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Assessment of Energy Customer Perception, Willingness, and Acceptance to Participate in Smart Grids—A Portuguese Survey

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Abstract: The adoption of smart grids is becoming a common reality worldwide. This new reality is starting to impact energy customers as they face a dynamic grid in which they can actively participate. However, if energy customers are not prepared to participate actively, they can have their energy costs increased. This paper provides a review of acceptance models and customer surveys around the world made to assess the customers' perception and willingness to participate in smart grids. Contributing to this assessment, this paper presents a survey undertaken in Portugal. The survey results demonstrate a willingness, from the customer's end, to actively participate in smart grid initiatives. It was found that 92.9% of participants are willing to plan their energy usage to face hourly energy prices and that 95.0% of participants are willing to accept an external control of at least one appliance, enabling direct load control demand response programs. Also, the results identified two cognitive tendencies, negativity bias, and loss aversion, which can impact how customers participate in smart grids. These cognitive tendencies and the literature acceptance models demonstrate the importance of conducting social science studies targeting smart grids to fully achieve the efficient participation of end customers.

Keywords: acceptance of smart grids; demand-side management; demand response; energy customer survey; loss aversion; negativity bias; transactive energy

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1. Introduction

The power grid as we know it has been changing in the last years. These changes will impact energy customers and require them to actively participate in the smart grid [1,2]. Energy customer participation can be achieved using different mechanisms to promote the balance between production and consumption, the reduction of grid overloads, or the assurance of grid stability [3]. Implementing smart grids will result in a more reliable and community-friendly system, allowing, for example, the democratization of energy [4].

The development of smart grids resulted from technological developments, mainly in hardware, which allowed (near-)real-time communication, monitoring, and control over the electricity grid and its components. The development of technological enablers of smart grids has been studied since the proposal of smart grids [5]. These developments allow the implementation of smart grids and energy management models to increase the sustainability, efficiency, and stability of smart grids.

One of the critical aspects of these new smart grids is the involvement of the energy customers, making use of each user's energy management to ensure the stability and efficiency of the system as a whole [6]. Therefore, assessing the energy customer's willingness to participate in smart grids actively is essential. In the literature, there are some participation strategies based on demand-side management [7], transactive energy [8], and demand response [9]. In [10], a demand-side management model for smart homes is proposed using a bat algorithm with exponential inertia weight. Also, for smart buildings, in [11], a demand-side management solution is proposed based on internet-of-things devices able to provide load optimization using a task-management-based predictive optimization mechanism.

Regarding the participation of customers, the work proposed in [12] applies a transactive energy model for multi-vector energy hubs considering the renewable energy resources' unpredictability to promote energy balance. In [13], the real-time transactive energy model proposed considers the household's preferences. In [14], it is demonstrated how aggregators can solve the flexibility aggregation issue to enable the balance of the grid using a mixed integer linear programming model considering load curves. To address the privacy issues related to the sharing of energy data, in [15], a privacy-preserving data aggregation algorithm is proposed to reduce communication overhead.

Although several active participation strategies are proposed in the literature, they focus their innovation and novelty on grid stability without considering the customers' willingness to participate. Some of the works, such as [16], [17], and [18], consider in their models the users' preferences. Still, no actual study on the energy customer side has been conducted to assess their willingness to accept such management models. To solve this issue, this work surveyed energy customers to evaluate their perception of smart grid topics and their desire to participate in the smart grid.

This paper reviews energy customer acceptance models and surveys that actively assess customers' willingness to participate in smart grids. After this review, a customer survey was presented by the authors in Portugal, based on previously reviewed surveys, to assess the readiness of Portuguese people to participate in smart grids. Participation in the survey was voluntary, and everyone was free to participate. The survey results are promising and indicate that energy customers are willing to face the new paradigm of smart grids. However, some issues were detected regarding the lack of information and the existence of cognitive tendencies relating to the type of participation. The customers' acceptance and adoption of smart grid technologies are necessary to boost the achievement of Goal 7 of the 2030 Agenda for Sustainable Development of the United Nations, namely, targets 7.1, 7.2, and 7.3 (https://sdgs.un.org/2030agenda (accessed on 28 October 2022)).

This paper is divided into seven main sections. After this first introductory section, a resume of smart grid strategies to influence customers' electricity consumption patterns is shown in Section 2. Section 3 presents prior literature regarding acceptance models and previously conducted customer surveys. Section 4 presents the survey that was conducted for this work. Section 5 shows the main results of the survey, and in Section 6, this survey is discussed in comparison to previous surveys. The main conclusions are presented in Section 7.

2. Smart Grids Strategies to Influence Customer's Electricity Consumption Patterns

In the old paradigm of power and energy systems, the transport of energy flowed from central production plants to end consumers, making the balance of both on the production side [19]. However, in the new paradigm of smart grids, the energy flows in different directions due to the distribution of energy sources, namely renewable-based, among end consumers that became known as prosumers [20]. The decentralization of energy generation in smart grids requires a (near-)real-time monitoring solution where information flows among grid entities, including, for instance, transmission system operators (TSOs), distribution network operators (DSOs), aggregators, and end consumers. These changes enable the balance between generation and consumption on the consumption side, required by the use of volatile renewable-based generation, and promote the efficiency of grid usage by decreasing the need for large production plants to satisfy small consumption peak periods during the day [21].

Increasing household energy efficiency is essential in reducing carbon emissions [22,23]. However, the appearance and adoption of smart grids enable the reduction of carbon emissions by increasing grid management efficiency [24]. Customer participation in smart grids is an important topic that is disruptive from the old power and energy system paradigm. In the smart grid, customers are called to participate using several active approaches. This section will present three strategies that enable the participation of end customers in smart grids by promoting a change in the customer's electricity consumption patterns: demand-side management, transactive energy, and demand response.

