Active consumer participation in smart energy systems

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A pressing task for future energy systems is the design and operation of systems that integrate large shares of renewable energy while improving overall system efficiency. Because buildings consume about 32% of the total global final energy use, they are of vital importance. In recent years, technical and socio-economic studies, as well as hands-on experience, have concluded that the integration and participation of consumer are crucial for smart energy systems. To reach challenging climate goals, individual consumer, social environment, physical environment, digital realities and economical conditions must be considered and integrated in successful solutions and business models. However, a holistic discussion of all these elements is scarce. This paper presents a comprehensive review of necessary steps and obstacles during the development and implementation of user centric business models, including a detailed discussion of required data and computational methods as well as psychological aspects of consumer participation. In addition, we aim to identify current challenges and future research needs.

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1. Introduction

The majority of scientific literature predicts that total energy demand as well as consumer energy demand will increase significantly in the coming years and decades [1–3]. Therefore, a pressing task for future energy systems is the design and operation of systems that integrate large shares of volatile renewable energy while improving overall system efficiency. In this paper, we argue that active consumer participation, modern information communication and computational technologies are key factors in successfully achieving this task.

Buildings are responsible for 32% of total global final energy use and 19% of energy-related greenhouse gas emissions [4]; in the European Union, buildings are responsible for 40% of the total energy consumption [5]. Residential buildings are responsible for 27% of final energy demand in the European Union [6]. Gram-Hansen [7] analyzed the importance of user behavior compared to efficient technology for energy consumption in buildings. She showed that the impact of user behavior on heating and cooling energy demand is at least as important as building physics. Furthermore, electricity consumption for lighting and appliances is more dependent on user behaviour than on energy efficiency. These findings clearly highlight the importance of the user.

In addition to reducing or curbing energy demand, increasing the use of renewable energy is essential. As volatile energy sources such as solar and wind energy expand, other parts of the energy systems must become more flexible to match the available energy from renewable resources with the demand in terms of location, time and quantity [8–10]. Energy systems must be considered across multiple sectors such as electricity, heating, cooling, buildings, transportation and industry to identify potential synergies and provide flexibility options [11].

The importance of the consumer in energy systems is stressed by Hampl [12], who expanded the three essential goals of energy policy (security of supply, economics and environment) with a fourth dimension: social acceptance/tolerance. As Hargreaves et al. [13] points out, the impact of new technologies such as smart meters on energy demand and demand flexibility depends heavily on social variables such as individual preferences, social relations, or daily routines in a household. Siano [14] presented a survey of demand response potentials and benefits in smart grids including a discussion about enabling technologies and systems. The acquisition of a technology is not considered to be the most important factor, however, but the domestication of that technology. Consumers have to embed new technologies and options into their daily routines [15]. As Vázquez-Canteli and Nagy [16] pointed out, the future of demand response depends heavily on the integration of human feedback into the control loop.

A key element of any smart energy system is thus the consumer. The present review investigates emerging trends and challenges for applications that should initiate and retain active consumer participation in smart energy systems.

1.1. Active consumer participation in smart energy systems

In this paper, we define consumers as persons who either use or both use and generate energy for domestic purposes in residential buildings such as energy for heating and cooling. The active participation of consumers in future smart energy systems is motivated by manifold factors: (i) consumers are motivated, enabled by the environment, and prompted to increase energy efficiency. This use case is referred to in this paper as energy demand reduction; (ii) Consumers are incentivized to provide flexibility through demand side management; This use case is referred to in this paper as demand side management. (iii) The process of user participation generates data that can be valuable to different stakeholders; an example would be the energy demand prediction for the optimal operation of districts or cities. This use case is referred to in this paper as energy demand prediction. Fig. 1 illustrates these aims in the context of a consumer’s load profile.

1.2. Main contribution and limitations

As the introduction highlighted the importance of consumer participation in energy systems, we elaborate on why consumers are participating, how the participation is enabled and if consumer participation is economically viable. The main contribution of this review paper is a critical discussion of potentials, possibilities, emerging trends and current barriers of active consumer participation in smart energy systems. The paper is going to examine practices of households within the buildings (e.g. energy demand reduction, energy prediction, identification of flexibilities) and not the building itself (e.g. insulation).
Some use cases of active user-participation, as presented in this paper, require the active control of heating, ventilation and air conditioning (HVAC) and storage equipment as well as smart appliances and legacy equipment. The extensive field of hardware and software (e.g. communication protocols) to interface to smart appliances and (legacy) equipment along with its technical challenges is beyond the scope of this paper. We therefore assume that active user integration can be seamlessly integrated into existing buildings with smart-control in the future, where major energy consuming domestic appliances can be controlled.

The paper is structured as follows: Section 2 investigates new business models that rely on data from consumers. Section 3 gives a review of different sources of data and computational methods; this includes a discussion on privacy issues. Section 4 discusses the role of the consumer from a psychological perspective. Section 5 presents challenges and Section 6 the conclusion of this paper.

2. Business models

Viable business models (BMs) are necessary to stimulate the development of technical solutions. Only if data and services provide value for consumers, BMs allow to harness the potential. Consequently, new markets may be established and competition increased. Since the companies operating BMs as well as the BMs themself are manifold, we use the "business model canvas" of [17].

In a first step (I), suitable companies are identified and clustered (see section 2.1). The BMs are identified on a canvas (Fig. 2) by nine elements showing which segment of customers the companies are targeting and describing the values gained by services and products (see section 2.2). In the second step (II), the individual BMs are described. As highlighted by the arrow in Fig. 2, section 2.2 starts with the description of potential consumers and ends with costs and revenues.

2.1. Companies

In the first step, it has to be understood who develops and operates the BM. We identify three relevant provider groups: utilities and retailers, manufacturers, and new market entrants, such as aggregators and platform providers. Fig. 3 also introduces the three groups.

Historically, utilities sell and distribute energy to consumers. Utilities are still the most relevant players in current energy markets. We use this term for utility companies (relevant for e.g. the USA or China) as well as energy retailing companies (relevant for liberalized markets as e.g. in Europe) [18].

While grid operators are a regulated monopoly, retailing companies participate in a competitive market. Nevertheless, their business model is changing as renewables are integrated into the markets and as generation and storages become more distributed [19]. Consumers have started to generate and store energy locally reducing the sales and revenues of utilities. In the face of this challenge utilities are forced to change their BMs, i.e., by entering or creating new markets and also to be more service-oriented [20]. Nevertheless, they have in-depth knowledge about the markets as well as an existing customer base, including the corresponding channels. The role of utilities is currently changing from being energy suppliers only to energy service companies. While utilities have the advantage that they are incumbent players in energy markets, aggregators are new market participants.

Companies of another kind focusing on consumer participation are technology or product manufacturers, such as Siemens, Samsung, Viessmann, Loxone, or Philips and also car manufacturers...
such as Tesla, Toyota or Volkswagen. They have the traditional role of producing and selling hardware and are currently focusing on smart home services and devices [21]. A differentiation can be made within these smart products between high cost consumer goods (e.g., electric cars, HVAC, heat pumps or batteries) and low-cost consumer goods (e.g., smart lamps or thermostats). As the competition in the consumer segment increased, manufacturers understood that they must provide additional value. As an example, the new BMs aim at entering new markets (e.g., demand response [22]) or providing new services (e.g., voice [23] or location-based control (geolocation) [24]). The advantages of manufacturing companies are that they know how to produce and sell goods, while they also have comprehensive knowledge about the technical capabilities of their products. Additionally, manufacturers have existing channels to the consumers (e.g., app or web-based or retailers).

