintentionally high heating significantly breaching the budget. This incident caused frustration and highlighted the seeming futility of their efforts when such accidents could undermine their careful planning:

> *"To be honest, I have to say that I lost a bit of motivation because it was already so high, and it was very unrealistic [for us to still keep within the budget]."*
>
> (participant C, translated from German)

In the final week, heightened electricity consumption from activities like laundry and cooking surplus food resulted in a budget breach. Participant D reflected on their changing willingness to conserve energy, stating:

> *"When we moved in, I was much more willing to do things, like taking cold showers […], but by the end I'm no longer willing to do them because of the stress of exams."*
>
> (participant D, translated from German)

The participants found the visualization of their emissions intriguing, though they struggled to interpret the abstract numerical data.

4.1.3. *Household 3: managing constraints*

HH3 exceeded two of their six carbon caps, managed to reduce their overall emissions by 48 %, and demonstrated their practical limitations of energy-saving measures. The initial week was straightforward, with participants quickly devising strategies to remain within budget limits:

> *"But yeah, I think on the first day I kind of checked how much we used for that day, and it was quite clear that it's going to be not that hard to reach the goal."*
>
> (participant E)

The third week presented more challenges, but adjustments in daily routines such as reduced showering and cooking allowed them to meet the 30 $kg_{CO2\text{-}eq}$ cap. Like earlier interventions, participants occasionally used external facilities for activities like showering and dining to minimize their household energy use. From week 4 onwards the air conditioning was running, which resulted in less energy consumption for heating and more electricity consumption for the air conditioning, necessitating a10 $kg_{CO2\text{-}eq}$ budget increase. Participants actively engaged in load shifting, timing appliance use to coincide with peak solar output. Despite careful timing, unexpected reductions in solar availability led to frustrations, as exemplified by a failed attempt to sync coffee making with solar generation:

> *"One moment I wanted to have a coffee and then pressed [the coffee machine button] while the sun was shining and then the sun was gone. [I] got really mad."*
>
> (participant E)

Despite sustained load-shifting efforts in weeks six and seven, HH3 could not further reduce their energy consumption, indicating they had reached the practical limits of their energy-saving behaviors within the experiment's constraints.

The participants expressed mixed feelings about the tariff structures, with some finding the financial incentives less motivating than the challenge of staying within the budget:

> *"The motivation was always to stay as low as possible."*
>
> (participant E)

They also expressed the psychological strain of adhering to strict carbon caps, particularly in the latter stages of the experiment, underscoring the challenges of relying solely on behavioral changes to achieve environmental targets. The inclusion of PV incentives was highlighted as a positive motivator for reducing emissions. However, in a real-world application a HCCT scheme could be motivating for both participants.

4.1.4. *Weeks with photovoltaic generation*

In HH1 and HH3, PV energy generation was integrated into the energy management plan, enhancing the participants' ability to manage their energy use by aligning consumption with peak solar output. However, technical issues prevented HH2 from using PV feed-in. Participants generally responded positively to the inclusion of solar power, finding it enabled more active and less restrictive energy management. Participant B, with a flexible schedule, particularly benefited, describing the shift to solar as a transition from mere limitation to proactive adjustment:

> *"Up until the solar challenge, it was a case of restricting everything and with the solar challenge it was just an adjustment. I liked this adaptation effect"*
>
> (participant B, translated from German)

This approach allowed participants to optimize their energy use more freely, reducing stress associated with strict budget adherence.

Participant E added that shifting their consumption towards the PV generation hours gave them more opportunity to play an active part in reducing their emissions. Participant A highlighted the practical challenges of aligning their less flexible schedule with peak solar times, noting difficulties in synchronizing daily activities with solar output, which peaks from noon to 3 pm. This misalignment was evident despite the theoretical advantages of living aligned with solar energy production, requiring substantial adjustments to daily routines:

> "I was actually looking forward to living with the sun. But that didn't work out at all, because it's mainly active between 12 and 3 pm. On a Saturday, I was able to take advantage of it. And I was really pleased that there was already sun on the roof, and I was able to use it. If I only ever wanted to use renewable energies [residential photovoltaic], then I would have to change my whole daily schedule."
>
> (participant A, translated from German)

Load profiles demonstrated significant shifts in energy use during peak solar periods, substantiating the effectiveness of the PV incentive in aligning electricity demand with solar availability, as Fig. 5 presents. Fig. 5 compares electricity demand (blue) and PV generation (gold) over two selected weeks for HH1 and HH3, before and during PV integration. The visible increase in demand alignment with PV generation in the second week for both households illustrates how participants actively timed their energy use to coincide with solar availability. For example, mid-day peaks in PV output during days 3 to 6 in HH1 (week 7) coincide with increased appliance usage, suggesting conscious load-shifting behavior. Specifically, in HH1, the share of electricity demand met by concurrent PV generation increased by 13 %, while in HH3, this share rose by 11 %, confirming that participants were responsive to real-time generation signals.

In contrast, HH2 relied solely on demand reduction to meet their carbon budgets. This contrast suggests that the visibility of electricity generation and self-consumption from PV may have served as a form of positive reinforcement, allowing HH1 and HH3 to shift from purely avoiding emissions to actively aligning behavior with renewable energy availability. This aligns with the notion that feedback mechanisms that allow for load shifting instead of shedding, especially when tied to personal agency, can complement economic signals and reduce perceived burden [63].

4.1.5. Heating demand

Heating demand significantly influenced participants' emissions, necessitating a balance between reducing heating and maintaining comfort.

To interpret heating-related energy use, we analyzed participants' heating setpoints in relation to outdoor temperatures and heating power. Throughout the study, participants adjusted their temperature setpoints in response to the carbon budgets, as Fig. 6 presents. Fig. 6 visualizes how ambient temperature patterns interact with behavioral adjustments, supporting the interpretation of shifts in setpoints and heating power. Due to missing ambient temperature data from the sensor for HH3, we used measurements from the German Meteorological

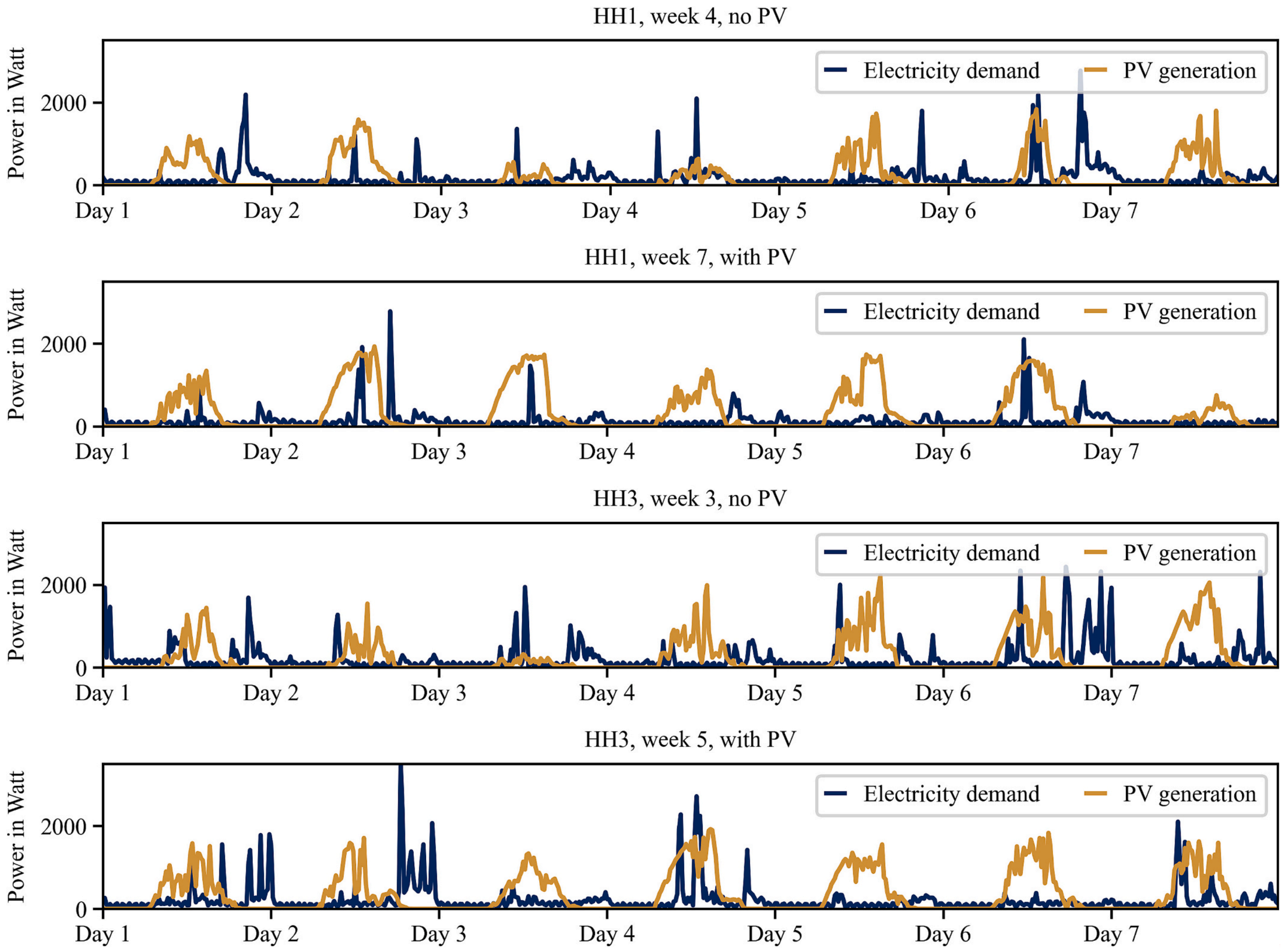


Fig. 5. Exemplary load profiles in household 1 (HH1) and household 3 (HH3) in weeks with and without photovoltaic (PV) generation.

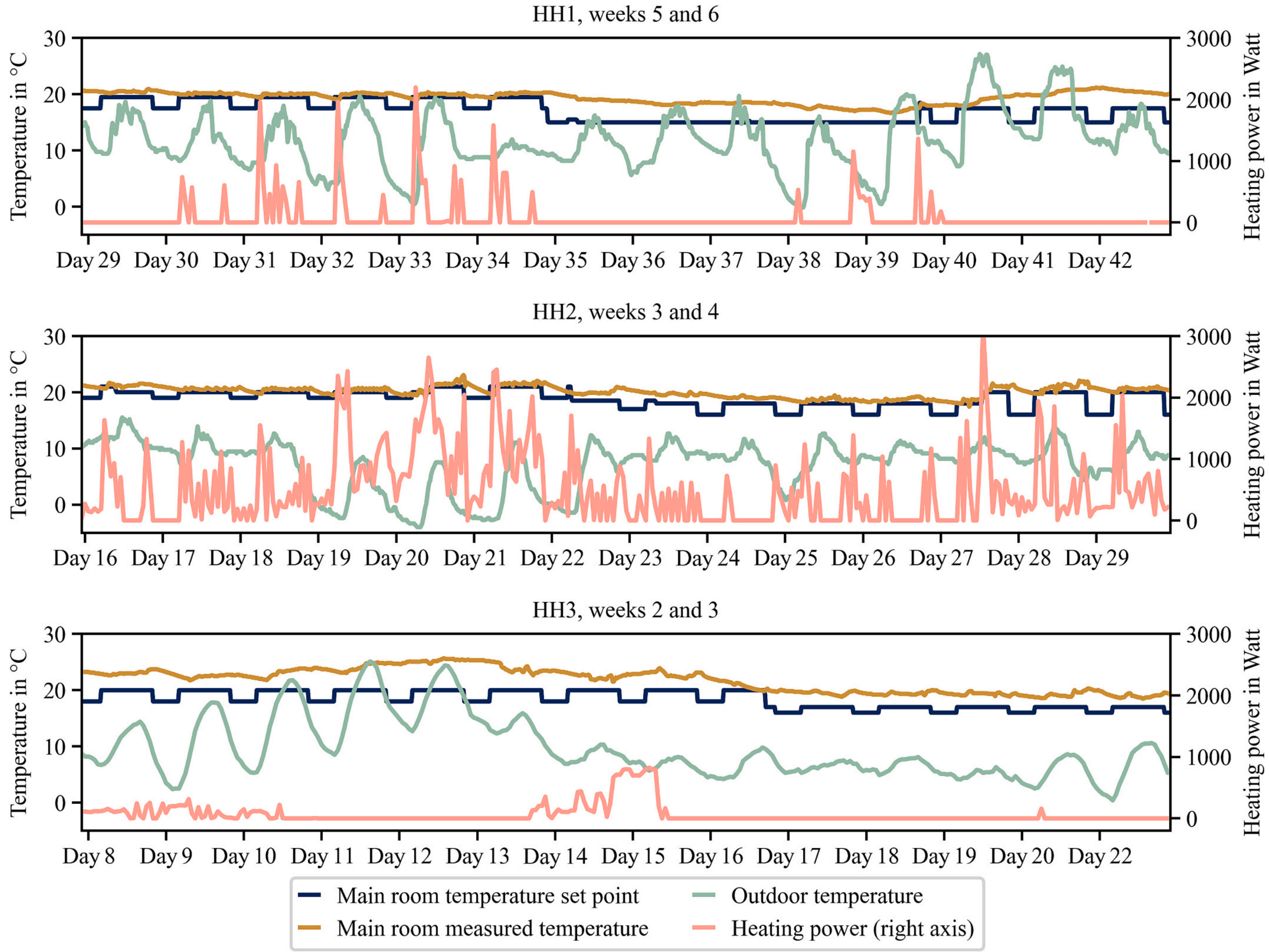


Fig. 6. Indoor temperature setpoints for the main room, measured main room temperature, outdoor temperatures, and heating power for HH1, HH2, and HH3 during selected intervention weeks.

Service for that period [74]. HH1 generally lowered their daytime temperatures but increased them in week three despite warmer weather. In contrast, HH3 set their temperatures on the first day and maintained them for two weeks.

Despite a low carbon budget in week five of HH1, participants initially reduced but later increased their heating to regain comfort, reflecting a tension between emission reduction and comfort. HH2 showed fluctuating temperature settings, as presented in Fig. 6. At the beginning of the fourth week, the participants reduced the setpoint, however increased it again after three days, indicating a loss in comfort that needed to be remedied, despite increasing ambient temperatures. Participant C elaborated:

> *"We turned up the heat again, didn't we? Last week (week 4), as I mentioned, we really turned down the temperature to save on our* $CO_{2\text{-}eq}$ *budget, and this time (week 5) we set it back to normal."*
>
> (Participant C)

Since the participants stayed well below the given cap in week four, the decrease in setpoint might have been due to comfort reasons and then kept low to comply with the budget as motivated by participant C above. In addition, the container heats up depending on the position of the sun relative to the season. Hence, during spring months the container might heat up more than during the winter months, despite the same measured ambient temperature. This seasonal effect was apparent in HH2 and HH3, influencing the required heating energy despite similar setpoints, as illustrated in Fig. 6. In HH3, one can see that the participants reduced the temperature setpoint of the main room in the third week, indicating that the carbon budget motivated them to reduce their heating consumption. However, it can also be seen that the main room temperature never fell below the set temperature, despite a very low heating power consumption. Participant E also confirmed:

> *"We haven't used any heating yet; it's never dropped below 22 (°C) here."*
>
> (Participant E)

Participants gained insights into heating management, realizing excessive heating in their absence led to unnecessary energy use:

> "[…] in the first few weeks, we really heated too much without anyone being there. […] So, heating means simply blatant consumption."
>
> (participant B, translated from German)

Participant A reflected on the balance between comfort and conservation, sharing a personal experience of overly restrictive heating:

> "It also showed me that I don't just have to turn off all the heating per se. After all, when the war in Ukraine broke out, my [partner] decided we wouldn't heat the house anymore. It was very cold then [Laughs] and I had a lot of colds then. […] you don't have to restrict yourself completely."
>
> (participant A, translated from German)

Both participants suggested that user-friendly automation in heating systems could optimize energy savings without significant personal inconvenience.

4.2. Flexibility provision during grid congestion

The ability of participants to adjust their energy use in response to grid congestion scenarios varied significantly across the three households of the study. HH1 demonstrated the highest adaptability, achieving most of the available incentives, followed by HH3, while HH2 showing limited success due to external pressures such as illness and exam stress.

All households generally recognized and responded to the congestion challenges, seeming to monitor the congestion hours closely, as the power peaks directly before and after the congestion period in Fig. 7 suggest. Each subplot in Fig. 7 represents one selected congestion day per household, highlighting both the daily power profile and the set power limit (2000 W). This often led to minor but manageable behavioral adjustments, such as delaying coffee or pizza preparation:

> “I found that interesting because it was a restriction, but it was usually manageable for me. I found that exciting and good. And I wouldn't find that dramatic in my own home either.”
>
> (Participant B, translated from German)

In each household, the effectiveness of the congestion management was critically dependent on the participants' daily schedules, their engagement with the energy management system, and the practicality of the incentives provided. To a certain degree, participants were willing to adjust their schedules or integrate their friends into the congestion constraints, however the monetary compensation was not enough to incentivize load shifting or shedding in all cases.

In week 5, participant B stated about the monetary incentive:

> “The money isn't much now. But when I think about how much a coffee costs and if I'd gone over the limit just for the coffee, then I could have had a coffee in a café for the money.”
>
> (participant B, translated from German)

For a detailed breakdown of the days and specific load shifting successes and failures, along with comprehensive participant feedback, please refer to the supplementary materials.

4.3. Value scale assessment

Values are defined by Schwartz as “desirable transsituational goals varying in importance, which serve as a guiding principle in the life of a person or other social entity” [75]. Steg et al. [76] have developed a framework that categorizes values into self-enhancement (hedonistic, egoistic) and self-transcendence (altruistic, biospheric), which aids in understanding environmentally relevant behaviors. The value scale framework suggests interventions should consider the hedonic impacts on behavior since these might oppose behavior change [76]. Results indicate varying motivational profiles. Although biospheric values were not regarded as extremely important by all participants, three participants put emphasis on it. Hedonic values reached the highest importance across participants, followed by altruistic values. Egoistic values were the least important, although one participant rated it as the most important value for them. Further details on the value scale results are presented in the supplementary materials.

5. Discussion

In the Energy Smart Home Lab, three households navigated weekly $\text{CO}_{2\text{-eq}}$ caps and grid congestion scenarios across three multi-week interventions. These setups offered insights into how non-economic and economic incentives influence energy consumption behaviors. While participants began the study with below-average household carbon footprints, all households further reduced their emissions during the intervention, albeit to varying degrees.

5.1. Interpreting energy consumption behavior through economic, psychological, and social mechanisms

In line with Parag et al. (2011), who identify three key mechanisms, economic, cognitive, and social, through which PCT schemes influence behavior, we structure this discussion around these mechanisms [13]. Before exploring these mechanisms, we briefly summarize the overall emissions outcomes across the three participating households to contextualize the observed behavioral changes.

The average per capita carbon footprint for Germany was 7.72 tons$_{\text{CO2-eq}}$ in 2020 [77], and 8.72 tons$_{\text{CO2-eq}}$ in 2021 [78]. If only accounting for heating, hot water, and electricity, the average emissions lie around

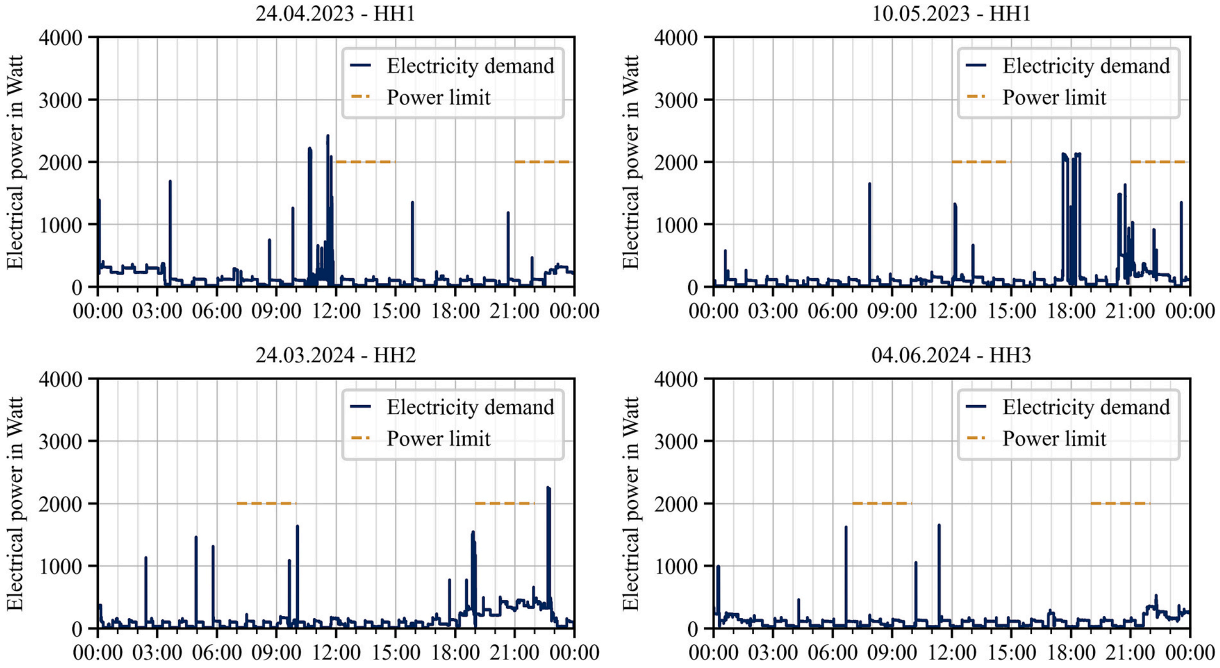


Fig. 7. Exemplary days with successfully shifted loads during grid congestion scenarios.

2.9 $tons_{CO2\text{-}eq}$ in 2023 [71]. Extrapolating the baseline carbon emissions to an annual basis, the participating households lay with 1.07, 1.39, and 1.18 $tons_{CO2\text{-}eq}$ per capita for HH1, HH2, and HH3, respectively, already at the beginning well below average. During the experiment the participants' performance in emission reduction varied. Comparing the first and the last week of the respective intervention, HH1 was able to reduce their carbon footprint by 73 % to 0.57 $tons_{CO2\text{-}eq}$, HH2 by about 19 % to 2.23 $tons_{CO2\text{-}eq}$, and HH3 by 46 % to 1.27 $tons_{CO2\text{-}eq}$. In HH2 the PV feed-in could not be factored in due to technical issues with the PV system. Hence, here the potential for reducing the footprint was limited. Despite that, all lay far below the German average by the end of the experiment.

These reductions compare favorably with findings from other PCT pilots. The NICHE study reported an 18 % reduction in household carbon emissions [37]. The members in CRAGs reduced their average per capita carbon footprint by 32 % in their first year, from 4.95 $tons_{CO2\text{-}eq}$ down to 3.36 $tons_{CO2\text{-}eq}$, the latter being 35 % below the UK average (5.2 $tons_{CO2\text{-}eq}$) for direct carbon emissions, not counting public transport emissions, but accounting for emissions from air travel [48]. Our findings fall within or above this range, despite the small sample size and contextual differences. Differences in carbon accounting methods, like the inclusion of public transport and air travel in the CRAGs study, complicate direct comparisons.

The following sections explore the ways in which economic, psychological, and social mechanisms contributed to these outcomes.

5.1.1. Economic mechanisms

The economic mechanism operates through financial incentives or penalties designed to steer behavior. In our study, carbon budgets were coupled with two tariffs for excess emissions as well as an economic tariff or bonus for the grid congestion scenarios.

Drawing on prior examples of PCA schemes, such as the CRAGs, financial penalties in these community-based initiatives ranged from 2 £ to 10 £ per excess kilogram of carbon emissions, translating to around 2.40 EUR to 11.88 EUR[2] per kilogram at current conversion rates [79]. Many CRAGs capped the maximum amount of what a member had to pay (typically at 100 £), which would translate to a weekly cap of 2.27 EUR in our experiment [79]. The cap from Howell would have been overtaken one time in HH1 (3.90 EUR), two times in HH2 (9.10 EUR for each week), and two times in HH3 (6.50 EUR for each week). By comparison, our tariffs, set at 0.65 EUR per excess kg CO_2-eq, where deliberately moderate, reflecting the goal of simulating a realistic, socially acceptable carbon price signal in early-stage piloting. Despite the presence of these financial incentives, their influence on participant behavior was limited. Interviews revealed that most participants were not strongly motivated by economic considerations. As such, participants attempted to reduce emissions consistently, whether or not they faced actual penalties. These findings echo Howell's conclusion that financial penalties often had minimal behavioral impact.

In the case of grid congestion scenarios, which offered a modest 3 EUR incentive for compliance, participants generally responded positively, but again, feedback and awareness played a more prominent role than the monetary reward itself. Overall, the economic mechanism appeared to function primarily as a reinforcing or symbolic structure rather than a dominant driver of behavior in this sample.

5.1.2. Psychological mechanisms

Psychological mechanisms refer to the intrinsic motivation driven through the allocation of allowances, the visibility of, and awareness to the carbon emissions related to one's individual actions [39]. In this study, these processes were primarily enabled through real-time feedback, transparent carbon budgeting, and weekly reflections during interviews. Participants were consistently exposed to data on their energy use, and received visual cues on whether their current behavior would remain within the assigned carbon cap.

Participants reported developing a deeper understanding of how their daily routines affected carbon emissions and, consequently, the feasibility of remaining within budget. This resulted in considerable behavioral changes, such as avoiding the use of energy intensive applications, or shifting those activities into peak solar hours. This enhanced understanding and the behavioral changes indicate that carbon literacy can be significantly improved through targeted interventions like this experiment. The increased carbon literacy and behavioral changes were also found in other pilots, such as the CRAGs in the UK. Howell [48] found that carbon literacy was one of the most obvious outcome of CRAG participation. In our study, this learning occurred not only through active experimentation but also via reflection during interviews, where participants described becoming more attuned to invisible energy flows and trade-offs, and actively inquired about, e.g. their energy consumption, the visualization and real-time feedback on the dashboard.

Despite these overall gains in carbon literacy and a considerable reduction of 45 % to 75 % in emissions from initial levels for all households, a further reduction of emissions proved challenging for the participants. Especially, as they contended with unmodifiable emissions from essential appliances such as the fridge or the freezer, or heating and cooling. This highlights the need for realistic carbon cap settings that consider unavoidable energy uses. It needs to be noted that, in this experiment, extremely low levels of carbon budgets were tested, to see if the participants would reach the lowest consumption possible (and practical) with their daily life.

Overall, our findings underline the essential role of psychological mechanisms in HCCT design. Learning, raising awareness, visibility, and the opportunity to experiment with the energy consumption behavior allowed participants to develop more effective strategies for managing their energy use, such as timing appliance use, prioritizing essential consumption, and adjusting comfort expectations rather than simply reacting to the carbon cap as a fixed constraint.

5.1.3. Social mechanisms

Beyond economic and informational cues, participants also referenced moral reasoning, environmental identity, and social norms when explaining their behavior. These social mechanisms often shaped engagement with the carbon budget in ways that were emotionally motivated rather than purely instrumental. Several participants described their motivation as a perceived environmental responsibility. Carbon caps and grid congestion scenarios were perceived as self-imposed challenges aligned with personal values. Participants adopted several strategies such as altering cooking habits, high-energy appliance use, turning the lights off when leaving a room, and scheduling energy usage during peak solar production hours to align with load-shifting incentives. Importantly, these adjustments were often maintained even in the absence of strong economic incentives, underscoring the influence of intrinsic motivation and value alignment.

However, social dynamics also introduced tension. In HH2, for example, participants were unable to comply with the power limit during one congestion event due to prioritizing comfort during an exam period. Similarly, social obligations, such as hosting guests, sometimes conflicted with load shifting incentives, leading to intentional non-compliance. This fits to previous observations in a previous intervention, where participants tried to adhere to the incentive and would fail to finish preparing a meal that needed more oven heat than expected [35].

Overall, these findings affirm the importance of social and normative mechanisms in HCCT participation. Moral identity, environmental concern, and lifestyle compatibility played substantial roles in shaping behavioral responses, sometimes reinforcing, and sometimes conflicting with, the HCCT scheme.

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[2] Exchange rate as of 30th August 2024.

5.2. Limitations

This study faced several technical and methodological limitations that affect its generalizability and highlight directions for future research:

Technical challenges included an occasionally unresponsive user interface that at times hindered participants' ability to control heating settings. Household-specific issues, such as initial high consumption in HH2 or malfunctions in PV and thermal sensors, further complicated data collection and analysis.