2.1. Demand-Side Management

The definition of demand-side management can be found in the 1985 IEEE glossary as "the planning and implementation of those utility activities designed to influence customer use of electricity in ways that will produce desired changes in the utility's load shape, i.e., changes in the pattern and magnitude of a utility's load. Demand-side management encompasses the entire range of management functions associated with directing demand-side activities, including program planning, evaluation, implementation, and monitoring. Opportunities for demand-side management can be found in all customer classes, including residential, commercial, industrial, and wholesale" [25].

The demand-side management concept enables the management of energy demand on the customer side, which can reduce consumption in on-peak hours (i.e., hours when the electrical grid has an increase in demand) [26]. Although this concept does not specify how such changes in the user consumption profile can be achieved, two possible mechanisms are proposed [27]: energy efficiency and demand response programs.

In Lissa et al. (2021), a deep reinforcement learning model is proposed to optimize the usage of solar renewable energy in a residential environment taking into account the users' comfort [28]. Another approach is proposed by Amasyali and El-Gohary (2021). Machine learning occupant-behaviour-sensitive models predict consumption and comfort conditions for ahead periods and then optimize energy resources using a genetic algorithm to reduce energy consumption and improve users' comfort [29]. In Malik et al. (2022), a comparative study regarding the optimization of energy usage and users' convenience was conducted over three optimization multi-objective techniques: a genetic algorithm, a hybrid genetic algorithm, and a particle swarm optimization [30].

2.2. Transactive Energy

Transactive energy is a relatively recent concept that can be used in smart grids to produce changes in the energy demand profiles of customers. Currently, two definitions must be considered when addressing transactive energy: "A system of economic and control mechanisms that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter." [31], and "a software-defined grid managed via market-based incentives to ensure grid reliability and resiliency. This is achieved with software applications that use economic signals and operational information to coordinate and manage devices' production and/or consumption of electricity in the grid. Transactive energy describes the convergence of technologies, policies, and financial drivers in an active prosumer market where prosumers are buildings, electric vehicles (EVs), microgrids, virtual power plants (VPPs), or other assets." [32].

Transactive energy mechanisms can be applied to use demand-side management employing economic and market-based signals that alter the energy prices, promoting the shifting of consumption on the end-uses side. According to Kok and Widergren (2016), transactive energy can be divided into four groups: top-down switching, centralized optimization, price reaction, and transactive control. These groups represent quadrants in a bi-dimensional matrix of type of communications (i.e., one- or two-way) x decision (i.e., made locally or centrally) [33].

In the literature, it is possible to find some examples of the use of transitive energy in case studies and pilots. Regarding energy price changes, von Bonin et al. (2022) proposed a dynamic electricity prices model for distributed photovoltaic generation and electric vehicle charging routines to increase the local usage of distributed generation units [34]. However, there are more specific cases such as the one proposed by Suhonen et al. (2020), where the variation in the price of energy focuses exclusively on heating, ventilation, and air conditioning (HVAC) systems in district areas [35]. However, the variation in the price of energy is not the only possibility of applying transitive energy, with the opportunity for consumers and producers to participate in the retail market (at the central or local level). Models of this same participation are proposed by Gazafroudi et al. (2019) [36], Olivares-Rojas et al. (2021) [37], and Crasta et al. (2022) [38].

The concept of transactive energy also enables the setting of local electricity prices. In Oprea and Bâra (2021), energy prices in a local electricity market are set using an auction-based approach. Several auction types are tests: uniform price, pay-as-bid, generalized second price, and Vickrey-Clark-Groves [39]. Javadi et al. (2022) proposed a pool-based energy market for local energy markets using a mixed-integer linear programming optimization to minimize the community energy costs and its members' demands [40]. Another approach is given by Talari et al. (2022), where a matching mechanism is used to combine sellers and buyers according to their preferences regarding green energy, the trading partner's reputation, and the partner's location in the grid, and the clearing price is then set for each transaction using the bidding prices average and premiums [41].

Transitive energy also includes the possibility of direct energy transactions among customers (i.e., peer-to-peer transactions). This allows customers to completely change their current passive role and become active players in an environment where they can buy and sell energy to whomever they want, allowing customers to search for lower or affordable prices. In Bangkok, Thailand, the T77 project is expanding but is already operating [42], enabling peer-to-peer transactions among neighbours since 22nd August 2018 [43]. To promote peer-to-peer transactions, some solutions are available, such as VOLTTRON [44] and μGIM [45], that can be deployed on the customer side and enable the customer representation in distributed energy transaction markets where energy can be transacted among customers.

2.3. Demand Response

Demand response programs are mechanisms that promote and allow the active participation of customers in the smart grid. The U.S. Department of Energy defined demand response as "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized." [46].

By analyzing the definitions of demand response and transactive energy, it is possible to observe similarities and overlaps. Therefore, some authors see demand response as part of transactive energy [47]. Nonetheless, the definition of demand response mentions its use for system reliability, while transactive energy only mentions the balance between generation and consumption.

Demand response can be price- or incentive-based [28]. In price-based programs, there is a variation in the price of energy that promotes the shifting or reduction of consumption on the customer side. In Allahvirdizadeh et al. (2022), two price-based programs, time of use (TOU) and real-time pricing (RTP), are tested with an optimization model using Monte Carlo and k-means to reduce the scenarios [48]. Price-based programs can also be applied in smaller contexts, such as microgrids and energy communities, to manage energy consumption [49]. An example of an energy community demand response application can be found in Zhou et al. (2022), where a scenario-based stochastic model of predictive control for energy management in energy communities is presented, considering the stochastic predictability of environment variables, such as building occupancy, temperature, humidity, and solar irradiance [50]. An incentive-based demand response program is also proposed by Fanti et al. (2022) for electric vehicles (EVs) relocation in an interactive process with the users to promote EV relocation using a crowdsourcing approach while increasing the incentive levels to engage users [51].