The third group of companies are new market entrants. They might be aggregators [25] or platform operators [26]. The European Commission defined aggregators as “a market participant that combines multiple consumer loads or generated electricity for sale, for purchase or auction in any organised energy market” [27]. Those companies are mostly startups (e.g., Electricify in Singapore [28], Piclo in UK [29] or Uplight in US [30]).

The disadvantage they most regularly face is that energy markets are not mature [31] and they also lack of hardware (e.g., Brooklyn Microgrid [32]). Since they often have roles which are not covered by existing market participants, new market entrants often form strategic alliances with utilities or manufacturing companies [33,23].

2.2. Business model description

2.2.1. Customer segments

Potential customers are evaluated in the following step. Since the typical customer is a consumer, we use the term consumer throughout this Section. The most important change for new BMs is the fact that consumer become active consumer, which have to be involved. Koirala et al. [34] investigated the role of citizens in community energy systems. 80% of the participants were aware of local energy projects, 53% were willing to participate but only 8% were willing to steer different activities within the community. It may be concluded from this that only every second consumer is willing to get actively involved.

The most prominent segment of consumers are residential and commercial consumers and generators of energy, including prosumers. As active participation often triggers the operation of flexibilities (e.g., storages or charging of electric vehicles), any consumer of energy might be of interest in future. The BMs investigated in this work aim at products for mass markets which cover consumer segments with similar needs and characteristics.

2.2.2. Channels and customer relationship

Channels are necessary for bringing a value proposition to the market. The phases of a successful channel are roughly awareness of the consumer, purchase, and delivery of the product/service and after-sales. While the traditional company has an established sale force (e.g., in–house or key partner), new market entrants focus more on web sales. The choice of the channel also depends on the type of consumers involved, e.g., digitally-savvy people prefer online transactions while others still prefer a paper format [33]. An advantage of mobile apps is that they offer an anytime, anywhere connection with the consumer, an open line for bidirectional communication and sending the consumer the contents of any marketing activity that is carried out [35].

As an example, Indiana Michigan Power provides consumers access to voice-activated energy information [23]. The relationship between the companies and consumers is manifold. On the one hand, incumbent market participants such as utilities and manufacturers provide personal assistance. On the other hand, new market actors developed efficient automated processes allowing consumer “self-service” with minimum supervision, e.g. chatbots.

2.2.3. Value proposition

As stated in [17] value proposition is the reason why consumers participate in a business model. By the provision of value, the company solves a consumer problem or satisfies consumer needs. Each value proposition consists of a selected bundle of products and/or services that cater to the requirements of a specific customer segment (see 2.2.1). The values of the business model investigated in this work are both innovative (i.e., disruptive) and existing market offers, but each with added features and attributes. Improvements in services and products mostly aim at cost reduction. This may include the increase of local self-consumption (e.g., a hard- and software-based solution by EnBW AG [36]) or energy savings (e.g., energy monitoring allowing the consumer to understand and manage consumption [37]). New services cover needs that consumers were previously unable to appreciate, because no similar provision was available. New data sources (e.g., smart meters or home automation) permits both increasing consumer awareness [38], and the valorization of the data [39]. Active control of flexibilities enables consumers to participate in current or future energy markets, i.e., using real-time pricing [40] or pooling concepts.
2.2.4. Key resources and activities

On the one hand, key resources describe the most valuable assets required to make a business model viable. On the other hand, key activities are the most essential operations a company has to perform. Key resources may be characterized in three categories: physical, intellectual, and human resources. While utilities and manufacturers rely on physical resources, new market participants characterized by intellectual and human resources. There is a big difference between those utilities that are vertically integrated, including transmission and distribution, and those that are unbundled, focusing on generation and retail [44].

As for the key activities, three categories may be introduced: market access, platform and data management, and consulting services. The first of these may be understood as the companies providing their consumers with access to energy markets, e.g., by means of aggregator services [45]. This might also include the provision, management, and maintenance of a platform together with the promotion of it. Data collected from consumers might be a key resource of the company. It could be either integrated into processes or used by key partners.

2.2.5. Key partners

Key partners describe the network of suppliers and partners that make the business model work [17]. In most developed markets, distribution system operators and metering companies are seen as enablers [46]. Since these organizations provide metering data, they are also strategic key partners for the companies. Other partners may be a cooperation with an ICT provider. In the US, a couple utilities team up with Bidgety to use artificial intelligence (AI) similar to Netflix clustering algorithms for consumer engagement [47]. The US utility company Duke Energy uses the platform for the energy savings service from the software company Tendril [48]. As some BMs require installations and periodical maintenance contracts, local handicraft businesses and retailers may also be partners in strategic alliances [49]. If the company is not able to provide the energy supply (e.g., lack of knowledge, limited market access), utilities may be suitable to form joint ventures. The same applies to manufactures if they do not provide the business model. Schneider has an alliance with AutoGrid (i.e., the products Energy Internet and Flex platform) to add AI-driven solutions for consumers’ distributed energy projects [50]. Tesla, on the other hand, cooperates with utilities to sell products (e.g., batteries [51]) or expand and operate it’s network of charging stations [52].

2.2.6. Revenues and costs

Most important for all BMs are the monetary streams, more precisely in- come from revenues and the costs of the value proposition. The business model investigated in this work presents three methods for generating revenues: selling of products and software, usage, and subscription fees. Product sales are linked to physical products (e.g., smart home hub [53] or energy sales [40]) or software licenses (e.g., [54]). Another source of revenues are fees. These result from providing market access [55] or service subscription [40].

The BMs of utilities, aggregators [56] and manufacturers [57] are characterized by high fixed costs, while the variable costs are low. Due to this cost structure, the economies of scale are very distinct [58]. Investment costs mainly consist of the purchase of gateways, smart meters, communication facilities, controllers, software and other IT components, in addition to the “sunk costs of previously installed traditional meters” [59]. Nevertheless, the companies would also face new operational costs for the new tasks such as the costs of communication and data transfer, new consumer engagement programs and personal costs, i.e., training existing personnel or recruiting new people [56]. New market entrants, such as internet companies, are characterized by more distinct economies of scale [60]. As a result of this, products and services are designed for scalability and multiple similar markets [61].

2.3. Requirements for successful business models

To set up a sustainable business model, consumers should be satisfied with the product in the long term. This is more likely to be achieved with the involvement of consumers (see section 4). It is also important to keep them motivated and entertained with various approaches, e.g. gamification.

The great potential of data has a value which must be used and exploited accordingly (see section 3.1). Privacy protection is essential, as failure will deter other customers. The different types of data sources are summarized in Tables 1 and 2.

Monetary incentives and the resulting cost reductions through e.g. demand response can also lead to the satisfaction of a need (see section 3.2.1). The interest in one’s own energy self-sufficiency or energy consumption creates awareness. With the help of prediction models not only the interest of consumers can be satisfied but also individual portfolios are optimized (see section 3.2.2).

| Table 1 |

| Source |
| --- |
| Building data | GIS Databases |
| Geometry data | BM, BES |
| Thermo-physical properties | OSM [75] |
| Location | CAD Tools |
| Weather and climate data | gXML [70] |
| National meteorological services | CityGML [76], EnergyADR [74] |
| Manual | WMO |
3. Data and computational methods

3.1. Data and information

Depending on the respective source, the manner in which data can be obtained varies and has to overcome different obstacles ranging from consumer motivation to technical and legal, ethical, privacy or ownership issues [62].

3.1.1. Obtaining data

A number of publications discuss the impact and possibilities of big data analytics and AI technologies on future smart grids [63,64]. While data from smart meters and internet of things (IoT) are considered in many investigations, the usefulness of data derived from active consumer participation (e.g. via smart phones) and their interaction with smart meters and IoT for monitoring, modeling and optimizing energy systems has not yet been examined in detail. We classify these data as follows: (i) external input, (ii) automatically gained data, and (iii) data conveyed directly by consumers and with methods of ambulatory assessment.

