Smart meters and consumer behaviour: insights from the empirical literature

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Abstract

This paper summarises the insights to be gained from a systematic literature review of empirical research devoted to behavioural considerations associated with the use of smart meters and energy information feedback. Above and beyond the mass rollout of smart meters, there are various behavioural considerations that can affect the way in which consumers react to information enabling the adaptation of their consumption behaviour in response to dynamic pricing. Indeed, many empirical studies have been conducted in various countries aimed at determining how consumers respond to feedback on their consumption and prices. However, if users fail to demonstrate a pro-active attitude, they cannot hope to take advantage of the opportunities afforded by new technologies. By reporting a systematic analysis of bibliographic references, this article seeks to further understanding as to why consumers behave as they do when managing their demand, a process that, ultimately, is for the benefit of the electrical system, in particular, and of the whole of society, in general. The policy implications that emerge from our analysis highlight the heterogeneity of consumer engagement in demand management programs, depending on the degree of preference satisfaction achieved by means of personalised contract terms and the degree and persistence of consumer change, which are dependent on the cost, frequency and quality of information.

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1. Introduction

The fact that we are currently moving towards a decarbonised economy is forcing us to reconsider how the current electricity system functions (IEA, 2018). Today, the combined effect of the penetration of renewable energies, the development of electric vehicles and, ultimately, the electrification of the entire economy is revolutionising grid function and relevance. The key element underpinning this transformation is the way we manage different energy flows in our efforts to endow the system with greater ‘flexibility’. And in order to achieve this, the element that emerges as a facilitator of change are the data from the electrical system and its associated services including the grids, with smart meters taking a leading role in improving the efficiency, reliability and security of the system (Martinez-Pabon et al., 2017).

Although, to-date, end-users have been passive actors in the electricity system, with the introduction of new services permitting greater consumer involvement, they have begun to take on an important role in the use and management of energy. The fact that users can have access to real-time consumption data – thanks to either a meter or other applications – means that a whole range of hitherto unimaginable uses can be implemented since consumers no longer lack access to the required information. If users are involved in deciding when and how to interact with the system, new business opportunities are sure to emerge and new system services are likely to ensure they participate more actively. First and foremost, users are likely to modify their behaviour so as to reduce their consumption, thus contributing to the promotion of a more responsible use of energy. Given that modern-day societies depend heavily on energy and its efficient management, the changes in energy-related technologies are likely to usher in fundamental forms of social change (Ellabban and Abu-Rub, 2016). However, if users fail to show a pro-active attitude, it will be impossible to exploit the opportunities afforded by new technologies.

Demand-side management (DSM), that is, any active management that the user exercises over their own demand, is based on three practices: peak clipping – user response to pricing or energy information feedback, which in turn is reflected in a decrease in peak demand; load shifting – moving consumption from peak to valley periods; and, strategic conservation – the execution of activities that reduce energy consumption. In terms of cutting costs and reducing the environmental impact, reducing energy consumption is the ultimate goal of DSM strategies. In this sense, strategic conservation is preferable to peak clipping and load shifting and while these last two strategies can also reduce electricity consumption – that is, in intraday time periods, the advantages of one over the other depend on the composition of the electricity mix of each geographical location.

With the aim of activating DSM, current efforts to build smart grids – which have acquired some importance in European electrical energy markets – mark the start of a gradual process of empowering domestic end users and ensuring they are able to play a more active role in the electrical system (IEA, 2017). Replacing electromechanical meters with electronic ones constitutes the first step in this process of empowerment (Barbu et al., 2013) as they provide users with a greater amount of higher quality information about their electrical supply. The lower transaction costs, resulting from the improved information flow facilitated by smart meters, allow the market to move towards satisfying the postulates of perfect competition. This is accompanied by changes in the energy management of households, which will seek to reduce consumption when hourly prices are high in order to avoid higher costs. Moreover, the creation of new energy tariffs that take advantage of real-time visualisations form a key part of most governments' strategies to ensure our future electricity supply is clean, affordable and secure (Nicolson et al., 2017).

In theory, we would expect the use of smart meters, in combination with dynamic energy tariffs, to allow consumers to manage their demand efficiently, starting with them modifying their patterns of electric power consumption based on the hourly electricity prices in effect throughout the day (Frederiks et al., 2015). However, for this change to be effective and to ensure consumers take advantage of all their potential, a change must first be instigated in their behaviour patterns. Determining consumption patterns is critical insofar as not all consumers share the same socioeconomic conditions or profile. And, it goes without saying, not everyone is guaranteed to react in the same way. Energy use is based essentially on routines and habits that are not easily changed. This is why it is critical that a close examination be undertaken of the technical, social and psychological factors that can facilitate the adaptation of consumer behaviour.