Incentive-based demand response programs are based on payments to energy customers according to their participation, usually measured by their effective demand reduction. This type of program usually requires an initial step to establish and define the involvement of each customer, and in some cases, may require the preparation of a prior contract (e.g., in direct load control programs [52]). Nguyen et al. (2022) propose a model for the setting of incentive-based pricing considering the maximization of the welfare of the participants with a sigmoid-curve satisfaction function with fuzzy logic to assess the costumer-side benefits [53]. A similar mechanism is proposed by Muthirayan et al. (2019), using the automatic reporting of energy customers' baselines (that is, the expected consumption profile for a given period, typically calculated using historical data) [54].

To actively participate in some demand response programs, customers must be part of a larger group to meet the amount of participation requested [52]. The concept of smart grids recognizes the existence of aggregator entities that enable the dynamic aggregation, in a given period, of small and medium players, such as customers, to represent them as a single entity in energy markets, energy transactions, and in demand response programs participation [55]. The European project CROSSBOW involves eight countries and is creating an aggregation platform to enhance demand-side management [56].

3. Acceptance Models and Literature Surveys

The participation of energy customers in the smart grid is a desirable goal. Mechanisms for this participation have been proposed, such as demand response programs and transactive energy models. However, customer acceptance will dictate the efficient implementation of these mechanisms, as the customer is responsible for their participation. This section presents state-of-the-art smart grid acceptance models and previously published surveys by other authors considering different geographic locations. Later in this paper, the previously conducted surveys will be compared to the results of the Portuguese-conducted survey.

3.1. Smart Grid Acceptance Models

End consumers' perception, acceptance, and active participation in smart grids are essential for achieving the expected benefits. The authors will focus on two customer acceptance models proposed in the literature: the acceptance model proposed by Ellabban and Abu-Rub (2016) and the acceptance model proposed by Park, Kim, and Yong (2017). These two models correlate external variables and knowledge with the acceptance of smart grid technology.

Ellabban and Abu-Rub (2016) proposed a smart grid acceptance model, shown in Figure 1, based on the technology acceptance model (TAM) [57]. This model creates a relation between external variables and the users' perceptions and intention to use technology provided by smart grids, enabling developers to assess the variables that impact the energy customers' acceptance. In Figure 1, a sequential link is visible between the "perceived eco-environment", "perceived usefulness", "intention to use", and "usage behaviour", indicating the importance of climate-friendly initiatives to increase the acceptance of smart grids among customers. Also, a sequential link is visible between "perceived performance concerns", "perceived risk", "intention to use", and "usage behaviour." To this extent, negative situations for customers should be avoided, as they impact their behaviour, active participation, and acceptance of smart grids. The acceptance model proposed by Ellabban and Abu-Rub (2016) is technology agnostic and can be used and a generic tool to help to understand the external variables that produce impact in the usage behaviour of energy customers. However, this model fails to separately identify positive and negative impacts.

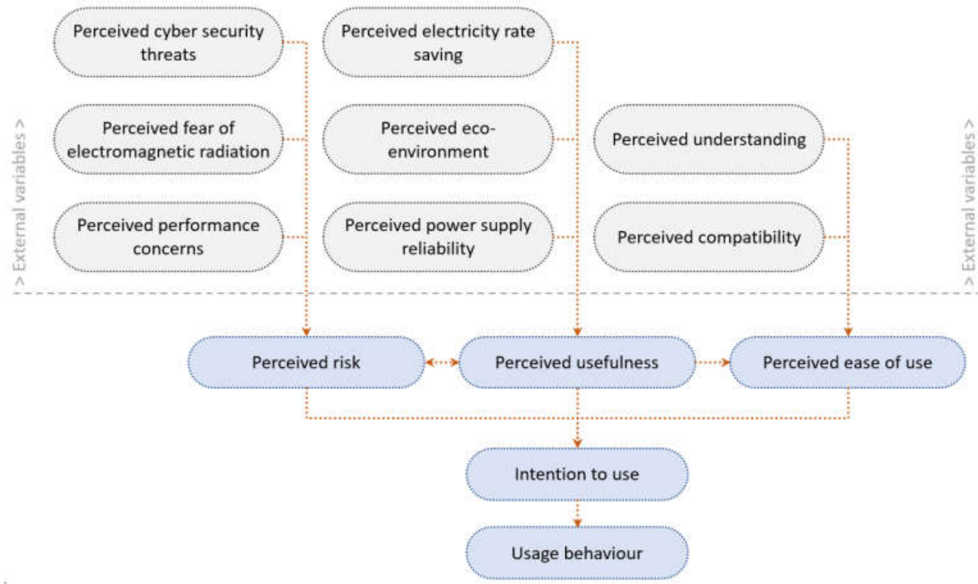

Figure 1. Acceptance model proposed by Ellabban and Abu-Rub (2016) [57].

Park, Kim, and Yong (2017) proposed an acceptance model for smart grids, shown in Figure 2, using a comprehensive cause–effect map to identify positive and negative effects [58]. Contrary to the Ellabban and Abu-Rub (2016) model, this model enables the identification of negative and positive impacts in the customer acceptance. This model also provides a better detail regarding external and internal variables that impacts the acceptance and usage of smart grid technology. In this model, the authors identified a chain of positive links between "education and advertisement", "perceived eco-environmental benefits", "perceived usefulness", "intention to use", and "actual use." This association follows the acceptance model of Ellabban and Abu-Rub (2016), shown in Figure 1. Regarding negative chains, it is visible that the following components have a negative impact on each other, "exposure to the risk of smart grid technology", "satisfaction", "gap between satisfaction and expectation", and "intention to use." Although more complete than the Ellabban and Abu-Rub (2016) model, the Park, Kim, and Yong's (2017) acceptance model lacks the ability to measure the impact regarding the significance of connections, presenting all connections as equal.