Data from external input comprises all data from external sources such as energy providers. They can deliver for instance energy prices depending on the time of day or smart meter data, which are valuable input to obtain possible load shifts etc. from optimization (see also Section 3.2.2).

Automatically gained data can encompass data from smart meters, websites and servers such as statistical and weather data. Obtaining these data requires methods for automated acquisition such as web scraping and database applications or specific software to access smart meter data via their client interfaces. If smart meter data is not transferred automatically, then it can also be conveyed by consumers themselves.

Examples of consumer-conveyed and ambulatory assessment data are occupancy availability, temperature set-points, information on heating/cooling systems and other appliances, parameters for the latter and times as well as possible time frames for their usage. Consumers can provide information automatically or manually and either electronically via their smartphone and computer or in an analogous manner via written diaries, verbally in a face-to-face interaction, or by telephone.

Considering data conveyed by mobile applications, we can distinguish between data that are generated specifically for energy related purposes such as apps for measurements, demand forecast, etc. and data that are generated primarily for other purposes, for example GPS data which might be useful to predict occupant behavior. While these data are widely used in other fields, their potential has not yet been discussed in detail for smart energy systems. A possibility is shown by Stopczynski et al. [65] who designed a large-scale study to measure human interactions across a variety of communication channels, with high temporal resolution and spanning multiple years.

Compared to external and automatic data, consumer-conveyed and ambulatory assessment data is relatively hard to obtain. Users have to provide data repeatedly, which means they need to be motivated (either intrinsically or extrinsically), are able and also remember to do so on multiple occasions. Therefore, the amount and quality of this data must be determined under consideration of both the requirements for simulation and what can be deemed acceptable to the consumer.

Data can be collected intrusively and non-intrusively. Intrusive data are collected under defined conditions and planned experiments to capture a wide range of working conditions. Non-intrusive data are collected under normal operations; in many cases, performing the tests required for intrusive-data is either not possible or not allowed [66]. Finally, data can be generated from simulation tools [67].

3.1.2. Data sources

Several data sources are of use when aiming to reduce, optimize and predict energy demand. They can address the urban scale or the more detailed neighborhood scale or even households. The types of data required to model smart energy systems depend to a great extent on the designated modeling approach (white-box, black-box, grey-box or coupled, see section 3.2.1), ranging from detailed physical properties to high-resolution measured parameters or a mixture of both.

In the following, data categories and examples of data sources are listed which are deemed important for simulating energy systems, taking into account the possibility of consumer participation. We wish to make clear that we raise no claim to encompassing all possibilities but aim to show in an exemplary manner that solutions which successfully process this information are available. We begin with static data that are used to initialize models, i.e. inputs that are not supposed to change once they are defined for a specific use case. Building Data: Building related data includes building envelope shapes and window opening ratios as well as terrain data [68]. This information can either be extracted from existing data sets or generated from scratch. City-wide Geographic Information Systems (GIS) databases have not only become commonplace in many regions of the world but are also increasingly accessible to the general public. Next to building geometry data, non-geometric properties have to be defined as well, including building construction data such as wall structures and thermophysical properties of construction elements [66]. General building data models and formats include BIM, CityGML, Open Street Map or 2D cadastre models. Digital represen-
tations of a built asset used by Building Information Modeling (BIM) typically consist of a 3D model of the building and can also hold different additional information such as materials, location data and energy related data. Using BIM as basis for Building Energy Simulations (BES) is a common approach - see [69–71]. CityGML [72] is an information model for 3D urban objects including object surface characteristics, defining classes and relations for the most relevant topographic objects in cities and regional models. Open Street Map is a database for open source geo data, which is increasingly used to model urban energy systems including application in different sectors ranging from electricity to heating and transportation [73]. Quality and availability of Open Street Map data are able to replicate urban energy systems effectively. Building data models specially designed for energy related applications are e.g. CityGML, Energy ADE or Green Building XML. EnergyADE [74] extends the CityGML standard with features necessary to perform an energy simulation and store the corresponding results. The Green Building XML Schema [75] is designed to facilitate the transmission of building information in BIM for analysis tools.

Location: Information on the building location is essential for (thermal) building energy simulation [66] since - when combined with the corresponding data bases - this yields further information ranging from climate and weather data to information on the environment of the building under consideration (urban, nature, etc.) as well as its construction (cf. [72]). The geographic location can be transferred manually or automatically via GPS.

Climate and weather data: Climate data such as solar radiation, air temperature, wind characteristics etc. are among the most significant parameters used in the development of BES models Harish and Kumar [66]. Historical and forecast data is provided by national meteorological services and by the World Meteorological Organization (WMO) [76].

Furthermore, the energy demand of buildings is affected by the surrounding microclimate usually derived from computational fluid dynamics or meteorological simulations [77–80].

Next, we discuss operational data which has to be provided repeatedly as varying inputs to the considered system. The role of consumers is vital in this context (see section 4). HVAC systems and home appliances: Relevant features of HVAC (heating, ventilation and air conditioning) systems, home appliances (such as washing machine, oven), and internal heat gains in general (such as those from people, lights, motors, appliances, and equipment, see [86]) for energy optimization are their type, ventilation rates, room air temperature and temperature set-points, usage schedule, as well as power and energy consumption. These can be measured via sensors and transferred manually by the consumer (see also Section 3.1.1) or directly via Smart Meters.

Occupancy: Occupant behavior and occupancy have a major influence on building performance at various levels: health, energy, functionality, comfort, and usability [81]. A detailed discussion on occupancy can be found in the references [82–85]. Information on occupancy and the current position of people in the building provide information such as heat gains by people, requirements for room temperature and the use of specific appliances. Occupancy data can be relayed by active user input or automatically via GPS, see for example [86] or Koehler et al. [87], where GPS data predict occupancy in buildings with 92.1% accuracy. Ahmad et al. [88] provide a review of occupancy measurement techniques and associated challenges.

Data enrichment, selection and aggregation: Tables 1 and 2 summarize different types of data sources. Apart from the question of obtaining data and information, depending on the overall model, it has to be determined which data are essential and how these can be aggregated. In addition to the apparent dependency of important data on the chosen model description and incentives for a specific application, selection of data can be realized by classical machine learning or statistical methods such as PCA, t-SNE [89], Isomap [90], Locally Linear Embedding (LLE) [91] or LaplacianEigenmaps [92] among others. Further aggregation can be achieved via deep learning, e.g. via using the latent space representation of deep autoencoders [93].

If specific information about the building is missing, data enrichment can be used to estimate this information [94]. For example, building data such as year of construction, building height, wall structures or shading (see e.g. [95]).

To enable valid energy demand prediction for the realization of the considered business model, it is important to ascertain - following an assessment of required data - that these data are precise, accessible and from reliable sources. Those key factors including the sources and tools for different kinds of data as well as potential challenges have been covered by this section, thus illustrating the feasibility of their integration for the overall goal of demand prediction under active consumer participation.

3.1.3. Privacy

Whenever data about buildings and consumers are collected, data privacy has to be considered. Any system and business model have to follow legal regulations. The European Union has for example established the General Data Protection Regulation (GDPR) [27] and Canada implemented the Personal Information Protection and Electronic Documents Act (PIPEDA). In the USA, on the other hand, there is no comprehensive law on a federal level, except some initiatives such as customer proprietary information (CPI) [96]. But adhering to legislation might not be enough. How consumers perceive data protection is also vital. Many consumers are hesitant to participate in smart energy systems, because they fear private energy consumption data could be exposed [97], especially if cloud computing services are involved [98]. Ensuring data privacy therefore plays a crucial role while designing energy systems and services.