Selection, participant, and sample bias may have influenced the results. Recruitment through academic and professional networks, along with the voluntary nature of participation, likely attracted individuals with above-average environmental awareness or comfort with digital technologies. The short duration of the interventions and the small, socio-demographically homogenous sample (three households, six participants aged 25–35) limit the generalizability of the findings. Additionally, some participants had prior exposure to sustainability topics due to their educational or professional background. Future studies should include more diverse age groups, income levels, and educational backgrounds, as well as a larger sample size, to assess broader applicability.

Displacement behaviors, such as charging electronic devices or showering elsewhere reduced the accuracy of the measured household emissions and underscore the necessity to apply a holistic carbon budget accounting.

Complexity in carbon allocation: To effectively apply carbon budgets in real-world settings, all these factors must be meticulously accounted for in the carbon allocation method. This requirement likely makes the allocation process complex and time-consuming, posing significant challenges for policy design based on individual or household behavior data.

Contextual limitations: While the study took place in a highly controlled environment, many of the core appliances used, such as the dishwasher and dryer, were standard models from 2010, representative of those still common in German households [80]. This supports some degree of realism in energy use behavior. Therefore, although the appliance baseline may reflect common household standards, the advanced sensor and measurement infrastructure limits full comparability to a typical German household. More research is needed to validate findings across a broader range of household types, technological setups, and longer timeframes.

Study duration: While the study duration did not cover a full annual cycle, some seasonal variation was included. The interventions were conducted through winter-to-spring and spring-to-summer periods, which allowed for observation of differing energy demands, such as heating in the colder months and cooling via the heat pump-based air conditioning in early summer. Nevertheless, longer-term studies are needed to fully capture the influence of broader seasonal patterns, as well as to assess the persistence and adaptation of behavioral changes over time.

Heating comfort: While participants clearly adapted their behavior in response to both carbon caps and thermal comfort, this study did not explicitly distinguish between psychological and physical comfort thresholds. Future research could integrate humidity and air movement measurements, as well as structured comfort perception surveys.

Baseline knowledge could be assessed more systematically. While some participants linked global events (e.g., the war in Ukraine) to personal restraint, the role of systemic awareness, climate policy understanding, or geopolitical salience in shaping engagement warrants deeper exploration in future studies.

5.3. Scalability and policy implications

This study demonstrates the conceptual feasibility of HCCT in a smart home setting but also highlights key barriers to scaling.

The behavioral changes observed in this study were strongly supported by real-time energy feedback, sensor-based monitoring, and smart home control systems, which are not yet widespread. Scaling HCCT would therefore require investment in hardware, user interfaces, and digital literacy support, particularly for older buildings and under-resourced communities. However, the EU-wide rollout of smart meters offers a foundation: while these devices lack appliance-level data, they can still enable real-time feedback on overall consumption. Although this would initially be limited to households' electricity consumption and only account for heating if electric heating (e.g. via a heat pump) was realized, it offers a potential pathway for a soft launch focused on electricity. Furthermore, smartphones are now widely owned across demographic groups, and developing user-centered apps for visualizing energy consumption based on smart meter data is technologically feasible [10]. The primary barriers may lie less in technological development than in establishing appropriate regulatory frameworks and data security standards.

Participants often treated carbon budgets as personal challenges, driven more by intrinsic motivation than financial incentives. Still, some experienced stress balancing comfort with carbon limits, indicating that HCCT systems must be psychologically sustainable. This includes setting realistic caps, offering adaptive options, and communicating clearly to avoid resistance or disengagement.

Displacement behaviors may shift rather than reduce emissions and could disproportionately affect those without access to alternative resources (e.g., public facilities or workspaces). To ensure equity, HCCT schemes must consider social safeguards, differentiated caps, or targeted support for vulnerable groups.

Financial penalties in the study played a limited role in driving behavioral change, calling into question the universal effectiveness of uniformly applied price signals in HCCT schemes. Policymakers should explore more nuanced pricing designs that align with household routines and values. Incentive systems should also prioritize clarity and transparency, particularly in households with limited digital or energy literacy, or where daily stressors reduce the capacity to engage with complex incentive systems.

At the policy level, HCCT could serve as a complementary, downstream mechanism within the EU-ETS2 framework, offering granular behavioral engagement where upstream carbon pricing remains abstract. To avoid overlap and double-counting, HCCT could operate as a soft-coupling approach using virtual caps at the household-level that are informational and tied to emissions budgets without formal market trading. Integration pathways could include municipal pilots nested within national targets. In the longer term, EU-ETS2 could evolve to formally accommodate PCT schemes, particularly if aligned with e.g. utility billing platforms.

In summary, while this study supports the conceptual feasibility of HCCT, practical implementation must address infrastructure costs, behavioral sustainability, fairness, and policy alignment. Concrete next steps could include:

- Piloting HCCT in lower-tech households or social housing to test minimum requirements, possibly through municipal utilities or housing cooperatives,
- Developing cap-setting methods that account for essential consumption, in collaboration with consumer groups and energy regulators to ensure fairness and transparency,
- Exploring integrating HCCT with carbon pricing schemes like EU-ETS2,
- Embedding support for vulnerable households, including differentiated caps or safeguard mechanisms, to avoid disproportionate burdens.

These actions could help transition HCCT from an experimental model to a scalable component of inclusive and effective climate policy.

6. Conclusion

This study demonstrates the feasibility and effects of household carbon caps and tariffs (HCCT) as a behavioral instrument for reducing residential emissions. Through a living lab experiment with three households, all participants significantly reduced their emissions, by 73 %, 33 %, and 48 % compared to their baseline emissions. Hence, all households actively adapted their behaviors to the constraints imposed by the carbon budgets.

The observed behavioral changes were shaped by economic, psychological, and social mechanisms. Economic mechanisms, such as carbon tariffs and economic incentives for grid load shifting were acknowledged by participants but were not the primary driver of behavior. Participants reported that financial penalties played only a secondary role, with their effectiveness varying by tariff design and personal circumstances. This suggests that while price signals may provide structure and reinforce behavioral boundaries, their standalone effect in HCCT schemes may be limited without complementary motivational strategies.

Psychological mechanisms proved more influential. Real-time feedback and visualized carbon caps fostered carbon literacy, enabling participants to experiment with and refine their energy consumption habits. Strategic adaptations, like shifting appliance use or aligning consumption with solar availability, reflected increased awareness and self-regulation. Importantly, the study revealed that the emotional and psychological responses to carbon caps ranging from stress over stringent limits to satisfaction from meeting reduction targets play critical roles in the efficacy of HCCT schemes. These insights suggest that HCCT can effectively drive behavioral changes necessary for emission reductions, although the emotional and psychological burden must be carefully managed to sustain long-term engagement.

Social and normative motivations, such as environmental values or personal commitment to the carbon budget, often outweighed economic considerations. Participants largely viewed carbon caps as self-imposed challenges rather than enforcement tools. At the same time, comfort and social obligations occasionally overrode these motivations, particularly when tied to social obligations or personal well-being.

This study contributes to the personal carbon trading (PCT) literature by demonstrating how a simplified, household-level variant, HCCT, can induce emission reductions in a real-world, digitally enabled environment. By integrating carbon caps, differentiated tariffs, and load shifting incentives, the study highlights how economic, psychological, and social mechanisms interact to shape household energy behavior. Unlike many prior PCT pilots that relied on self-reported data or focused solely on mobility, this experiment shows the feasibility of applying dynamic, digital, and feedback-based carbon budgeting to residential energy use.

Future research could explore more diverse demographic settings to understand the broader applicability and potential barriers to widespread adoption. Long-term studies could provide insights into the sustainability of behavioral changes induced by HCCT and whether initial reductions in emissions are maintained over time. Additionally, integrating a wider range of emission sources and examining the interplay of various types of incentives could offer deeper insights into enhancing HCCT schemes for different residential contexts and individual preferences.

CRediT authorship contribution statement

Leandra Scharnhorst: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Thorben Sandmeier:** Writing – review & editing, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Max Kleinebrahm:** Writing – review & editing. **Wolf Fichtner:** Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1
Literature overview on policy proposals discussing PCT schemes for different regions.

Reference	Year	Region	Category	PCT scheme	Scope	Addressees
Raux and Marlot [14]	2005	France	Policy proposal	CO_2 permits	Transport (domestic car fuel consumption)	Per capita
Fleming [41]	2007	UK	Policy proposal	Trading energy quotas	Household energy, personal travel	Per capita
DEFRA [50]	2008	UK	Pre-feasibility study	PCT system	Household energy, personal travel	Per capita
Darrell [81]	2008	Ireland	Policy proposal	Pollution authorization permits	Presumably all sectors, not further detailed	Per capita
Niemeier et al. [49]	2008	California, US	Policy proposal	Household carbon trading system	Household energy (electricity and gas consumption)	Households
Duscha [22]	2014	Germany	Policy discussion	Comparison of PCT-schemes	Household energy, personal travel	Per capita, per household

(*continued on next page*)

Table A1 (*continued*)

Reference	Year	Region	Category	PCT scheme	Scope	Addressees
Guzman and Clapp [5]	2016	British Columbia, Canada	Policy proposal	Carbon Health and Savings System	Household energy, personal travel (excluding public transport)	Per capita
Woerdman and Bolderdijk [11]	2017	Europe	Policy proposal	Emission trading for households in the EU-ETS	Household energy use and personal surface transport (no air travel)	Per capita

Table A2
PCT pilot's reduction targets, challenges and take-aways for the present study design.

Project	Reduction targets		Challenges	Take-aways for our study	Ref.
	Annual baseline in kg$_{\mathrm{CO2\text{-}eq}}$	Reduction targets from baseline in %			

Carbon Rationing Action Group (CRAG)	4950	10 % from UK average of direct emissions	• Sporadic unforeseen issues
			• Make children walk too long distances
			• Diversity in PCT designs
			  • Debates on PCT scopes and conversion factors
			  • Undecided in accounting children
			  • Fairness concerns for elderly in per capita schemes
				• Transparency in allocation and conversion factors is crucial
				• Regular or real-time feedback essential for effective carbon budgeting
				• Motivated individuals can achieve carbon footprints well below UK average
				• Financial penalties in PCT viewed as negligible by participants, even at high carbon prices
				• High allowance prices necessary to motivate environmentally indifferent participants
				• Simplified purchasing of additional allowances needed for those exceeding caps
					[48]

Sevenoaks CRAG	20,000-15,000 ≤ 5000	25 % 5 %			[48]
Fownhope CRAG	Individual	10 %			[48]
Leeds CRAG	Members choose own targets lower than baseline of previous year				[48]
Redland Bristol CRAG	Members choose own targets lower than baseline of previous year[a]				[48]
Langport CRAG	9240	10 % reduction of group average			[48]
Glasgow CRAG	2200	10 % reduction on estimated global footprint			[48]
Norfolk Island Carbon and Health Evaluation (NICHE)	633 1 1012 2 1083 3 4 1249 & 5 Per member household	10 %	• Poor internet connectivity hindered trading schemes • Sharp decline in participation due to economic and political instability, and subsequent island emigration • Questionnaire fatigue	• Unforeseen events impact participation • Technical difficulties obstruct emission trading implementation • Increased carbon literacy noted among participants	[37,51,52]
CitiCAP	844	20 %	• Decline in participation and reduced mobility due to COVID-19 pandemic	• Unforeseen events affect mobility and participation	[38]
Energy Smart Home Lab	2,077[b] 3384 2091	75 % HH1 54 % HH2 63 % HH3	This study		

[a] After one year with a fixed target.

[b] The baseline taken here is the average of the actual emissions of the first few weeks before the first budget lower than the actual emissions was set and multiplied by 52 to receive a value comparable to the annual values of the other studies.

Appendix B. Participant recruitment and selection

Participants were recruited in November 2022 and December 2023 via an open call for applications disseminated through multiple channels, including university mailing lists, social media, and professional networks. The flyer provided information about the smart home setup and the planned residential intervention. Interested individuals were asked to submit a short application, including a CV, a brief motivation statement (½ DIN A4 page) explaining why they wished to participate in the study, and their availability to begin an 8-week stay in November, December 2023 or January, February, March 2024.

All applicants were invited to a short video call for clarification of study expectations and assessment of eligibility. Hard exclusion criteria included employment at KIT (due to legal restrictions), lack of availability over the full intervention period (e.g., planned vacations), and unwillingness to cohabitate with another participant in the smart home. Preference was given to working individuals or recent graduates with limited home-office days, to ensure a more realistic approximation of everyday residential energy use.

No formal screening process was conducted for environmental attitudes or technical literacy. However, we aimed to avoid participants whose academic or professional background was closely related to the research topic to minimize bias. This goal met with mixed success, largely due to the limited pool of applicants. In both 2022 and 2023, we received eight applications per year. As a result, some selected participants had backgrounds adjacent to energy or environmental studies. Among eligible candidates, final selection was based on the date of application submission, following a first-come, first-served principle.

Appendix C. Socio-demographic characteristics

This section provides an overview of the socio-demographic characteristics of the six participants, aged between 25 and 35, including four women and two men. The descriptions below are based on participants' self-assessments collected through a Likert-scale questionnaire (1 = not existent to 5 = very extensive) and supported by insights from final in-depth interviews conducted after the intervention. Ratings such as “average” or “below average" reflect the participants' own positioning on the scale, and comparisons are made within the small study sample rather than against an external reference group. Household one (HH1) comprised one employee and one student, both environmentally conscious, with one participant very active in integrating sustainability into all aspects of life, including choosing sustainable service providers. Household two (HH2) involved two students with varying experience with smart appliances, average knowledge of energy saving measures, below-average knowledge of residential electricity prices, and high motivation to respond to environmental and economic incentives. Household three (HH3) included two employees experienced in interacting with smart technologies and average knowledge of electricity prices, being both highly motivated by normative, environmental and economic incentives.

Appendix D. Behavioral data collection and analysis

To assess participant attitudes, behavioral change, and incentive engagement, we conducted weekly semi-structured interviews, a final in-depth interview, and a survey across all three interventions. Instruments were refined iteratively over the course of the study to deepen insights and improve coverage of relevant constructs such as environmental values, perceived control, and response to incentives.

Interviews

All participants took part in weekly semi-structured interviews, as well as an in-depth interview conducted at the end of the residential period. The weekly interviews took between 15 and 30 min, the final in-depth interview between 30 and 60 min. All interviews were recorded, transcribed, and subsequently analyzed and coded. The interviews explored changes in daily routines, comfort trade-offs, behavioral strategies, and emotional responses to the incentive prompts communicated via the dashboard (see Appendix H and Appendix I for the interview protocols of the semi-structured weekly and the final in-depth interviews). The interview transcripts were analyzed using an inductive thematic coding approach. Initial codes were identified manually through close readings of the transcripts, focusing on recurring behavioral patterns, emotional responses, and contextual factors. These codes were then iteratively grouped into broader themes such as "comfort vs. compliance," "adaptation strategies," and "motivational shifts," which structured the qualitative findings presented in the results. This process enabled a grounded understanding of participant experiences without imposing predefined analytical categories [66].

Survey

Each intervention concluded with a survey designed to capture participants' perceptions of the smart home experience, their engagement with carbon budgets and grid signals, and their broader attitudes towards energy consumption and environmental responsibility. All surveys included a standardized value scale adapted from Linda Steg, assessing the importance of 16 personal and environmental values on a 9-point scale ranging from -1 (opposed to my values) to 7 (of supreme importance) [76].

The remainder of the survey content evolved between the first and the last two interventions:

For HH1, the survey focused on six Likert-scale items measuring environmental concern (e.g., "I take potential environmental impacts into account when making decisions"), alongside basic socio-demographic[3] and employment-related questions (e.g., net income, weekly working hours, home office share) (see Appendix J). For HH2 and HH3, the survey was expanded to include more detailed items regarding (see Appendix K):

- Smart appliance familiarity and energy knowledge,
- Perceived openness to energy management system based behavioral prompts (for cost, environmental, and social reasons),
- Motivation and willingness to comply with real-time incentives,
- Reflections on the learning experience and behavioral changes, and
- Open-ended feedback on organizational aspects of the intervention and the Living Lab setup.

This extended version allowed the analysis of participants values, motivations, and reflection on the incentives and the living lab setup.

Appendix E. Data measurements and cleaning

Data for the electric energy consumption in the Energy Smart Home Lab is available for every household device and socket with a temporal resolution of one second. To get the electric energy consumption for the calculation of the carbon emissions, we sum up the consumption of all devices inside the living area, calculate the average consumption since the start of the current cap interval and aggregate it over the respective period. For the assessment of the grid congestion scenarios, we again sum up the consumption of all the appliances in the living area and then check the resulting time series with a temporal resolution of 1 s for exceedances of the defined power limit.

The heating energy consumption is measured by a heat meter located between the heat pump and hot water storage. This means energy used for space heating as well as hot water is considered. For the period from the third day in week five to the second to last day in week six[4] during the third intervention the data transmission from the heat meter to the database malfunctioned, resulting in a loss of data. We reconstructed the missing data by approximating the thermal energy consumption profile with the heat pump's electricity demand profile and the average coefficient of performance (COP) for this period.

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[3] Income data were only collected from one participant in HH1. The corresponding survey questions were omitted in HH2 and HH3, limiting our ability to assess the financial relevance of the incentive structure across households.

[4] Overall, for a time of 12 days, 18 h and 3 min

Appendix F. Household carbon allocation

As in the Californian policy proposal by Niemeier et al. (2008) [49], allowances are allocated to the overall households which means here the two participants living in the Energy Smart Home Lab, in contrast to the equal-per-capita allocation in other PCT schemes. The smart home's energy consumption can be automatically monitored. However, allocating the respective energy consumption to each participant would require a non-negligible effort from participants who would need to document when and how they used appliances, which was considered impractical for this study. Furthermore, household-level allocation better reflects how energy consumption decisions are made in shared living environments, where consumption is typically collective and not easily disaggregated to individuals [37]. Energy consumption and costs generally do not grow proportionately with the number of household members [82]. So, while single-person households may exhibit higher per capita emissions, this can be addressed through household-level allowance structures, e.g. using differentiated tiers accounting for the amount of household members [83].

While individual-level carbon accounting may be appropriate for personal consumption goods or mobility-related emissions, it is considerably more difficult to attribute household energy use, such as electricity and heating, to specific individuals [37,38]. In this sector, assessing emissions at the household level is often both practical and sufficient. Such an approach aligns with existing billing systems and can be more easily implemented [49]. In the context of a broader individual-based carbon trading scheme, household emissions could still be integrated by retrospectively dividing the measured total among household members and allocating it to their individual carbon budgets. For this study, a household-level carbon budget was therefore deemed the most efficient and behaviorally realistic approach. Intra-household dynamics and individual responses were captured through interviews with all household members.

Appendix G. Carbon price deduction

The carbon price was deducted by taking the average of the yearly average carbon prices of the EU-ETS in 2021 and 2022 [84], which resulted in 66.41 EUR/t which we rounded off to 65 EUR/t and multiplied by ten to give the participants a tangible incentive to deploy low-carbon energy consumption behavior in their daily live [69,85]. This relates to the approach of Kuokkanen et al. [38] who further argue, that the EU-ETS rather reflects system design, including oversupply of allowances, than social cost of carbon. Their overview about the highly varying social cost of carbon stated in literature still ranges from 125 $\$/t_{CO2\text{-}eq}$ estimated by Van den Bergh and Botzen in 2015 [70] to up to 1500 $\$/t_{CO2\text{-}eq}$ by Ackerman and Stanton in 2012 [86]. More recent studies estimate the social carbon costs at similar levels, such as 120–340 $\$/t_{CO2\text{-}eq}$ by the U.S. Environmental Protection Agency [87] and 1065 $\$/t_{CO2\text{-}eq}$ by Bilal and Känzig [88]. Kuokkanen et al. [38] set a starting price for their urban mobility PCT scheme at 1 EUR/$kg_{CO2\text{-}eq}$, which corresponds to 1000 EUR/$t_{CO2\text{-}eq}$, as rewards or penalties for under- or over-emitting their freely allocated allowances. Thus, we lie in the medium range of these studies with our carbon price estimation.

Appendix H. Semi-structured interview protocol

The following questions were used in the weekly semi-structured interviews conducted during the intervention. The interviews aimed to explore participant experiences with the HCCT scheme, behavioral adaptations, heating comfort perceptions, and responses to carbon caps and grid congestion events.

1. Introduction and general questions

- How are you doing, and how have the last days in the smart home been?
- Is everything functioning as expected, or do you have any remaining questions, requests, or comments?

2. Reference week (baseline) questions

- **Settling In and Initial Impressions**
  - o How have you settled into the smart home over the past few days?
  - o Have any questions or uncertainties come up during your first days here?
  - o Do you feel comfortable with the living situation in the smart home?
- **Familiarity with devices and interfaces**
  - o Have you familiarized yourselves with the household appliances?
    - o Household appliances: e.g., washing machine, coffee machine, dryer
    - o Heating system: adjusting temperature, using the dashboard to set room temperatures
  - o Are there any household appliances in the ESHL you haven't used yet? If so, which and why?
  - o Are there any appliances you expect not to use during the intervention? Why?
- **Thermal comfort and heating behavior**
  - o What temperature have you currently set in your room? Why did you choose this setting?
  - o Would you describe this as your comfort temperature (assuming standard clothing and no additional measures)?
  - o At home, would you typically set the heating to the same temperature? If not, why is it higher or lower?
    - o Prompt: If the difference is cost-related (e.g., due to the energy crisis), how did you heat your home in the previous winter (2021/22)? Has your behavior changed since then?
  - o If the temperature in your room/home doesn't match your comfort level, what adjustments do you typically make? (e.g., wearing extra clothing)
- **Daily routines and space use**
- o Where do you spend most of your time during the day in the smart home? Is this space at a comfortable temperature for you?
- o Over the past few days, have you mostly stayed at home (e.g., for remote work) or have you spent time outside the smart home?

3. Reactions to incentives

Last week, you received a new incentive message on your tablet. How did that affect you, and what was your reaction?

4. CO_2 budget

- Did you adjust your energy consumption behavior in any way to meet last week's CO_2 budget?
- Have you developed new habits?

5. Heating comfort

- How did you find the daytime indoor temperature in the living lab?
- Have there been any disagreements or discussions between you regarding preferred indoor temperatures, for example, one of you preferring it warmer or cooler—or has everything gone smoothly so far?
- Did you change the heating set points?

6. Grid congestion scenarios

- How did you experience the grid congestion scenario?
- Did you adapt your electricity consumption to it?
- What motivated you to adapt your consumption?
- Did the tariff have any effect on your energy consumption behavior?
- Did the information about the photovoltaic electricity feed-in motivate you to adjust your energy consumption?

7. Daily routines and representativeness

- How often were you at home during the day, and how frequently were you away for work or other activities?
- Was this a representative week for your usual schedule?

8. Closing
   [Planning the interview date for the upcoming week.]

Appendix I. Final in-depth interview protocol

The final interview, conducted at the end of the intervention phase, lasted approximately 30–45 min and was designed to elicit participants' reflections on living with carbon budgets and grid constraints, their behavioral adaptations, heating comfort perceptions, and potential long-term impacts.

I. Reflections on the final week of the intervention.

[Questions of the weekly interviews].

II. Overall reflections on the intervention

1. How would you describe your overall experience living in the smart home? Was it comfortable throughout, or were there less comfortable periods?
2. Did the incentives (CO_2 budget and congestion signals) pose any challenges?
3. In which areas did you feel you restricted yourself the most to stay within the carbon budget?
   Potential prompt: e.g., fewer showers, no baking, reduced coffee machine use, etc.
4. When did you feel most restricted during the intervention?
5. Which of the different incentive structures motivated you the most?
6. Did the integration of the photovoltaic electricity generation influence your behavior in any way?
7. How did you experience the grid congestion events?

- Did you actively try to comply, or were there times when it didn't matter to you?

8. Did the credit balance display on the dashboard motivate you to comply with the incentives?

- [Total earnings from participation were: __ €]

III. Long-term impact on energy use, comfort, and values

1. Do you think this experience will have a lasting impact on your energy consumption behavior? If so, how?
2. What was your comfort temperature in the smart home?
3. What is your usual comfort temperature at home?
4. In which areas did you feel most restricted? Would you be willing to accept similar restrictions in daily life?
5. Would you accept CO_2 budgets in your everyday life?
6. What types of restrictions would you be willing to accept long-term or short-term - and which would you not?

7. How does it feel to live without grid congestion signals now? Is it more comfortable? Are you aware this could change in the future?
8. Would you describe yourselves as environmentally conscious individuals?

- If yes: What actions do you take in everyday life?
- What motivates you to act sustainably?
- Do you believe incentives help you act more sustainably?
- Are you more motivated by economic incentives or by environmental concern (e.g., climate change mitigation)?

IV. **Closing**

1. We will send you the final online survey in the next days.
2. Would you be willing to participate in a similar research project again?
3. What would your expectations be for future participation? What could be improved?

Appendix J. Final survey protocol HH1

Residential Phase in the Energy Smart Home Lab.
Institute for Industrial Production (IIP)
Hertzstr. 16, Bldg. 06.33, R110
76187 Karlsruhe
Web: www.iip.kit.edu

Analysis of user acceptance and behavior regarding CO_2 budgets and grid constraints in the Energy Smart Home Lab

Dear Participants,

Thank you for participating in the residential phase at the Energy Smart Home Lab. We would like to conclude with the following survey. This is intended to analyze your self-assessment, and your environmental attitudes. This survey will take approximately 10 min to complete.

Thank you for your participation!

Leandra Scharnhorst Tel.: +49 721 608-44578	Thorben Sandmeier Tel.: +49 721 608-44402

Section 1: environmental attitudes

[Response scale: 1 = Strongly disagree, 5 = Strongly agree].
It is important to me that the products I use do not harm the environment.
I consider the potential environmental impacts when making many of my decisions.
My consumption behavior is influenced by concern for the environment.
I am concerned about wasting the Earth's resources.
I would describe myself as environmentally conscious.
I am willing to accept inconvenience in order to act in environmentally friendly ways.

Section 2: socio-demographic and occupational information

Please enter your year of birth: [Short text field].
What is your highest level of education? [Single choice].
What is your current employment status? [Dropdown].
How many hours do you work on average per week? [Short text field].
How many days per week do you work from home? [Short text field].
In which industry or sector are you employed? [Short text field].
What is your monthly net income? [Dropdown or income bands].
Do you have any further feedback for us? [Open text field].

Appendix K. Final survey protocol HH2 and HH3

Residential Phase in the Energy Smart Home Lab.
Institute for Industrial Production (IIP).
Hertzstr. 16, Bldg. 06.33, R110
76187 Karlsruhe
Web: www.iip.kit.edu

Analysis of user acceptance and behavior regarding CO_2 budgets and Grid constraints in the Energy Smart Home Lab

Dear Participants,

Thank you for participating in the residential phase at the Energy Smart Home Lab. We would like to conclude with the following survey. This is intended to analyze your self-assessment, your expectations for the residential phase, and your motivation for participation and collaboration during the residential phase. This survey will take approximately 10 min to complete.

Thank you for your participation!