The study and analysis of acceptance models and acceptance surveys regarding smart grids enables the understanding of the perception and acceptance of the energy customers towards smart grids and their active participation in this new environment. The increase in knowledge regarding customers' acceptance and which variables can impact, positively and negatively, allow the design of suitable participation models and the creation of communication strategies to appeal to the participation and involvement of the consumer.

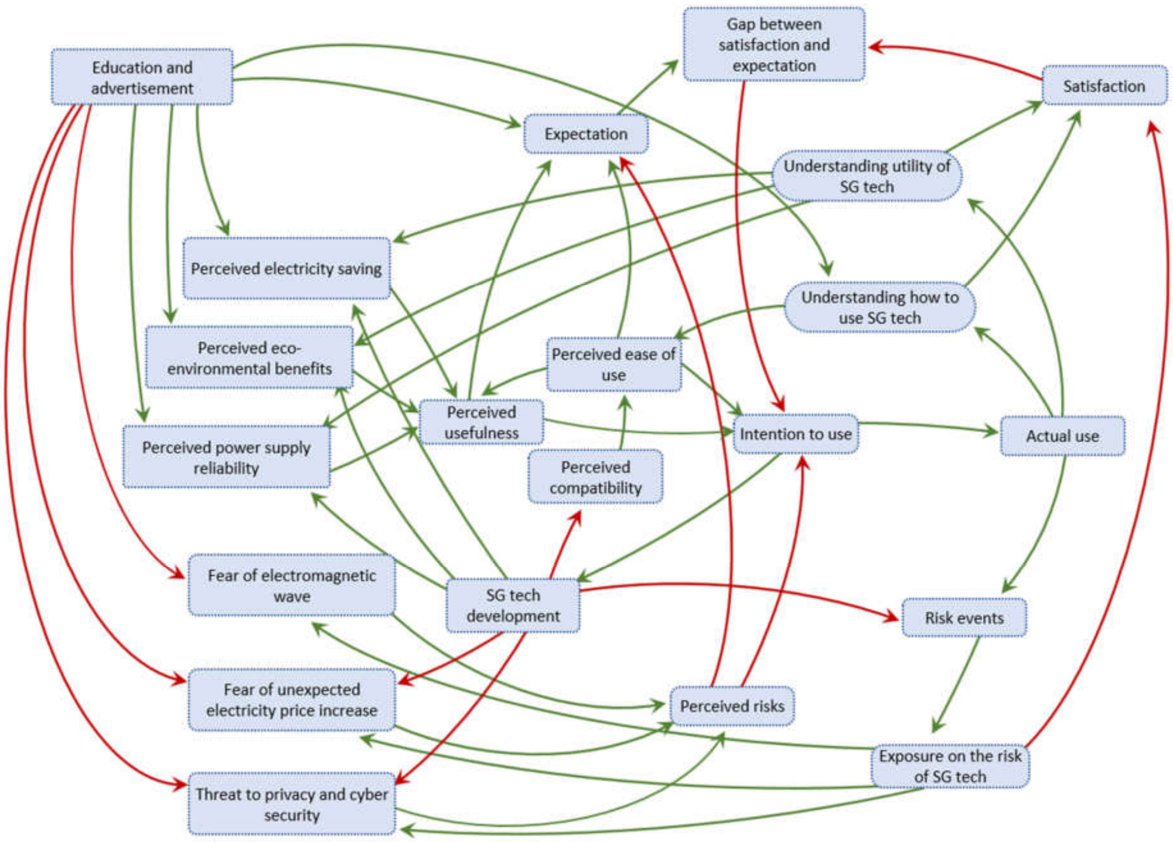

Figure 2. Acceptance model proposed by Park, Kim, and Yong (2017) [58].

3.2. Past Smart Grid Surveys

The results of a study conducted in Israel involving 554 participants demonstrated an overwhelming acceptance by participants of the existence of external control by a resource management system (e.g., 84.9% would accept an external control over their dishwasher, and 74.9% would accept an external control over their heating systems) [59]. The availability of customers could enable the use of flexibility in the smart grids.

A study at the University of Qatar involving 1071 participants achieved a degree of trust of 95% with an error of ± 3%, showing that most participants (75.43%) are willing to change their consumption profiles. In contrast, more than half (56.0%) are willing to plan their consumption profile according to energy prices [60]. However, this study raises a concern regarding the use of smart meters. A total of 42.76% of participants have the misleading opinion that using smart meters does not violate data privacy. This can be an issue in customer acceptance, as the models in Figures 1 and 2 demonstrate that the perception of risks reduces the acceptance of smart grids.

Similar results were obtained in a study conducted at the University of Imam Abdulrahman Bin Faisal, Saudi Arabia, involving 228 participants [61]. Where 73.0% are willing to shift their washing machine to night periods if energy prices are lower, this study also revealed that 55% of participants believe there is insufficient information for customers regarding smart grids.

On the island of Tilos, Greece, a study concerning smart grid acceptance involving 226 residents was conducted, with a 95% trust and a ±3% error [62]. This is a significant study because the island has already installed smart grid technology. The overall result shows that 82% of the residents have a favourable view of the installed smart grid, and only 1% object to the installed grid. The results obtained in the Tilos community demonstrate a significant positive acceptance by customers of smart grids. However, the results also showed that 68% of participants would accept a smart meter to reduce their energy consumption. This demonstrates a misperception about smart meters and can negatively affect the acceptance of the smart grid.

In [63], a survey to access the acceptance of direct load control was conducted in Germany and Switzerland with 622 participants. The results shown that 58% and 57% of participation would accept direct load control over electric boilers and heat pumps, respectively. However, only 25% and 23% of participants would accept the direct load control over washing machines and dishwashers, respectively.