The term “privacy by design” was introduced by Cavoukian [99], who proposes seven foundational principles: (i) proactive not reactive, (ii) privacy as the default setting, (iii) privacy embedded into design, (iv) full functionality, (v) end-to-end security, (vi) visibility and transparency and (vii) respect for user privacy. To achieve a certain level of data protection within the architectural goal of privacy by design, several strategies have been developed (see Fig. 4) [100]. For the sake of simplicity, we consider the subject (e.g., a consumer generating data), a controller (e.g., company collecting data) and an authority (enforcing data protection law). The controller provides subjects with a clear explanation and timely notification on the processing of personal data (inform). The controller also provides the subject with means to consent to, choose, update, and retract from personal data processing in a timely manner (control). The authority obliges the controller to demonstrate ensuring available evidence to test, audit, log, and report on policies and technical controls regarding personal data. To conform with the data privacy legislation, the controller may reduce the probability of privacy violations by hiding and separating data. Hiding involves mixing, obfuscating, dissociating, or restricting access to any data, whereas separation means distributing or isolating personal data. To reduce the impact of any violation, the controller may use abstracting (i.e., limiting the detail of personal information) and minimizing data (i.e., limiting usage of personal information). Most importantly, the controller commits to enforce (i.e., continually create, maintain, and uphold policies and technical controls) those strategies.

In planning smart energy systems, consumers’ acceptability is often only an afterthought [101], even though consumers may fear potential negative implications [102]. To increase acceptability,
one has to build trust and confidence [103]. Because perceived behavior control is a crucial psychological factor influencing acceptability [104], the above mentioned data protection strategies including inform and control could increase consumers’ willingness to provide data.

3.2. Computational methods

Modeling, simulation and optimization are necessary for energy demand prediction and to facilitate energy demand reduction and demand side management. Aiming at a valid representation of the (energy) system, thorough information on its properties is needed to be able to build, initialize and parameterize a model. The various kinds of data and how these can be obtained is explained in detail in section 3.1. Work on optimized control of buildings energy systems has pointed out that the integration of the users data and feedback into the control loop is vital [16,105]. The following inputs and feedback from users would facilitate the optimized control of building energy systems: Setpoints for heating and cooling, occupants availability, possible flexibilities, feedback on comfort and preferences with regard to the objective of optimization (comfort, economic savings, environmental savings).

3.2.1. Modeling and simulation

Models can be used in the area of active user integration for the following purposes: (i) Simulation-based what-if analyses. To learn about the reaction of the system under specific conditions (e.g., energy consumption at different temperature setpoints for heating and cooling), simulations with different inputs are required. (ii) Optimization. To optimize a system in terms of a specific goal (e.g., reducing energy consumption while maintaining a desired comfort level) a model of the system is required. Often a simpler model is used for optimization than for what-if simulations. Some general considerations on modeling and simulation.

- For certain models, there may be considerable computational restrictions and restrictions with respect to the structure of the model, such as requirement of derivative information or restrictions to continuous problems without integer variables. These apply in particular to models for optimization procedures.

- Depending upon the application and the outcome of the interest, a specific fidelity of the model is necessary; the fidelity of the model is constrained by the quality of the raw data and the quality of the model itself.

- The modeling approach (white-box, grey-box, black-box) used for the respective application depends heavily on the available data (e.g. is information on the building envelope available? See also Section 3.1.1).

The energy consumption of buildings can be assessed by various methods and tools [66,106,107,105]. Wang and Zhai [108] gives an overview of existing approaches and the advances of the last 30 years in this field. Modeling and simulation approaches and tools can be distinguished at various levels (see Fig. 5).

A general distinction is made between physical-based modeling (also known as white-box modeling), data driven modeling (also known as statistical- or black-box modeling) and grey-box modeling [109,66,110]. White-box models: White-box models are described by equations and are derived from first principles. Tools for white-box modeling can be classified into special-purpose and general-purpose tools. General-purpose tools that have been used for building energy simulations are IDA Ice, Modelica tools or TRNSYS [111,112]. Special-purpose tools can be further classified into energy simulation graphical user interfaces, energy simulation engines and integrated modeling tools that combine both functionalities (graphical user interface and a simulation engine) [113]. Graphical user interfaces support the modeling process including the geometric modeling process of the building without performing the simulation itself. Tools that belong to this category are OpenStudio, DesignBuilder, BEopt, Revit or eQuest. To perform simulations, these tools require a simulation engine such as EnergyPlus or DOE-2. Integrated modeling tools are DOE-2, EnergyPlus, ESP-r, HASP/ACLD or HOT2000 [113,66,114–116]. An online data
base with detailed information about tools for simulating white-box and grey-box models of buildings and district energy systems can be found in Schweiger et al. [111]. Modeling paradigms for white-box modeling can be divided into causal and acausal modeling paradigms. In causal modeling, the modeled system is described by a system of ordinary differential equations in explicit form. In acausal modeling, the modeled system is expressed as a system of implicit differential algebraic equations. A detailed discussion on causal and acausal approaches can be found in Schweiger et al. [117].

The drawbacks of white-box modeling are: (i) many of the required mode parameters are unobservable, unknown or uncertain; (ii) the modeling requires great competence and knowledge of the system and its operation [118]; (iii) models are time-consuming to validate and (iv) the computational speed is low [119]. Consequently, white-box modeling may be feasible in an academic environment where enough time and effort in modeling, but outside academia white-box approaches are limitedly suited, especially when buildings with more complicated structures are modeled [120].

Black-box modeling: Data driven black-box modeling techniques examine the system from the outside using input/output relations; models are learned from data. Compared to white-box models, data driven models are computationally efficient [110]. The learning process is discussed under the term machine learning and artificial intelligence in the statistics literature and system identification in the control literature [118]. In the field of building modeling, supervised [67,121,122] and reinforcement learning machine learning algorithms [16,123,124] are mainly used (see Fig. 5). While the first is a machine learning task that maps input features to output features based on labeled training data, i.e. input and target output pairs, the latter uses a reward function that is tried to be maximized by learning the best actions that can be taken by software agents in their environment, also focusing on the finding a good balance between exploration and exploitation. Vázquez-Canteli and Nagy [16] have pointed out that reinforcement learning techniques are well suited for directly integrating the feedback of users into the control loop. Methods based on artificial neural networks are currently most widely used because they are very accurate and it is possible to model nonlinear systems [66,67]. Data-driven models are used to predict e.g. room air temperature, weather parameters, thermal comfort or energy consumption by HVAC systems [67]. The input parameters are often weather parameters, operational data of HVAC and equipment as also occupant behavior.

The drawbacks of data-driven black-box modeling are: (i) the model extensibility is limited to the quality of the training data [119]. A rich data set is required which comprises of all possible working conditions; and (ii) missing data cause significant complications [125].

Grey-box modeling: Grey-box models are in between white-box and black-box models; they are based on simplified physical models. So called aggregated physical parameters are estimated using collected measurement data. A detailed discussion can be found here [66,126].

The drawbacks of grey-box modeling are similar to those for white-box modeling [118]. Additionally, great competence is required to estimate the parameters [66]. It should be noticed that the distinction between grey-box and white-box is not clear since almost every white-box model also uses simplified physical submodels. Monolithic and co-simulation: When modeling complex systems such as buildings or even a compound of several buildings, one can divide the system up into several subsystems. Modeling such systems can be done in two ways: (i) the entire system is modeled and simulated in a single tool. This is called monolithic simulation. (ii) The tools for the individual subsystems are coupled in a so-called co-simulation. Recent work in the field of building energy modeling and simulation has highlighted the importance of co-simulation [115,111,127]. A recent study on promising standards and tools for co-simulation shows that the Functional Mockup Interface [128] is the most promising standard for co-simulation [129]. The Functional Mockup Interface is a tool independent standard for co-simulation and the exchange of dynamic models which is currently supported by more than 140 tools.