It is precisely in this field that we find an increasing number of empirical studies aimed at identifying these factors and seeking the enhanced participation of consumers in relation to domestic demand. Thus, most studies test more than one demand-side response (DSR) measure, be they, the use of different types of tariff or different combinations of pricing and automation technologies. In this context of the rollout of smart meters and grids, this paper focuses its attention on articles that have sought to quantify and explain empirically the determinants of consumer behaviour in relation to electricity consumption. More specifically, we present a systematic review of bibliographic references in which different methodologies are employed for undertaking their empirical analyses. We then describe their respective outcomes in terms of the modification of the load curve and their potential energy savings with the aim of extracting valuable insights on smart meters and consumer behaviour.

The rest of this article is structured in four sections. The first details the systematic approach adopted in undertaking the literature review. The second section describes the specific elements of the methodological designs employed in the empirical studies reviewed. The third explains the quantitative and qualitative insights that emerge from these empirical studies in relation to active demand management in the residential sector. The fourth concludes.

2. Literature review: A systematic approach

The analysis of the role played by demand in operating the electricity system, beginning with more active participation, has attracted the growing interest of scholars as evidenced by an increasing number of publications. Below, we explain the approach adopted herein as we conduct a systematic review of this literature on DSR in the residential sector, focusing specifically on their respective areas of analysis and empirical methodologies.

The papers selected for this review were identified in two stages. In the first, a series of keywords were identified in relation to this field of study from a review of leading publications. In the second, these keywords were used to run a systematic search in the *Web of Science* and *Scopus* databases, in line with the methodology described by Del Río et al. (2016) and Solnørdal and Foss (2018). These two bibliographic resources are different; yet, they complement each other in terms of their respective strengths and weaknesses (Del Río et al., 2016). The keywords used, along with their substitutes, correspond to the specific two areas with which we are concerned here: smart meters and consumer behaviour.

In the list of keywords related to smart meters and smart metering, we included terms specifically related to this technology, the means by which feedback on energy consumption is presented and the information that consumers receive in order to modify their load curves. The terms included were the following: *Smart Meters, In-Home Display (IHD), Energy Management System (EMS)* and *Real-Time Feedback.* The list also included keywords related to the types of incentive that have proven to be effective: *Eco-Feedback* (Pereira et al., 2013), *Conservation Incentives, Dynamic Prices, Time of Use Tariffs (TOU).* The keywords related to consumer behaviour included concepts related to the impact of the feedback received on users: *Demand Side Response, Demand Side Management, Household Energy Consumption* and *Loss Aversion.*

Our search yielded 260 results, of which 32 were immediately excluded as they were concerned with non-residential sectors. Of the remaining 228 references, the earliest dates from 1986. This paper – Rosenfeld et al. (1986) – describes a pioneering experimental study in the United States and the United Kingdom which “explores the exciting possibilities for dynamic pricing technology” at a time when radio communication (not digital) technology was prevalent. The three most recent papers were published in the first quarter of 2019 and focus their attention on smart metering technology (Gosnell et al., 2019; Kowalska-Pyzalska and Byrka, 2019; Wang et al., 2019). By date of publication, it is apparent that the study of DSR in this field has increased since 2010. Indeed, from that year until 2019, just over 94% of the papers identified were published.

Of the 228 papers, 170 were Empirical Works (EW), 12 were Theoretical Works (TW), 41 were Reviews (R) and five were technological proposals related to smart metering technology (MT). Employing the classification criteria developed by Khosrowpour et al. (2018), the 170 EW can be divided into four methodological approaches: Surveys (31%), Experiments (23%), Analytics (18%) and Simulations (2%). This breakdown is illustrated in Figure 1 below. The Surveys include interviews/questionnaires that seek to identify consumer opinions on various issues related to the best way, both technologically and conceptually, of providing the information needed to change their energy consumption behaviour. The Experiments, which include field trials and pilots, are studies that seek to determine or evaluate the demand response to specific conditions of energy information or prices. The Analytics, which draw on natural data (with no experimental intervention), seek to determine load profiling and clustering, energy use disaggregation and occupancy detection. And finally, Simulations are used to imitate real world energy feedback processes based on mathematical and stochastic models.