An older survey made in Flanders, Belgium, in 2010 was able to create a TAM-based acceptance model supported by a 500 households survey participation [64]. The proposed acceptance model is similar to the Ellabban and Abu-Rub (2016) model, shown in Figure 1, where the perceived usefulness and ease of use have shown an impact in the intention of use. A similar result was achieved by the only survey conducted in Denmark, Norway, and Switzerland, where a TAM-based acceptance model was also supported by energy customers [65].

The previous surveys seam to demonstrate a general willingness of customers to participate, to some extent, in smart grids. Many participants are willing to enable external control of their appliances and/or plan their energy consumption taking into account an hourly variation in energy prices. This desire, often motivated by the possible decrease in energy costs, can significantly drive the implementation of smart energy grids.

4. Conducted Survey Description

This section presents a survey conducted in Portugal by the authors involving 140 voluntary participants. This survey was created to assess customers' knowledge and motivation to actively participate in smart grids, namely their intention to participate. The survey results published in this paper contribute to the characterization of the possible energy customer's active participation willingness. Also, the results of this survey will be compared to previous surveys to compare customer acceptance in several countries. The survey was open, allowing responses, for 37 days, from the 28th March 2020 to the 3rd May 2020.

Portuguese customers define the population of the survey, that is, anyone who makes daily use of any electrical equipment. Such a population encompasses almost all people. The public interest in smart grids justifies the size and description of the population because the active participation of customers has a close connection with all the people who use electricity daily, and it can, very certainly, come to impact their energy use. The sample used for this survey consisted of volunteers who agreed to answer the online survey. The survey was publicly and directly disseminated among people, including people who are professionally involved in the field of smart grids, thus allowing the acquisition of a sample with two subsets: people with no knowledge of the subject and people with experience in the field of smart grids.

The survey consists of twenty questions divided into seven sections: participant profile, smart grids, smart meters, energy cost, energy sources, energy transactions, and energy reports. The survey was written, and distributed among participants, in Portuguese, however, the questions and answers were translated, by a native-speaking English person, to enable its presentation in this paper. Table 1 shows the questions included in the survey, their type, and possible answers. The question of Section 3, 'smart meters' with the ID of 3.1, was only presented to participants that answered 'yes' to question 2.2. All questions, excluding questions 3.1 and 4.4, were mandatory. Question 4.4 was multiple choice, and participants could not select any option.

Table 1. Questions included in the survey.

ID	Question	Answer Type	Possible Answers
1.1	Gender	Single	{“Woman”, “Man”, “Rather not answer”}
1.2	Age	Single	{[18–25], [26–30], [31–40], [41–50], [51–60], “Above 60”}
2.1	Do you know what a smart grid is?	Single	{“Yes”, “No”}
2.2	Do you know what a smart energy meter is?	Single	{“Yes”, “No”}
2.3	Would you like to have a smart meter?	Single	{“Yes”, “No”, “Yes, if it results in a reduction of energy costs”}
3.1	Do you think the use of smart meters can violate your privacy?	Single	{“Yes”, “No”, “It depends on how they communicate the data.”}
4.1	Do you think the energy price, without taxes, is:	Single	{“Low”, “Fair”, “High”}
4.2	You would reduce your energy consumption for one hour if the energy price rose above:	Single	{“10%”, “20%”, “25%”, “50%”, “80%”, “I would not reduce”}
4.3	Assuming that 1 kWh corresponds to having a fan heater turned on for 25 min, you would agree to reduce your energy consumption for 1 h if you were given a minimum incentive of:	Single	{“0.05 EUR for each kWh”, “0.10 EUR for each kWh”, “0.15 EUR for each kWh”, “0.20 EUR for each kWh”, “0.30 EUR for each kWh”, “0.50 EUR for each kWh”, “I would not reduce”}
4.4	In order to reduce the energy cost, you would allow an external entity to control automatically:	multiple	{“The fridge (ensuring that there is no damage to the food)”, “The brightness of the television”, “The start and cycle of the washing machine”, “The start and cycle of the clothes dryer”, “The start and cycle of the dishwasher”, “The water heater”, “The lighting of the house (turning off the lights or dimming their intensity)”, “The mobile phone charger”, “The heater or heating system of the house”, “The cooling system of the house”}
4.5	Would you be willing to plan your daily consumption considering the hourly variation of the energy price (assuming the existence of periods with lower prices)?	Single	{“Yes”, “No”, “Only on days when I am at home (e.g., days off)”}
4.6	Would you be willing to change your dinner time to reduce energy costs?	Single	{“Yes”, “No”}
5.1	Would you be willing to pay more for renewable energy?	Single	{“Yes”, “No”}
5.2	Would you prefer only to use renewable energy sources in your country?	Single	{“Yes”, “Yes, but only if the energy cost does not go up”, “No”}
6.1	Would you be willing to sell your energy to the grid?	Single	{“Yes”, “No”}
6.2	Would you be willing to sell your energy to your neighbours?	Single	{“Yes”, “No”}
6.3	Would you be willing to share energy with your neighbours?	Single	{“Yes”, “No”}
6.4	For energy transactions with your neighbours, you would prefer to adopt a posture such as:	Single	{“Cooperative and collaborative (minimizing the cost of energy among all)”, “Competitive (trying to minimize only your cost)”}

7.1	Would you like to receive comparative reports between your consumption and other identical households?	Single	{"Yes", "No"}
7.2	Would you like to receive detailed reports on your consumption by equipment or type of equipment?	Single	{"Yes", "No"}

5. Results of the Conducted Survey

After sharing the survey among participants, the results were analysed. Figure 3 shows the participants' profiles regarding questions 1.1 and 1.2 related to Section 1 of the survey.