### 3.2.2. Operational optimization

Optimization can be used in the area of active user integration for the following purposes: (i) minimize the energy demand based on user preferences and (ii) demand side management, where the goal is that building energy consumption is adjusted/shifted in an optimal way based on external signals such as price signals while maintaining the consumer's needs and comfort levels. While intensive research has been carried out in recent years to develop methods for optimizing the energy consumption of a building, classic proportional-integral-derivative controller or ON/OFF controllers are still the most commonly used. Shaikh et al. [105] reviewed optimized control systems for building energy and comfort management of buildings. They conclude that the realization of intelligent systems, building occupants' behavior, activities and preferences are the most important feedbacks for smooth building automation.

Model predictive control (MPC) methods are control optimization approaches that have become very popular in building energy control [67,119,118,120,105]. General trends and opportunities for MPC in buildings are discussed in [118,67]. Previous research has shown that MPC of HVAC systems could reduce the energy consumption and operating cost significantly (up to 50%) [131,132,67]. The dynamic response of a model (e.g. a building and its HVAC system) is affected by the model characteristics as well as by the inputs (e.g. temperature set-points for HVAC systems). MPC control methods use this model to predict future responses as a function of controlled inputs. MPC is based on repeated optimal control (see Fig. 6); while the optimization yields an optimal sequence spanning the prediction horizon (e.g. 12 h), only the first sequence is applied to the system (e.g. 1 h). Beside a model of the system (see section 3.2.1), MPC methods require an optimization algorithm that computes the optimal control inputs based on the given model and boundary conditions such as occupant activities or weather data. Distinctions between different optimization approaches can be made on several levels (see Fig. 7).

For all optimization applications discussed in this paper, it is important to consider (nonlinear) dynamic effects of the building and its HVAC system and domestic appliances within the optimization procedure [118,66,120]. Buildings with high thermal inertia are particularly suitable for demand side management strategies, because the slow response of the thermal inertia building can shift peak loads using sophisticated control strategies such as model predictive control [133]. When the energy price is low, buildings are preheated (or precooled), while not violating thermal comfort limits. Studies show that these could lead to cost savings up to 14% [134]. The model of the system can be based on white-box, grey-box or black-box approaches [135] (see section 3.2.1). Control inputs might be trajectories such as temperature or mass flow and/ or operation modes and set points. Candidates for the objective function are energy consumption, indoor air quality, operating costs or peak demand [135,136]. In addition several (conflicting) optimization goals can also be defined such as minimizing the energy consumption and maximizing the thermal comfort. Multi-objective optimization methods are thus required. In the simplest version, the multi-objective problem is transferred into a single-objective problem by adding weight factors to the individual objectives and summarizing them [105].
The structure and complexity of the underlying optimization problem depends on the mathematical characteristic of the systems model (e.g. linear/non-linear, continuous/discrete/hybrid, see Fig. 7) and the choice of control inputs (e.g. trajectories, set-points, operation modes) [119,137]. Many optimization applications in the field of building energy optimization can be described by so called mixed-integer nonlinear optimal control problems. These systems depend on continuous control inputs (e.g. temperature and mass flow trajectories) as well as discrete control inputs (e.g. on/off control or operation modes) and a nonlinear system model [138]. Most optimization approaches in the literature either linearize the model equations [139] or separate the discrete problem from the continuous problem [140]. Solution methods can be classified as derivative-based (sometimes referred to as gradient-based) and derivative-free methods. Derivative-based methods require derivative information of the model constraints and the objective function. Derivative-free methods do not require derivative information.

4. Consumer participation

Smart energy systems rely on active consumer participation. Consumer have to accept, install, and use smart products and services. They need to provide data and adjust their behavior. Even highly automatized solutions require some user involvement and if automation is not given, intensive consumer participation is essential. For the sustainable energy transition, it is important to embrace consumers as active contributors in energy systems [35,103,141,16]. To built a smart energy system, one does not only need to understand the economic aspects of the market and technological opportunities and restrictions, one also needs to understand the consumer as a human being and the forces behind human behavior and behavior change.

4.1. Determinants of behavior and behavior change

Consumers, as active parts of the smart energy system, shape, change, and influence the system with their behavior - either with their energy consumption behavior or with providing crucial data. To understand consumer’s acceptance of and engagement with sustainable solutions such as smart grids is therefore essential [142]. Generally, people hold different values, beliefs, and norms and have different attitudes, all of which influence their motivation to participate actively. But even if they are motivated to perform a certain behavior, they need to be able to perform it and also remember to do so. There are therefore three main components to behavior, which have to be considered in any business model involving consumer participation:

- Motivation – is the behavior desired by the person?
- Ability – can the person comply with the behavior requirement?
- Opportunity – is the behavior facilitated or prompted by the environment?

4.1.1. Motivation

Motivation is the driving force behind behavior. If a person wants or desires something, he or she is motivated to pursue this goal and to act accordingly. Central motivational factors from previous research to participate in energy system interventions are the reduction of or control over energy bills, environmental concerns, and better comfort [103]. There are two fundamentally different ways to be motivated - intrinsically and extrinsically. Intrinsic motivation describes people’s drives that come from within. People demonstrate intrinsically motivated behavior, because it is satisfying to them, such as exploring and engaging in challenges. In contrast, extrinsic motivation is driven by outside forces. People act because they gain fame, money, or praise from their action [143].

Values are a prominent way to strengthen intrinsic motivation to act pro-environmentally [144,102]. Stern [145] postulated a value-belief-norm theory in which personal values influence con-
sumers’ beliefs about the environment and the impact of their actions, which in turn influences personal norms, i.e., what they think is the right thing to do. Those personal norms are then thought to lead to behavior such as pro-environmental behavior at home or at the workplace.

A powerful extrinsic motivator for pro-environmental behavior is subsidizes and rewards. People perform a behavior because they get something in return [146]. However, this motivation often last only as long as the rewards are present. Therefore, motivation by incentives can be costly and impossible to sustain in the long term. Moreover, being extrinsically motivated can overshadow and diminish people's initial intrinsic motivation [143,146]. Steg et al. [144] argue that increasing the value of pro-environmental goals is a better long-term strategy than subsidizing pro-environmental behavior. Increasing people’s wish to act sustainable is the one side, making it easy for them and reminding them to do so, is the other one.

4.1.2. Ability and opportunity

Pro-environmental behavior is often only attainable by sacrificing substantial amounts of resources - in terms of time, money, and brainpower. Thus the design of a product or a service does not only need to address the beliefs, values, and norms people have to increase motivation, it also need to provide a context so that the desired behavior require less resources [147].

A prime example of cleverly designed context to stimulated desired behavior without demanding many resources are nudges. Nudges operate by modulating the path of least resistance – and act as prompts to draw attention to opportunities. They are subtle but transparent cues in the environment, put in place to trigger desirable behavior without coercion or punishment of alternative behavior [148,149]. A classic example for nudging is to place fruit on eye level to make it more visible and more easily accessible to promote healthy eating.