Leandra Scharnhorst Tel.: +49 721 608-44578	Thorben Sandmeier Tel.: +49 721 608-44402

1. Have you had contact/interaction with smart appliances (e.g. washing machine where you can set the time, robot vacuum cleaner, energy management system in your flat) before starting the residency period in the Energy Smart Home Lab.?
   - ○ Yes
   - ○ No
2. How would you rate your knowledge level considering energy economics?
   - ○ Very extensive
   - ○ Extensive
   - ○ Average
   - ○ Less than average
   - ○ Not existent
3. How would you rate your knowledge level about saving energy in your household (e.g. switching light in a room off, when you are not in the room for a longer period of time)?
   - ○ Very extensive
   - ○ Extensive
   - ○ Average
   - ○ Less than average
   - ○ Not existent
4. How would you rate your knowledge about current electricity prices of private households?
   - ○ Very extensive
   - ○ Extensive
   - ○ Average
   - ○ Less than average
   - ○ Not existent
5. How would you rate your own energy consumption behavior in the household (electricity consumption) in comparison to the average inhabitant?
   - ○ Very low consumption
   - ○ Low consumption
   - ○ Average consumption
   - ○ High consumption
   - ○ Very high consumption
6. Would you consider yourself to be open to calls to action from your apartment's energy management system (EMS) in order to optimize your energy consumption behavior regarding energy expenses?
   - ○ Very open
   - ○ Open
   - ○ Neutral
   - ○ Less open
   - ○ Not open
7. Would you consider yourself to be open for calls to action from your apartments EMS in order to optimize your energy consumption behavior regarding environmental reasons?
   - ○ Very open
   - ○ Open
   - ○ Neutral
   - ○ Less open
   - ○ Not open
8. Would you consider yourself to be open for calls to action from your apartments EMS to optimize your energy consumption behavior regarding social aspects (e.g. helping your neighbor or your neighbor helping you by adapting your energy consumption according to your respective needs)?
   - ○ Very open
   - ○ Open
   - ○ Neutral
   - ○ Less open

   - ○ Not open
9. How would you rate your motivation to participate in the experiments after experiencing various daily incentives during the residential phase?
   - ○ Very motivated
   - ○ Motivated
   - ○ Neutral
   - ○ Less motivated
   - ○ Not motivated at all
10. How would you rate your willingness to follow the incentives during the residential phase? (Turning devices on/off, saving/using energy, scheduling the use of your devices)?
    - ○ Willing to follow every call to action
    - ○ Willing to follow almost every call to action
    - ○ Willing to alternately following calls to action
    - ○ Less willing to follow calls to action
    - ○ Not willing to follow any call to action
11. How much do you agree with the following statements? **I have expanded my knowledge about smart energy usage in private households during the residential phase.**
    - ○ Strongly agree
    - ○ Agree
    - ○ Agree Somewhat
    - ○ Neutral
    - ○ Disagree somewhat
    - ○ Disagree
    - ○ Strongly disagree
12. Please briefly describe your experiences with the calls to action and incentives during the residential phase. How did you feel when you tried to follow them? (Was it a motivating, challenging, frustrating, or interesting experience?)
13. How much do you agree to the following statements: **I contributed to optimize my energy consumption and helped pushing forward the implementation of the energy transition by doing so.**
    - ○ Strongly agree
    - ○ Agree
    - ○ Agree Somewhat
    - ○ Neutral
    - ○ Disagree somewhat
    - ○ Disagree
    - ○ Strongly disagree
14. How much do you agree to the following statements: **I am content with my performance during the residential phase, regarding following the calls to action.**
    - ○ Strongly agree
    - ○ Agree
    - ○ Agree Somewhat
    - ○ Neutral
    - ○ Disagree somewhat
    - ○ Disagree
    - ○ Strongly disagree
15. How much do you agree to the following statements: **I want to live in a similar smart home setting in the future.**
    - ○ Strongly agree
    - ○ Agree
    - ○ Agree Somewhat
    - ○ Neutral
    - ○ Disagree somewhat
    - ○ Disagree
    - ○ Strongly disagree

16. How much do you agree to the following statements: **I would again participate in such an experiment.**
    - ○ Yes
    - ○ No
    - ○ Depends, on… please elaborate:
17. What opportunities for improvement do you see in the residential phase in the Energy Smart Home Lab? Taking into account: - the organization - the living lab setup - the messages sent - the surveys - the interviews

Organization:

Living lab setup:

Messages and communication via dashboard:

Interviews:

Final survey:

18. Value scale by Linda Steg, see [76].

Appendix L. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.erss.2025.104294.

Data availability

To protect the anonymity of the study participants, only a subset of the data can be made publicly available. The anonymized energy consumption data is accessible as open-access on RADAR4KIT via the following link [65]: https://dx.doi.org/10.35097/txjj7yawp9gr4ts8.

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Paper B

Understanding household preferences for the security of energy supply: insights from a choice experiment in Germany

Reference

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Understanding household preferences for the security of energy supply: insights from a choice experiment in Germany

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Abstract

Amidst the war in Ukraine and the ongoing energy transitions, the security of energy supply has become a pressing concern across Europe. The increasing reliance on intermittent renewable energy sources and the electrification of demand sectors make demand-side flexibility more important than ever. Given these circumstances, we examine to what extent private households accept potential electricity outages as a load-shedding option for flexibility. Given the diversity of methodological approaches among existing studies, we extend the current understanding by conducting a choice experiment with 682 German residential consumers. The study investigates willingness to accept controlled electricity interruptions incentivized by a tariff design that varies the frequency, duration, and advance notice of interruptions, as well as the financial compensation offered. Using a joint mixed logit and a latent class model, we estimate both continuous and discrete preference heterogeneity and explore how socio-demographic and household characteristics influence participation decisions. Results reveal that about two thirds of respondents accepted a tariff with the possibility of a power interruption, suggesting broad willingness to participate. Preferences are primarily driven by compensation level, followed by interruption frequency and duration, while longer advance notice increases utility with diminishing returns beyond 12 hours. The latent class analysis identifies three consumer segments: likely adopters, convenience-oriented participants, and non-participants, differing in their sensitivity to incentives and reliability concerns. Overall, the findings indicate that well-designed, compensated outage programs could mobilize household flexibility, contribute to renewable integration, operational grid stability, and potentially ease pressure on grid expansion needs during Europe's energy transition.

Keywords: willingness to accept, residential sector, electricity interruptions, choice experiment, demand-side flexibility

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1. Introduction

The global transition toward more sustainable energy generation is fundamentally reshaping the electricity sector (Röck, 2021). The shift away from centralized, dispatchable generation toward intermittent renewables coincides with the increasing electrification of the demand side. In the residential sector, this is largely driven by the uptake of electric vehicles and heat pumps (Wetzel, 2013). These developments not only strain the grid but also create opportunities to integrate end users more actively into grid management, for example, by leveraging demand-side flexibility during periods of congestion or critical grid conditions, support short-term balancing, improve renewable integration, and deliver bill savings for consumers (Agora, 2024).

Compounding these structural and technological shifts are climate-related and geopolitical risks. Climate change is expected to affect electricity generation capacity by increasing the frequency of extreme weather events and by altering the temporal and spatial patterns of both supply and demand (IEA, 2024). At the same time, the war in Ukraine has exposed Europe's vulnerability to fossil fuel dependency. Since 2021, gas exports from Russia has progressively been curtailed , leading to energy supply bottlenecks, particularly during the winter of 2022–2023 (European Council, 2023). In response, the European Council has called for an accelerated diversification of energy sources and rapid deployment of renewables (European Council, 2023). Germany, for example, has eliminated its reliance on Russian energy carriers (Bundesregierung, 2023; Statista, 2025).

Although electricity supply in Germany remains highly reliable, the ongoing electrification of demand sectors and the volatility of renewable generation are placing increasing stress on the system (Bundesregierung, 2023; Li et al., 2023). In recent years, grid congestion and imbalance events have become more frequent, underscoring the need for effective demand-side flexibility measures. The blackout on the Iberian Peninsula at the beginning of this year further illustrated how a single technical disturbance can propagate rapidly through interconnected grids, highlighting the critical importance of electricity security as systems become more complex (IEA, 2025). While industrial demand response programs such as Germany's, now discontinued, interruptible load scheme have historically served this role (Federal Network Agency, 2024), similar mechanisms are now being considered for residential

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applications. To date, residential demand response has been examined through surveys, discrete choice experiments, and analyses of real consumption data, covering a wide range of price-based and behavioral interventions (e.g., Sloot & Scheibehenne, 2022; Sloot et al., 2022; Srivastava et al., 2018; Yilmaz et al., 2021). However, controlled and time-bound electricity interruptions, as a more intrusive form of demand-side flexibility, have so far been explored only in a much narrower set of studies. Existing work is largely limited to theoretical assessments, small-scale pilots, or ex-post analyses of unplanned outage events, with few empirical investigations into household acceptance of planned interruptions (Paterakis et al., 2017; Scharnhorst et al., 2023). A more recent pilot's results indicate that consumers accept interruptions if they are compensated for it, ranked 24 h advance notice as top priority, far above frequency or compensation, and were able to adapt quickly to form new routines (Scharnhorst et al., 2023). The EU Internal Market Directive (EU) 2019/944 supports the growing integration of households into demand-side flexibility schemes by requiring Member States to enable access to smart meters and dynamic electricity tariffs (European Parliament and Council, 2019). However, the current policy framework does not yet address more drastic flexibility measures such as controlled, timed electricity interruptions.

Assessing the value of uninterrupted electricity supply for households presents unique challenges. Unlike industrial users, whose outage losses can often be quantified in monetary terms, residential consumers may suffer a mix of material (e.g., spoiled food) and immaterial (e.g., inconvenience, anxiety) consequences during outages (Morrissey et al., 2018). Preferences for supply reliability are also likely to vary across households, shaped by socioeconomic and demographic factors (Morrissey et al., 2018). Although several studies, including discrete choice experiments, have examined household preferences for electricity supply interruptions, many suffer from strong status quo bias, where respondents overwhelmingly favor uninterrupted supply, and typically do not distinguish between forced choice and opt-out designs (Abrate et al., 2016; Ladenburg et al., 2022; Zemo et al., 2019). These studies used a free choice design within which the respondents had the possibility to choose between two to three tariff options, as well as an opt-out or status-quo option. Thus, a respondent that opts for the status-quo option does not reveal their preferences for any of the other tariff options, leading to a loss in information. To advance the evidence base, our study combines a representative sample with an experimental design that accounts for a forced choice, where respondents have to choose between three tariff alternatives and a free choice, where they can indicate if they opt for the status quo or the previously chosen tariff. This enables a more nuanced understanding of how households evaluate electricity interruptions under realistic trade-offs.

We conducted a representative online survey in Germany in December 2023 (N = 751). The study investigates consumer preferences for controlled and timed electricity interruptions and combines direct self-assessments of willingness to accept (WTA) and willingness to pay (WTP) for outages of varying durations with a discrete choice experiment. This experiment examines how different interruption characteristics, such as frequency, duration, advance notice, and compensation, affect preferences. Sociodemographic characteristics and prior outage experiences are incorporated to capture heterogeneity in household responses.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature and outlines the study's contribution. Section 3 describes the survey design and analytical approach. Section 4 presents the empirical findings. Section 5 discusses the implications for energy policy and offers directions for future research.

2. Literature review, research questions, and hypotheses

Ensuring a reliable and stable electricity supply is becoming increasingly challenging due to the rising share of intermittent renewable energy sources and growing electricity demand. As energy systems evolve to become more flexible and sustainable, temporary or controlled electricity interruptions may become a necessary tool to manage demand. However, such measures must be designed in a way that is socially acceptable and economically viable. This requires a clear understanding of how households value electricity reliability, specifically, how much compensation they require to accept controlled power interruptions (WTA), or how much they are willing to pay to avoid them (WTP).

Several methods have been employed to estimate the value that consumers place on electricity reliability. Among them, production function approaches, stated preference methods such as contingent valuation and discrete choice experiments are most common, while a few studies have used revealed preference methods to investigate consumer reactions to experiencing blackouts (Motz, 2021). Production function approaches rely on macroeconomic data (income, rate of employment, electricity consumption) to estimate lost income or leisure to infer the value of lost load (VoLL). However, they often neglect psychological or situational characteristics (Motz, 2021). They also assume that the benefits from improved reliability are symmetrical to the costs of reduced reliability, an assumption that may not hold in practice (Motz, 2021). In contrast, stated preference methods, including contingent valuation and discrete choice experiments, offer greater flexibility. They allow a more nuanced understanding of consumer preferences, accounting for different scenarios that include attributes such as blackout duration, frequency, timing, and advance notice, as well as the heterogeneity across individuals and their preferences (Motz, 2021). See (Motz, 2021) for more details on the benefits and drawbacks of discrete choice experiments for the analyses of consumer preferences regarding power interruptions.

The following sections review the existing literature on household preferences for power outages and compensation mechanisms, identify key research gaps, and formulate the research questions and hypotheses guiding this study.

2.1. Literature overview

A growing body of research has explored how households value electricity reliability, focusing on planned or controlled electricity interruptions as part of demand-side management and flexibility schemes (Motz, 2021; Pepermans, 2011). Table 1 provides an overview of existing stated preference studies, most of which use discrete choice experiments or contingent valuation methods to estimate WTP or WTA of controlled electricity interruptions.

In discrete choice experiments, WTP represents the amount of money an individual is willing to give up to obtain an improvement in an attribute, while WTA is the minimum compensation they require to tolerate a deterioration. Both are derived as the ratio of a non-monetary attribute's coefficient to the monetary coefficient, reflecting marginal rates of substitution between attributes (Holmes & Adamowicz, 2003; Train & Weeks, 2004). A majority of these studies include outage duration as a key attribute, with durations ranging from a few minutes to several hours (Abrate et al., 2016; Frondel et al., 2019; Morrissey et al., 2018). Outage frequency is also often included (Ladenburg et al., 2022; Motz, 2021; Pepermans, 2011). However, advance notice time, which is essential for preparation and planning, remains underexplored. Only a few studies, such as (Zemo et al., 2019) and (Meles et al., 2021), both conducted in Ethiopia, explicitly vary the notification period. Recent findings show that in other demand sectors, such as the manufacturing industry, advance notice time can be an important factor for demand response provision, due to organizing work schedules, delivery times and more (Scharnhorst et al., 2022). A pilot study on residential consumer acceptance of controlled electricity interruptions in Germany also highlights the perceived importance of advance warning for acceptability (Scharnhorst et al., 2023). Other attributes that have been investigated by previous studies on power interruptions include the timing (per season, or per day), external control of domestic heating or electricity, the access to electricity meter information by third parties, or the method of notification (Broberg & Persson, 2016; Meles et al., 2021; Pepermans, 2011; Zemo et al., 2019).

In terms of geographic focus, most European studies center on Germany, Belgium, and the UK, with a few studies from Italy, Switzerland, Denmark, and Sweden (Frondel et al., 2019; Lehmann et al., 2022; Morrissey et al., 2018; Pepermans, 2011; Schubert et al., 2013). The Ethiopian case studies are notable for assessing preferences in a context with frequent power outages, providing a contrasting backdrop to high-reliability systems like Germany.

Across diverse contexts, consumers consistently prefer brief and infrequent power interruptions and demand compensation for disruptions (Zemo et al., 2019). People tend to prefer day-ahead outage notifications over week-ahead notifications, but advance notice on sub-day timescales has not yet been investigated (Meles et al., 2021; Zemo et al., 2019). Furthermore, no study that investigates controlled power interruptions has employed a dual-response format to distinguish between hypothetical and actual acceptance of proposed tariffs, despite known issues with status quo bias in single-response discrete choice experiments (Lehmann et al., 2022; Pepermans, 2011). The only study that accounted for dual response in their choice experiment investigated curtailments, not power interruptions (Lehmann et al., 2022).

2.2. Research questions and hypotheses

This study expands on the existing literature by applying a contingent valuation, as well as a dual-response discrete choice experiment in Germany, capturing stated preferences for accepting planned electricity interruptions. The contingent valuation accounts for self-assessed WTA and WTP values without prior information, covering the first research question:

RQ1. *What are consumers' stated values for willingness to accept (WTA) and willingness to pay (WTP) in the context of controlled power interruptions?*

The choice experiment assesses consumer preferences according to four different attributes, leading to our second research question:

RQ2. *What are consumer preferences regarding the design of compensation schemes, considering the attributes of duration, frequency, advance notice time, and financial compensation?*

Regarding RQ2, and based on our literature review, we derive hypotheses H1 to H4 that account for the investigated attributes:

H1. Consumers prefer power interruptions with a shorter duration.

Duration: The longer a power interruption lasts, the more consumers must adjust their habitual behavior, leading to a greater loss in comfort (Lehmann et al., 2022). Studies that examine preferences with regard to power outages or controlled power interruptions typically account for the duration attribute (Meles et al., 2021; Pepermans, 2011; Zemo et al., 2019). The duration in most studies ranges from 15 minutes to four or six hours (Ladenburg et al., 2022; Meles et al., 2021; Pepermans, 2011; Zemo et al., 2019). Some studies occasionally also account for shorter periods such as one minute (Abrate et al., 2016) or longer periods to up to 24 hours (Morrissey et al., 2018). (Morrissey et al., 2018) find that the WTP to avoid an outage decreases as the duration of the outage increases. Furthermore, longer power interruptions mean a higher disutility in peak periods than in off-peak periods (Pepermans, 2011).

Table 1: Stated preference studies on electricity interruptions.

			Attributes							
Study	Country, region	Method	Electricity interruption	Willingness to accept	Willingness to pay	Duration	Frequency	Advance notice	Others	Dual response
Pepermans (2011)	BE	DCE	✓	✓	✓	✓	✓	(✓)	✓	
Schubert et al. (2013)	DE	CV	✓	✓	✓					
Abrate et al. (2016)	IT	DCE	✓	✓		✓				
Broberg and Persson (2016)	SE	DCE	✓	✓					✓	
Morrissey et al. (2018)	NWE	DCE	✓		✓	✓			✓	
Frondel et al. (2019)	DE	DCE	✓	✓	✓	✓				
Zemo et al. (2019)	ET	DCE	✓		✓	✓	✓	✓	✓	
Meles et al. (2021)	ET	CV, DCE	✓		✓	✓	✓	✓	✓	
Motz (2021)	CH	DCE	✓		✓		✓		✓	
Ladenburg et al. (2022)	DK	DCE	✓	✓		✓	✓			
This study	DE	CV, DCE	✓	✓	✓	✓	✓	✓	✓	✓

NWE: Northwest England
DCE: Discrete choice experiment, CV: Contingent valuation

H2. Consumers prefer less frequent power interruptions (i.e. fewer power interruptions per month).

Frequency: Frequency is the second most commonly considered attribute in studies examining the acceptability of power interruptions or load shifting and reduction (Ladenburg et al., 2022; Lehmann et al., 2022; Meles et al., 2021; Pepermans, 2011; Zemo et al., 2019). (Ladenburg et al., 2022) find that the expected compensation increases exponentially with the number of annual power interruptions. (Zemo et al., 2019) investigates power interruption frequencies of up to 10 per month. (Meles et al., 2021) account for a power outage frequency of up to 6 per times per month. However, here it must be considered that (Zemo et al., 2019) and (Meles et al., 2021) conducted their studies in Ethiopia, a country with regular power outages. E. g. in the study of (Meles et al., 2021) the frequency of the proposed controlled interruption tariff would actually be reduced compared to a status quo of 8 outages per month, with the alternatives' highest frequency stating 6 outages per month. Despite the different framing of the frequency attribute, (Meles et al., 2021) and (Zemo et al., 2019) find that participants prefer reduced frequency of power interruptions.

H3. Consumers prefer longer advance notice times (of at least one day) prior to a power interruption, as they are more likely to be able to prepare and adapt their daily schedules with more time.

Advance-notice time: Few studies include the advance notice time in their assessment of power interruption preferences. (Pepermans, 2011) asks in their choice experiment whether there was an advance notice or not, not specifying the preference for advance notice time. However, prior to the choice experiment, the survey asked about an appropriate period of advance notice, finding that about 34% of households find one working day, and about 40% three working days an appropriate advance notice time (Pepermans, 2011). (Zemo et al., 2019) specifies four levels regarding the advance notice time (two weeks prior, one week prior, three days prior, one day prior) and find that respondents prefer a longer advance notice of one to two weeks. In contrast to these findings, (Meles et al., 2021) considered the two levels "one day prior notification" and "one-week prior notification" and find that participants showed a preference in receiving a one-day over a week advance notification. The previous studies show contradicting results, and have a minimum advance notice time of one day prior to the power interruption. (Scharnhorst et al., 2023) find in their pilot study where actual controlled power interruptions occurred for a two person household during an intervention of multiple months that participants preferred an advance notice of at least one day to sub-day timescales.

H4. Consumers prefer a higher financial compensation for accepting controlled and announced power interruptions, though this factor is not equally important for all.

Willingness to accept financial compensation: As human activities become more and more dependent on a stable electricity supply, a power outage can have a significant impact on daily routines and comfort of residents (Abrate et al., 2016). To compensate for this, financial incentives are often cited as the most important design attribute of demand response programs (Parrish et al., 2020). According to (Knetsch, 2010), in a domain of losses, such as the investigation of more frequent and longer power outages, e.g. of four hours, that clearly imply a degradation from the status quo in Germany, the value of changes will be more accurately assessed with a WTA instead of a WTP measure. Furthermore, consumers may expect continuity to be an inherent characteristic of the electricity provision service they are paying for (Carlsson & Martinsson, 2008). Hence, a power interruption would be considered the provider's responsibility, so that consumers could find it unacceptable to pay more to avoid this situation from occurring. This is further supported by the findings of (Woo et al., 2014), where consumers frequently answered with zero WTP for a power interruption. We hence account for WTA in our discrete choice experiment design. However, several studies found that there are also consumers who are insensitive to financial incentives (Asensio & Delmas, 2015; Gyamfi et al., 2013).

Furthermore, we examine heterogeneity in household preferences in two complementary ways: (a) by assessing how demographic and living-condition characteristics shape choices, and (b) by identifying whether distinct latent consumer segments with systematically different preferences exist. This leads to our third research question:

RQ3. *How do demographic characteristics and living conditions influence the acceptance of power interruption tariffs?*

The previous literature on WTA or WTP for electricity interruptions or outages that applied discrete choice experiments all employ choice sets with two to three alternatives plus a none-option (Ladenburg et al., 2022; Zemo et al., 2019), or status-quo option (Meles et al., 2021; Pepermans, 2011). (Pepermans, 2011) find significant alternative-specific effects, meaning that the respondents chose the status quo above any of the other alternatives. They summarize that only a small fraction of Flemish households would be willing to switch to a different power outage profile in exchange for substantial compensation (Pepermans, 2011). (Morrissey et al., 2018) completely omitted a none-option, deploying a forced choice between two electricity interruption tariffs and motivating their decision by arguing that this would be consistent with a utility service, meaning that customers cannot do without the service, so that the only choice that remains is the one between attributes of the service. However, realistic options are recommended to be included in choice experiments, such as opting-out or maintaining the status-quo (Determann et al., 2019). Not offering an opting-out choice, which would be a viable option as in (Morrissey et al., 2018), may lead to overestimating the participation (Ryan & Skåtun, 2004). In addition, if there is a none-option provided, the selection of the none-option does not provide information on the relative attractiveness of the available alternatives (Brazell et al., 2006; Diener et al., 2006). This can be avoided by applying a dual-response format, where respondents first choose from a set of available alternatives in a forced-choice task, and then choose again in a free-choice part between the selected alternative from the forced choice and a none-option (Schlereth & Skiera, 2016). Only (Lehmann et al., 2022), who investigated consumer preferences for the design of a demand response quota scheme, accounted for dual response in their study. To account for the status quo bias and bridge this information gap, we deployed a dual response format in our discrete choice experiment. Based on results from previous discrete choice experiment with a strong preference for the status quo, we formulated our last hypothesis:

H5. *Consumers prefer to maintain the status quo when given the option to opt out.*

2.3. Our contribution to the literature

This study contributes to the literature on consumer preferences regarding electricity reliability in four ways:

(1) We implement a dual-response discrete choice experiment with 12 choice sets, each including a forced-choice and free-choice task. To our knowledge, only one previous study (Lehmann et al., 2022) has applied this format in a similar context and previous studies investigating controlled electricity interruptions detected significant status quo bias (Gensler et al., 2012; Pepermans, 2011). (2) We include advance notice time as a design attribute, a factor rarely studied outside of the Ethiopian context, despite its practical importance in flexibility planning (Meles et al., 2021; Zemo et al., 2019). (3) We link discrete choice experiment responses to a rich set of demographic and contextual variables, including housing conditions. (4) The compensation attribute is individually tailored to each respondent's stated monthly electricity costs and is scaled according to the share of the German grid tariff (see 3.2 for further details). Thus, we make the compensation relatable for every participant, while accounting for the participants' heterogeneity (Gensler et al., 2012).

3. Methodology

This section describes the survey, the experimental design of the choice experiment, data preparation, and the modeling approach.

3.1. Survey and sampling

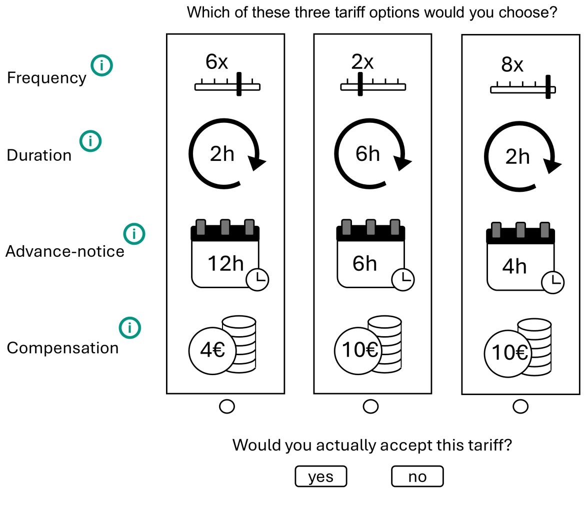
The survey was fielded online in December 2022 using the Sawtooth Software Lighthouse Studio (Sawtooth, 2025). Using a professional panel provider, we recruited a sample that was representative of the German population regarding age and gender. In total, 1,784 individuals started the survey. Pre-programmed quality checks included attention and straightlining checks, reducing the sample to 751 respondents who successfully completed the survey (Abbey & Meloy, 2017; Schonlau & Toepoel, 2015). An ex-post analysis accounted for very short response times on item questions ($< 2s$) as well as randomized choices in combination with speeding with the latter defined as being faster or slower than 95% of respondents, resulting in the final sample of 682 respondents (Orme, 2002;

Schlereth & Skiera, 2016).

The questionnaire first captured demographics and monthly electricity expenditure, followed by direct single-item questions on WTP/WTA for hypothetical one-, two-, and four-hour interruptions. The core stated-preference module was a dual-response discrete choice experiment with 12 choice tasks per respondent. In each task, participants first made a forced choice among three unlabeled interruption tariffs. Immediately afterwards they made a free choice between the selected tariff and a none-option (i.e., refusal to participate in controlled interruptions). The dual-response format preserves information from forced choices while allowing an explicit opt-out in a second step (Brazell et al., 2006).

3.2. Choice experiment

Following the recommendation of Backhaus et al. (2015), a total of 12 choice sets were presented for processing, to collect as much information as possible with a limited number of observations, while not tiring the respondents and adhering to the survey budget. Of these 12 choice sets, 10 choice sets were randomized and two were fixed. For each choice set, three unlabeled alternatives were presented as tariffs for power interruptions designed as forced choice, followed by a free choice for the non-option (dual-response). Each choice set presents three alternatives described by four attributes: (i) frequency of interruptions per month, (ii) duration of each interruption in hours, (iii) advance notice in hours, and (iv) monthly compensation. An exemplary choice set is shown in Figure 1.


Which of these three tariff options would you choose?

Would you actually accept this tariff?

Figure 1: Example choice set with the forced choice (all attributes) and free choice task. Translated from German.

The attribute levels are shown in Table 2. Compensation levels are individualized as a fraction of each respondent's reported monthly electricity bill D_{el} in EUR. The proportion used to determine compensation was chosen so that it reflects the typical percentage of the total electricity bill that goes toward grid tariffs (the cost for using the electricity network) in Germany. In 2022, the grid fee made up 23% of the household electricity prices (Federal Network Agency, 2025). In case D_{el} was unknown, it was imputed from published averages by household size and housing characteristics (building type, electric warm water) (Weißbach, 2024). Table 3 shows the allocated compensation level to each household size and the level of the compensation attribute. This design scales payments to realistic magnitudes and improves comparability across households.

Table 2: Attributes and levels of the choice experiment.

Attributes	Level
Frequency per month	2, 4, 8
Duration in hours	1, 2, 4
Advance notice in hours	0.25, 1, 6, 12, 24
Compensation in EUR	$0.1 \times D_{el}$, $0.15 \times D_{el}$, $0.247 \times D_{el}$

Table 3: Compensation level depending on household size.

Household size (no. of inhabitants)	1	2	3	4	5	6	7	≥ 8
Level 1 in EUR	7.5	10	11.5	13	16.5	18	20	22.5
Level 2 in EUR	15	20	23	26	33	36	40	45
Level 3 in EUR	22.5	30	34.5	39	49.5	54	60	67.5

3.3. Data preparation and sample description

Self-reported electricity bills were used to compute respondent-specific compensation amounts shown in the discrete choice experiment. To limit leverage from extreme entries, compensation shown in tasks was winsorized at the 98th percentile (60 EUR). This approach preserves realistic variation across participants while maintaining robustness against extreme values (Thomas & Ward, 2006).

The sample closely matches the national age and gender distribution, as Table 4 presents. Education skews toward higher qualifications, and household composition toward two-person households. Income is broadly comparable to national figures, with minor deviations.