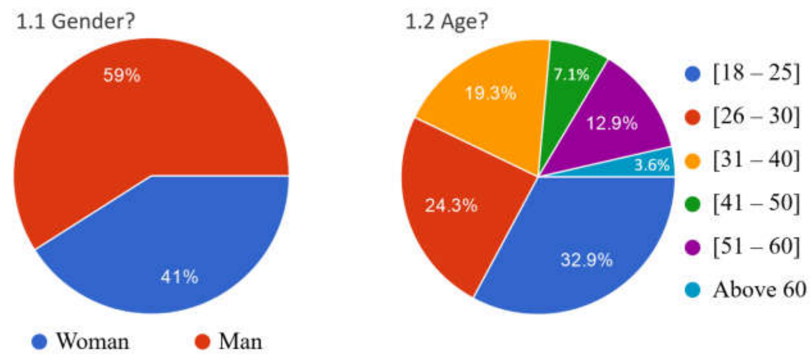

Figure 3. Participants' profile (questions 1.1 and 1.2).

In the survey, 37.7% of participants replied "yes" in question 2.3, and 60.9% responded "Yes, if it results in a reduction of energy costs", meaning that 98.6% are considering the acceptance of smart meters in their facilities. The remaining 1.4% that replied "no" also answered "no" to question 2.1. A total of 98.6% would like to have a smart meter in their residence, while 57.0% showed concern with data privacy issues raised by smart meters.

Questions 4.1 and 4.2 assess participants' perceptions regarding energy prices and their willingness to change their demand profile according to energy prices. The perception of 40.6% of participants is that the energy price is "fair", while 53.6% indicate that the energy price is "high". The 46.4% that consider the energy price "low" or "fair" suggest that they are willing to change their demand profile if energy prices go above 30%. In contrast, participants who think energy prices are "high" are willing to change their demand profile if they go above 25%.

Question 4.3 is similar to question 4.2, differing in the type of problem presented to the participant. While question 4.2 presents a scenario with percentual values, question 4.3 presents a scenario with monetary values. The results of question 4.2 indicate that if the energy price increases more than 20%, it will lead to 37.9% of participants changing their demand profile. If energy prices rise above 50%, 87.2% are willing to change their demand profile. Using a standard energy tariff applied in Portugal, a 50% increase in energy price is equivalent to a rise of 0.11 EUR. However, in question 4.3, only 20.4% of participants considered decreasing their energy consumption if they were paid 0.10 EUR per kWh reduced. The detailed results can be seen in Figure 4.

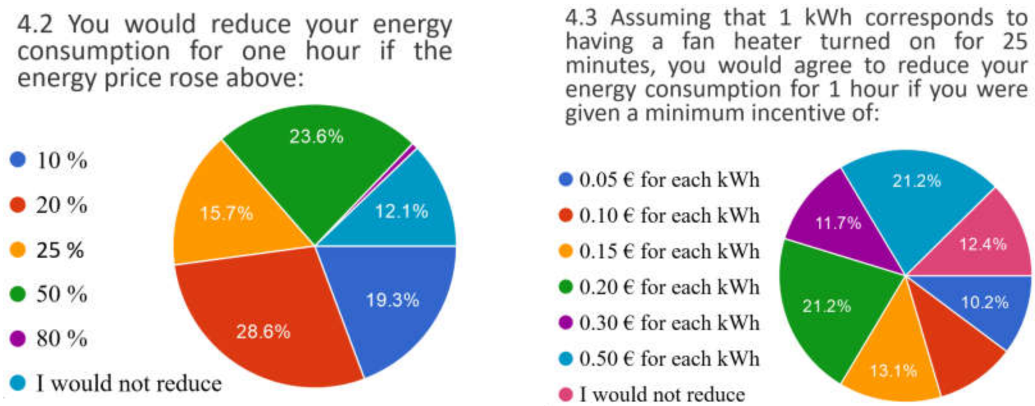

Figure 4. Questions 4.2 and 4.3 replies.

When asked whether they would make external control of their energy loads available to third parties, the participants showed motivation to do so. This will enable direct load control in smart grids and demonstrate users' acceptance of the use of home energy management systems. Figure 5 shows the replies to question 4.4. The control of the "start and cycle of the washing machine" and the control of the "refrigerator" were the options with the highest acceptance, 59.4%, and 58.6%, respectively.

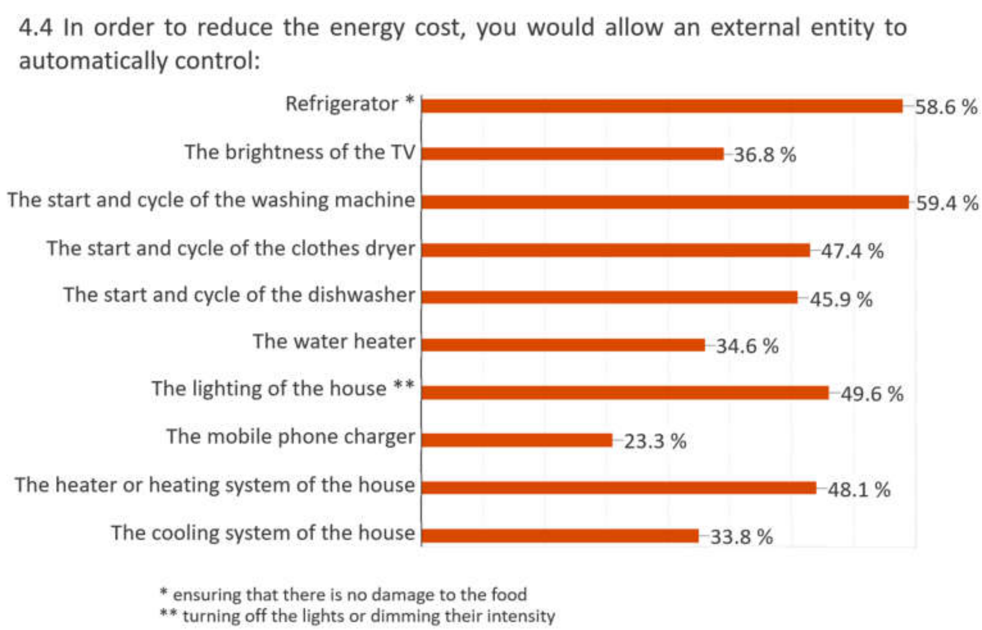

Figure 5. Replies to question 4.4.