There have been many attempts to nudge sustainable behavior. For example, Klege et al. [150] ran a successful nudging project to reduce energy consumption in a non-residential setting. A review by Lehner et al. [151] revealed that the most popular applications of nudging in household energy consumption give feedback and general information, facilitate energy savings through appliance design, provide prompts, update default settings, and make social norms accessible. The effect of these nudges were small to significant in some and unclear or not reported in other studies. Apparently, the behavioral effectiveness of nudges is highly context-dependent [152]. However, Kasperbauer [153] makes a compelling case that nudging is well-suited to support consumers making the right choices when it comes to energy consumption. Nudges aim to provide a path of least resistance and thereby accomplish behavior change even with very low motivation. Behavior change due to active consumer participation with the energy system could also be achieved by other means.

4.1.3. Behavior change models

As outlined above, the occurrence for a certain behavior depends ultimately on motivation, ability, and opportunity. Within psychology, which aims for understanding humans thinking, feeling, and behavior in general, and within many applied fields, aiming for understanding or influencing specific behavior like health behavior or consume behavior, there is an abundance of specific theories and models dealing with one of the three aspects or related concepts. However, there are fewer models trying to provide a theoretical base considering all three aspects at the same time and thereby creating a general framework. One of these is the Fogg Behavior Model [154] and another one the Behaviour Change Wheel [155]. These two models are specifically designed to aid the development of complete concepts for behavior change.

In his behavior model for persuasive design, B.J. Fogg [154] argues that behavioral occurrence is a product of motivation and ability, paired with a trigger or prompt. To elicit a certain behavior, the interaction of motivation and ability to perform a behavior must be above an action threshold, so a prompt can trigger the target behavior. A highly motivated person, who lacks ability, cannot be prompted to perform the target behavior. Similarly, a person who is perfectly able to perform the target behavior, but has no interest in doing so, can also not be prompted to perform. However, when someone’s motivation and ability to perform the target behavior is sufficiently high, a prompt in the environment is enough to elicit behavior. Fogg [154] stresses that a behavior can only occur if all three elements are present at the same time. Therefore, any attempt for behavior change needs to target all three elements to reach its full potential.

Similar components, but a different interpretation can be found in the Behaviour Change Wheel. Susan Michie and colleagues [155,156] integrated 19 behavior change frameworks into one comprehensive and coherent overarching model. The resulting Behaviour Change Wheel presents three sources for behavior: capability, opportunity, and motivation. Contrary to the Fogg Behavior Model, it aids developers in focusing on a source of behavior that needs to change and suggests appropriate functions to address this source (e.g., coercion, modeling). It also includes policy categories (e.g., legislation and service provision) to define how the intervention, product or service should be administered. The Behaviour Change Wheel facilitates choosing a combination of sources of behavior, intervention functions and policy categories that will presumably lead to behavior change. Furthermore, it stresses that a successful design not only considers effectiveness, but also affordability, practicability, acceptability, side-effects, and social equity [156,157].

Behavior change models provide a theoretical base for designing products and services within a smart energy system involving active consumer participation and relying on establishing new behavior or changing old behavior. Because every product is unique, design has to be adjusted to specific target behavior. A service which requires consumers to repeatedly interact with the interface needs a different design than a service that only needs consumer input once [158]. For example, installing smart home features to enable demand response is different to accepting a dynamic electricity tariff and adjusting behavior manually. In the first case, the opportunity to show the desired behavior occurs only rarely (e.g. while building a new home) and substantial resources are necessary (e.g., costs could be high). Furthermore, motivation might be diminished by fear of loosing control or by concerns about data privacy Annala et al. [97]. In the second case, consumer first have get the opportunity to chose such a tariff, but if offered, all consumers have the ability to do so. However, the more crucial behavior change is altering everyday electricity consumption. Even though ability to do so is for many, but not all, consumers high and opportunities occur every day, consumers might not be aware of opportunities and have to be reminded or prompted. Furthermore, to overcome habits, a strong motivation is crucial. Potential reduction in the electricity bill might not be substantially enough to encourage such a change. Thus, the content of the service or the product have to fit to the desired behavior. The behavior change models help to identify important aspects and suggest fitting methods (e.g. [159]). But not only the content, also they way of delivery to the targeted consumer is crucial for the impact of a service or a product.
4.2. Delivering behavior change attempts

Web interfaces and mobile applications are prominent tools for delivering products and services within smart energy systems. Even though existing applications are often limited to access bill statements and self-service options [35], the possibilities are far greater. Mobile apps could flexibly combine several elements such as feedback, information, and simulation and thereby provide the opportunity to tailor each service to the individual consumer or the consumer segment.

4.2.1. Tailoring

Energy systems and their interfaces affect consumers differently. To attain any consumer behavior change, it is important to understand consumer needs and preferences and to deliver the service accordingly. For example, services aligning with consumer values - focusing on sustainability when people's biospheric values are high, and on personal gains when their egoistic values are high - will have a greater impact on consumer behavior than services that are misaligned to consumer values.

Besides the issue of what is important for a consumer, it is also necessary to tailor to what a consumer can do. Some people are skilled in using sophisticated mobile applications, while others are discouraged when asked to navigate through a complex mobile application. Similarly, some have more and others less time to devote to an interaction with a product or a service. It is therefore vital to involve future consumers in the design process as it is the case in the co-creation approach. This is the most evident way to ensure that they will be satisfied with it.

Lastly, the starting point of consumers matters. Are they already planning to change their energy consumption and simply do not quite know how - or are they not even aware of any problems arising from their behavior? He et al. [160] proposed a motivational framework to initiate sustainable energy consumption via feedback, drawn largely from motivational psychology literature. The framework contains five stages, which should be addressed to guide consumers from being ignorant about their problematic energy consumption to forming sustainable habits. These five stages roughly reflect stages of change in the Transtheoretical model of (health) behavior change [161], which differentiates motivation at various stages of readiness, willingness, and ability to change. The model gives an overview of phases consumers traverse to lead a more sustainable lifestyle. The phases are: pre-contemplation (being unaware of the problem), contemplation (awareness), determination (willingness to change), action (actual behavior change), and maintenance (continued new behavior). There is always a risk of relapse - consumers who fail to sustain their motivation find themselves in one of the previous stages and then need to re-build their motivation to work their way back towards behavioral maintenance. Designers can use those phases as a way to think about which features and offers should be included to address consumers in all possible stages. Especially the final stage - maintenance - have to be considered to ensure long lasting effects.

4.2.2. Gamification

One popular method for continuously engaging people is to gamify a product or a service. In gamification, principles and elements of game-design are used in other contexts. For example, one could remodel a staircase to look and sound like a piano when walking up or down [162]. Implementing elements such as achieving, exploring, competing, or connecting with other people in a behavior-change-tool stimulate people and increase engagement and motivation [163]. Weiser et al. [164] provide an overview of game design, mechanics, and elements grounded in well-established models of motivation and behavior change.

Nicholson [165] distinguishes between reward-based and meaningful gamification. These influence extrinsic and intrinsic motivation respectively. As pointed out above, providing rewards can harm intrinsic motivation [166]. Reward-based gamification should thus only be used to initiate participation, for short-term behavior change, or if rewards can be handed out indefinitely. To enhance intrinsic motivation, mechanisms of meaningful gamification should be the focus of any gamified tool. Those meaningful mechanisms give consumers the opportunity to explore a narrative, choose how to engage with the service or the product and make meaningful decisions, get information (e.g., about real world effects of their behavior), engage with others, play elements to develop solutions for real-world problems, and reflect - and with others - about what they have learned. After some time, a well-designed gamification system fades itself out to the benefit of habitual real-world behavior. AlSkaif et al. [167] describe a detailed gamification framework guiding the development of gamification elements specifically for residential consumer participation in energy applications.