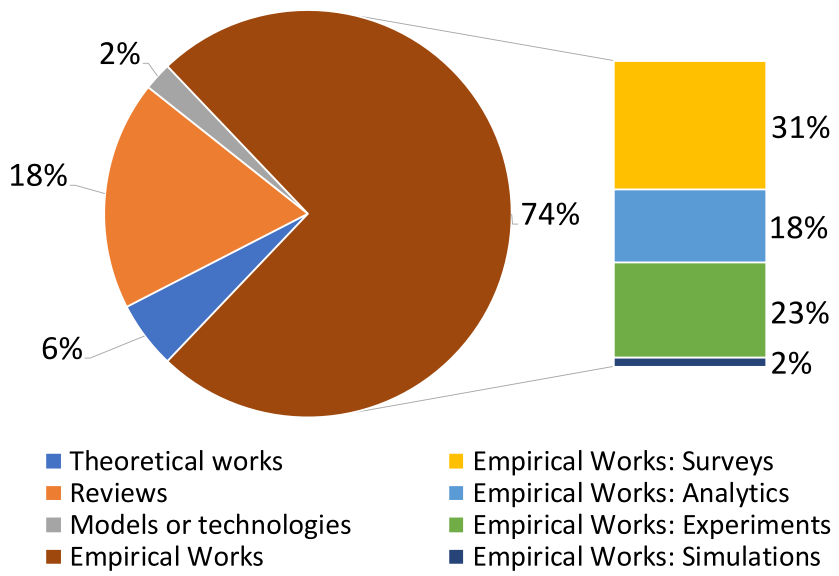

Figure 1. Types of study of DSR in the residential sector. Source: Own elaboration.

The EW were further divided according to their research objectives: group one included 57 papers, their objective being to characterise the load profile of electrical consumers; group two included 113 papers, their objective being to analyse the three types of Demand Side Response (DSR) we specifically study in this paper, namely, peak clipping (PC), load shifting (LS) and strategic conservation (SC). Figure 2 shows the distribution of these group two papers, while Figure 3 shows the shape of the representative load curve for each response based on the descriptions presented by Eid et al. (2016). Then, in order to meet our research objectives, these 113 EW were sorted according to their methodological approach and their PC, LS and SC results in relation to the impact of energy information feedback and the exposure of electricity consumers to dynamic price schemes.

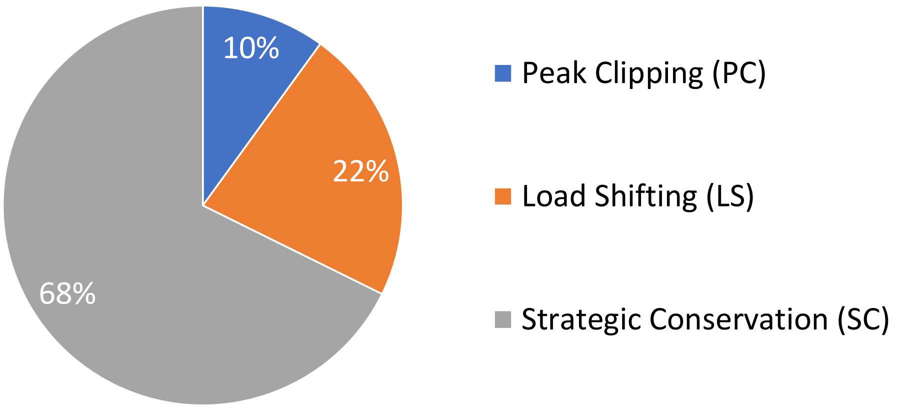

Figure 2. Study objectives of DSR in the residential sector. Source: Own elaboration.

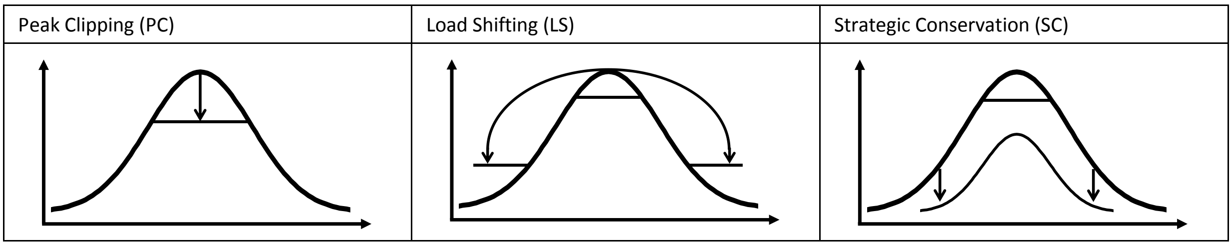

Figure 3. Demand response and shape of load curve obtained. Source: Own elaboration.