When asked whether they would be willing to plan their daily consumption taking into account the hourly variation in energy prices, 22.1% indicated that they would be willing to do so for the days they were at home (for example, days off and weekends), and 70.7% indicated that they would be willing to plan their daily consumption. In question 4.6, when asked if they would be willing to change their dinner time to reduce their energy cost, 36.4% said "yes", and 63.6% indicated they would not be willing to do so.

The survey also concluded that 55.0% of participants would be willing to pay more for renewable energy. When asked whether they preferred that Portugal's (the country where the survey was carried out) energy grid be exclusively based on renewable energy sources, 97.9% replied affirmatively. However, of this 97.9%, 48.9% answered, "yes, but only if the energy cost does not go up."

Regarding local transactions, 83.5% were willing to sell or share their energy with their neighbours. Regarding energy transactions between neighbours, 86.3% said they would adopt a "cooperative and collaborative" transaction (minimizing the cost of energy among all). The remaining 13.7% would adopt a "competitive" transaction (trying to minimize only your cost). When asked about a possible sharing of energy with their neighbours, 72.9% of the participants expressed their willingness to share.

The last section of the survey was intended to assess the participants' interest in viewing and accessing their energy data. Among the participants, 82.9% showed interest in receiving comparative reports between their demand and the demand of other homes identical to their own. When asked if they would like to receive detailed reports on their consumption discriminated by equipment or type of equipment, 95.7% of participants expressed interest.

A correlation study was made, but no significant correlations were demonstrated besides the natural aggregation of questions in the same section. The correlation result can be seen in Figure 6.

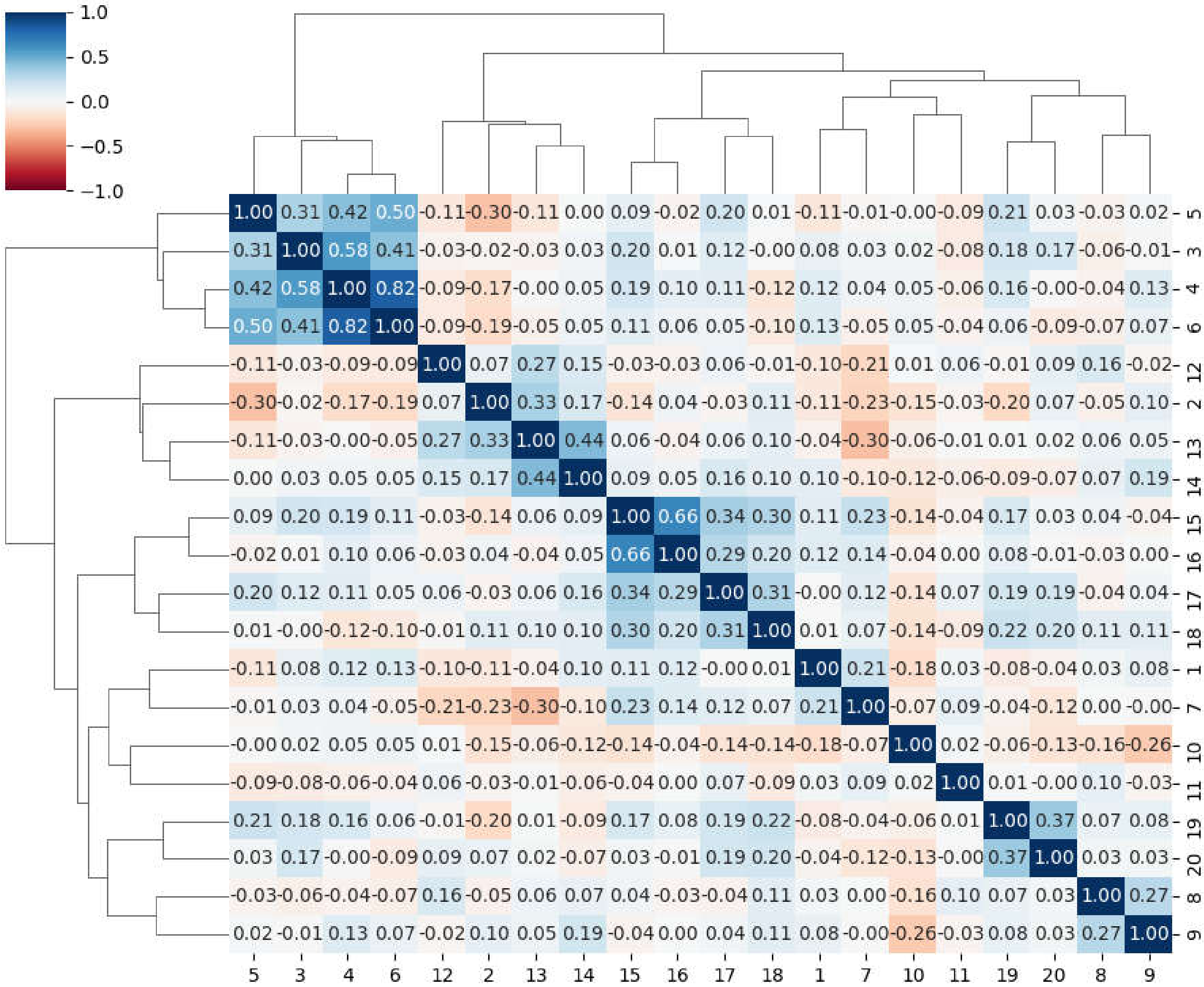

Figure 6. Correlation heatmap considering the question of Table 1.