A review on gamification to facilitate pro-environmental behavior for energy efficiency from 2017 found only four studies on gamified tools [168]. Two of these were web-based platforms and the other two ones were mobile applications. One study could show an initial reduction in energy consumption, but consumer effort to participate and reduce energy consumption quickly decayed. Another one stimulated short term energy reduction with initial behavior change. Even at follow-up, some habits had formed and consumers had a tendency to stay below baseline in their energy consumption. The remaining two studies could show that consumers were more aware of their energy consumption, but did not report significant behavior changes.

Analyzing gamified tools and serious games (i.e., video games to convey an intervention) for energy conservation, another review found 25 studies within the domain of domestic energy consumption [169]. The most commonly used elements of gamification were feedback, challenges, social sharing, rewards, and leaderboards. Most tools or games included two to five elements. Ten of those studies analyzed real world behavior and nine of those ten found positive results of the gamified tool on real world behavior. Even though empirical evidence is still thin, those first studies show that there is great potential in using gamification to help make smart energy system tools more effective.

However, in 2019 a review of 57 gamified mobile energy apps shows that in the real world, gamification and game design elements are still heavily underutilized [170]. To further facilitate the transition to a more sustainable smart energy system, companies should be aware of the potential of gamification during business model identification (see Section 2).

4.2.3. Retention

While it is essential to provide the best possible experience for consumers and to meet many of their needs and wishes within the interaction with a product or a service, there are additional retention strategies that can be utilized during implementation to keep consumers engaged.

Coday et al. [171] provide a list of such retention strategies from studies targeted towards disease prevention. Even though the content is quite different, the challenges are similar in both types of project. Both require participant effort to start and maintain behaviors that they would not have engaged in otherwise. They also do not provide immediate gains for participants, but rather long-term effects. One strategy is a well-maintained tracking system to send out timely reminders if consumers fail to engage with the product or service (e.g., if they do not open their mobile app for a few days) [171]. Personal reminders can be effective in reacquiring consumer attention and participation. Another principle is
flexibility. Overburdened consumers will not answer all the ques-
tionnaires and forms that are provided for them, so central mea-
ures should be presented first. To reduce the possibility of
overburdened consumers dropping out entirely, the opportunity
should be given to opt out of certain tasks. This gives consumers
additional control and minimizes burdens. Finally, the benefits
of active participation should be emphasized not only within the
specific service but also on other channels to remind consumers
who are not yet using the service or who hardly interact with
the service of its value.

Thus, involving the consumer actively in the energy system by
providing data or by adjusting behavior comes with a challenge,
but also with the opportunity to gain data and impact that is not
easily available otherwise.

5. Challenges

Active consumer participation has been widely discussed across
individual disciplines in recent years [43,172]. In all of this, how-
ever, there is a lack of integrated analysis that merges the technical
possibilities and requirements (What data are required?) with
the perspective of the user (Under what circumstances do users partici-
pate?) and possible business models (How to generate value?).

In this section, the key issues, highlight possible challenges and
propose various approaches together with ideas for improvement
are presented. First, we will discuss the impact of consumer data
for the three use cases. We will then discuss four phases of use-
case realization: product development, launch, maintenance and
evaluation. Thereby we will focus on the use case demand side
management. This represents the most complex of the presented
use cases (energy demand reduction, demand side management,
energy demand prediction) concerning user participation, data
and computational methods. Furthermore, most of the issues
brought forward are relatively similar for all the use cases and
thus concern them all. For the sake of simplicity, the term product
includes all the components and services connected with the use
case.

5.1. Impact of consumer data

Based on the thorough literature research made in the course of
this paper, we give an insight into the dependencies and impacts of
the different kinds of data on the three use cases energy demand
reduction, demand side management and energy demand predic-
tion. For the development of a product, a matter of particularly
importance is whether data can be provided automatically or man-
ually by users (for data sources see section 3.1.2).

Building data (including construction, geometry and geographic
location data) can be transferred both automatically and manually
(e.g. based on construction plans). The extent to which residents
possess information about their buildings is not discussed in the
literature. Clearly, this knowledge does vary and the number of
residents who are barely informed about the construction data of
their building might well be significantly high and thus relevant
for product development. If this assumption holds, an application
that requires manual data for the building would be difficult to
generalize. Occupancy availability can be determined manually
(e.g. using schedules on apps), automatically (e.g. using GPS infor-
mation of smart phones) or it can be obtained from historical data.
The willingness of users to provide data such as GPS data from
smartphones automatically is of central importance. This issue,
however, has not yet been investigated. Demand prediction can
be achieved using manually parameterized models or by learning
from historical data. Temperature set-points, preferences (comfort
vs. cash or emissions savings) and the quantification of flexible
loads are highly individual and thus have to be given by the con-
sumers manually. Algorithms can learn from these settings and
preferences, however, and derive suggestions from them or, if
desired, operate automatically after a learning phase.

We wish to stress that the impact of the different kinds of data
varies from use case to use case. Demand prediction, for example,
is of the greatest importance for energy demand prediction, less
important for demand side management and has a low impact
on energy demand reduction. Personal comfort is more important
for energy demand reduction and prediction than it is for demand
side management. Set-points, occupancy availability (is the user in
the building or not) and individual preferences have a great impact
for all use cases, whereas we have come to consider the accurate
position of people within the building as being of relatively low
importance for every use case.

Thus, consumer data are needed to different degrees for differ-
ent use cases and consumer participation is nearly always neces-
sary to some extent. Unfortunately, empirical evidence of the
impact of gamification, tailoring, and product development based
on behavior change frameworks on consumer participation and
data provision in smart energy systems is still scarce. Furthermore,
the interaction of all data sources has not yet been sufficiently
investigated. We see it as a key challenge to identify the sweet-
spot of consumer participation, indicating a balance between ben-
efits based on consumer data and costs, for the consumer or other
stakeholders, involved to obtain these data.

5.2. Product development

The goal of a successful product development is to find an
appropriate solution considering the requirements of the con-
sumers, the business model, and the model of the energy system.
Only if the developers are able to identify and solve consumer
needs, will the business model be successful and value can be gen-
erated. Thus, the choice of consumer segment is of great impor-
tance for the product development. The chosen consumer
segment, however, will influence the data available for the model
of the energy system and the availability of data will influence
the type and the specification of the model. At the same
time, the model must perform satisfactorily to allow a realization
of the business model. Thus, all three elements are greatly
dependent on each other.

Coming back to the product “demand side management”, the
building energy consumption should be optimally adapted or
shifted based on a (simulation) model of the system. The model
must be able triggering flexibilities such as HVAC systems and
domestic appliances basing on external inputs (e.g. price signals)
and consumer preferences (e.g. set points, occupancy and usage
habits). Several approaches are possible for modeling such a sys-
tem and the decision depends on aspects such as: What data are
required to create the model? What data can be collected automatic-
ally and how easily can the consumer provide missing data?
The data consumers will need to provide will depends to a great
extent on the underlying model of the system. While white-box
models require detailed information about physical properties of
the building and appliances, black-box models learn from data
using input/output relations and thus require large amounts of
measurement data. Among the disadvantages of pure white-box
models discussed in the literature [118,120] is the need for unob-
servable or unknown data about the building construction. Black-
box models do not require understanding of the building physics
in detail but they suffer from poor generalization capabilities and
require a significant amount of training data. Thus, during product
development the decision must be made on whether it is more fea-
sible to obtain relatively complex and detailed information about the building or frequent but simpler information about consumer behavior and energy consumption.

To obtain the data required for the model, one can also develop a generic workflow that extracts information from existing data sets. This could be data needed for white-box models such as regional building requirements or data for black-box models such as past energy consumption based on smart-meter readings. However, this is difficult because standards and availability are very different for countries and regions. To increase the ease of data extraction, a database describing country specific standards and data availability would be valuable.