The PC response, addressed by 10% of the empirical papers reviewed herein, is a strategy aimed at reducing consumption at times of peak demand. The hourly demand for electricity fluctuates throughout the day, normally peaking around noon and in the early evening. During these peaks, in order to meet demand, more costly generation technologies have to be used. Given their economic and environmental implications, a major objective of any energy policy is to reduce these peaks. It is here where the emergence of smart meters and their associated new functionalities can help manage electricity demand. The deployment of this new technology will be facilitated by new grid and measuring technologies, providing greater efficiency in the markets over the forthcoming years. New measures that facilitate the introduction of dynamic price indications linked to the energy market and the transmission of information related to the state of the electricity system at the time of consumption would provide the consumer with sufficient incentives to modify their behaviour patterns.

The LS response, addressed by 22% of the empirical papers reviewed herein, is a strategy aimed essentially at shifting electricity consumption from one time period to another, that is, advancing or deferring the use of an appliance to another time. The idea is that by shifting the load to another time period, the returns generated by way of energy cost savings or DSR participation are greater than the potential well-being loss from the behavioural change. Unlike other energy cost-saving strategies, the issue directly tackled by LS is the *when* rather than the *how much*. Hence, with load shifting, overall energy consumption remains the same, what changes is the moment *when* it is consumed.

The SC response, addressed by 68% of the empirical papers reviewed herein, includes all efforts related to energy storage that lead to a reduction in the load curve. Increasing the energy efficiency of buildings or devices that consume energy in the home (i.e. heating, cooling and other appliances) is included in this area. Reducing consumption so as to increase savings is one of the main energy strategies employed in those countries or regions that depend on external energy resources. In the case of DSR in the residential sector, conservation strategies seek to encourage households to modify their patterns of behaviour and reduce consumption in response to information about their consumption and/or prices. Unlike PC and LS, consumption reduction is not necessarily affected during a specific intraday period (e.g. during periods of peak demand) nor is consumption shifted to other periods. However, it is possible that as a result of changes in behaviour resulting from these two responses, there will be an overall difference in end-user consumption.

The tree diagram in Figure 4 summarises the stages in the systematic literature review reported in this article. As can be seen, the process begins with the selection of references and continues with the classification of the types of study conducted in relation to DSR in the residential sector. The focus then shifts to the empirical works (EW) and the kind of analyses conducted, the references being classified in relation to the methodological approach adopted. The results of these studies are then analysed and the process concludes with a description of the insights they offer. In adhering to this approach, we address most of the limitations of analyses of this kind and provide an in-depth study of the existing literature, successfully classifying this corpus of heterogeneous papers examining DSR. The sections that follow outline the key insights obtained from the empirical study of DSR in domestic electricity systems.