To capture systematic preference heterogeneity, several sociodemographic and contextual covariates were assessed, see Table 5. Gender, age, education, income, home ownership, and residential region were included as standard demographic controls. Age was initially modeled using six separate binary indicators. This specification introduced unnecessary complexity and yielded only statistically meaningful effects for the older age groups. To avoid over-parameterization and retain only behaviorally relevant contrasts, the six categories were collapsed into three broader age groups. This approach follows the reasoning of Pepermans (2011), who similarly found that specifications with more granular age brackets did not improve explanatory power and ultimately reduced age to broader categories into two age groups. Living conditions were represented by binary indicators for home office use, electric heating, and electric hot water generation. "Don't know" responses for electric heating and hot water were recoded as "No," since the observed shares (14.8% and 29.6%, respectively) already exceed

Table 4: Demographic representation of survey respondents (N=682).

Feature	Sample (N=682) (%)	German average[a] (%)
Gender		
Female	49.27	50.61
Male	50.73	49.39
Age		
15-20	4.55	5.50
20-25	5.87	6.30
25-30	5.87	6.82
30-35	7.77	7.96
35-40	6.45	7.57
40-45	6.74	7.38
45-50	7.33	6.84
50-55	9.24	8.57
55-60	10.26	9.62
60-65	8.94	8.47
65-70	7.48	6.96
70-75	6.30	5.92
> 75	13.20	12.09
Education		
No degree	1.03	2.68
Secondary school graduate	11.29	19.56
Secondary school or comparable	35.63	43.08
General higher education	52.05	34.67
# people per household		
1	30.50	40.84
2	42.52	33.75
3	13.49	11.99
4	10.41	9.65
> 5	3.08	3.77
Net income in EUR		
< 1,500	12.32	19.69
1,500-1,999	11.73	13.34
2,000-2,499	13.05	13.31
2,500-2,999	11.14	10.21
3,000-3,499	9.24	8.95
3,500-3,999	10.26	7.36
4,000-4,999	11.14	10.91
> 5,000	11.00	16.23
Not specified	10.12	-
Owner		
Flat owner	14.96	-
Homeowner	27.86	-
Rent	54.40	-
Miscellaneous	2.79	-

[a] Own calculation based on the Federal Statistical Office of Germany (Tables: 21211-0009 [Education 2022]; 12211-0001 [Gender, age 2022]; 12211-0300 [Net income, number of people per household 2022] (Destatis, 2025).

national averages of 10.5% in 2019 and 13.4% in 2020, respectively (BDEW, 2019; BMWK, 2022). Experience with power outages was included by two binary indicators for having experienced any blackout in the past three years and for the duration of past blackouts (short < 1 h and long ≥ 1 h). Because most respondents reported none or only one to two short blackouts, the ordinal scale was collapsed to reduce model complexity. All covariates were initially included with interactions across all attributes, as well as the opt-out alternative. Variables with weak or theoretically ambiguous effects were gradually pruned to improve model parsimony.

3.4. Models

To account for heterogeneity in respondents' preferences and choice consistency in different ways, two complementary discrete choice models were estimated: a joint Mixed Multinomial Logit (MIXL) model and a Latent Class Model (LCM). The joint MIXL captures continuous heterogeneity across individuals through random parameters, while the LCM identifies discrete segments of respondents that share similar preference structures. The MIXL was estimated as a joint model that simultaneously captures individuals' preferences in the forced- and free-choice stages of each choice task.

Estimation was performed using the statistical software "R", (version 4.4.2 for Windows) and the "apollo" package version 0.3.5 (Hess & Palma, 2019). A hierarchical Bayes (HB) estimation based on Markov Chain Monte Carlo (MCMC) simulation combining Gibbs sampling and the Metropolis–Hastings algorithm was applied for the joint MIXL, while the LCM relied on classical log-likelihood maximization. Both models are described in the following. The high data demands associated with HB estimation are met by the large and well-balanced sample, consisting of 8,184 observations (682 respondents × 12 choice tasks) for both the forced- and free-choice stages (Hess & Train, 2011). Competing model specifications were compared using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to balance model fit and parsimony (Backhaus et al., 2015; Temme, 2007).

3.4.1. Joint MIXL

We estimate a joint mixed logit (MIXL) model using hierarchical Bayes (HB) methods to capture random preference heterogeneity across respondents. The deterministic utility of respondent n for alternative j in task t in the forced-choice stage consists of an alternative-specific constant $asc_{j,t}$, a vector of part-worth utilities β_n, and a design matrix $X_{n,j,t}$ containing the coded attributes and selected covariate interactions:

$$V_{n,j,t} = \mathrm{asc}_{j,t} + \beta_n^\top X_{n,j,t}. \tag{1}$$

The observed values of attributes frequency and duration enter the equation as their numerical levels, whereas advance-notice is transformed into dummy variables for 1 h, 6 h, 12 h, 24 h, with 0.25 h as the reference level. The compensation attribute is entered as $\beta_n^{\mathrm{comp}} = log(X_{n,j,t}^{\mathrm{comp}} + 1)$ to capture diminishing marginal utility of monetary rewards and to reduce the influence of extreme values. Alternative-specific constants capture systematic differences in choice probabilities that cannot be explained by observed attributes or covariates (Pepermans, 2011). Random taste heterogeneity is introduced via independent normal priors:

$$\beta_{k,n} \sim \mathcal{N}(\beta_{k,0}, \sigma_k^2) \quad \text{for all random coefficients } k \in \mathcal{K}, \tag{2}$$

where $\mathcal{K}$ denotes the set of attribute-specific parameters (frequency, duration, advance-notice dummies, compensation, and μ_{accept}). Systematic heterogeneity is captured via interactions between the attributes and selected covariates accounting for sociodemographic characteristics (e.g., age, gender) and living conditions (e.g., home ownership, electric heating). The effective individual-specific coefficients are shifted by observed covariates z_n for a selected subset $\mathcal{K}_{\mathrm{int}}$ of attributes:

$$\widetilde{\beta}_{k,n} = \beta_{k,n} + \delta_k^\top z_n, \qquad k \in \mathcal{K}_{\mathrm{interacted}}. \tag{3}$$

Only a parsimonious subset $\mathcal{K}_{\mathrm{int}}$ of interactions was retained based on statistical significance and theoretical relevance. For

Table 5: Description of covariates.

	Covariate name	Value range[a]	Transformations	Description[b]
Sociodemographic characteristics	Gender	{0,1}	-	(1) Female [49.2%] (2) Male [50.73%]
	Age class	{0,1}	One binary variable per group (three discrete categories), with one omitted as reference category.	Three binary variables: (Reference) Younger (≤ 39) [30.51%] (1) Middle (40 - 59) [33.57%] (2) Older (≥ 60) [35.92%]
	Education	[-2.39, 0.61]	Mean centering	(0) No degree [1.03%] (1) Secondary school graduate [11.29%] (2) Secondary school or comparable [35.63%] (3) General higher education [52.05%]
	Income class	[-1.81, 2.43]	Mean centering, division by thousand	Net household income, measured in eight classes and EUR per month (1) <1,500 EUR [12.32%] (2) 1,500-1,999 EUR [11.73%] (3) 2,000-2,499 [13.05%] (4) 2,500-2,999 [11.14%] (5) 3,000-3,499 [9.24%] (6) 3,500-3,999 [10.26%] (7) 4,000-4,999 [11.14%] (8) >5,000 [11.00%]
	Homeowner	{0,1}	-	(0) Not owning any property [57.18%] (1) (Co-) owns a residential property [42.82%]
	Region	{1,2,3}	One binary variable per group (three discrete categories), with one omitted as reference category.	(1) Urban [37.39%] (2) Suburban [35.04%] (3) Rural [27.57%]
Living conditions	Home office	{0,1}	{1,2,3,4,5} survey to {0,1} binary transformation	(0) Working from home ≤ 1 day per week [61.14%] (1) Working from home >1 to 5 days per week [38.86%]
	Electric heating	{0,1}	-	(0) No electric heating [85.19%] (1) Electric heating [14.81%]
	Electric warm water	{0,1}	-	(0) No electric warm water [70.38%] (1) Electric warm water [29.62%]
Other	Outage experience (frequency)	{0,1}	Binary transformation of five classes	In the last three years: (0) No blackout experience [37.54%] (1) Any blackout experience [62.46%]

[a] Value range in the statistical model after transformations.
[b] Relative shares in square brackets.

example, the compensation coefficient is modeled as

$$\widetilde{\beta}_n^{\text{comp}} = \beta_n^{\text{comp}} + \delta^{\text{income}} \cdot z_n^{\text{income}}, \tag{4}$$

so that the transformation β_n^{comp} captures diminishing marginal utility of money while allowing the normal taste coefficient to vary with income.

In the free-choice stage, respondents decided whether to accept their previously selected interruption tariff or to reject it by choosing the none-option. Systematic heterogeneity was incorporated via the alternative-specific constant. Utilities are specified as:

$$V^{\text{free}}_{n,\text{taketariff},t} = \mu_{\text{accept},n} \beta_0^\top X_{j(t),t} + \alpha_0 + \gamma^\top z_n, \tag{5}$$

$$V^{\text{free}}_{n,\text{none},t} = 0. \tag{6}$$

Here $j(t)$ denotes the forced-choice alternative carried into the free-choice task, $\mu_{\text{accept},n}$ is a random scale factor, and $\alpha_0 + \gamma^\top z_n$ is the alternative-specific constant for accepting the tariff with covariate interactions. Note that $\mu_{\text{accept},n}$ multiplies the *base tastes* (population means) to avoid double-counting covariate shifts across stages. The model structure is summarized in Figure 2.

3.4.2. Latent Class Model

While the mixed logit (MIXL) model captures continuous preference heterogeneity through random parameters, it assumes that tastes vary smoothly across individuals according to a pre-specified distribution. In many applications, however, heterogeneity may instead arise from distinct subgroups of respondents with systematically different but internally consistent preferences. To complement the continuous representation of the MIXL and to identify such behaviorally meaningful segments, a Latent Class Model (LCM) was estimated. The LCM assumes that the population consists of a finite number of unobserved (latent) segments, each characterized by its own set

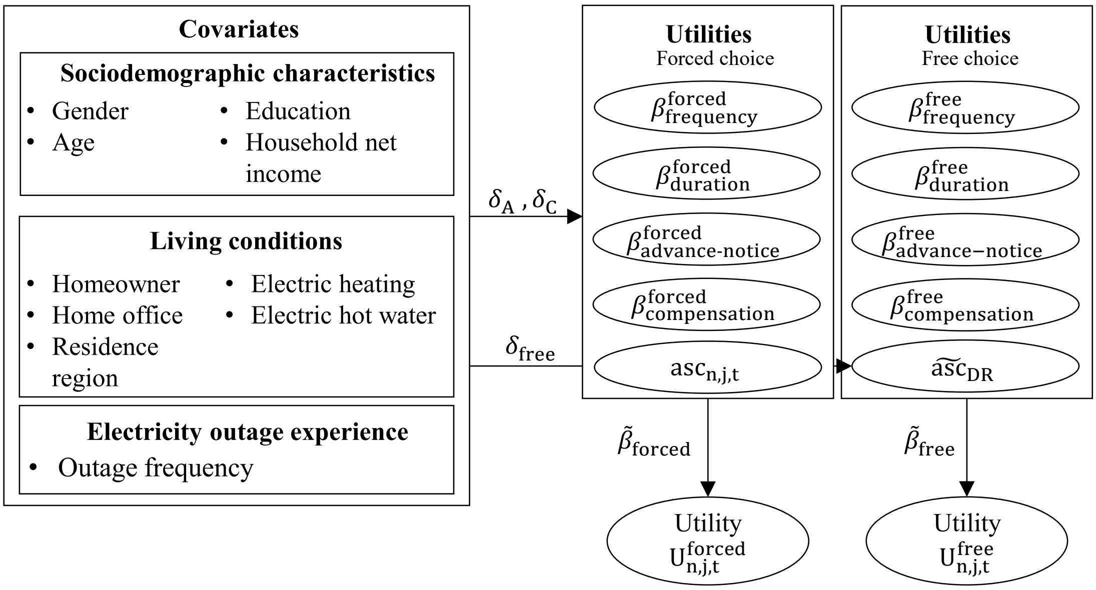


Figure 2: Structure of the joint MIXL model. Sociodemographic and contextual covariates z_n interact with random coefficients β_n and alternate-specific constants (e.g. $asc_{n,j,t}$) to form individual-level utilities for the forced and free-choice stages.

of preference parameters. This discrete representation provides an interpretable segmentation of respondents and allows class membership probabilities to be related to observable sociodemographic and contextual characteristics.

Each respondent n faces a series of choice tasks $t = 1, \dots, T_n$, choosing among J alternatives j. Conditional on class membership s, the utility of alternative j in task t for respondent n is specified as

$$U_{n,j,t|s} = \beta_s x_{n,j,t}^\top + \varepsilon_{n,j,t}, \tag{7}$$

where $x_{n,j,t}$ is a vector of observed attributes (frequency, duration, advance notice, and compensation), β_s is a vector of class-specific taste parameters, and ε_{njt} is an extreme-value error term. Within each class, this yields a standard multinomial logit (MNL) choice probability:

$$P_{n,j,t|s} = \frac{\exp(x_{n,j,t}^\top \beta_s)}{\sum_{k=1}^J \exp(x_{n,k,t}^\top \beta_s)}. \tag{8}$$

Given panel data, the joint probability of respondent n's sequence of choices, conditional on class s, is:

$$P_{n|s} = \prod_{t=1}^{T_n} P_{n,j(t)|s}, \tag{9}$$

where $j(t)$ denotes the chosen alternative in task t. Class membership probabilities are modeled using a multinomial logit specification, with one class normalized as the reference group:

$$\pi_{n,s} = \frac{\exp(z_n^\top \gamma_s + \delta_s)}{\sum_{r=1}^S \exp(z_n^\top \gamma_r + \delta_r)}, \tag{10}$$

where z_n represents individual-specific covariates (gender, age group, education, income, home office, home ownership, and electric heating), γ_s are the corresponding coefficients, and δ_s are class-specific intercepts. Positive $\gamma_{k,s}$ values indicate that higher values of covariate z_k increase the probability of belonging to class s relative to the reference class.

The unconditional probability of observing respondent n's choices integrates over all classes:

$$P_n = \sum_{s=1}^S \pi_{n,s} P_{n|s}, \tag{11}$$

and the model is estimated by maximizing the log-likelihood:

$$\mathcal{L} = \sum_{n=1}^N \ln(P_n). \tag{12}$$

The LCM was estimated as a joint model covering both the forced choice and the free choice. Alternative-specific constants (ASCs) were included for the choice alternatives, and separate scale parameters (μ_{forced} and μ_{free}) allowed for different error variances between the forced and free choice contexts.

4. Results

This section first presents the descriptive evidence from the dual-response component of the choice experiment, which provides an initial benchmark for respondents' willingness to accept tariff-based interruptions. Section 4.1 reports the contingent valuation results, and sections 4.2 and 4.3 present the model-based analysis of the choice experiment using the MIXL and LCM specifications, respectively.

In the dual-response setup, respondents first selected an alternative in a forced-choice task and were subsequently given the option to reject this alternative in a free-choice stage. Across all observations, 65% of the alternatives chosen under forced choice were also accepted when an opt-out was available. This suggests that respondents preferred the offered tariff to the current situation, in which outages are rare, unplanned, and come without compensation. It further indicates that many households would accept to provide flexibility for certain degree of reduction of security of supply. So H5 is rejected, as the study results show that the majority of respondents do not prefer to maintain the status quo when given the option to opt out.

4.1. Contingent valuation

Respondents were asked to directly state their willingness to pay (WTP) and willingness to accept (WTA) compensation for electricity interruptions lasting one, two, and four hours. This self-assessment provides an initial indication of their perceived monetary value of reliability, before moving on to the choice experiment.

When asked about WTP for short interruptions of up to one hour, 65% of respondents either provided no value or entered zero. This absence of positive WTP values cannot be clearly interpreted. It may reflect either a genuine lack of WTP or simply item non-response. As the outage duration increased, and especially when the framing switched from WTP to WTA, the share of respondents providing specific amounts rose notably. This pattern is consistent with prior research showing that consumers typically demand higher compensation for supply interruptions (WTA) than they are willing to pay to avoid them (WTP) (Frondel et al., 2019). In reliability valuation, this reflects the fact that power supply security is perceived as a quasi-public good (Frondel et al., 2019). As shown in Figure 3, median values remain low for all durations, but mean values are considerably higher, driven by a few large outliers. To maintain clarity, the scale is truncated at 200 EUR per outage. The large gap between mean and median in both WTP and WTA distributions reveals a strong right skew, a common characteristic of contingent valuation data in this context (Frondel et al., 2019; Schubert et al., 2013). The observed skewness and the presence of extreme responses underscore why discrete choice experiments are a valuable complement to contingent valuation. They offer a more structured way to elicit preferences and reduce some of the biases inherent in open-ended stated amounts. Placing a concrete monetary value on WTP and WTA is often an abstract and difficult task for respondents, as many lack precise knowledge of their electricity costs, which can lead to inflated and economically unrealistic WTA values. In practice, such compensation levels would more plausibly be anchored around the grid fee portion of the electricity bill, as it reflects the cost of ensuring security of supply (see section 3.2 for more details of how we tied this into the design of the compensation attribute).

4.2. Joint MIXL Model

We calculated the HIT rate, which measures the percentage of correct predictions in a given dataset, for each model component (Louviere et al., 2000). The model correctly predicts 83.5% of choices in the forced choice task and 89.1% in the free choice task, substantially outperforming the naive model HIT rates of 36.2% and 64.9%, respectively. Additional burn-in may further stabilize posterior means. The model results presented here reflect the model that achieved the best overall fit, with a log-likelihood of −9146, an AIC of 18403, and a BIC of 18796, to reach a balance between model fit and parsimony.

4.2.1. Attributes

The attribute parameters all show the expected signs (see Table 6). The estimates are based on posterior means after 300,000 burn-in iterations. H1 and H2 are confirmed, as an increase in duration and frequency of power shutdowns lead to a reduction in utility. The standard deviations of these parameters (0.688 and 0.349, respectively) indicate substantial heterogeneity in preferences, particularly for duration. For advance notice, the results show a steadily increasing utility with longer warning times, which supports H3, that consumers prefer longer advance notice to plan for and adapt to the power interruption. However, the marginal gains are not uniform across levels: the increase in utility is particularly pronounced when moving from 0.25 h to 1 h and from 1 h to 6 h (approximately +0.73 in each step), suggesting that consumers derive the greatest additional benefit from relatively short extensions of the warning period. Beyond 12 h, the incremental utility gain diminishes substantially, with only a modest increase from 12 h to 24 h (+0.16). This pattern indicates diminishing marginal returns to longer advance notice times, implying that once a sufficient planning window is provided, further extensions become less valuable to respondents. These findings shed further light on intra-day preferences for outage notifications, complementing existing evidence that consumers generally prefer one day to three day-ahead over week-ahead notifications (Meles et al., 2021; Pepermans, 2011; Zemo et al., 2019). The positive coefficient for compensation supports H4: higher compensation increases utility, implying that respondents expect monetary rewards to offset the inconvenience of power interruptions. However, the large standard deviation (1.945) signals strong preference heterogeneity and indicate that some consumers require substantially higher compensation to accept interruptions than others. The left-right effects show that the center option carries a modest positive bias, indicating a small but consistent tendency toward the middle alternative, possibly reflecting a compromise or positioning heuristic in decision-making. The positive mean of the scale parameter (μ_{accept}) indicates that, on average, choices in the free-choice component were less random than those in the forced-choice task. Yet the large standard deviation reveals pronounced heterogeneity, suggesting that some respondents made highly consistent accept/reject decisions while others behaved with greater randomness.

The attribute importance values indicate that respondent's tariff choices are primarily driven by the amount of compensation, followed by the frequency and duration of power interruptions, and lastly by the advance notice period (see Table 7). In the forced-choice component, compensation exhibits the highest median importance (39.7%), confirming its

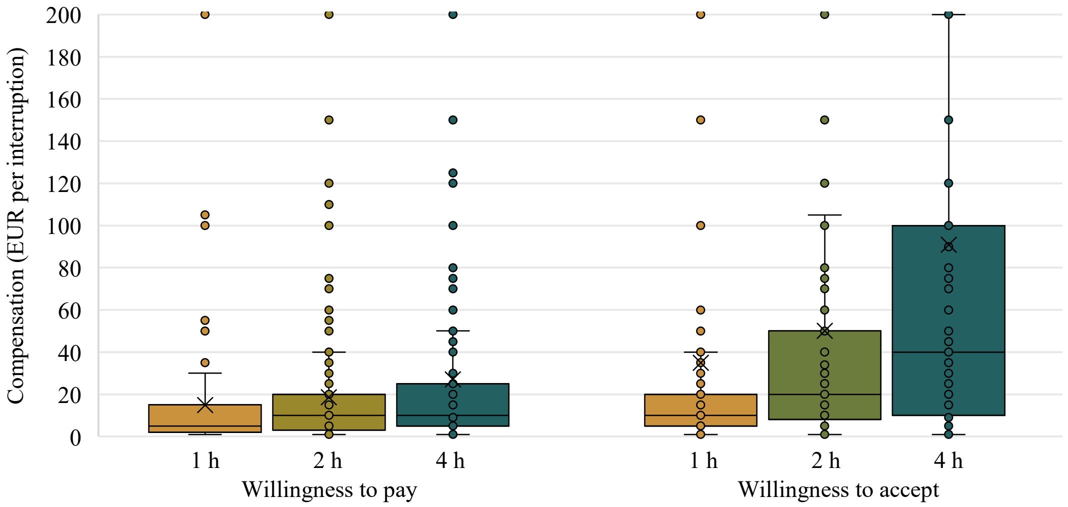


Figure 3: Self-assessed willingness to pay (WTP) and willingness to accept (WTA) compensation for power outages of different durations. Zero and non-responses are excluded to highlight the variation in positive valuations.

Table 6: Results for the parameters of the joint MIXL.

		Posterior means		Distributions	
Attribute	Level	post μ	post σ	post μ	post σ
Frequency	2, 4, 8	-0.462^{***}	0.026	0.349^{***}	0.017
Duration	1h, 2h, 4h	-0.846^{***}	0.054	0.688^{***}	0.035
Advance notice	0.25h (reference)	–	–	–	–
	1h	0.764^{***}	0.110	0.876^{***}	0.082
	6h	1.464^{***}	0.102	0.469^{***}	0.080
	12h	1.880^{***}	0.099	0.704^{***}	0.083
	24h	2.036^{***}	0.128	0.997^{***}	0.083
Compensation	$0.1D_{\mathrm{el}}$, $0.15D_{\mathrm{el}}$, $0.247D_{\mathrm{el}}$	1.390^{***}	0.097	1.945^{***}	0.104
Left–right effects	Left	0.072	0.048	0.432^{***}	0.059
	Center	0.217^{***}	0.048	0.369^{***}	0.054
	Right (reference)	–	–	–	–
μ_{accept}	Free choice scale factor	1.153^{***}	0.108	1.442^{***}	0.111
Free choice	Take tariff (asc)	0.243	0.3578	–	–

$p < 0.10 :\ +$, $p < 0.05 :\ *$, $p < 0.01 :\ **$, $p < 0.001 :\ ***$; based on equal-tail 95% credible intervals and two-sided posterior tail probabilities.

dominant role in shaping preferences. Interruption frequency ranks second (23.8%), followed by duration (16.6%) and advance notice (13.7%). In the free-choice component, this prioritization remains broadly consistent. Compensation again dominates (39.1%), while duration gains in relative importance (20.9%), approaching frequency (22.2%) but without surpassing it. These results suggest that respondents value compensation and the direct reliability impacts of interruptions (duration and frequency), regardless of whether participation is framed as a forced or voluntary decision.

Table 7: Attribute importances in percentage across respondents by model component based on individual-level part-worth utilities after (Orme, 2002).

Component		Frequency	Duration	Advance notice	Compensation
Forced choice	Mean	25.4	18.3	16.1	40.2
	Median	23.8	16.6	13.7	39.7
Free choice	Mean	23.7	21.4	15.7	39.2
	Median	22.2	20.9	13.2	39.1

The empirical distributions of individual attribute importances in Figure 4 further confirm this pattern. The cumulative distributions of the forced and free choice components almost entirely overlap, indicating very similar relative preferences across both contexts. Respondents appear to have applied a consistent internal trade-off structure when evaluating tariffs under forced-choice and free choice conditions.

4.2.2. Covariates analysis

To better understand sources of preference heterogeneity, we examined interactions between sociodemographic and contextual covariates and the model's main attributes in Table 8. No significant interaction effects were found for gender, suggesting that preferences for outage attributes are broadly similar across male and female respondents. Older respondents are significantly more inclined to keep the chosen tariff compared to younger respondents. This age effect is consistent with previous studies (i.e. Broberg and Persson (2016) and Lehmann et al. (2022)), which find that older respondents tend to express a higher utility for accepting and providing flexibility. At first this result may seem unintuitive, as older people tend to be more cautious with adopting new technologies Berkowsky et al. (2017). One possible explanation could be that older people may have routines that rely less on electricity or are more flexible, as they often spend more time at home (Gram-Hanssen et al., 2025; Kessels et al., 2016). For education, the interaction with advance notice is positive and significant: respondents with higher education derive more utility from longer advance-notice periods. This likely reflects a greater ability or willingness to make use of information to prepare for outages, and possibly higher expectations for predictability and service quality. The negative interaction between income (mean-centered) and compensation indicates that the marginal utility of monetary compensation decreases with increasing income. Respondents with lower incomes value compensation more strongly, whereas for higher-income respondents, the effect of compensation is attenuated. Homeowners exhibit significantly higher disutility for

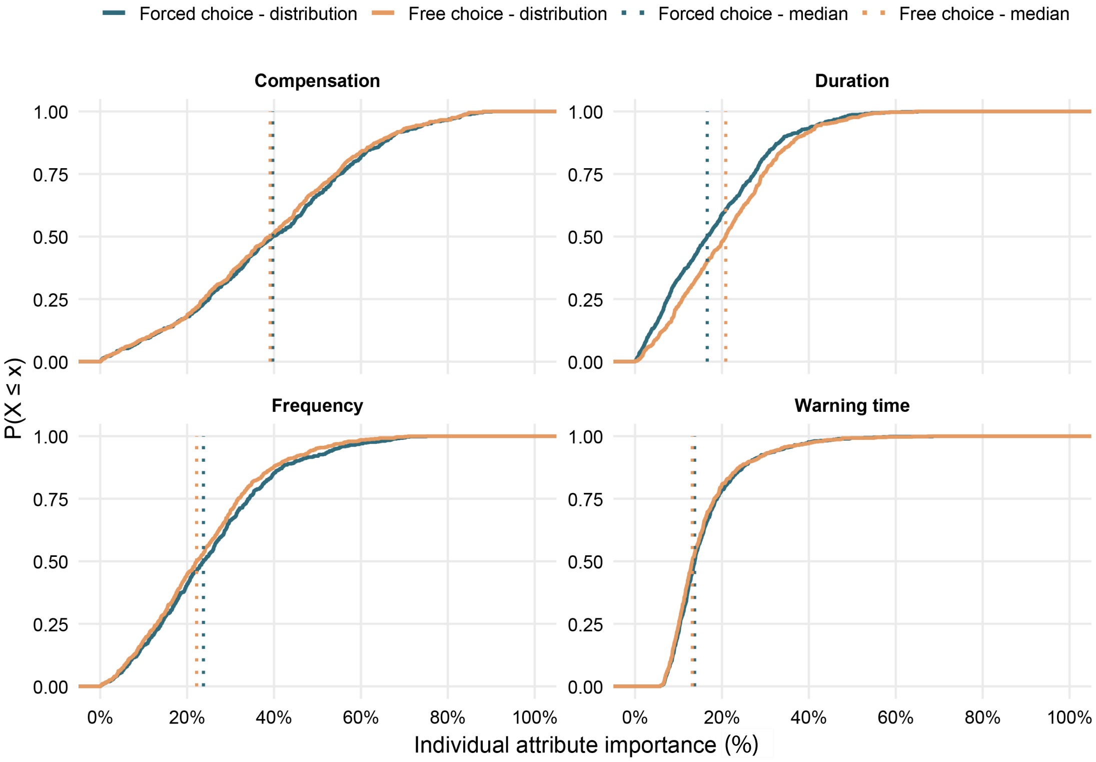


Figure 4: Empirical distribution of individual attribute importances for the forced and free choice components.

longer outage durations than non-owners. A plausible explanation may be their higher exposure to infrastructure-related risks and costs, since they bear full responsibility for their property. Respondents who work from home are significantly more likely to retain the offered tariff. A plausible explanation, consistent with prior research, is that increased home presence provides greater temporal flexibility for organizing electricity-using activities. Studies of home-based work suggest that remote workers often develop more adaptable daily routines and exercise greater control over appliance use, facilitating shifts in energy consumption when needed (Hampton, 2017; Stikvoort et al., 2025). Similar patterns were observed during the COVID-19 pandemic: in an incentivized household flexibility pilot, participants who spent most of their time at home due to the lockdown in Germany in 2020 demonstrated substantial adaptability, even complying with relatively demanding load-shifting requests regardless of economic or non-economic incentives (Bosen & Thurau, 2021; Scharnhorst et al., 2021). For urban residents, the interaction with 12 h advance notice is negative indicating that while they still value longer warning times, the increase in utility from additional advance notice is smaller compared to rural respondents. This may reflect greater infrastructure redundancy and shorter recovery times in urban areas, reducing the relative benefit of extended notice periods. Respondents with electric heating are less sensitive to outage duration, but their disutility increases for longer warning times, which may reflect concern about heating system recovery after the outage or the discomfort of anticipating outages. Finally, previous blackout experience strongly predicts tariff preferences indicating that respondents with firsthand experience of prolonged outages are markedly more reluctant to accept new or uncertain tariff arrangements, even when compensation is offered.