During product development, decisions about the model not only depend on which data are easily available, but also on the system that needs to be modeled. Different building types and products might require different models, which might further be simulated via a monolithic approach or a co-simulation. Since this depends on the complexity of the system model and the choice of modeling paradigms as well as corresponding tools, there is no generally applicable choice. Guidelines along which this could be decided according to basic information on the considered system would be very helpful in early development phases. The establishment of such guidelines is bound to be very challenging owing to the variety of modeling approaches and coupling methods available. Creating a systematic database for collecting research data and also demonstrations comparing different approaches for different systems and product could be a first step.

The existing research results, however, differ significantly in quantifying the potential of different optimization and control methods for building energy [131,132,67]. Identifying the cause of this variation is a vital challenge.

Another useful step would be to define test cases for different building energy systems and use cases. Such test cases are essential for transparent comparison of different modeling approaches and optimization methods. We propose that these test cases should not be developed by tool vendors or specific modeling language experts, to avoid potential biases. The characterizations of the test cases should be specified instead, by domain experts who can be expected to be more neutral.

During product development, once the best business model to satisfy the need of the consumers is identified and the optimal model of the energy system given the business model, the system and the available data about the consumer are specified, the focus could shift toward how the model will influence the system. In some cases, this influence might be automated (e.g., in a smart home the thermostat is regulated by the model), but in many cases the consumer will be involved. Work on optimized control of buildings has pointed out that it is vital to integrate consumer feedback in the control loop [16]. How this feedback might appear in practical terms is not discussed in the literature.

Depending on the business model, a variety of target behavior by the consumer will influence the energy system. This behavior might vary from periodical behavior involving daily tasks, to less frequent or single act behavior, that might require a high initial effort. How much time and effort each consumer is able and willing to invest depends on the target behavior, circumstances in which the target behavior is required, the consumer's values, motivation, ability, the social environment, and many more factors. To acknowledge the central role of the consumer, we suggest considering the principles of human-centered design, behavioral models, gamification, and tailoring during product development. Furthermore, empirical evidence based on (semi-structured) interviews, focus groups, surveys, experiments in the laboratory and in the field or by acquiring existing data from social media, governmental facilities, or companies, will all be considered.

5.3. Launch

The next step is conducting trial studies. Trials have an impact on the ongoing development and improvement process, since flaws and design errors may be identified and solved. Launching new products and the trials and tests of them usually face problems in acquiring the critical number of participants they need, e.g., demand-response applications require a sufficient number of flexibilities to ensure high liquidity.

Some consumers with reservations about participating can be persuaded to do so by using community approaches - for example by cooperating with local authorities or established environmental initiatives. Other consumers in a residential setting might be more receptive for requests via their electricity provider or landlord, as they have a common basis of trust. The conveying of trust to potential consumers is a vital condition.

Apart from a large consumer basis required for smart energy systems, some forms of intervention only unfold their environmental and/or economic impact after a long period of data provision - of several months for example, in the case of black-box approaches (section 3.2). Whenever such data cannot be accessed from existing sources, the product relies on consumer inputs. Depending on the quantity and quality of data provision, consumers may lack motivation. Due to the lack of immediate gratification innate to a behavior, other ways to stir and maintain motivation need to be present in interventions. These can for example draw from gamification or follow use-of-ease principles introduced to such a marginal extent that they are barely noticeable for consumers.

5.4. Operation

When operating such a project, consumer effort must to be kept to a minimum. Data collection should be automatized to the greatest possible extent in order to make this process easy, quick, and infrequent for the people involved. Unfortunately, automatic measurements and data transfer are not standard feature that can be counted on. The percentage of smart meter roll-out, for example, is highly country-specific (although high goals are set for America, Europe, and Asia-Pacific, cf. Section 3.1.2) and the support software for client interfaces is mostly scarce. Moreover, the consumption data are summarized for a household and thus not easily obtainable for individual appliances or the HVAC system, which would be essential for some kinds of models. On the other hand, whenever consumer action is needed, motivation, ability, and opportunity should be considered. Moreover, consumer motivation needs to be well-tended and kept at a high level. This can be achieved by making the interaction possibilities personal, fun, and playful. Some people like to compete by collecting virtual rewards, others like to explore new possibilities - such as performing new tasks and finding ways to solve puzzles. There are many sides to a gamified project [163]. Consumers should be given the option to personally tailor the interaction frequency and content to their needs and wishes to diminish the chance of them becoming iritated and losing their motivation.

Entertaining interventions might prove likely to gain acceptance from consumers. Yet, trustworthiness remains a big topic. Consumers need to have the certainty that there will be no data misuse. Only on this condition will they accept an intervention that has access to such personal domains of their lives.

At product launch, many newly designed products have limited functionalities. If these are attractive to consumers, further developments may be initiated and new services added. As the products discussed in this paper are elements of a bigger picture or may be embedded into other services, interoperability is highly relevant. The design must thus include appropriate and established inter-
faces. While a great many new products and services have emerged in recent years, there is no guarantee for any of them that they will be able to stay in the market. This is relevant, since operation and security may only be guaranteed by periodical updates.

5.5. Evaluation

When evaluating to what extent a product has succeeded, certain specific factors should be taken into account. Firstly, it matters how many consumers participated and how representative this sample is for the population and also how many consumers dropped out using the product and what reasons were for them doing so. Secondly, the more consumers are exposed to a product, the greater the chances that the intended effects can unfold and develop. It is advisable not only to look at total product exposure, but also at the amount and depth of interaction with any components or modules within the product. Those effects should then be reflected in consumer changes in norms, values, behavioral intentions and actual behavior. During evaluation, one should also keep in mind, that any product could have unwanted side effects. Thus, assessing behavior, norms, and values outside the intended focal point could be helpful to discover such effects. The results of evaluations should be reported in a manner that will facilitate meta-analysis, has not always been the method practiced in previous studies in the field. Hofmann et al. [173] provide guidelines on how interventions should be reported. If these guidelines are followed, intervention efficacy can be determined and interpreted in a more general way.

6. Conclusion

The integration of consumer feedback and preferences into the control loop is crucial to reduce the energy demand and to leverage energy services such as demand-side flexibility. The objective of this paper was to present a review of the state-of-the-art and to promote a discussion of key challenges to the developing, launching, maintaining and evaluation of energy services based on consumer participation. In order to provide a holistic perspective in this context we analyzed psychological aspects of consumer participation, data, and computational methods, enabling the integration of consumer feedback and preferences.

In the past, the consumer has often been portrayed as passive, uninformed individual striving to maximize egoistic (material) gains [174]. In this context, efforts to optimize an energy system have often meant to bypassing any active involvement of the consumer whatsoever. This essentially negative understanding of the role of the consumer is too limited and partially outdated [175,176]. Changes in our society (e.g. heightened awareness of climate change), the energy market (e.g., increase of private energy generation), technologies (e.g., smartphones and computational power, renewable generation) and the personal skills the average contemporary consumer possesses (e.g. digital natives), create an advantageous environment for an active consumer involvement. Designing energy services with a human-centered approach will allow us to rely on consumers not only as executors of changes in energy consumption, but also as providers of data. The data gathered by this means will help to leverage sophisticated control strategies and to optimize computational models, business models and the energy system in general.

Smart energy systems are a complex puzzle of very different elements. Individual consumer, social environment, physical environment, digital realities and economical conditions must be considered and integrated to allow successful operation. In order to reach challenging and important climate goals, many scientific fields are putting much effort into advancing technologies, developing interventions and finding new solutions. This effort, however, is often scattered and isolated. If we are to solve the puzzle, we need to provide the infrastructure for integrating insights and research results from many different fields and countries. Making people aware of the benefits and necessity of such an integration is an important step in this direction.

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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