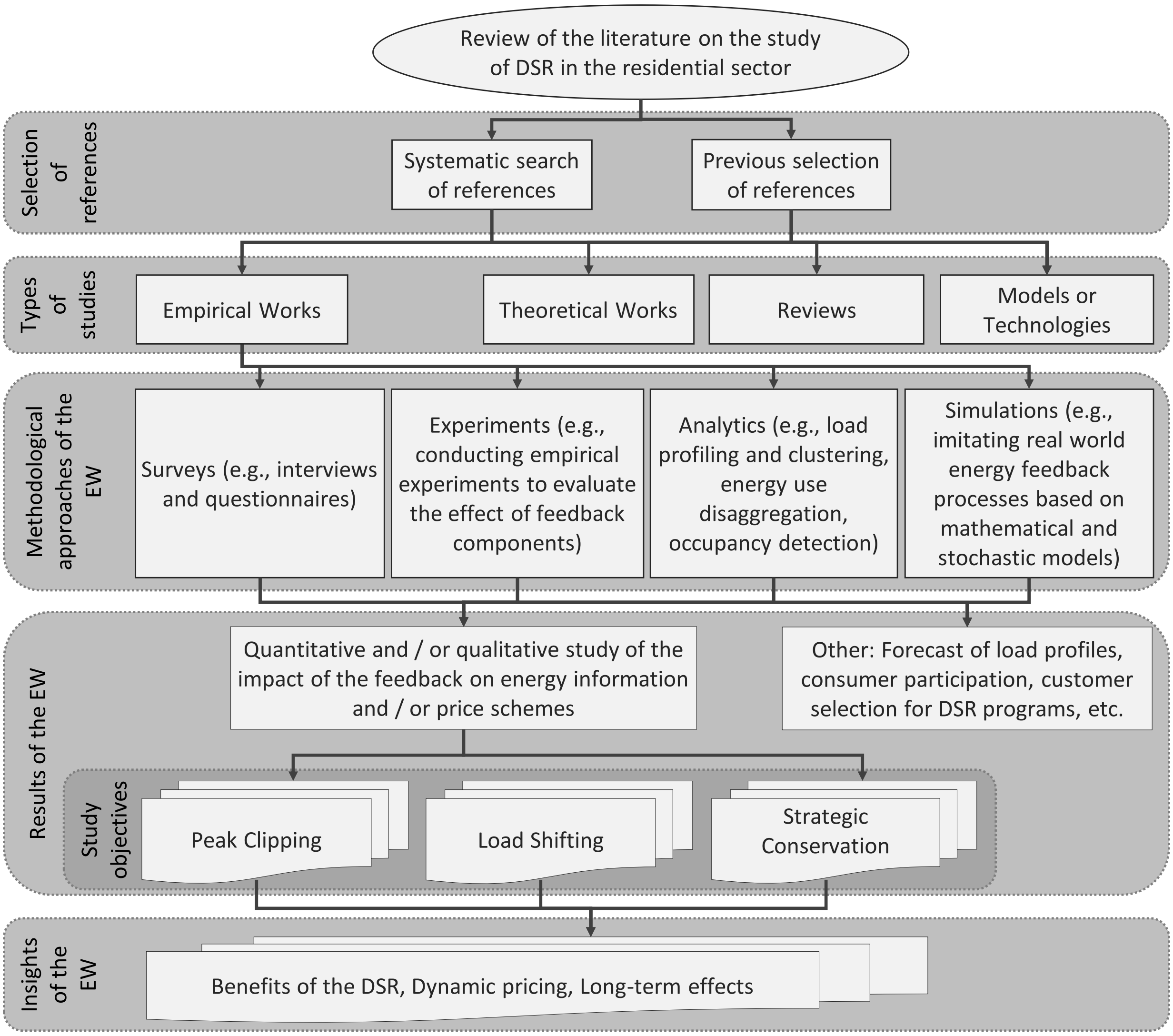

Figure 4. Tree structure of the literature review sequence followed. Note: EW, Empirical Works. Source: Own elaboration.

3. Aspects of the methodological design

This section describes the general characteristics of the empirical methodologies employed by the 113 selected empirical works, focusing on the data used, the sample and the participant incentives promoting the DSR mechanisms.

3.1. Level of information and data comparison methods

Outlines of the methodological design in the selected empirical works typically begin with a description of the data and how they were obtained. The first characteristic of the data we are interested in concerns the geographical location (rural or urban) of the residential population sample. These data may be obtained during different phases of the empirical research process and, just like the type of data being used, the phases depend on the research paper's specific methodological focus. If it is Experimental, Analytical or a Simulation, the data may be quantitative and obtained either naturally or during a controlled process that includes various phases: *Pre-experimental*, *Experimental* and *Post-experimental*. If the methodological focus comprises a Survey, then the data may be obtained when the empirical study is being completed or during any of the experimental phases.

The use of different methodological approaches within the same empirical study typically seeks to exploit their relative advantages. For example, an experiment aimed at determining the effect of different dynamic pricing schemes may employ a sample based on a previous analysis; compare these experimental results with those obtained from simulations and, thus, create various scenarios; and ascertain the opinion of the individuals included within the sample using a survey. Prior to the rollout of smart meters, experimental studies were based on pilots (addressing small samples of residential population) to determine how effective, in economic terms, it would be to use remotely managed measuring devices to reap the benefits of DSR. With smart meters now rolled out, methodological approaches other than surveys have gained in importance due to the large amount of data that can be collected. In this way, user consumption patterns can be identified in much greater detail and so tariffs can be structured according to the behavioural characteristics of the population.

Data may be obtained at different points in time depending on the type of measuring technology employed, be it in the *Pre-experimental* or *Experimental* phases. Smart meters allow consumption data to be gathered at intervals of less than an hour, even at five-minute intervals. The *Post-experimental* phase serves to analyse the data obtained during the experimental stages or to continue collecting data in relation to the control group, i.e. in a period when the control is no longer exposed to the intervention, thus, allowing the researcher to ascertain the persistence of the intervention made during the *Experimental* phase.