4.3. Latent Class Model

The latent class model identifies three distinct groups of respondents that differ systematically in their preferences for the attributes of the controlled outage tariffs. The estimated class membership probabilities indicate that approximately 46% of respondents belong to class I, 31% to class II, and 23% to class III.

Several model specifications were tested to ensure robustness. Different transformations of the attribute variables (dummy-coded, linear, and logarithmic) were compared, as well as alternative numbers of latent classes. The three-class specification reported here achieved the best balance between model fit and parsimony, with substantial improvements in the log-likelihood, AIC, and BIC relative to simpler models, showing a log-likelihood of −9817, AIC 19724, and BIC of 20071. A four-class model was also estimated but collapsed back into three classes due to singular convergence, indicating that an additional segment was not empirically supported.

As Table 9 indicates, class I members display comparatively weak aversion to more frequent or longer interruptions. These

Table 8: Sociodemographic characteristics and living conditions interacting with model components.

	Sociodemographic characteristics					Living conditions					Other
Attribute	δ_{Gender}	$\delta^{a}_{\text{Age (middle)}}$	$\delta^{a}_{\text{Age (older)}}$	$\delta_{\text{Education}}$	δ_{Income}	$\delta_{\text{Homeowner}}$	$\delta_{\text{Homeoffice}}$	$\delta_{\text{Region (urban)}}$	$\delta_{\text{Region (suburban)}}$	$\delta_{\text{Electric heating}}$	$\delta_{\text{Blackout frequency}}$
Frequency	–	–	–	–	–	–	–	0.026	–0.001	–	–
Duration	–0.019	–0.103	–0.042	–0.104*	–	–0.134*	0.045	–0.014	0.013	0.132+	–
Advance notice	–	–	–	–	–	–	–	–	–	–	–
1 h	–	0.098	–	0.018	–	0.230+	–	–	–0.177	–	–
6 h	–	–0.025	–	0.153	–	–	–	–0.183	–	–	–
12 h	–	0.095	–	0.366***	–	–	–	–0.363*	–	–0.355*	–
24 h	–	0.055	–0.328*	0.228*	–	–	–	–0.242	–	–0.522**	–
Compensation	–	–	–	–	–0.172**	–	–	–	–	–	–
Keep tariff	–0.244	–0.658*	2.252***	–0.531*	–0.290*	–	0.682*	–	–	–	–0.948***

$p < 0.10 :\ +$, $p < 0.05 :\ *$, $p < 0.01 :\ **$, $p < 0.001 :\ ***$; based on equal-tail 95% credible intervals and two-sided posterior tail probabilities.

[a] Age (younger) serves as the reference category.

attributes still lower utility, but to a much smaller extent than in classes II and III. Members of this group are comparatively tolerant of program participation requirements and derive substantial utility from financial compensation. Because compensation enters the model in logarithmic form, the positive coefficient indicates that higher payments increase utility, albeit at a diminishing rate. Overall, class I respondents appear willing to participate, especially when offered a moderate financial incentive. Class II shows the strongest disutility for longer event durations and a pronounced preference for longer advance notice periods, suggesting that members of this class place high value on predictability and convenience. Their sensitivity to compensation is somewhat lower than that of class I, and the alternative-specific constant in the free-choice scenario indicates a neutral stance toward program enrollment. This group could be interpreted as cautious or indifferent participants—interested in maintaining comfort and flexibility but not fundamentally opposed to the program. Class III demonstrates the most negative evaluation of the demand response scheme. Although their sensitivities to individual attributes are less extreme than those of class II, the strongly negative coefficient for the opt-in (free-choice) alternative indicates a clear preference for nonparticipation.

The estimated class-specific constants δ reflect baseline differences in class prevalence relative to the reference class (class III). Positive δ values for classes I and II indicate a higher inherent probability of belonging to these classes compared to the reference group, while holding all covariates constant.

Table 10 presents the estimated covariate effects on class membership. Older respondents are significantly more likely to belong to class I, suggesting a generally more accepting or pragmatic attitude toward participation, possibly reflecting more flexible routines or a greater sense of control over household energy use. In contrast, middle-aged individuals are more likely to fall into class III, indicating stronger resistance to program participation, perhaps due to family-related constraints (e. g., caring for children) or time pressure (e. g., working full-time). Gender is significant for class II, with women being more likely than men to belong to this intermediate group rather than to the opposed group (class III), implying a somewhat more neutral or open attitude toward the program. Working from home and using electric heating both increase the likelihood of belonging to class I, consistent with greater engagement in household energy management and stronger incentives to benefit from participation. The higher the education, the higher seems to be the disutility for belonging to class I. The same indicates a higher income, although for both covariates the effects are barely significant. Similarly, the higher the education of respondents in the study of (Abrate et al., 2016), the less inclined they were to accept an interruption, while (Broberg & Persson, 2016) found the opposite.

These findings reveal a clear segmentation of preferences and participation attitudes. Class I represents likely adopters who respond positively to financial incentives and tolerate moderate participation requirements. Class II consists of indifferent or comfort-oriented participants who value advance notice and short durations but are not strongly opposed. Class III comprises non-participants who are unlikely to engage, regardless of incentives. This segmentation suggests that differentiated program design and communication strategies may improve overall participation, emphasizing convenience and reliability for class II and targeted incentives or reassurance for the skeptical respondents.

5. Conclusion and policy implications

With rising shares of intermittent renewables and electrification, policy measures that incentivize consumer flexibility can help address emerging grid congestion. In principle, direct load control or planned, time-bound interruptions could

Table 9: Latent class model with three classes

Attribute	Across classes	I μ (s.e.)	II μ (s.e.)	III μ (s.e.)
Frequency		-0.18^{***} (0.01)	-0.28^{***} (0.02)	-0.27^{***} (0.02)
Duration		-0.39^{***} (0.03)	-0.59^{***} (0.04)	-0.49^{***} (0.04)
Advance notice 1 h		0.39^{***} (0.07)	0.61^{***} (0.08)	0.58^{***} (0.10)
Advance notice 6 h		0.70^{***} (0.07)	0.99^{***} (0.09)	0.84^{***} (0.10)
Advance notice 12 h		0.81^{***} (0.08)	1.37^{***} (0.11)	0.90^{***} (0.11)
Advance notice 24 h		0.72^{***} (0.08)	1.61^{***} (0.11)	0.99^{***} (0.13)
Compensation (log)		0.82^{***} (0.07)	0.54^{***} (0.06)	0.56^{**} (0.09)
$asc_{\text{Free-taketariff}}$		2.50^{***} (0.19)	0.04 (0.18)	-3.44^{***} (0.25)
$asc_{\text{Free-none}}$		0.00 (Reference)		
δ		0.45^{*} (0.27)	0.77^{**} (0.27)	0.00 (Reference)
$\text{Scalefactor}_{\text{Forced}}$	0.15^{*} (0.07)			
$\text{Scalefactor}_{\text{Free}}$	0.00 (Reference)			
Left	0.07^{*} (0.03)			
Middle	0.12^{***} (0.03)			
Right	0.00 (Reference)			

$p < 0.10$: +, $p < 0.05$: $*$, $p < 0.01$: $**$, $p < 0.001$: $***$
Standard errors in parentheses.

Table 10: Covariate effects on class membership

Covariate	I μ (s.e.)	II μ (s.e.)	III (reference)
Gender (male=1)	−0.24 (0.21)	-0.57^{**} (0.23)	–
Age (mid)	-0.55^{*} (0.27)	-0.44^{+} (0.28)	–
Age (old)	0.70^{**} (0.28)	−0.30 (0.31)	–
Education	-0.23^{+} (0.15)	0.09 (0.17)	–
Income	-0.14^{+} (0.09)	0.00 (0.09)	–
Home office	0.62^{**} (0.23)	0.11 (0.25)	–
Home owner	0.04 (0.23)	0.15 (0.25)	–
Electric heating	0.54^{*} (0.32)	0.03 (0.35)	–

$p < 0.10$: +, $p < 0.05$: $*$, $p < 0.01$: $**$, $p < 0.001$: $***$
Standard errors in parentheses.

provide valuable system flexibility. However, in Germany the limited penetration of intelligent metering systems (only 15% of mandatory locations as of early 2025) and the uneven state of distribution-grid digitization imply that large-scale deployment remains technically and institutionally constrained (FfE, 2025; Monaco et al., 2024). Moreover, empirical evidence on household acceptance of flexibility provision in the form of controlled, time-bound power interruptions remains limited. Therefore, we conducted a survey (N=682) in Germany, to assess a demand side management approach that considers direct load control for timed electricity interruptions at the households level. The survey combined a contingent valuation module with a joint discrete-choice experiment (forced choice followed by free choice). We estimated (i) a joint mixed logit model with hierarchical bayes estimation to capture continuous heterogeneity and (ii) a latent-class multinomial logit model to uncover discrete preference segments. Attributes covered interruption frequency, duration, advance notice, and compensation. The choice set provided a forced choice and a free choice section. The forced choice provided three tariff choices without a status quo (the present case with any compensation for spontaneous blackouts) and the free choice allowed participants to accept the chosen tariff or reject it for the status quo.

5.1. Key findings, implications and future research

Our results show that consumers' choices for a power interruption tariff are mainly driven by financial compensation, followed by the frequency, and duration of the interruptions per month. Advance notice plays a comparatively minor role. Furthermore, acceptance of power interruption tariffs is high: in the free choice stage, respondents accepted the previously chosen tariff in roughly two thirds of tasks, indicating that, given clear conditions and compensation, a substantial share of households would opt into controlled, time-limited interruptions rather than remain with the uncompensated status quo. Rather than aiming for an unattainable level of absolute security of supply, system operators may be able to rely on well-designed interruption schemes as one component of a broader reliability strategy, potentially easing pressure on grid infrastructure investment needs where marginal reliability improvements become disproportionately costly. Beyond alleviating periods of system stress, controlled household interruptions could also support renewable integration, reduce dependence on costly short-term balancing resources such as redispatch, gas-fired electricity generation and reserve capacity, lower system costs, and provide participating consumers with financial benefits through compensation. Moreover, broader participation would allow outages to be distributed across a larger pool of households or tailored to individual preferences, for example, offering higher compensation for those willing to accept more frequent interruptions, or rotating events among participating homes. Consumers prefer shorter and less frequent shutdowns, while longer advance notice raises utility with diminishing gains beyond 12 h. The results for compensation show that respondents prefer higher compensations. There is also pronounced heterogeneity in how respondents evaluate financial incentives. In other words, while most consumers value compensation positively, a nontrivial share are either insensitive to additional payment or require very high compensation to accept interruptions. The latent class model results confirm this diversity. The most likely adopters class (class I) exhibits the strongest responsiveness to compensation, accepting moderate interruptions in exchange for even modest rewards. The intermediate class (class II) values predictability and convenience but still responds to financial incentives, whereas the reluctant class (class III) remains largely unresponsive to compensation, reflecting a fundamental aversion to participating in demand-response schemes. This segmentation implies that while compensation can motivate participation for many, it cannot fully overcome resistance among consumers with entrenched reliability preferences.

The sociodemographic and living condition effects in the mixed logit model and the segmentation from the latent class model jointly reveal groups with different participation propensities. People with higher education value longer notice, higher income dampens the marginal utility of compensation, homeowners dislike longer durations more, and respondents with prior blackout experience are more likely to opt for the status quo. The latent class model identifies three interpretable classes: likely adopters (compensation-responsive), convenience-oriented participants (value notice and short events), and non-participants. Women are more likely to belong to the convenience-oriented participants (class II), while older consumers are more likely to adopt a tariff (class I), as well as people who work frequently from home, or consumers who own a heat pump. The results underline that financial incentives are effective, but only up to a point and not universally. The diminishing returns suggest that once a reasonable threshold is reached, further increases in payment yield limited gains in acceptance. Instead of very high uniform tariffs, utilities could design tiered or performance-contingent compensation schemes that reward actual flexibility events rather than fixed premiums. Differentiated bundles could address varying preferences. For instance, higher payments could be offered for longer and more frequent interruptions, whereas shorter and less frequent events could be paired with longer advance notice and lower compensation. The results overall support targeted rather than one-size-fits-all programs.

Marketing and communication could emphasize predictability for convenience-oriented households, highlight compensation for price-sensitive adopters, and address reliability concerns for skeptics, e. g. with attention to older, female consumers, people who often work from home, or who own a heat pump. Payments could be framed as a "participation bonus" or "flexibility dividend" rather than as "outage compensation" to strengthen the sense of agency and positive engagement, especially among the middle and adopter classes. The described tariff options could be provided as add-ons to the electricity tariffs in months where the electricity providers anticipate system stress such as grid congestion, tight balancing situations (low renewable availability, high expected demand e.g. peak hours, or other situations where short-term[1] flexibility is needed. Finally, pilot studies should be conducted to measure actual acceptance and operational behavior, allowing compensation levels and advance-notice options to be refined before wider roll-out. Any conclusions about system-level impacts should be grounded in these observed participation rates and real operational constraints rather than purely theoretical potential.

Future research could conduct a pilot study with dynamic compensation, examine learning and fatigue over repeated events, assess spillovers to household investments (e.g., battery storage and automation), and track how acceptance evolves with real blackout experience. Furthermore, acceptability can change with time, so the long-term changes in preferences could be an interesting follow-up study.

5.2. Limitations

The findings of this study should be interpreted in light of several limitations. First, because controlled electricity interruptions are largely unfamiliar to household consumers and unplanned outages in Germany are rare and brief, some respondents may not have fully internalized the implications of the design attributes or may have found the number of choice tasks demanding. This potential misunderstanding was mitigated through careful survey design, including clear introductory explanations, visual aids, and interactive information buttons. However, this risk cannot be entirely ruled out (Coast et al., 2012). Second, as in most stated-preference studies, hypothetical bias remains a concern (Lehmann et al., 2022). Respondents were not exposed to real economic consequences, which may have led to overstatement or understatement of willingness to accept certain outage conditions. Although such limitations are inherent to contingent valuation and discrete choice experiments, especially for non-market goods, they warrant cautious interpretation (Beck et al., 2016). This challenge is further amplified in online surveys, where researchers cannot control for environmental distractions or verify participant attentiveness, and where self-selection bias may occur (Mariel et al., 2021). Third, the results capture a snapshot of current preferences among German household consumers. As attitudes toward reliability, risk, and energy systems may evolve with experience, particularly in the context of the ongoing energy transition, the findings should not be extrapolated uncritically to future conditions (Abou-Zeid & Ben-Akiva, 2014). Finally, the sample is nationally confined to Germany, which limits cross-country generalization. Institutional frameworks, reliability norms, and cultural attitudes toward electricity supply vary across Europe, suggesting that replication in other countries would be valuable. Cross-national comparisons could illuminate how contextual and policy differences shape willingness to participate in demand response and load shedding.

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[1] In this study, short-term flexibility refers to advance-notice periods between 24 hours and 15 minutes.

Future research could extend the present analysis by incorporating emerging prosumer characteristics such as electric vehicle ownership, rooftop photovoltaics, battery storage, or home energy management systems to examine whether these groups differ in their sensitivity or resilience to controlled power interruptions. Longitudinal or incentive-compatible experiments could also help validate the robustness of stated preferences under real-world conditions.

6. Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Paper C

Barriers to demand response in the commercial and industrial sectors - An empirical investigation

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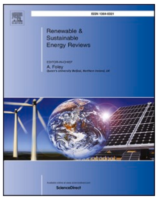

Barriers to demand response in the commercial and industrial sectors – An empirical investigation

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ABSTRACT

Demand response can be an effective mechanism to balance electricity demand and supply. While there is an increasing research interest in demand response for private households, its realistic potential in industrial and commercial sectors remains largely untapped, with limited research on the barriers hindering adoption. This study identifies and examines the barriers in industrial and commercial sectors, shedding light on their significance. We conducted 20 semi-structured interviews with experts from German industrial and commercial companies and national industry associations. The most frequently cited barriers encompass concerns about diminished product quality, disruptions to production processes, human resource management, and revenue uncertainty. Despite some recent industrial participation in demand response programs in Germany, our findings suggest that numerous barriers impede widespread participation, which can partly be explained by the heterogeneity of production processes and facilities. Overcoming these barriers entails bridging knowledge gaps and allocating sufficient resources within an organization. Moreover, adapting external incentives and policies may be necessary to encourage widespread demand response adoption. Recognizing these challenges, alongside the underlying motivations and apprehensions, can guide policy makers in devising strategies to support the adoption of demand response among industrial and commercial consumers.

1. Introduction

To alleviate the effects of climate change, the reduction of greenhouse gas emissions is of central importance [1]. This has led to ambitious targets of greenhouse gas neutrality in national and international agreements and obligations [2]. Emission reduction efforts include a transition to renewable electricity generation and the electrification of energy demand, for example, in the heat and mobility sectors. The ongoing transformation from centralized and predictable electricity generation to more distributed and volatile generation, which is highly dependent on weather conditions, introduces new challenges of balancing electricity demand and supply, especially on a local level [3]. To manage the growing fluctuations in energy supply and demand, demand response (DR) measures are becoming increasingly important. DR measures aim to shift electricity consumption patterns in time or quantity in response to a signal (e.g., a monetary incentive) [4]. They can thus help to balance electricity supply and demand [4,5]. Participation in DR measures can take on different forms. Load shifting describes temporary decreases in electricity consumption by interrupting and rescheduling specific processes or appliances to shift demand in time [6]. Load shedding involves temporary decreases in electricity consumption, but without making up for consumption at a later point in time [7]. Another option is a temporary switch from electricity to other energy carriers, such as natural gas, to decrease power peaks while keeping production processes running [8]. In the following, we refer to the time interval in which a DR measure is applied as a DR event.

The industrial sector is with around 40 % of the total electricity consumption by far the largest consumer worldwide, while the commercial sector ranks third with a world average of around 20 % in 2019 [9]. In Germany, the industry and commercial sector make up 44 % and 27 % of the electricity consumption in 2021, respectively [10]. The high shares in electricity consumption also suggest a high technical DR potential. DR programs in the German manufacturing industry are gaining momentum and, compared to other demand sectors, is already involved in demand response programs, especially to provide ancillary services such as frequency control reserve [11] and interruptible loads [11,12]. However, due to various entry barriers, the actual amount of DR participation is small and falls short of the technical potential suggested by modeling studies, e. g. identified by Gils 2014 [13]. Existing DR participation is mainly limited to energy-intensive industries such as paper manufacturing or aluminum electrolysis [14]. Other industrial or

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Abbreviations

DR	Demand response
C&I	Commercial and industrial
GWh	Gigawatt hours
T	Technological
I	Information
R	Regulatory
E	Economic
B	Behavioral
O	Organizational
C	Competences
NIMBY	Not in my backyard

commercial sectors have received almost no attention so far [15], even though some studies find considerable DR potentials in this sector [13]. Kirkerud et al. [16] also found DR potentials for space heating and ventilation, and Tina et al. [17] further identified DR potentials for air conditioning in commercial buildings.

Harnessing the technical potential of DR in the commercial and industrial (C&I) sectors requires companies to actively participate in DR programs by adequately reacting to DR signals (e.g., monetary signals). Therefore, it is crucial to identify the drivers and barriers to DR program participation. Most research so far focuses on the residential sector, indicating a range of drivers and barriers affecting households' decisions beyond purely economic considerations [18,19]. For example, a recent review of DR enablers and barriers found that most empirical studies focused on residential DR and thus excluded the commercial sector from the review [19]. While companies are assumed to assess the costs and benefits mainly from a financial perspective, it is unclear what (other) factors may play a role in their decision-making regarding DR participation. For example, these other factors could include cultural, regulatory or structural barriers [20,21], or participatory and awareness related barriers [21]. Yet, empirical research on DR barriers in the C&I sectors is scarce. Existing research either focuses on the commercial or the industry sectors, often including other stakeholders to form a market or regulatory perspective. Furthermore, previous present research has focused on discrete barrier dimensions to group the identified demand response barriers, without considering possible interrelations between barrier dimensions. Moreover, while private households share considerable homogeneity regarding their electric appliances, C&I consumers are highly heterogeneous regarding electric appliances, production processes, or regulations. This requires empirical research studying industrial DR barriers in different contexts. To the best of our knowledge, no research so far has conducted interviews with C&I consumers and associations all over Germany to identify new demand response barriers and furthermore accounts for interrelations between barrier dimensions.

This study contributes to the literature in two ways: (1) First, we propose a new taxonomy for demand response barriers in the C&I sector, derived from the recent literature that studied relevant barrier dimensions. On the basis of new empirical data, we assess the relevance of each of the derived barrier dimension. Furthermore, we assess the interrelations between the dimensions, meaning that a specific barrier can relate to multiple barrier dimensions. We thereby extend previous research that conceptualized these demand response dimensions as independent from each other. (2) Second, we extend the empirical basis of previous studies by conducting interviews with not only industry companies, but also commercial companies and C&I associations, some of which have so far not been examined, despite their technical potential. Due to the heterogeneity of C&I sectors, we analyze our data using a hybrid deductive-inductive approach. Specifically, we deduced four overarching barrier dimensions from the previous literature, which we used as a guiding framework for the inductive part of the data analysis. This allowed the flexible identification of new specific barriers present in our sample of 20 semi-structured expert interviews with German[1] C&I companies and associations, and at the same time allowed for a better comparability with the barriers identified in other studies. These barriers are allocated to their respective barrier dimension in a new dimension taxonomy that accounts for interrelations regarding barriers that relate to more than one barrier dimension.

Specifically, we aim to answer the following two research questions (RQ).

(RQ1). *What are industrial and commercial companies' perceived barriers to participate in DR programs?*

(RQ2). *Which dimensions can the identified DR barriers be categorized into, and how are they interrelated?*

The remainder of this paper is structured as follows. Section 1.1 of this study provides an overview of the existing literature on DR barriers in a C&I context and outlines a framework for the assessment of barriers of DR participation, proposing four distinct barrier dimensions in Section 1.2. Section 2 presents our research methods, comprising the recruiting of interview participants, the interview structure, and data analysis. Section 3 comprises the results, specifically the barriers identified in the interviews. Section 4 then discusses these results in light of related studies. Section 5 concludes with a summary of the findings and suggestions for practitioners and policy makers to encourage future participation in DR programs.

1.1. A review of demand response participation and barriers in the commercial and industry sectors

A growing body of literature assesses the benefits and challenges regarding the uptake of DR in the C&I sectors. However, the vast majority of these studies adopt a technical or utility perspective [22]. For example, DR benefits and challenges are discussed from a systems perspective for the UK by Strbac [23] and for Finland by Annala et al. [24]. By contrast, Murthy Balijepalli et al. [25] perform a literature review from a smart grid perspective, while Good et al. [26], as well as Nolan and O'Malley [27] classify barriers and enablers regarding DR in this context. Other studies take on a technical perspective and identify industries with high potentials for DR [e.g., 28] or provide an overview of DR enabling technologies, DR types, and the present state of existing international DR programs [e.g., 29]. Gils [13] identifies a technical DR potential of 25 GW in industry and 31 GW in the tertiary sector in Europe. As Dranka and Ferreira [30] show in their review and assessment of DR potential categories, technical DR potential is only one part towards reaching the realistic potential. The latter considers the level of acceptance regarding DR interventions by consumers, which is necessary to realize a successful implementation of DR programs in practice [30,31]. Nonetheless, studies that take on the DR consumer perspective are so far underrepresented. This is especially true for C&I consumers (as opposed to private consumers) [19].

Going beyond purely technical assessments of DR potential, some initial studies have investigated the barriers that C&I companies might face when it comes to DR participation. Most (though not all) of this work is qualitative and indicates a variety of potential barriers to participation that are described and categorized in different ways. Grein and Pehnt conduct personal and phone interviews with plant operators, research institutes, equipment manufacturers, industry associations, and the statistical offices and administrations in the German city of Mannheim to analyze the DR potential of refrigeration systems, as well as perceived barriers toward participation in DR [32]. Overall, they identify legal, informational, and organizational barriers in addition to

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[1] By focusing on Germany, this study accounts for the regulatory framework of one specific country.

technological and economic barriers. The first comprehensive approach regarding the manufacturing industry provide Olsthoorn et al. [33] who examine the industry's perspective by conducting a survey on DR barriers in Southern Germany. In their survey, Olsthoorn et al. distinguish technological, informational, regulatory, economic, behavioral, organizational, and competency barrier dimensions [34].

Cardoso et al. are the first to provide an overview of DR barriers in the commercial sector as a whole [31]. They conduct a literature review on DR barriers by taking on theoretical perspectives from orthodox economics, behavioral economics, organizational perspectives, and social practice theory as a categorization method. They find that a company's small electricity loads combined with a complex internal decision-making process can impede DR adoption and cite hidden costs of participation, issues of bounded rationality and the actual end-use of electricity within the company as identified DR barriers.

A further empirical study by Alcázar-Ortega et al. presents findings from comprehensive stakeholder interviews that adopt a market and regulatory perspective [35]. Based on their interviews, these authors identify and weigh 34 barriers to DR implementation, including regulatory and economic barriers as the most significant barriers. Lashmar et al. [36] present an empirical investigation explicitly focusing on the consumer perspective of C&I companies. Their interview study focuses on C&I companies in Australia that had already enrolled successfully in DR programs [36]. They find that financial benefits are a primary motivation for participation but few consumers associate DR participation with the benefits of providing balancing services to the system and managing intermittent renewable energy generation. Lashmar et al. conclude that with a growing investor focus on the energy transition, communicating these non-financial benefits could be used as an opportunity to stimulate participation [36]. More recently, Leinauer et al. [37] conducted 16 interviews focused on obstacles to DR faced by industrial companies in Germany. They identify the risk of production process disruption, insufficient revenues and cost savings, legislative contradictions, as well as missing IT standardization and interoperability as the main barriers in their case study. Furthermore, Alasseri et al. [38] underline the factor of regionality in their review of implementation strategies for DR in Kuwait and highlight the need for a study on barriers for DR implementation on a national level.

Several observations can be made about the present literature on DR barriers. Some early studies on DR barriers consist of literature reviews [31] or surveys [33] and do not use interviews to get information about perceived barriers to DR adoption [36]. Surveys often ask for a rating of a given set of options (in this case, different DR barriers) [33] and therefore lack the ability to identify new barriers [36]. Furthermore, due to the lack of an established taxonomy on DR barriers, the early studies on DR barriers draw from the literature on energy efficiency (e.g., Cagno et al. [34] and Sorrel et al. [39]). Although DR and energy efficiency are both part of a company's energy management, there are inherent differences between the two concepts, suggesting that barriers on energy efficiency may not directly apply to DR adoption [36]. Studies that use an empirical approach did not specifically focus on consumers, but also interviewed other stakeholders, such as grid operators, aggregators, retailers, and others not directly belonging to the category of consumers [15,24,35,36]. Studies that conduct interviews focusing specifically on consumers find new barriers, e.g., in the household, industrial, or commercial sectors, thus helping to improve the understanding of DR barriers for consumers [36,37,40–42]. More recent studies, such as Lashmar et al. [36] or Leinauer et al. [37], provide a holistic approach for Australia and Southern Germany, and the C&I or industry sectors, respectively. As regulations and DR programs may differ significantly between countries, these are likely to considerably impact the perceived DR barriers of a study. Furthermore, focusing on companies already participating in DR neglects companies that are holding back on DR participation due to the barriers in question. In summary, barring a few initial studies, research on the barriers to DR in the C&I sectors is still scarce. We therefore build upon the findings of the studies cited in the preceding paragraph. Our study takes both the commercial and the industrial (i.e., manufacturing) sectors into account by presenting interview findings from 20 representatives from companies and national industry associations in Germany. Based on these interviews, 16 barriers to DR participation were identified, thus broadening the so far scarce literature on factors that impede DR program participation from the perspective of C&I consumers.