6. Discussion

The survey results were compared with previous surveys to assess if different geographic areas were in line with their availability to participate in smart grids actively.

Regarding the acceptance of smart meters, 98.6% of the conducted survey participants replied that they would like to have a smart meter in their residence, surpassing the result obtained in [60], where the acceptance of smart meters was 76.43%.

The results of question 4.4 (to reduce the energy cost, you would allow an external entity to control automatically) showed a similarity to the results in [59]. Regarding the external control over the refrigerator, the survey had a 58.6% positive response, similar to the 59.9% positive response in [59]. Regarding the washing machine and dishwasher, the results in the conducted survey were lower than the results of [59]. In the study undertaken, the positive responses were 59.4% and 45.9%, respectively, while in [59], the positive reactions were 83.2% and 84.9%, respectively.

Regarding selling and sharing energy, 89.2% of the survey participants were willing to sell their energy to the electricity grid. This result is slightly higher but similar to the 74.64% obtained in [60].

Regarding the reduction in consumption (questions 4.2 and 4.3), the survey found that a 50% increase in the energy price per kWh (corresponding to around 0.11 EUR in Portugal) would lead to 87.2% of participants reducing their consumption. While if a 0.10 EUR benefit per kWh reduced were given to participants, it would only make 20.4% of them reduce their consumption. Although the answers obtained may indicate a lack of knowledge on the part of participants about the price of energy due to one question being in percentage and the other in euros, the results are in line with two concepts: negativity bias and loss aversion. Negativity bias is the cognitive notion that a negative episode has a more significant impact than a positive episode, making the person more susceptible to giving importance to negative experiences. Loss aversion indicates a cognitive tendency that leads the person to avoid losses to seek gain, so it is better not to lose than to gain. This could explain why participants were more willing to reduce energy consumption when facing a penalized scenario and not so keen to make the reduction when encountering a gain/rewarded scenario.

The findings in this survey are in line with the results published in [66], where a comparison between incentive- and punishment-based demand response programs was analysed and where it was concluded that the punishment-based is equally effective in achieving active participation, and that brings benefits regarding the collective perception of the customers regarding the community needs. However, this can be due to the loss aversion bias.

The identification of negativity bias and loss aversion is one of the most important findings of this survey because they go beyond state-of-the-art studies and provide a better perception of the customer in the smart grid context. The analysis of the state-of-the-art does not mention the impact that negativity bias and loss aversion have on the active participation of the energy customer. However, in this survey, it is possible to identify the effect caused by these cognitive trends on the willingness of customers to participate in smart grids actively.

Issues impacting the acceptance of smart grids from the end-customers' side should be identified and addressed. One of the issues identified by Spence et al. (2015) is that people with lower social grades are less likely to accept energy data sharing (for demand response and transactive energy purposes) and demand-side management solutions [67]. This observation and the negative bias could penalize lower social grades in smart grids, provoking an increase in energy costs and making it challenging to balance the grid on the consumer side.

When discussing the engagement of users, gamification can increase the participation and interest of people, being used in several sectors [68,69]. This concept can be used to engage and boost the involvement of energy customers trying to avoid the impact of a negative bias to increase participation and, therefore, the acceptance of active participation actions in smart grids. In energy, gamification is also proposed as an efficient engagement mechanism, as seen in [70], applied in energy-related behaviour changes in residential consumption, and in [71], where a solution for office employers is proposed to increase the awareness of consumption.

To avoid penalizing lower social-grade customers, participation models can also adopt fairness techniques to offer equal opportunities for energy customers [72]. A previous study observed a link between perceived procedural fairness and the acceptance of energy-related projects [73]. Therefore, fairness strategies should be deployed in active participation in smart grids to increase acceptability and promote customer equality.

7. Conclusions

The acceptance of customers regarding smart grids is an important aspect that can affect the effective implementation of smart grids, namely the use of demand-side management, demand response programs, and energy transactions.

This paper proposes a survey applied in Portugal among 140 participants to evaluate their intention to participate in smart grids considering several methods of participation. The survey's positive results showed that 95% of the participants would accept the control of at least one electrical appliance by an external entity and that 92.9% would be willing to plan their energy consumption in case of applying hourly energy prices.

The proposed survey also identified the influence of negativity bias and loss aversion. This was an important conclusion in this survey, indicating that customers are more likely to reduce expenses than to maximize gains. In this way, the advantages presented by the active participation of customers in smart grids may not have the desired effect, as penalized scenarios could represent an increase in the participation rate. Therefore, because this survey's objective was not to study the negativity bias and loss aversion, it is necessary to have dedicated surveys and interviews to assess the real impact they can have on the active participation of customers in the smart grid. The identified bias and the literature acceptance models highlight the significance of conducting social science studies and surveys on smart grids to understand the energy customers fully. Only then will it be possible to increase the participation rate of end customers to achieve seamless integration of consumers in the smart grid to enable the balance between energy consumption and generation.

The survey results suggested that the actual participation of end customers in smart grids can be impacted by cognitive bias. This should be studied in future work, also addressing other cognitive biases such as the farming effect and confirmation bias that limit the actions and decisions of persons. The cognitive biases are not considered during the conception and proposal of new participation models and energy management models for smart buildings. However, future works should address the acceptance of such models among the end customers. These demonstrate the need for pilot frameworks and living labs that enable the fast and straightforward deployment of energy-related models in a (un)controllable environment among persons to assess the model's acceptance, efficiency, and usage/usefulness.

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