The main features of the methodological design include the geographical representativeness of the data and specific data gathering techniques. The data may refer specifically to rural or urban populations, on the understanding that their consumption behaviour differs. The type of data and the duration of the empirical phases vary depending on the methodological approach employed. For example, in the experimental phases, the intervention groups are compared so as to verify the effectiveness of different types of stimuli (eco-feedback, analytical, quantitative, or graphic information). Alternatively, the intervention groups can be compared with the control group, this latter serving as a baseline to compare variations in energy consumption. In either case, with or without a control, the data obtained from the groups undergoing the intervention can be compared with a natural data baseline corresponding to a previous period.

Among the analyses of the intervention groups, some authors test for the Hawthorne effect to determine whether individuals modify their behaviour in response to their awareness of being observed (Faruqui et al., 2013; Schwartz et al., 2013).

3.2. Sample selection, participant motivation and sample comparisons

The selection of the sample and the individuals included are clear determinants of the development of each empirical study. The sample may be made up of two types of individual: households or individuals responsible (or otherwise) for paying electricity bills. To study a context in which the motivation was pecuniary, households or individuals responsible for paying bills were selected, whereas to study environments (i.e. non-residential sectors) in which the motivation was non-pecuniary, workers or students were selected (Delmas and Lessem, 2014). Although both types of empirical work have their own research objectives, single-family households are studied in greater proportions because their electricity consumption is greater than that of those living in apartments (see Grønhøj and Thøgersen, 2011). The sample and the individuals from which it is comprised were selected in the phases prior to the intervention, during which the individuals were also assigned to a control or intervention group, either randomly or employing a recruitment process that, in some cases, involved a form of motivational payment. Two types of motivational strategy were identified:

- Payment: Includes a single payment made at the beginning or end of the empirical work (Houde et al., 2012; Kahn and Wolak, 2013), or a repeat payment made at various points during the study (Di Cosmo et al., 2014; Faruqui et al., 2013).
- Savings: The payment offered is based on the savings obtained thanks to the reduction in consumption (Lossin et al., 2016). When no savings are made or consumption increases, the consumer might either have to face the consequences or invoke the warranty on non-incremental energy costs, which may be available depending on the experimental approach (CER, 2011; NV Energy, 2015).

In the experimental phases, the intervention groups are compared to verify energy consumption responses when provided with some sort of stimuli (energy information feedback or price schemes) or to discover preferences for a specific type of feedback (eco-feedback, analytical, quantitative, or graphical information), analytical data or delivery method.

3.3. Energy information feedback and price incentives

This section describes the two types of information used to stimulate consumer demand response: energy information feedback and price schemes.

The basic information contained in the feedback is energy consumption and cost. The next level of information may include incentives for savings based on such social norms as comparing an individual's consumption with that of others (Lossin et al., 2016) or details concerning the impact of energy consumption on the environment or public health (Asensio and Delmas, 2016). The type of information offered to the sample might not be in numeric form but may be presented visually to facilitate comprehension (Maan et al., 2011; van Dam et al., 2010; Wood and Newborough, 2003). A tendency in the empirical works studied herein is to use the category *Eco-feedback* (Anderson et al., 2017; Jain et al., 2013b), defined as the technology and information that provides feedback on individual or group behaviour with the goal of influencing future energy saving strategies (Pereira et al., 2013). Other technological means to ensure the demand response is automatic employ devices that interrupt or activate electrical consumption by pre-programming to a certain signal. These devices include the Blue Line Power Cost Monitor (PCM) (Alahmad et al., 2012), the Direct Load Control Device (DLC) (Fell et al., 2015; Larsen et al., 2017), the Programmable Communicating Thermostat (PCT) (Ivanov et al., 2013); and Smart Appliances (EMS) (Chen et al., 2015; D'hulst et al., 2015).

In the case of incentives based on price schemes, there is a rapidly growing body of literature showing that dynamic pricing, i.e. lowering peak demand during critical hours, can result in substantial benefits to utilities and customers by avoiding expensive capacity and energy costs in the long term and lowering wholesale market prices in the short term. In the specific case of price schemes, dynamic pricing means employing different time-varying price tariffs. Unlike flat rates, where consumers pay a set price (in terms of kWh), time-varying prices reflect wholesale price volatility to varying degrees. With a lower degree of consumer exposure to price volatility and, therefore, risk, there are price schemes which take into consideration the amount of energy consumed (inclining block rate), seasonal changes (seasonal rate) or the time of day when consumption takes place (TOU rates) (CER, 2011; Torriti, 2012). Although these schemes allow for price discrimination, making it possible to reflect existing differences in the cost of the electricity system more efficiently, schemes of this type are not typically dynamic in nature insofar as prices are determined *ex ante* and are based on estimates of expected costs for the consumption period in question.