1.2. Towards a common framework of demand response barrier dimensions

This study proposes a framework comprising four DR barrier dimensions based on the existing literature with its different attempts to identify and classify barriers to DR participation, as presented in Table 1. The work of Lashmar et al. [36] distinguishes between economic (and market/regulatory), technical, social, and behavioral barriers derived from Good et al., who provide a review and classification of DR barriers from a smart grid perspective [26]. Similarly, Olsthoorn et al. [33] organize their identified barriers into seven dimensions (see Table 1). Leinauer et al. [37] use the same barrier dimensions as Olsthoorn et al. [33] and Cagno et al. [34]. The elaborate barrier dimensions presented by Olsthoorn provide a good overview of different barrier categories. This study proposes similar barrier dimensions, yet group the behavioral and competence barriers into the organizational barrier dimension, since these barriers are inherent to the commercial organization that consists of individuals working together [26]. Informational barriers are also mostly inherent to the organizational dimensions, as individuals make decisions within an organization based on the information that they possess at a certain point in time. This leads to a more parsimonious taxonomy of barrier dimensions comprising (i) economy, (ii) technology, (iii) policy, and (iv) organization. These dimensions are used to identify and categorize the barriers mentioned by our interview participants and briefly describe each dimension.

The first dimension *Economy* comprises costs, such as transaction costs or hidden costs and (uncertain) revenues of DR participation [26]. Lashmar et al. find DR barriers such as additional cost, comprising, among others, idle labor, wear and tear on equipment, and updating control systems [36]. Furthermore, both Cardoso et al. and Olsthoorn et al. emphasize the critical role that predictable cost play and that these costs can vary significantly between companies [31,33]. The *Technology* dimension captures risks considering the safe and functioning operation of (production) processes. Olsthoorn et al., as well as Leinauer et al., identify in their study that technical risk is a barrier to DR adoption [33]. Other DR barriers in this dimension comprise the risk of lower product

Table 1
Existing DR barrier dimensions used in literature.

Barrier Dimension/ Study		T	I	R	E	B	O	C
Olsthoorn et al.	[33]	x	x	x	x	x	x	x
Leinauer et al.	[37]	x	x	x	x	x	x	x
Lashmar et al.	[36]	x		(x)	x	x		
Good et al.	[26]	x		x[a]	x	(x)	(x)	
Cardoso et al.	[31]				x[b]	x[b]	x[b]	
This study		x	(x)	x	x	(x)	x	(x)

T: Technological I: Information R: Regulatory E: Economic.
B: Behavioral O: Organizational C: Competences.
x: Barrier dimension applied in study.
(x): Barrier dimension applied as sub-dimension of another barrier dimension.

[a] Not belonging to the fundamental barriers, but the secondary barriers, presented in their study (these further include: market structures, physical, and understanding barriers) [26].

[b] Cardoso et al. do not specify the dimensions above in their study, but draw their conclusions from different theoretical lenses [31]. We assigned the perspectives and conceptual barriers of Cardoso et al. to the above dimensions: O:"organizational perspectives", E:"cost related barriers", B:"behavioral economics".

quality, high effort, and complexity within IT systems, lack of computational capacity, or technical infeasibility of peak load reduction according to findings of Leinauer et al. [37]. The *Policy* dimension represents barriers identified on the regulatory level, which are barriers emerging from government policies, usually implemented via regulation [26].[2] Leinauer et al. specify regulatory DR barriers from literature, as well as their case study in Germany, highlighting the existence of complex, restrictive or contradictive regulatory frameworks and further identifying barriers such as prioritization of energy efficiency measures, high costs and effort for prequalification or globally heterogeneous legislation [37]. Barriers relating to internal organizational processes that need to be managed are accounted for in the *Organization* dimension. In addition to behavioral, competence-related, and informational barriers, following Sorell's identification, two main organizational barriers can be allocated to this dimension [26]: culture and power [43]. Lack of power relates to a person's inability to implement a DR program in their organization, e.g., by training staff or providing the necessary technology [26]. Linked to power is the culture barrier, meaning the prevailing company culture [26], that may hinder the adoption of DR if the company's values do not align with seeing participation in DR as important. Similar to Leinauer et al. [37], we account for the interdependencies and relations of barriers between dimensions so that one barrier may be categorized into more than one dimension.

2. Method

This study examines the role of drivers and barriers of DR participation. The empirical analysis is based on 20 semi-structured interviews with representatives of C&I companies and associations in Germany. Section 2.1 provides information on the sample characteristics, followed by Section 2.2 detailing the interview structure. Section 2.3 outlines the data analysis.

2.1. Sample characteristics

Participants were recruited in two stages. First, 23 German industry and commercial sector associations were contacted, asking whether experts from their association were willing to participate in an interview. Second, the associations were asked to forward our interview request to companies that were members of the respective association. Overall, 20 interviews were conducted, including eleven interviews with representatives of C&I companies and nine with interviewees from C&I associations. The interviews can be categorized into the following eight C&I sections from the German federal statistical office [44] (see Fig. 1).

Since experts from the respective C&I sectors were contacted, most participants were division managers of either energy procurement, climate protection, resources or circular economy. In six cases, the managing directors of the respective company or association participated in the interviews (see Fig. 2).

In contrast to Lashmar et al. [36], more than half of the companies in this study already provided flexibility at the time of the interviews, one company had been providing flexibility in the past, and three companies did not provide flexibility, with one having examined the option and decided against it afterwards (Fig. 3).

Regarding the companies that partake (or had partaken in one case) in flexibility provision, six companies provided balancing power for the secondary control reserve and one company for the tertiary control reserve, as shown in Fig. 4.

In addition to participation in the balancing power market, Fig. 5 visualizes that one company provided interruptible load, a second had been pre-qualified and about to participate, while seven companies did not participate in this flexibility option [12].

2.2. Interview structure

The interviews took between 30 and 60 min and were conducted via video calls due to COVID-19 travel and contact restrictions during that time. The interviews' audio was recorded after written consent was obtained from the participants. We used a semi-structured interview method in order to both cover relevant aspects of DR participation but also to allow participants to express their own ideas and views regarding specific DR potentials and barriers [45]. The interview guideline was structured into three sections: In the first section, the interviewees were asked to introduce themselves, identify their field of work, and provide some general information about their companies' energy use and whether they were already participating in DR programs. The second section focused on questions about processes and technologies that could potentially provide flexibility, accounting for the technological and, if applicable, economic barrier dimensions. The third section assessed potential difficulties regarding participation in the DR program by assessing economic, political, and organizational barriers in more detail. The interviews closed with open questions about further barriers.

2.3. Data analysis

The audio recordings of the interviews were transcribed using the software *f4transkript* [46]. Subsequently, the transcribed interviews were coded by using a hybrid inductive-deductive approach to identify the different DR barriers [47]. The hybrid inductive-deductive approach is a method used in qualitative content analysis. Relevant aspects (e.g., mentioned barriers to DR) are denoted as categories of a content analytic category system and text passages are allocated to this category system [47].

Fig. 6 details the process of the inductive-deductive approach. The deductive part of the analysis consisted of a pre-defined category system that was derived theoretically, in this case the barrier dimension framework. The specific barriers mentioned by the interview participants were then formed inductively and allocated to one or more dimensions [47]. In other words, the theoretically derived barrier dimensions from the literature (organizational, political, economic, and technological) were used as an a priori coding structure. The coding process consisted of analyzing the transcript regarding these barrier dimensions, subsequently identifying and defining specific barriers that could be connected to them. During this process, all text passages were coded. More specific sub-codes for individual barriers were inductively derived during the coding process to precisely differentiate between the barriers mentioned by the interviewees [49]. In the last step of the analysis, the identified barriers were analyzed and interdependencies between barrier dimensions were documented. Specifically, we examined what barriers were identified across C&I companies and associations and how they related to their respective barrier dimension.

3. Results

In this section, the barriers identified by the interviewees are presented and assigned to the barrier dimensions derived from the literature, taking into account interdependencies and relations to other dimensions. This is followed by the assessment of the most frequently identified barriers across C&I associations and companies.

3.1. Demand response barriers: identification and categorization

Overall, our analysis identified 16 barriers to DR participation. Table 2 presents the barriers and provides a short definition in which context the barrier was mentioned by the interviewees. Furthermore, this study organizes the identified barriers according to the overarching barrier dimensions policy, technology, economy, and organization (see

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[2] Since this study focuses on German companies and associations, the barriers in the policy dimension have to be interpreted in the context of German legislation.

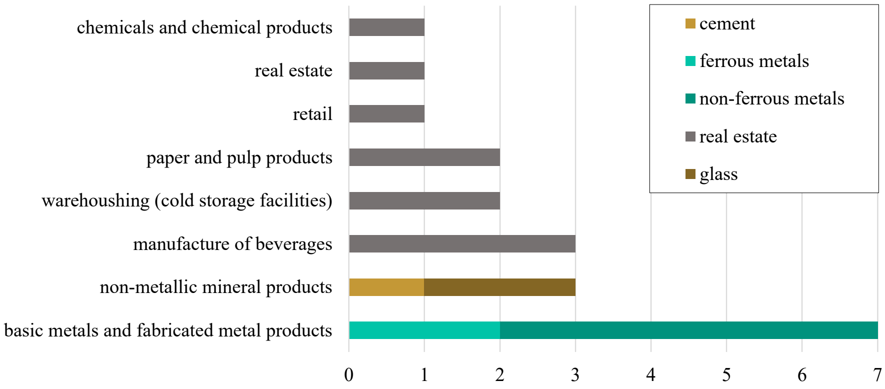

Fig. 1. Number of interview participants sorted by industry branch and distinctive products.

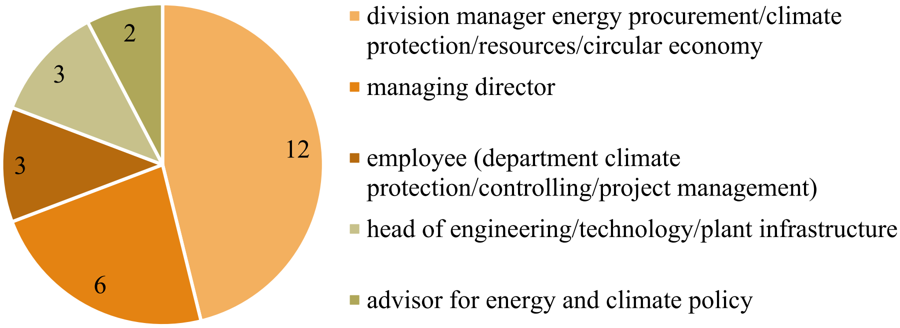

Fig. 2. Classification of interview participants by job description.

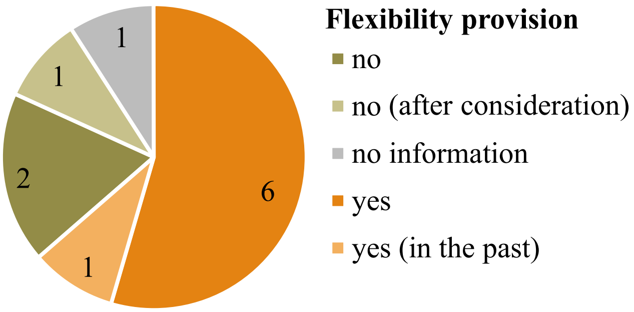

Fig. 3. Number of interview participants representing a company that already partake in demand response programs.

Fig. 7). As some DR barriers are related to more than one overarching dimension, we use a Venn diagram instead of discrete categories to visualize the interrelations between the dimensions.

Some of the specific barriers could be uniquely allocated to one overarching barrier dimension. The barriers equipment wear and up-/downstream processes are distinct technical barriers, directly linked to the risks regarding the safe and functioning operation of production processes during a DR event. The barriers concerning profitability and supply contracts were allocated to the economy dimension, which represents underlying cost and revenue uncertainties. The organizational dimension comprises barriers that need to be overcome within a company in order to participate in a DR program. Both a reluctance to accept third-party control and a general lack of acceptance are barriers mentioned by several interviewees that are uniquely connected to the organizational dimension. The first involves an aversion to giving up autonomy over production processes in case of a DR event that requires production to be ramped up or down for a certain period. A general lack of acceptance can have a multitude of reasons, which are described in more detail in Section 3.2. No barriers were identified that solely belong to the policy dimension, regarding the barriers regulatory complexity and regulatory restrictiveness. This can be explained by the fact that a multitude of barriers is related to more than one barrier dimension.

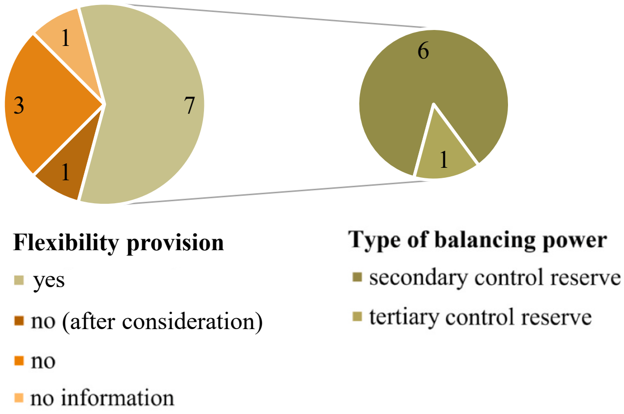

Fig. 4. Number of interview participants representing a company that participates in demand response by providing balancing power in the secondary or tertiary control reserve.

While we did not find barriers solely related to the policy dimension, regulatory complexity emerged as one barrier in the shared space between organization and policy. This barrier refers to the organizational cost of allocating human resources to questions regarding the regulatory

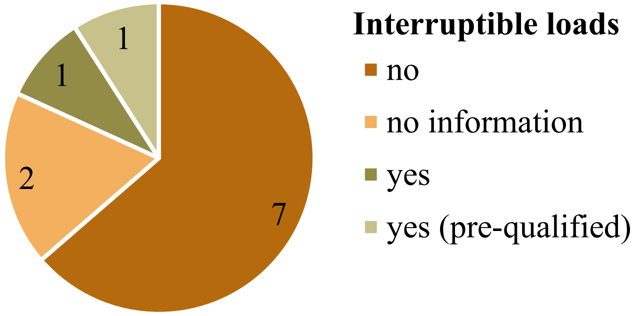

Fig. 5. Number of interview participants providing interruptible loads.

framework for DR implementation. The overlap between the two dimensions indicates that the issue is not about a general lack of clear regulations or policies allowing the participation in DR, but about these regulations often being complex and thus requiring a significant amount of organizational capacity to manage them. A similar issue arises for regulatory restrictiveness that refers to conflicting or contradicting regulations which may result in financial disadvantages if a company decides to participate in DR. The German regulatory framework, for example, stipulates that energy-intensive companies (i.e., those with more than 10 GWh of electricity consumption per year) only receive a reduced grid fee if their electricity consumption is constant (i.e., 7000 full-load hours per year). Several interview partners remarked that their eligibility for the reduced grid fee might be contradictory with participation in DR events, as the latter would require greater fluctuations in consumption to react to DR events. Similarly, in the case of atypical grid usage, a company's peak consumption may not fall within a time window specified a-priori by the local grid operator [50]. However, participating in DR programs may entail short-term load shifting or load shedding, possibly breaching the legal threshold for individual grid fees.

Some barriers were related to both the technological and economic dimensions. This included, for example, the interviewees' concerns about product quality, which could arise from non-optimal temperatures at certain production steps, resulting in deviations from specified standards. Product quality is also related to economic concerns, as a deviation from specified standards can result in products unsuitable for selling or breaching supply contract specifications, which can again result in monetary penalties. Furthermore, the risk of a loss in production was

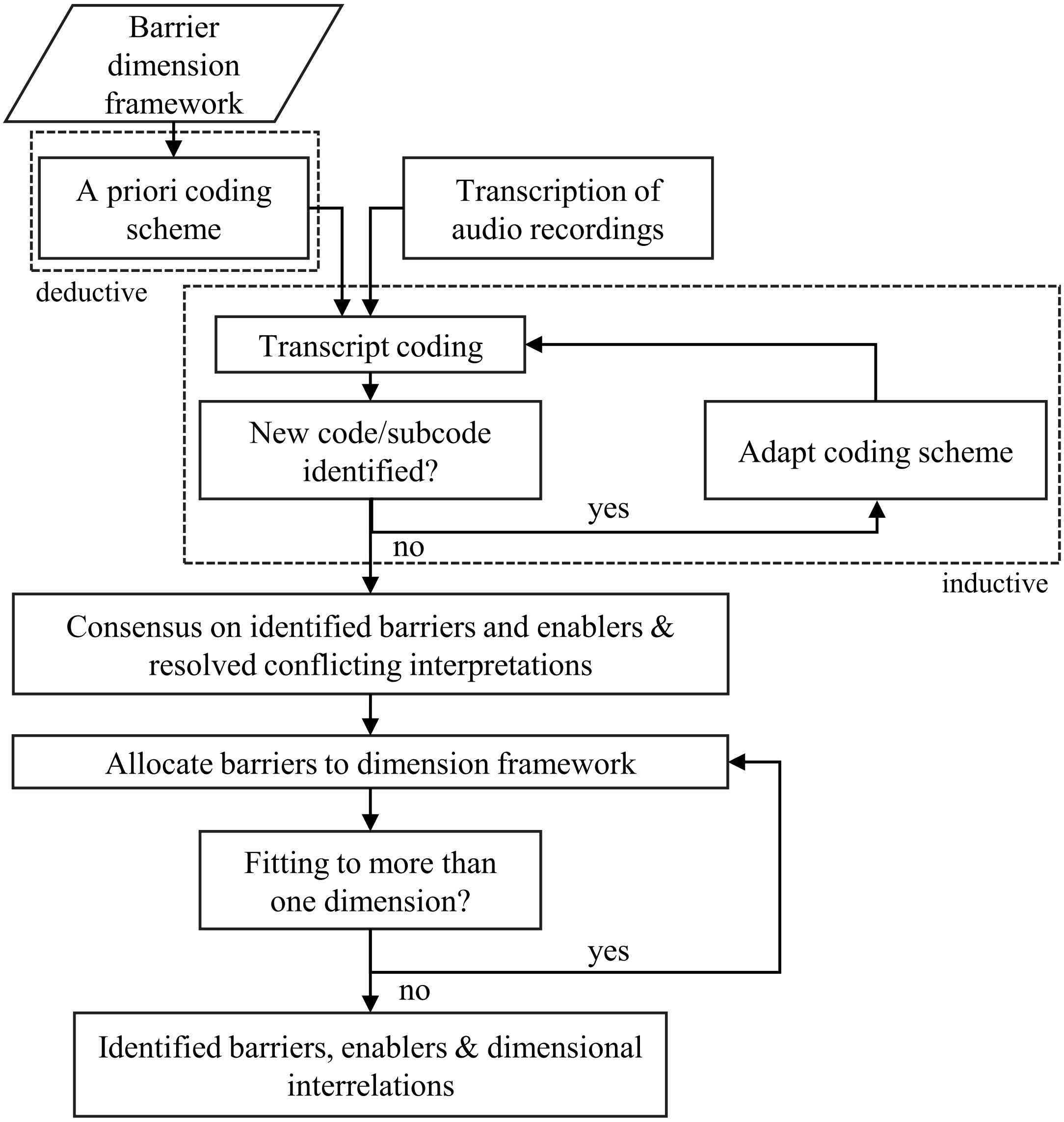

Fig. 6. Hybrid inductive-deductive approach (adapted from Ref. [48]).

Table 2
Inductively identified barriers to demand response participation.

ID	Barrier	Description
1	Advance-notice-time	• Time and staff needed to check and/or adapt production and or personnel schedules
2	Core business	• DR is not or will not become a core business, so that developments in this area are not prioritized
3	Energy efficiency	• May decrease at the cost of providing DR
4	Equipment wear	• Fear of equipment wear: more frequent and/or more extensive up/down ramping of production processes with potentially negative effects on machinery
5	Overall missing acceptance	• Obstacles within the organization (individual employees/supervisors that need to be convinced of the changes/need for DR)
6	Personnel planning	• Personnel planning may need to be re-scheduled spontaneously • Economic implications for re-scheduling and increased hourly wages for night-shifts, weekends or holidays • Regulative specifications need to be accounted for
7	Production capacity	• May need to be increased to make up for the time lost during the DR event since existing capacity runs near 100 %
8	Product quality	• Fear of decreased product quality due to (spontaneous) DR events (power band limits are exceeded or undercut)
9	Profitability	• Value of DR unclear or too small to actually profit • Hidden (unforeseen) costs may be too high
10	Regulatory complexity	• Organizational effort to allocate human resources to regulation questions regarding DR implementation
11	Regulatory restrictiveness	• Existing regulations interfering with participating in DR • Economic disadvantages when dealing with regulatory requirements • Technological conditions (e.g., size of plant, technical DR potential) may not fit to program requirements
12	Storage capacities	• Need to increase storage capacity to produce more in stock prior to DR event (physical and electricity storage)
13	Space requirements	• Space limitations in case production or storage capacities need to be increased
14	Supply contracts	• May be breached or needed to be re-negotiated in case DR event leads to production delays
15	Third party control	• Unwillingness or fear of dependence on external signals that may directly interfere with the production process (e.g., automatized control from grid operator) • Fear of equipment wear, external signals may harm the equipment if they come at the wrong time or give a wrong target value forcing the process to ramp up/down
16	Up-/Downstream processes	• Linked processes may hinder DR due to technical requirements (storage, continued production)

mentioned, as machinery may not be fully utilized. In addition, deviating from optimal technical configurations in production during a DR event can lead to a loss of energy efficiency, thereby increasing the overall energy input, which, in turn, leads to an increase in costs. Several interviewees cited production and storage capacity limits in the context of the need for pre- and post-production of goods. More specifically, as production decreases or stops during a DR event, it is necessary to increase production before or after to meet the production targets. In both cases, a direct relation to the technology (the production process) as well as to the economy (the entailed cost of investment, running cost, etc.) dimension exists.

In two cases, three dimensions related to an identified barrier. The barrier concerning space requirements refers to the technological aspect of providing the space, e.g., for an expansion of production capacity (technology dimension), where space requirements not only incur costs for the space itself (economy dimension), but also for space management (organization dimension), which was mentioned by several interviewees. Finally, personnel planning entails the required staff schedule planning to prepare for DR events (organizational dimension) and the related costs for additional staffing and weekend and holiday bonuses (economic dimension). Furthermore, interviewees emphasized the expenses for organizational and legal matters to be considered as well, e.g., negotiations with trade unions or juridical questions regarding labor law (organizational dimension). As in the case of the policy dimension, there also exist dimension interrelations that no barrier could be allocated to, such as policy-technology (see Fig. 7). This does not necessarily mean that no barriers exist that could be allocated to these dimensional interrelations, but the interviewees in this study did not identify barriers corresponding to these kinds of interrelations.

3.2. Demand response barriers: perception

Following the categorization of barriers and their respective relations and interdependencies between dimensions, we analyzed the specific barriers in more detail, in particular regarding the frequency with which they were mentioned.

The most frequent barriers are those that were identified by at least ten interview participants and are ranked in Table 3. By far the most often mentioned barrier was profitability, or the lack thereof, with 17 interview partners citing this barrier. More specifically, revenue uncertainty was mentioned regarding uncertainty about the number of DR events and the compensation from participating in DR programs potentially being too little to cover the related costs and risks. The interview partners described the additional costs as the costs of human resources due to changes in work schedules, e.g., overtime or holidays, and the human resources needed for planning and rearranging shifts. These costs further entailed running costs, such as idle labor, costs of lost production, costs of intermediate products to decouple interlinked processes, the risk of equipment wear and tear or an increase in energy carrier costs due to an overall increase in energy consumption, and additional costs such as investments in additional production capacities. Regarding the latter, our respondents generally planned with short payback periods (e.g., of two years) to make investments worthwhile. Lastly, some interview partners also pointed out a substantial degree of international competition, which means that the additional costs of DR participation must be covered to not jeopardize competitiveness.

The most cited barrier in relation to the technology dimension was product quality. Fourteen interview partners made statements on this barrier dimension, and this barrier was described in different ways. Some processes were described as technically non-interruptible (at least not without serious harm to equipment or products). Some interviewees went into more detail about technical restrictions to ensure product quality and cited, for example, narrow temperature bands in manufacturing or product waste due to quality deficiencies. In this regard, one interview partner said:

> “[…] the product quality and the achievement of an appropriate product quality must be the absolute priority.” #interview5 (translated from German)

Another interviewee remarked that manufacturing costs in Germany are already among the highest relative to other countries, and superior product quality is often a central aspect of maintaining competitiveness in the international market. Companies in the manufacturing sector would therefore be reluctant to jeopardize product quality. Interdependent processes, described here as up-/downstream processes were mentioned by half of the interviewees, who stated that some (production) processes are too closely linked and either do not possess or do not allow buffers (e.g., such as product storages) to operate the processes independently of each other for a certain time interval, as stated by one interviewee:

> “For all things in the foundry it’s like this: When I melt, I also have to form. And when I form, I also have to be able to cast, and then I need

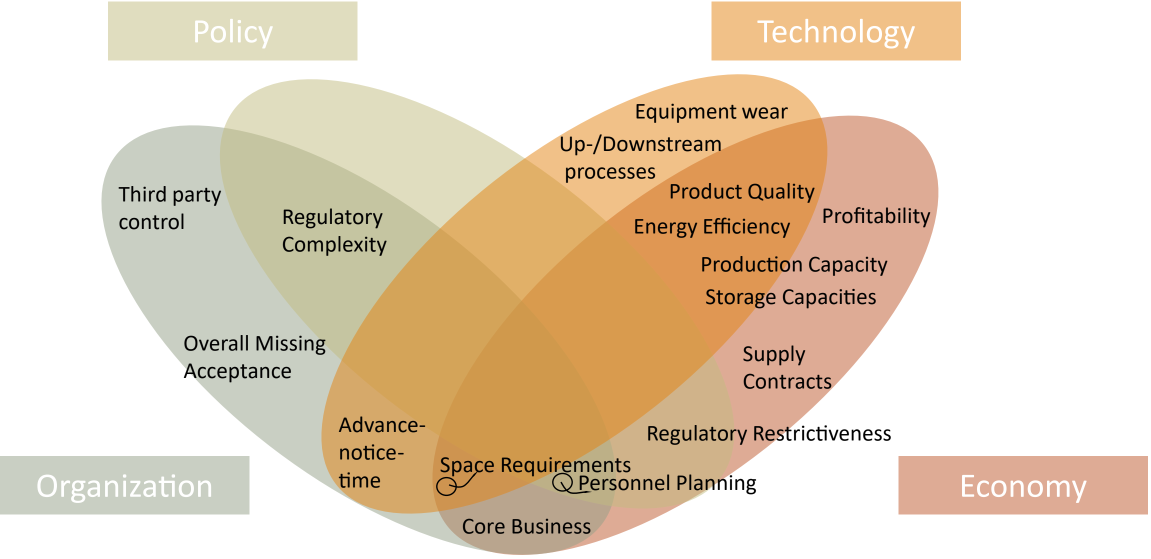

Fig. 7. Assignment of DR barriers identified by C&I companies and associations to the four superordinate dimensions.

Table 3
Most frequent mentioned demand response barriers, ranked by number of nominations.

Rank	Counts	Barrier	Reasons
1	17	Profitability	• Revenue uncertainty • Too little compensation to cover costs/ risks • Cost of human resources • Transaction cost • Not enough capacity to offer to become profitable • International competition
2	14	Product quality	• Non-interruptible processes • Restrictive product quality specifications • Fear of product waste
3	11	Personnel planning	• Idle labor • Employees' aversion to room temperature adaption • Staff availability in DR event • Inflexible shift planning • Non-acceptance of work schedule change • Consolidation with union and labor law
	11	Overall missing acceptance	• Aversion to changing the status quo • Obstacles within the organization • Heterogeneity within certain industrial sectors impedes systematic DR planning • Lack of knowledge within the organization • Not enough potential; therefore too little economic incentive to participate
4	10	Up-/Downstream processes	• Processes too closely linked, no buffers

> the cores for that. […] I need everything. The whole chain." #interview12 (translated from German)

Idle labor was mentioned in terms of personnel planning by 11 interviewees, further accounting for the challenge of rearranging shifts in accordance with employees on short notice. In addition, in some cases an inflexible shift planning was stated, as well as the possibility of non-acceptance of a change in shifts, e.g., from workdays to the weekend or holidays. As one interview ironically remarked:

> "Then you have to tell your employees to make up for the production loss on Saturday or Sunday. Everyone will be extremely pleased. (ironic undertone)" #interview16 (translated from German)

However, this point of view varied greatly between industrial companies, with some interviewees pointing out a high prospective motivation of employees to work on weekends or holidays due to extra compensation (holiday and weekend premiums).[3] Interviewees from the retail sector indicated that flexibility measures targeting office temperatures might cause aversion from employees with a potential increase in sick days. In most cases, the identified barriers to personnel planning also led to concerns about confrontations with trade unions and German labor law.