In the light of such price schemes, the emergence of smart meters and the new functions they offer make it possible to incorporate new ways of managing electricity demand (supported by new grid and measuring technologies), allowing for greater efficiency in electricity markets. New price schemes also make it easier to introduce dynamic price signals linked to the energy market so that consumers have ample incentives to modify their consumption patterns (Campillo et al., 2016; Kahn and Wolak, 2013; Zhang et al., 2016). Real-time pricing (RTP) constitutes the purest form of dynamic pricing given that customers pay the full generation cost on an hourly basis. Critical peak pricing (CPP) also provides a price signal that reflects energy costs, but only for a small percentage of hours, that is, the most critical for the system. If this critical peak price varies during this period, then what is implemented is a variable peak pricing (VPP) scheme. Similar to CPP, under a peak-time rebate (PTR) mechanism, the incentive to reduce consumption on peak days comes from discounts for other consumption rather than from higher prices (see Faruqui et al., 2014).

Both types of incentive rely on a specific means of communication or technological component, which impacts the effectiveness of the information on consumption, price and cost. This information can be provided indirectly, by using measures such as more detailed, more frequent and more accurate billing. Feedback may also be provided directly via a web portal (computers, mobile, tablets) by reading the meter directly, or via a dedicated display device (Darby, 2006; Fischer, 2008; McKerracher and Torriti, 2013).

Having drawn this distinction between incentives based on price schemes with different modalities and those based on informative feedback for consumers, the following sections of this paper present the key results obtained in the specific areas of PC, LS and SC responses. Likewise, it should be borne in mind that the empirical approach adopted is one of the factors conditioning the results presented.

4. Insights from the literature's methodological design components

Efforts aimed at achieving a more efficient and responsible use of energy so as to achieve carbon emission reductions are dependent on the active management of demand by the consumer, that is, users need to reduce their consumption at the most critical moments for the electrical system (PC), shift their consumption from peak periods to valley periods (LS), and adopt practices that reduce their overall energy consumption (SC). Our study of these three demand responses within the empirical works reviewed herein reveals a number of common characteristics in their methodological design components. Table 1 below summarises the percentage distribution of these design elements with respect to each of the three demand responses to energy information feedback and price schemes.

Overall, the studies typically rely on smart meter data and direct energy information feedback that take advantage of this technology (note, indirect feedback includes e-billing and readings from electromechanical electricity meters or smart meters, while direct feedback includes the use of technologies other than smart meters that allow users to monitor their consumption, such as IHD and/or specific web portals or phone and tablet apps, or smart appliances (SPP)). Moreover, around 30% of the papers focusing on each of the three types of demand response compare their intervention groups with controls, with the aim of comparing the effect of different types of energy information feedback and/or price schemes on their respective load curves. This is the approach most usually employed in studies to compare load shifting. The distribution of the independent variables employed is largely similar across the three types of demand response study. These variables serve to identify the consumer's behavioural characteristics, typically by employing econometric methods of calculation. Finally, as regards their goals, the papers show certain limitations in their analysis of the persistence of the effects of interventions. This indicates that studying dynamic pricing and the price elasticity of energy consumption demand are not especially decisive aims in the study of strategic conservation.

The majority of the 113 references selected are empirical works carried out in urban areas of developed countries. The empirical procedures employed in these works can be divided into three phases: pre-intervention, intervention and post-intervention. The works of Anderson and Lee (2016), Kahn and Wolak, (2013) and Kendel et al. (2017) clearly describe the processes employed in the pre- and post-intervention phases. The pre-intervention phase may constitute periods during which natural data of electric consumption are obtained (9.1% of the selected works). Data collected in the post-intervention phase serve to study the long-term persistence of the DSR (18.2% of these selected works). The duration of the intervention phase of studies of this type is between 1 and 30 months (see Barnicoat and Danson, 2015). If the chosen methodological approach includes a survey, the data may be qualitative, informing of the likelihood that energy information feedback or price signals may produce changes in the load curve.

Table 1. Percentage use of methodological design elements in the empirical works reviewed in relation to demand responses. Note: PC, Peak Clipping; LS, Load Shifting; SC, Strategic Conservation. Source: Own elaboration.