Eleven interview partners discussed the issue of a general acceptance of DR participation. This included a general aversion to changing the status quo, identifying established structures and expectations with regard to work processes and work environments within the organization, as well as the effort to convince supervisors and staff of the necessary changes and the necessity of DR participation. Interestingly, concerns about changing the status quo were often not discussed as a barrier for the interviewees but as a concern towards other people in the organization.

For example, interviewees that worked as energy managers in their company often expressed a positive attitude towards participating in DR but voiced the concern that participation would be less accepted among employees responsible for manufacturing processes or product quality, as shows the following remark:

> "The next problem is that the person in charge of food safety in the store yells out and says, 'You guys are nuts! What are you doing to the food?' Because if the network operator then leaves the electricity switched off for too long in ten minutes and then the cold chain is interrupted, then I can throw the whole batch away" #interview14 (translated from German)

Moreover, participants from industrial associations pointed out the great heterogeneity within certain industrial sectors, impeding a systematic DR planning and implementation. Some interviewees that were potentially open towards DR participation had already assessed its

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[3] In Germany, companies are not required by law to pay weekend and holiday premiums. However, this is common practice in many industries, even though the premiums differ considerably between industries.

potential. However, due to market barriers such as minimum capacities (e.g., minimum bid sizes in the balancing power market) or too little technical potential in the company, these interview partners concluded that participation would be economically unattractive, particularly in conjunction with current regulatory restrictions. Multiple interviewees agreed with the importance of participating in DR programs, but pointed to other technologies, industry sectors, or even to the residential sector with the expectation of exploiting their respective DR potential first. In other cases, a lack of knowledge within the organization about DR programs or the organization's technical DR potential was expressed, making it difficult to assess whether participating in DR would be feasible or not.

Some barriers were not mentioned as frequently as the previously presented ones, which does not, however, lessen their importance for the respective interviewee. Supply contracts (mentioned by eight interviewees) describe the fulfilment of services, for example obligations to companies or private customers in the retail sector. In this context, interviewees especially mentioned supply contracts as the binding priority over DR program participation. One interviewee stated the importance of upholding delivery times, as well as the risk of reputational damage if contracts cannot be fulfilled.

> "The customer is king and wants his products delivered at the agreed time. That is a completely different way of thinking." #interview12 (translated from German)

Restricting regulatory frameworks (stated by eight interviewees) were mentioned by interviewees with regard to conflicting and contradicting regulations. In Germany, for example, the grid charges for metered consumers (usually industrial and large commercial consumers) are calculated based on a capacity price component and an energy price component. Therefore, DR participation could result in additional costs, as DR events could push peak power consumption to make up for the lost production. Additionally, the fear was expressed that if energy intensive consumers would reduce their energy consumption as a result of DR adoption, they could fall out of the individual grid fee option leading to higher electricity costs, as one interview remarks:

> "And if you then somehow reduce the power too often and use too little power, you then lose the individual grid fee, which then accordingly, yes, would not be made up for by other compensation that currently exists." #interview13 (translated from German)

Regulatory complexity (mentioned by seven interviewees) was cited in terms of unclear and fast changing frameworks interfering with planning security, as well as the immense bureaucracy involved in managing regulatory interdependencies. The aversion to cease control over production processes and appliances to a third party (mentioned by five interviewees) varied among interviewees. Some interviewees consider handing over control at predefined time intervals to be acceptable, while others see no possibility of allowing direct or automated access to internal processes at all. Even though third party control was in some cases completely rejected, some interviewees agreed to prior notification and (indirect) automatized third party control, partially with override control or in pre-defined time intervals, as expressed by one interviewee:

> "If we can specify time windows where we can say that you are free to dispose of it […]. Then something like that would definitely be externally solvable. Definitely. But there must be the possibility for us to prevent this external shut down for a short time in special situations." #interview8 (translated from German)

3.3. Analysis of barrier count by sector, interviewee and flexibility provision

We next considered the prevalence of the specific barriers in light of the companies' engagement in flexibility provision. Fig. 8 shows the barriers encountered by companies participating in flexibility programs with those that do not. As the majority of companies (seven) has experience with flexibility provision, the barrier count is correspondingly higher. Furthermore, it can be seen that companies that provide flexibility also identified slightly more unique barriers than companies that do not. In particular, only the companies already partaking in flexibility programs mentioned barriers such as regulatory restrictiveness and regulatory complexity. Identifying these barriers indicates that the concern for companies that already have experience with DR have encountered the challenges around regulatory restrictiveness and complexity in the qualification process of flexibility provision.

Regarding the variety of barriers, the interviewed associations and companies did not vary significantly, as presented by Fig. 9. Regulatory concerns about complexity and restrictiveness were mainly identified by associations. The lack of profitability presented in both categories the most important barrier, while companies also prioritized up- and downstream processes, product quality and personnel planning. This also accounts for autonomy and the advance-notice-time, which might be due to their closeness to their respective production processes and equipment, resulting in protectiveness.

The investigation of DR barriers by industry branch in Fig. 10 shows that no barrier was exclusively applicable to one industry. Regulatory complexity and restrictiveness were identified across almost all sectors, as well as the lack of profitability. Autonomy was identified in half of the industry branches comprising glass, manufacture of beverages, non-ferrous metals, paper and pulp products and warehousing. The non-ferrous metals industry had the highest number of interview participants (and thus the best representativeness) and also the highest amount of barrier counts and variety. In this industry, product quality, up-/downstream processes, and lack of profitability were the most prominent barriers. In real estate, the most important and only barrier identified was personnel planning, which mainly concerned employee satisfaction regarding possible temperature changes when tapping into the heating or cooling flexibility of office buildings.

3.4. Enabling activities

In addition to identifying DR barriers, interview participants also mentioned activities that could enable them to overcome these barriers. Following the example of Lashmar et al. (2022), we further analyzed the interview transcripts for enabling activities to overcome the mentioned DR barriers and found 13 enabling activities that are presented in Table 4.

In accordance with Lashmar et al., the most often discussed enabling activity concerned the selection of the demand DR type. This comprised the company accounting for technological restrictions, safeguarding the production process equipment, and upholding standards (e.g., narrow temperature bands), but also included ensuring client or employee temperature comfort. Thus, barriers such as product quality reduction, energy efficiency, personnel planning and lack of profitability could be addressed. In addition, the incentive design of the demand response program could play a major role in the program's selection. One participant identified a fixed payment regardless of the amount of DR events per year that required load shifting or shedding as one way to counter revenue uncertainty. Almost half of the interview participants mentioned a sufficient advance-notice-time as an enabler to foster DR participation. While six participants stated that at least a day or two prior notice would be needed to prepare for the DR event (e.g., adapting production and personnel schedules), two participants agreed to at least 15 min and one participant to one week prior notice. This variation likely reflects the heterogeneity in production processes or services across different sectors.

As Table 5 shows, an enabling activity can address multiple barriers and vice versa. Due to the multifaceted nature of the barriers despite an identified enabling activity, the activity might not be sufficient or

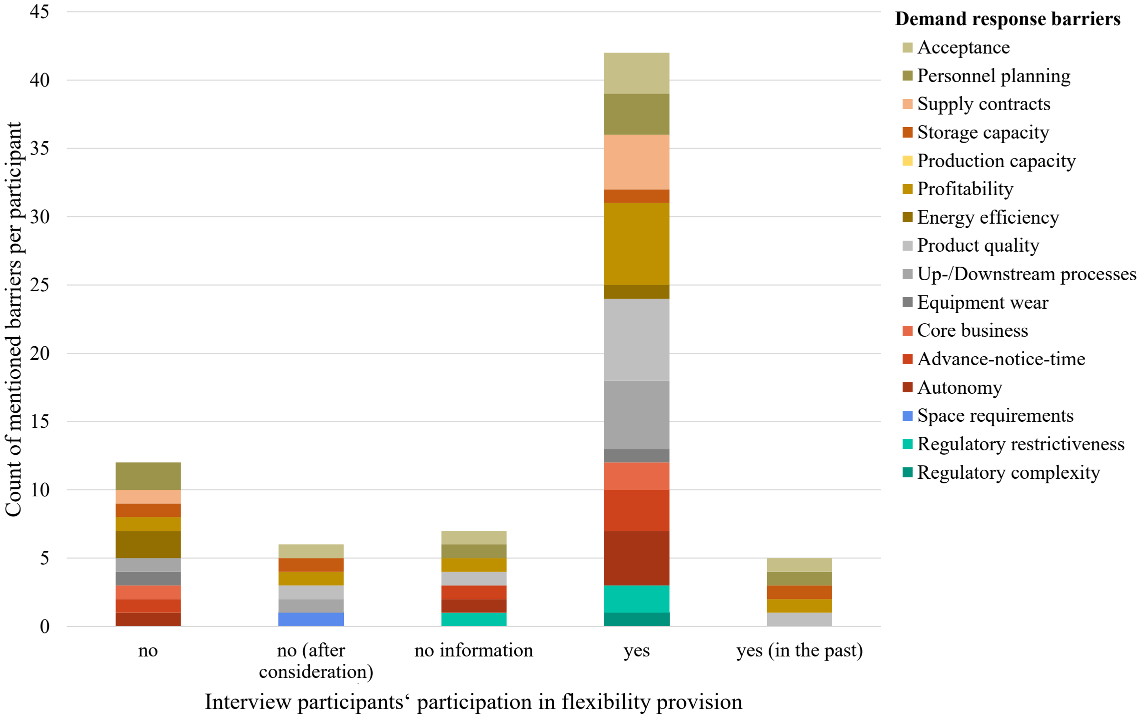

Fig. 8. Counts of identified barriers by interview participants (companies), distinguished by their respective participation in flexibility programs.

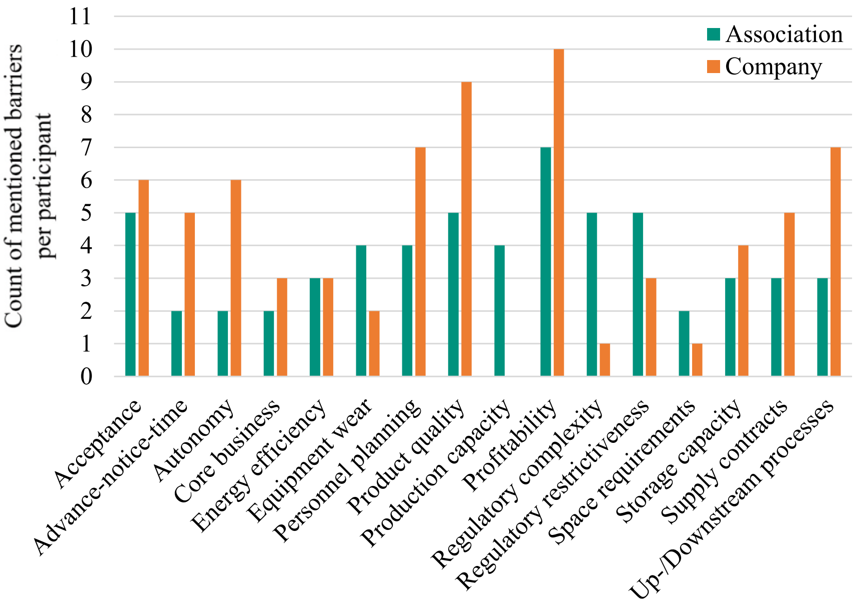

Fig. 9. Counts of identified barriers distinguished by company and association.

applicable to account for all the facets of the respective barrier. However, the identified enablers build directly on the participant's perceptions and requirements, suggesting that a company can overcome some barriers internally [36]. For some enabling activities, the pre-requisites do not only depend on the consumers. To choose a suitable demand response program type, fitting demand response programs need to be implemented in the first place.

4. Discussion

Commercial and industrial organizations can participate in DR measures through load shifting or load shedding. This research aimed to examine the barriers to DR adoption in the C&I sectors by conducting 20 semi-structured interviews with experts from C&I companies and associations. The DR barriers identified by the interviewees have been analyzed and categorized into four barrier dimensions (i) economy, (ii) technology, (iii) organization, and (iv) policy, by accounting for interrelations between dimensions. This section discusses the critical barriers in the context of the present state of research in Section 4.1 and details the limitations of the empirical investigation in Section 4.2.

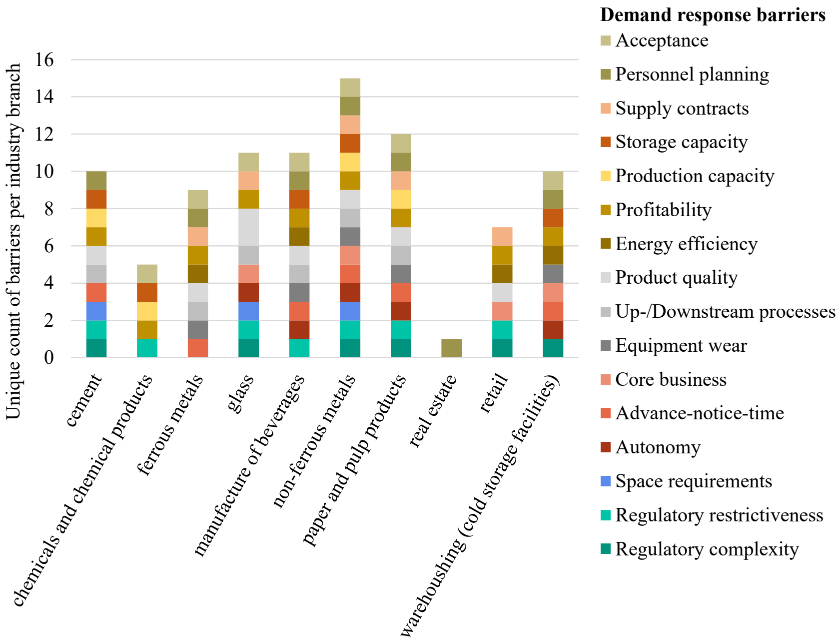

Fig. 10. Industry specific demand response barriers.

Table 4
Enabling activities the interviewees identified to overcome the mentioned barriers.

Enabling activities	Count
Demand response program type	11
Sufficient advance-notice time	9
Managing expectations within the company	5
Overcoming space requirements and storage on site	3
Third party access acceptance	3
Existing excess storage capacity	3
Voluntary participation	2
Existing excess production capacity	2
Automation	2
Third party access acceptance	1
Enhance knowledge on processes and their up-/downstream linkages	1
Mitigate additional running costs (e.g., flexible workforce)	1
Voluntary participation	1

4.1. *Critical barriers*

From the 16 distinct barriers identified in our analysis, five barriers emerged as the most frequently discussed barriers by our interviewees from the C&I companies and associations. These critical barriers comprise (i) the lack of profitability, (ii) the fear of reduced product quality, (iii) multiple aspects regarding personnel planning ranging from additional expenditures to consolidation with the labor union, (iv) an overall missing acceptance and (v) the technical interdependencies with upstream and downstream processes.

Profitability is discussed as the main driver for DR participation. In turn, a lack of profitability (i.e., revenue uncertainty and insufficient financial incentives) was described as the main barrier for participation, which corresponds to the findings by Leinauer et al. and Lashmar et al. [36,37]. Our interviewees further identified the risk of a decrease in delivery reliability, possibly resulting in the loss of additional business opportunities due to supply shortages, which matches the findings from Leinauer et al. [37]. Uncertainties about profitability could be addressed with simplified regulations and incentive structures, as well as by providing adequate and tailored information about the consequences of participation. The interviewees highlighted the risk of *reduced product quality*, which is consistent with Leinauer et al. and Lashmar et al. [36, 37]. However, this kind of barrier can be overcome by precisely setting the specifications for participation in a DR program that, in any case, is entailed in the prequalification process. Such a prequalification process ensures safe load shifting, shedding, or energy carrier switch during a DR event while maintaining the technical specifications to not damage the production equipment and maintain product quality. Fears like a decrease in product quality further point out a certain lack in knowledge or an aversion to thinking about DR participation in general, since the prequalification process for the adoption of DR programs could solve

Table 5
Enabling activities, their impact on specific barrier and barriers without enablers.

Enabling activity	Addressed barriers	Barriers without enablers
Demand response program type	Product quality; energy efficiency; profitability; personnel planning	Regulatory restrictiveness
Sufficient advance-notice time	Advance-notice-time; personnel planning; product quality	Regulatory complexity
Managing expectations within the company	Personnel planning, overall missing acceptance	Equipment wear
Space requirements and storage onsite	Space requirements, storage capacities	
Third party access acceptance	Autonomy	
Existing excess storage capacity	Storage capacity	
Voluntary participation	Profitability; product quality	
Existing excess production capacity	Production capacity	
Automation	Autonomy	
Delegation of DR management to third party	Autonomy; personnel planning; core business	
Enhance knowledge on processes and their up-/downstream linkages	Up-/downstream processes	
Mitigate additional running costs (e.g., flexible workforce)	Profitability	
Voluntary participation	Product quality; supply contracts	

these concerns.

A critical barrier identified in our study is *personnel planning*. Our participants mention multiple essential aspects in this regard. They express their concern about employee satisfaction when having to work very flexible shifts. Furthermore, the change in shifts would possibly lead to conflicts with labor unions and juridical questions regarding labor law. The occurrence of a DR event on short notice could possibly lead to idle labor and hence, to additional personnel expenditures. The risk of higher personnel expenditures is consistent with Leinauer et al. [37], while Lashmar et al. [36] categorizes additional work for personnel as a social barrier. However, the findings about employee satisfaction or the implications to the need of consolidation with the labor union and labor law have not been described in previous literature and are hence newly identified. Announcing a DR event multiple days in advance, as opposed to short-notice events, could possibly help overcome this barrier. Barriers such as competing *business resources and additional work* were identified by the interviewees in our study and support the findings of Lashmar et al. [36], who declared these two barriers as newly identified by their interviewees compared to the existing literature.

The fact that DR programs or energy management are often *not part of the core business* is a critical barrier in our study and is consistent with Leinauer et al. [37]. Even though this barrier is not identified by Lashmar et al. [36], a relation to the *aversion of changing the* status quo, identified in this study as part of an *overall missing acceptance* as well as by Lashmar et al. [36] may exist, since this inertia may come from DR and energy management not being a priority in organizations. In this study, the barrier was expressed by multiple interviewees and can be further related to the NIMBY (not in my backyard) problem. Most interviewees showed some interest in DR which they express both by their willingness to participate in the interviews and their statements during the interviews. However, when asked about their potential participation they often referred to other sectors stating that these had higher DR potentials, so that their own participation would not make much of a difference. The issue of technological interdependencies between production processes has also been identified by Lashmar et al. [22], which supports our assumption that also country independent, general barriers exist.

As the comparison to similar literature targeting the C&I sectors reveals in this section, the demand response barrier dimension framework deduced in this study can be extended to account for further barriers found in studies beyond the interviews conducted here. Additionally, we suggest that the framework may be applicable to further demand response barrier research in other sectors, such as the transport sector (bi-directional charging) or the residential sector. The latter indicates promising applicability, as Alasseri et al. [51] formulate challenges in demand response implementation in the residential sector, such as governmental support, consumer awareness, policies/regulations, costs, and technical requirements, which can very well be allocated in the four dimensional framework considering policy, economy, organization and technology related demand response barriers.

4.2. Limitations of the empirical investigation

The generalizability of our results is subject to certain limitations. The limited number of interviews and variety of interview partners regarding industry branches and sectors, make it difficult to assess the comprehensibility of the results from this study. The interview partners varied concerning their position, ranging from energy managers and members of the management board of companies to association representatives. This may lead to different levels of knowledge about DR programs and potentials, leading to different motivations, opinions, and identified barriers. Of course, the variety of interview partners (associations, medium to large-scale companies, less and more energy-intensive industries/commercial companies) leads to very different perceptions of barriers. Hence, it is possible that further barriers exist and need to be identified, and that barriers that interviewees in this study did not mention often may be actually crucial in a different industry sector or company. In addition, the variety in industry sectors and interview partners did not allow for further significant conclusions considering the commonalities and differences between sectors. Focusing on this in follow-up studies would allow a considerable contribution to this research area. Nevertheless, we managed to interview experts from a variety of commercial and industrial sectors. We found a substantial degree of commonalities in the identified barriers as well as distinctions between sectors and companies. Our study thus continues to develop the still scarce body of literature on barriers in different C&I sectors, enabling more robust and generalizable conclusions about the importance of different barriers. In our study, we identified DR barriers relating to German legislation. Hence, differences in the regulatory frameworks across countries may result in more or different barriers for C&I companies.

Furthermore, since conducting the interviews, a lot has happened in the geopolitical context within Europe. With the start of the Russian invasion of Ukraine in 2022, a so-called energy crisis with gas shortages [52] and a rise in gas and electricity prices [53], among others, has led to substantial challenges for consumers from all sectors, especially energy-intensive industries [54–56]. These new circumstances would likely lead to very different results if we repeated the interviews in the present situation. In a situation with high uncertainty (regarding energy carrier supply and prices), companies may become more risk averse, which could lead to perceiving more barriers in the realm of DR adoption or the categorical non-acceptance of even considering DR adoption. Conversely, substantially higher energy prices may encourage innovative decision-making beyond the core business, including DR participation, which could offset some of the higher energy costs. Generating new data from interviews or surveys specifically targeting this situation could shed more light on these recent developments.

5. Conclusion and future directions

In this empirical study, we investigated DR barriers by conducting 20 interviews with representatives from German commercial and industrial (C&I) companies and associations. Our analysis revealed 16 barriers, allocated to organizational, economic, policy, and technological dimensions, accounting for interdependencies among them. Notably, technology and economic barriers exhibited pronounced correlations, while many barriers exhibited multiple relations to different dimensions. Additionally, barriers within the policy dimension consistently exhibited links to at least one other dimension.

In-depth analysis and a comparison with recent literature identified five critical barriers: (i) lack of profitability, (ii) fear of reduced product quality, (iii) implications for personnel planning, (iv) overall missing acceptance, and (v) technical interdependencies with upstream and downstream processes. Other noteworthy, if less frequently mentioned, barriers included compliance with supply contracts, restrictive regulatory frameworks, and regulatory complexity, often linked to German regulatory frameworks. This study also identified 13 enabling activities for overcoming barriers in DR adoption, the most frequent mentioned ones comprising an adequate DR program type, an adequate advance notice time, and managing expectations within the company.

Identifying DR barriers and enablers supports the development of strategies to overcome these challenges. While some barriers may be addressed through internal resources and information dissemination, our findings emphasize the necessity of adapting external incentives and regulations to facilitate DR adoption. Raising awareness about DR programs and their associated barriers and benefits may encourage C&I companies to surmount these challenges. Focusing on reducing fears may lay the groundwork to overcome the barriers related to fears, such as a reduction in product quality that, e.g., could be resolved by raising awareness about the already existing extensive prequalification process that precedes participation in German DR programs. Furthermore, regulatory frameworks should be enhanced to reduce legislative contradictions and competition among financial incentives. By simplifying corporate decision-making processes, DR participation can be promoted, aiding C&I consumers. Examining the barriers identified and the underlying motives and fears can help decision-makers devise strategies to support C&I consumers in participating in DR.

Further research could delve deeper into variations in barriers across different industrial sectors, enabling targeted strategies for specific segments. Expanding the study's scope internationally can enrich the understanding of barriers, especially in the context of divergent legislative frameworks and unexplored best practices. Shifting the research focus from barriers to enablers and measures for resolution can assist policy makers and market operators in improving regulatory frameworks and promoting the advantages of DR participation.

Author contributions

Leandra Scharnhorst: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Validation; Visualization; Writing - original draft; **Daniel Sloot:** Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Project administration; Resources; Software; Validation; Visualization; Writing - review & editing; **Nico Lehmann:** Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Writing - review & editing; **Armin Ardone:** Funding acquisition; Supervision; Writing - review & editing; **Wolf Fichtner:** Funding acquisition; Supervision; Project administration; Writing - review & editing.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly and ChatGPT in order to mitigate grammatical errors and improve language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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Paper D

Techno-economic analysis of future process-specific demand response in European industries

Reference

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Techno-Economic Analysis of Future Process-Specific Demand Response in European Industries

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Abstract—**The evolving European energy transition, characterized by an increasing reliance on intermittent renewable energy sources, necessitates a paradigm shift in the electricity supply-demand dynamics. To enhance grid stability and reliability, demand response adoption by electricity consumers is crucial. The manufacturing industry, a significant electricity consumer with a history of contributing flexibility to power systems, is poised to play a pivotal role in future balancing power provision. Presently, the industry is providing demand response below its actual potential. This study explores the future techno-economic potential of demand response in energy-intensive industry processes. Present and future process-specific flexibility potentials are derived through an extended industry demand simulation model. The analysis incorporates diverse decarbonization measures, doubling the demand response potential by reaching about 29 GW in load decrease and 11 GW in load increase potential in the target scenario for Europe in 2050.**

Index Terms – **Demand response, Load management, Manufacturing industries, Decarbonization, Energy consumption**

I. INTRODUCTION AND STATE OF THE ART

The European initiative towards a sustainable, low-carbon economy, aims to transition from a centralized electricity system dominated by large conventional power plants to one primarily powered by renewable energy sources [1]. This transition leads to a decentralized and highly intermittent electricity supply structure, necessitating increased flexibility to balance supply and demand [2],[3]. Furthermore, the transition extends to demand sectors, particularly the manufacturing industry, where policies such as the Green Deal Industrial Plan [4] and the Net-Zero Industry Act [5] seek to promote the adoption of net-zero technologies. Decarbonization efforts within the manufacturing industry are anticipated to significantly increase electricity consumption due to electrification of production processes [6].

As of 2021, the industry sector accounted for 38% of electricity consumption in Europe [7]. Historically, the industry sector has been the largest provider of demand response (DR) [8]. DR refers hereby to the measures that allow load shifting or load shedding in response to a (price) signal [9]. Estimates from a recent IEA study suggest that buildings, hydrogen electrolysis, the transport sector, and the industry will play significant roles as DR providers [10]. Harnessing DR from production processes is particularly advantageous due to existing control, measurement, and communication infrastructures, reducing the need for additional investment in such infrastructure [11]. However, various technical, economic, organizational, and policy barriers still prevent DR from reaching its full potential [12].

Several studies have investigated process-specific DR potentials. For instance, authors in [13], [14], [15] explored theoretical and technical potentials, while others in [16], [17], [18] considered economic potentials. Nevertheless, few studies have addressed the techno-economic potential in a European context and either focus on technical or economic potential, specific countries, or aggregating DR potential across entire industries.

Therefore, this study presents a techno-economic assessment of future process-specific DR potentials in Europe building on an industry demand simulation model. The simulation model computes bottom-up energy and emission balances of energy intensive production processes, while accounting for the deployment of decarbonization measures until 2050. Building on the electricity balances, our study determines future technology-specific hourly DR potentials and estimates the costs associated with DR implementation and provision per process. The paper is structured as follows: We start with an introduction of the methodology for deriving techno-economic DR potentials for process-DR. Further, we present and discuss our results before drawing conclusions from our analysis.

II. METHODOLOGY

The methodology for calculating DR potential draws upon the approaches in [13] and [16], encompassing both technical and economic aspects of negative and positive DR potentials. Positive potential refers to load reduction or shedding through partial load reduction, complete process shutdown or a delayed start-up [16]. Negative potential covers load increase through

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partial or full load augmentation or an advanced start-up [16]. Load shedding is a non-compensated shift in load, whereas load shifting is eventually compensated [16].

A. Technological demand response potential

In (1), the installed capacity $P_{c,i}^{\text{inst}}$ of every process i and country c is computed from the annual electricity consumption $W_{i,c}$ and the number of hours of one year N_{hours}, the utilization level u_i and the level of revision s_i^{rev}, which is assumed to lie at 5 %, since the yearly revision interval is not known [13].

$$P_{c,i}^{\text{inst}} = \frac{\text{W}_{c,i}}{\text{N}_{\text{hours}} * u_i * (1 - \text{s}_i^{\text{rev}})} \ \forall c, i \tag{1}$$

The maximum capacity $P_{c,i}^{\text{max}}$ considers the revision time of the installed capacity, and therefore, cannot exceed the installed capacity, as (2) shows,

$$P_{c,i}^{\text{max}} = P_{c,i}^{\text{inst}} * (1 - s_i^{\text{rev}}) \ \forall c, i. \tag{2}$$

The minimum capacity $P_{c,i}^{\text{min}}$ is calculated in (3) using the installed capacity and the positive flexibility factor s_i^{pos}, which denotes the proportion by which the load can be reduced from the installed capacity. The hourly load $P_{c,i}(t)$, as shown in (4), is the product of the hourly standardized load profile share $s_{c,i}^{load}(t)$ and the annual electricity consumption. The hourly positive DR potential $P_{c,i}^{\text{pos}}(t)$, representing potential load reduction, is derived in (5) as the difference between the hourly load and the minimum capacity. In equation (6), the negative DR potential $P_{c,i}^{\text{neg}}(t)$, indicating potential load increase, is obtained by subtracting the actual load from the maximum capacity and multiplied by the negative DR factor, s_i^{neg}, which quantifies the proportion of production capacity available for load increase.

$$P_{c,i}^{\text{min}} = P_{c,i}^{inst} * s_i^{\text{pos}} \ \forall c, i \tag{3}$$

$$P_{c,i}(t) = s_{c,i}^{load}(t) * W_{c,i} \ \forall c, i \tag{4}$$

$$P_{c,i}^{\text{pos}}(t) = P_{c,i}(t) - P_{c,i}^{\text{min}} \ \forall c, i \tag{5}$$

$$P_{c,i}^{\text{neg}}(t) = \left(P_{c,i}^{\text{max}} - P_{c,i}(t)\right) * s_i^{\text{neg}} \ \forall c, i \tag{6}$$

B. Deriving the hourly demand response costs

Hourly flexibility costs comprise capital expenditures (CAPEX), as well as operational expenditures (OPEX). Steurer [16] provides an extensive dataset distinguishing between installation expenditures (investment and fixed operation costs) and utilization expenditures (variable operation and provision costs). This data is utilized and the computation of CAPEX and OPEX shortly presented in the following.

The annual $\text{CAPEX}_{c,i}^{\text{ann}}$ represent the costs of information and communication technology (ICT) components and their installation, commissioning, and parametrization. They are calculated by multiplying the technology specific capital expenditures, drawn from literature [16], [18], [19], [20], by the annuity a_i and the yearly mean flexibility potentials, as shown in (7). The annuity a_i is determined based on the technical lifetime of the ICT-components (=20 years) and a 6 % interest rate.

$$\text{CAPEX}_{c,i}^{\text{ann}} = a_i * c_i^{\text{inv,sp}} * \frac{\sum_{t=1}^{\text{N}_{\text{hours}}}(P_{c,i}^{\text{pos}}(t) + P_{c,i}^{\text{neg}}(t))}{\text{N}_{\text{hours}}} \quad \forall c, i \tag{7}$$

The hourly $\text{CAPEX}_{c,i}(t)$ are derived from the annual $\text{CAPEX}_{c,i}^{\text{ann}}$ and the hourly shares of negative and positive DR potentials (see (8)).

$$\text{CAPEX}_{c,i}(t) = \text{CAPEX}_{c,i}^{\text{ann}} * \frac{P_{c,i}^{\text{pos}}(t) + P_{c,i}^{\text{neg}}(t)}{\sum_{t=1}^{\text{N}_{\text{hours}}} P_{c,i}^{\text{pos}}(t) + P_{c,i}^{\text{neg}}(t)} \quad \forall c, i \tag{8}$$

The hourly $\text{OPEX}_{c,i}^{v}(t)$ comprise the fixed $C_{c,i}^{\text{fix}}$, variable $C_{c,i}^{\text{var}}$, and provision costs $C_{c,i}^{\delta}$ and differentiate between load shifting and load shedding (see (9) and (10)).

$$\text{OPEX}_{c,i}^{v}(t) = C_{c,i}^{\text{fix}}(\text{t}) + C_{c,i}^{\text{var},v}(\text{t}) + C_{c,i}^{\delta}(\text{t}) \ \forall c, i \tag{9}$$

$$v \in \{load\ shedding, load\ shifting\} \tag{10}$$

Steurer defines the annual fixed costs $C_{c,i}^{\text{fix}}$ as the sum of the ICT maintenance, repair, electricity, and internet connection costs [16]. However, he only provides the overall specific annual fixed costs $c_i^{\text{fix,sp}}$. Further literature also presents data on specific annual fixed costs, without specifying their components. We use these specific annual fixed costs to compute the hourly fixed costs $C_{c,i}^{\text{fix}}(\text{t})$, as depicted in (11).

$$C_{c,i}^{\text{fix}}(\text{t}) = \frac{c_i^{\text{fix,sp}}}{\text{N}_{\text{hours}}} * (P_{c,i}^{\text{pos}}(t) + P_{c,i}^{\text{neg}}(t)) \ \forall c, i \tag{11}$$

Variable costs arise from staff, material or energy expenses; if manual activation of production plants is needed [16]. Load shifting and shedding have different variable costs due to higher production losses during load shedding. The hourly variable costs for either load shifting or shedding $C_{c,i}^{\text{var},v}(\text{t})$, are derived from the specific variable costs $c_i^{\text{var,sp},v}$, and the combined positive and negative flexibility potentials, presented in (12). The specific variable costs are drawn from literature (see Table A-I). Steurer defines the specific variable costs for load shedding as the maximum willingness to pay in the electricity market, considering revenue, electricity costs, other variable costs[1] and annual electricity demand [16].

$$C_{c,i}^{\text{var},v}(\text{t}) = c_i^{\text{var,sp},v} * \left((P_{c,i}^{\text{pos}}(t) + P_{c,i}^{\text{neg}}(t)\right) \ \forall c, i \tag{12}$$

Provision costs $C_{\delta,i,c}(t)$ occur whenever DR is possible. These costs include plant operation under suboptimal conditions or maintaining increased inventory [21]. They arise only if a load reduction or load increase is marketed in the electricity or balancing power market. The specific provision costs $c_i^{\delta,\text{pos}}$

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[1] Not further defined in Steurer [16].

and $c_i^{\delta,\mathrm{neg}}$ are assumed constant for each hour h (=24), as presented in (13).

$$C_{c,i}^{\delta}(\mathrm{t}) = \frac{c_i^{\delta,\mathrm{pos}} * P_{c,i}^{\mathrm{pos}}(t) + c_i^{\delta,\mathrm{neg}} * P_{c,i}^{\mathrm{neg}}(t)}{h} \quad \forall c, i \tag{13}$$

C. *Techno-economic parameters*

The hourly electricity demand until 2050 is derived for two scenarios by an industry demand simulation model. The two scenarios consist of one reference scenario and one target scenario. The reference scenario (RS) describes the narrative of a future development of the industry that follows present trends such as energy efficiency measures but no further process specific decarbonization measures [22], [23], [24]. The target scenario (TS) describes an ambitious implementation of decarbonization measures on process and application level, including energy carrier substitution, circular economy, material efficiency and process route changes, as decarbonization strategies [25], [26], [27]. As in [26], qualitative scenario storylines are converted via a descriptor-parameter matrix to quantitative input data for the simulation model. Exogeneous model parameters comprise e.g., production volume development, energy carrier share in the electricity mix development, energy carrier and EU ETS certificate price development, as well as decarbonization measure specific parameters such as start of measure implementation, technology exchange rate and CAPEX.

Table I. Input data on positive and negative demand response factors per production process

Process	s_i^{pos}	s_i^{neg}	**Ref.**
EAF	0	0	[6],[18]
DRI-EAF	0.3 (DRI); 0 (EAF)	0	[6]
HDRI-EAF	0 (H_2) 0.3 (DRI) 0 (EAF)	0	[6]
Ammonia Haber Bosch process	0.2	1	[28]
Ammonia electrolysis	0.1	1	[28]
Methanol electrolysis[a]	0.1	1	
Aluminum electrolysis	0.75	0	[13]
Alu HH inert anodes[b]	0.75	0	
Alu carbothermic reduction[b]	0.75	0	
Alu kaolinitic reduction[b]	0.75	0	
Container glass	0.67	1	[20]
Flat glass	0.67	1	[20]
Cement	0.5	1	[13]
Paper	0.7	1	[13]
Meat	0	1	[29]
Milk[c]	0	1	
Baked goods[c]	0	1	
Sugar	0	1	[30]

[a] For methanol electrolysis, the same flexibility potentials are assumed as for ammonia electrolysis.

[b] The same potentials as for aluminum electrolysis are assumed, as these decarbonization processes are allocated to the primary aluminum production route.

[c] For milk and baked goods the same flexibility potential as for meat is assumed, due to the similar needs in process cooling and unavailable data.

Overall, 127 decarbonization measures are applied for 16 processes, 13 applications and 13 sub-sectors for EU27 + Norway, Iceland and the UK. The model results provide the yearly electricity demand, which is then allocated to synthetic load profiles for 18 processes that have been identified with the technical potential to provide flexibility. The process-specific load profiles have been derived from open data [31], as well as scientific literature and industry project reports [32], [33] and have been synthetized regarding typical days, holiday dates for EU27 + Norway, Iceland and the UK until 2050. The processes and the respective technical DR potential derived from literature, are presented in Table I. If $s_i^{pos} = 0$, the process can be turned off completely. The negative flexibility factor $s_i^{neg} = 0$ indicates, that the process either already runs at maximum capacity or that due to technological constraint such as specific temperature specifications, the load cannot be increased for that process [34]. Table A-I in the appendix depicts the process-specific costs for flexibility provision. It has to be noted, that the provision costs were only defined and given in detail by [16], while other studies only describe the fixed costs. Therefore, we assume that in these studies, the provision costs are already included in the yearly fixed costs [20], [19]. For the combined direct reduced iron and electric arc furnace route (DRI-EAF) and the hydrogen DRI-EAF (HDRI-EAF) route, the same costs are assumed as for the EAF route.

III. RESULTS

The results indicate that there is overall a higher load reduction than load increase potential among all countries in Europe. The overall European average DR reaches about 17 GW positive, and 8 GW negative potential in 2020 and may increase to 29 GW, and 11 GW, positive and negative potential in 2050, respectively, according to a scenario with an industry moving towards a net-zero economy. In 2050, the average load reduction potential of the industry could make 64.4 % of the present pumped hydro storage capacity with 45 GW in Europe [35] for the optimistic scenario. For both, negative and positive flexibility provision, Germany presents the country with the highest potentials, followed by France, which is presented exemplary for 2030 in Figure 1 for the target scenario and in the appendix for the reference scenario (see Figure A-1).

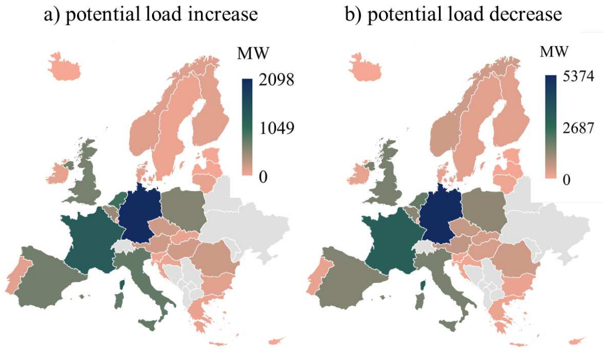

Figure 1. Annual average a) load increase and b) load decrease potentials of the target scenario in 2030

Figure 2 illustrates the development of load increase and decrease potential by process for the reference and the target scenario, exemplary for Germany. The results indicate that the amount of flexibility potential can double for both load increase and decrease in 2050, with an ambitious decarbonization of the industry sector, that comprises electrification and fuel switch to green hydrogen.

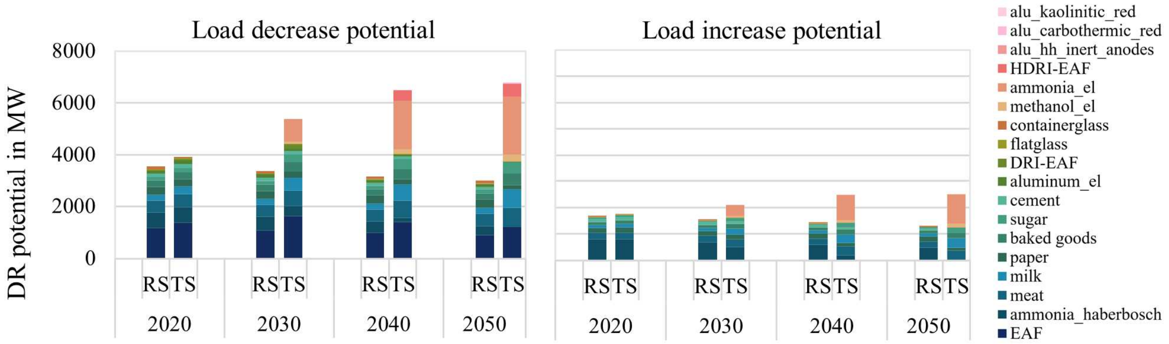

Figure 2. Annual average load increase and decrease potentials by process and scenario (RS: reference scenario, TS: target scenario)

The largest effect can be seen for ammonia electrolysis, due to the gradual shift from the previous ammonia production process that relied on steam reformation.

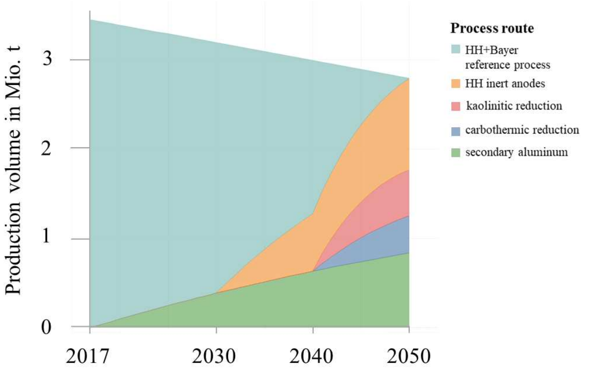

Figure 3. Technology diffusion of the aluminum production routes primary aluminum and secondary aluminum (target scenario)

This is a noteworthy observation, since ammonia electrolysis has not yet been mentioned often as an enormous potential source of future flexibility provision [28]. Furthermore, new processes such as hydrogen direct reduction of iron combined with an electric arc furnace (HDRI-EAF) are introduced and may provide load decrease potential. This also accounts for the primary aluminum process route, where a shift from the previous Hall-Héroult and Bayer (HH+Bayer reference process) to the HH process with inert anodes, carbothermic reduction and kaolinitic reduction can be observed until 2050 (see Figure 3). In contrast, the paper industry's potential decreases for both negative and positive flexibility, due to energy efficiency measures applied to this sector. Further production processes are phased out and substituted by electrified ones, such as the container and flat glass production. For the glass production, this goes hand in hand with a reduction in flexibility potential since the auxiliary electric heater for the melting tank is not needed in the electrified glass production [34]. However, a fully electrified glass production needs to maintain strict temperature levels during the glass heating/melting process, which effectively does not (yet) allow for flexibility provision in this production process [34].

Figure 4 illustrates the three production processes with the highest flexibility potential, and their load profiles in Germany in 2050 over an exemplary week. Dependent on the load profile, the amount of flexibility potential may vary significantly. E. g., the electric arc furnace (EAF) shows a high fluctuation in electricity demand, and can only provide positive flexibility due to utilization levels close to the installed capacity at 1855 MW. However, the EAF can even provide load shedding [36].

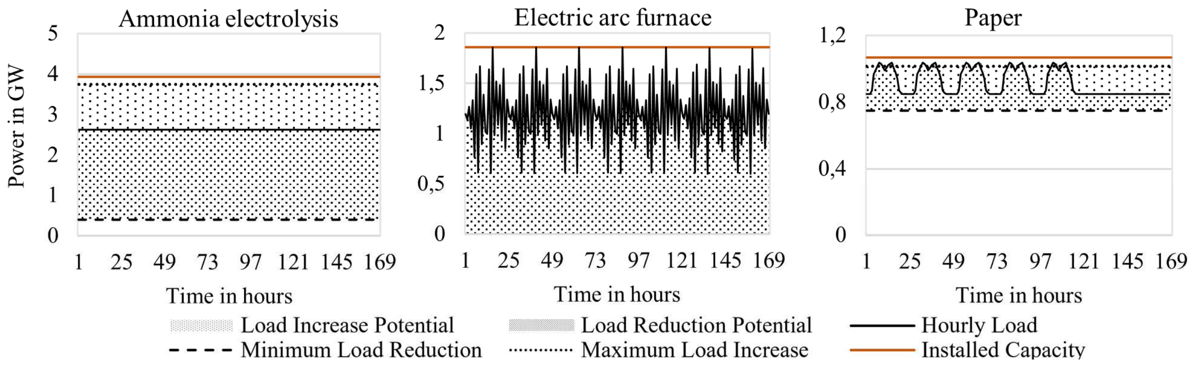

Figure 4. Load reduction and increase potentials and load profiles of the processes with the highest flexibility potentials in the target scenario in Germany for one week in May in 2050

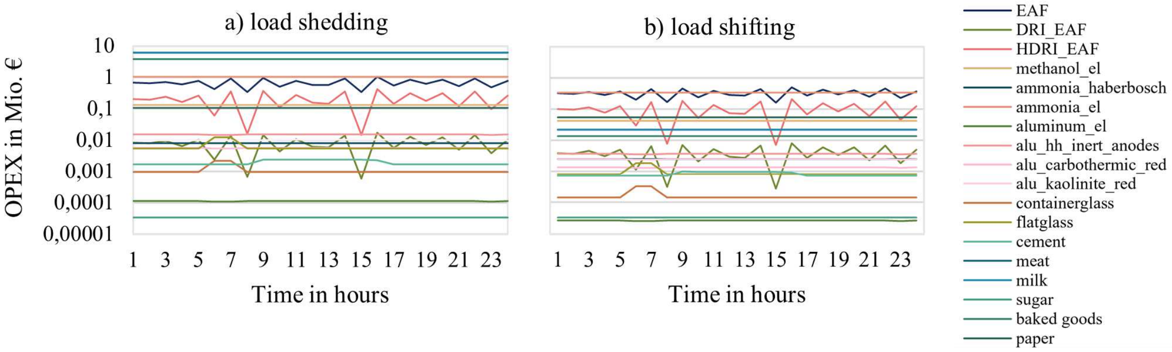

Figure 5. Hourly load shedding and shifting OPEX in Germany in 2050 by process (target scenario)

Hourly flexibility potentials are lower on weekends in some industries, e.g., in the paper and food (see Figure A-II) industry due to a decreased production in those times. The ammonia electrolysis in contrast can provide high load reduction by reducing the load by 90 % maximum [28].

Figure 5 presents the process-specific hourly OPEX, exemplary for Germany in 2050. Food products dominate the opportunity costs for load shedding, making these processes possibly better suited for load shifting (due to process cooling inertia, and lower opportunity costs). Ammonia electrolysis, electric arc furnaces, HDRI-EAF, methanol electrolysis, and paper production are one order of magnitude lower in their OPEX compared to the food sector.

Considering the load shifting costs, ammonia electrolysis, EAF and HDRI-EAF represent the more costly processes, followed by methanol electrolysis, paper production and food products (milk, baked goods). The costs for aluminum electrolysis, container glass, flat glass and cement production are considerably lower than for the other processes, e.g., due to low production volumes, such as in the case of cement that has in 2050 been substituted by autoclaved aerated concrete (AAC) and belite cement production, as well as experiencing a decrease in overall production volumes to 100 Mt in Europe.

The CAPEX are illustrated in the appendix in Figure A-III and are significantly lower than the above described OPEX. Food processes as well as ammonia electrolysis present the highest CAPEX.

IV. LIMITATIONS

The subsequent discussion addresses the limitations and future prospects of this study. It is important to acknowledge that this approach serves as an initial indication of techno-economic potentials and developments within the industry sector, predicated on several assumptions, thus exhibiting certain constraints. For example, the techno-economic parameters of the decarbonization measures, underlie high uncertainty, as e.g., technology readiness levels or CAPEX may progress differently than anticipated. Load profiles have been obtained from process-specific literature and synthesized load profiles from open databases, as a more extensive database, such as metered data, was unavailable. Furthermore, the present approach accounts for revision time by differentiating between the installed capacity and a maximum capacity that deviates from the installed capacity by the averaged revision time over the whole year. Accounting for the revision time in the respective load profiles can mitigate this approach in the future. Notably, the present approach does not factor in technological constraints such as time intervals or limitations on the frequency of DR interventions by process. Therefore, in further assessments, flexibility potentials will be validated by considering process-specific constraints and utilized to incorporate flexible industry demand into an agent-based electricity market model to analyze potential effects on electricity prices and economic potential in the day-ahead electricity spot market.

V. CONCLUSION AND OUTLOOK

In this study, we examined the future theoretical DR potentials for energy intensive industry processes in Europe until 2050. Eighteen processes have been assessed for their load shifting and shedding potential on an hourly basis. The findings provide insight into areas with significant amounts of sheddable and shiftable loads and how these potentials may evolve within the context of decarbonizing the industry sector. The aggregated DR potential for all countries amounts to hourly averages of about 16 GW to 17 GW for load reduction and 7 GW to 8 GW for load increase in 2020 and 13 to 29 GW, as well as 6 GW to 11 GW in 2050, under the reference and target scenarios, respectively. These results underscore the potential for increased flexibility with an ambitious decarbonization agenda in the industry sector, supporting the progression of process electrification and the adoption of green hydrogen.

Highest future load increase potentials could be realized by ammonia electrolysis, meat, and milk production, while load decrease or shedding is mainly associated with processes such as ammonia electrolysis, electric arc furnace, meat, and milk production. However, from an economic standpoint, load shedding, especially in the food sector, incurs considerable variable costs, indicating that these processes may be better suited for load shifting provision. Certain processes, such as cement or direct reduced iron-electric arc furnace (DRI-EAF) production, may appear attractive in the short term but may not be as viable in the long term due to process route switches or energy carrier substitution. For cement, a further examination of prospective flexibility potentials in the belite cement and AAC route is suggested. Additionally, flexibility potentials vary significantly by country, correlating with the capacity of energy-intensive industries, with Germany, possessing the highest industrial electricity demand, also exhibiting the highest flexibility potentials in Europe.

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APPENDIX

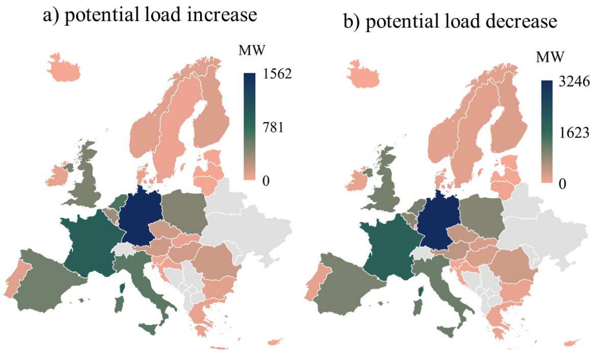
Table A-I. Process specific input data on the costs for flexibility provision

Process	$c_i^{\text{inv,sp}}$ **[€/MW]**	$c_i^{\text{fix,sp}}$ **[€/(MW*a)]**	$c_i^{\text{var,sp,lshift}}$ **[€/MWh]**	$c_{c,i}^{\text{var,sp,lshed}}$ **[€/MWh]**	$c_i^{\delta\text{,pos}}$ **[€/(MW*d)]**	$c_i^{\delta\text{,neg}}$ **[€/(MW*d)]**	**Ref.**
EAF	600	2800	270	564	33	100	[16]
DRI-EAF	600	2800	270	564	33	100	[16]
HDRI-EAF	600	2800	270	564	33	100	[16]
Ammonia Haber Bosch process[a]	770	625	100	316	0	0	[19]
Ammonia electrolysis[a]	770	625	100	316	0	0	[19]
Methanol electrolysis[a]	770	625	100	316	0	0	[19]
Aluminum electrolysis	0	2000	115	471	0	0	[16]
Alu HH inert anodes[b]	0	2000	115	471	0	0	
Alu carbothermic reduction[b]	0	2000	115	471	0	0	
Alu kaolinitic reduction[b]	0	2000	115	471	0	0	
Container glass	1500	19100	120	820	45	93	[16]
Flat glass	1500	19100	120	820	45	93	[16]
Cement	1500	19100	200	487	45	93	[16]
Paper	2300	2000	200	390	0	44	[16]
Meat	5000	150	20	5590	0	0	[20]
Milk	5000	150	20	5590	0	0	[20]
Baked goods	5000	150	20	5590	0	0	[20]
Sugar[c]	6200	450	0	0	0	0	[18]

[a] The variable costs data does only differentiate between minimum, average and maximum costs [19]. It is assumed that the average variable costs apply for load shifting and the maximum variable costs to load shedding, respectively.

[b] These processes are allocated to the primary aluminum production route and hence the same costs as for aluminum electrolysis are assumed.

[c] The heat applied for sugar refining is allocated in Gruber as process heat and as a cross section technology for which the variable costs are assumed to be negligible [18]



a) potential load increase

b) potential load decrease

Figure A-1. Annual average a) load increase and b) load decrease potentials of the reference scenario in 2030

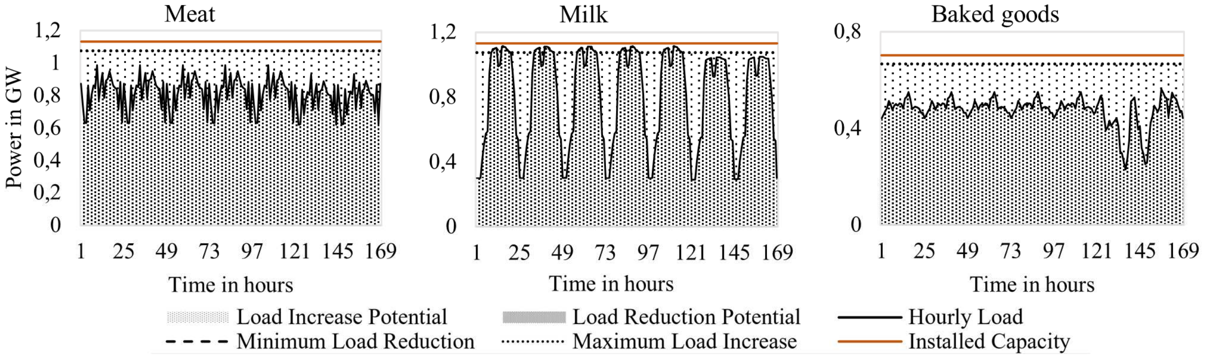


Figure A-II. Food production processes with high flexibility potentials in Germany for one week in May 2050 (target scenario)

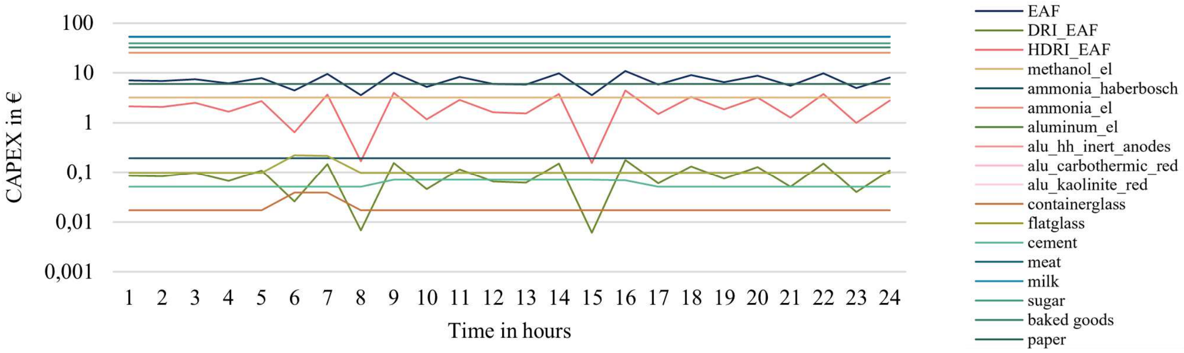


Figure A-III. Hourly load shedding and shifting CAPEX in Germany in 2050 by process (target scenario)

Own Publications

Own Conference Papers

Scharnhorst, L., T. Sandmeier, B. Appel, A. Ardone, and W. Fichtner (2023a). “Empirische Untersuchung zum Wert von Versorgungssicherheit in Privathaushalten – eine Fallstudie im Energy Smart Home Lab”. In: *13. Internationale Energiewirtschaftstagung (IEWT 2023)*, pp. 1–21. DOI: 10.5445/IR/1000156813.

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