Elements category	Elements	PC [%]	LS [%]	SC [%]
Natural data	N/A	15.38	17.24	7.95
Smart meter data	N/A	84.62	89.66	79.55
Type of feedback	Indirect	61.54	44.83	25.00
	Direct	38.46	55.17	75.00
Sample Comparison	Group Surveyed	7.69	10.34	5.68
	Intervened Groups	23.08	24.14	23.86
	Periods (Pre-intervention period vs Intervention period)	15.38	24.14	17.05
	Control Group vs Intervention Groups	23.08	31.03	30.68
	Periods and Control Group vs Intervention Groups	30.77	3.45	10.23
	Periods and Between Intervened Groups	0.00	3.45	1.14
Independent variables	Socioeconomic	38.46	34.48	26.14
	Demographic	30.77	37.93	35.23
	Weather	61.54	48.28	22.73
	Dwellings (building)	53.85	48.28	37.50
	Home appliances	30.77	24.14	10.23
	Environmental concern	0.00	10.34	12.50
Goal	Long-lasting effects	15.38	10.34	20.45
	Elasticity (Flexibility)	46.15	65.52	12.50

The demand curve represents the amount of energy users require throughout the day and, although it has a characteristic shape in each country, being dependent on certain country-specific variables (economy, seasonal changes, meteorology, culture, location etc.), it is possible to draw conclusions about the impact that the rollout of intelligent grids and meters has had on the load curve in relation to energy information feedback (impact of feedback) and dynamic pricing schemes (impact of pricing). Conclusions are presented separately below, according to each of the three demand response types.

4.1. Peak Clipping (PC)

Table 2 identifies the studies focusing on peak clipping as a DSR and reports the quantitative results of its impact. The majority of these studies involved pilot projects, the main objective of which was to further understanding of domestic consumer behaviour in response to the implementation of intelligent telemetry devices combined with different tariff structures with time discrimination (dynamic rates) and feedback containing various types of information (quantity and quality).

The results tended to differ with the methodological approach employed. However, in all cases, with the exception of the study undertaken in Ireland (CER, 2011), the impact of the combination of digital counters and price signals or information feedback was positive and statistically significant.

Indeed, most of the papers combined the use of these two elements, with relatively few focusing exclusively on consumer information feedback (Ivanov et al., 2013; Asensio and Delmas, 2016). In the first of these papers, the simple fact of incorporating an in-home display device providing a daily message about energy consumption and associated costs combined with a warning system (‘red alert’ on critical peak days) saw users consuming 15% less energy during peak hours on an average red alert day. In the second study, the information provided to the consumer was more detailed, providing not only economic cost data (cost-savings frame) but also information related to the impact on human health stemming from the greater consumption and increased emissions associated with the use of older generation technology. With the cost-savings information, the authors observed a 15.7% reduction during peak times, rising to 21.7% when users received health-based messages. A second element worth highlighting in Asensio & Delmas’ paper is that of the impact of the persistence of this intervention over time. Whereas the more traditional cost-savings frame caused a sharp attenuation in treatment effects after 2 weeks with no significant savings vs control after 7 weeks, the health-based frame, in which households were made aware of the human health effects of their marginal electricity use, induced persistent energy savings behaviour of 8–10% over 100 days.

In the case of dynamic pricing schemes, among those papers seeking a reduction in the peak demand of the electrical system, analyses focused on the impact of TOU schemes (CER, 2011; Filippini, 2011; Minchala-Avila et al., 2016), on the impact of the introduction of a demand-based TOU tariff on CPP (Faruqui and Wood, 2008) or on both aspects (Charles River Associates, 2005). This last study reported greater absolute percentage reductions in energy use during peak periods in response to higher prices in households with central air conditioning than those found in homes without air conditioning.

Geographically, the majority of the pilot projects analysed herein were conducted in the United States with the exception of Bartusch et al. (2011), Di Cosmo et al. (2014) and Filippini (2011) These studies examined the impact of the introduction of a demand-based TOU tariff on a pilot or trial basis in a group of households in Ireland, Sweden and Switzerland, respectively.

Table 2. Empirical works on Peak Clipping. Note: A, Analytic; E, Experiment; L, Simulation; S, Survey; (*) Not statistically significant. Source: Own elaboration.

Study objectives	Reference	Methodological approaches in the applied order	Country	Result
Impact of Feedback	Ivanov et al., 2013	E	USA	15.0%
	Asensio and Delmas, 2016	E	USA	15.7-21.7%
	Di Cosmo et al., 2014	E-S	Ireland	2.2-37.1%
Impact of Pricing	CER, 2011	E-S	Ireland	0.3-2.2%(*)
	Spurlock, 2015	E	USA	1.20-4.37%
	Di Cosmo et al., 2014	E-S	Ireland	2.2-37.1%
	Faruqui et al., 2013	E	USA	5.8-19.4%
	Zhang et al., 2016	E	Japan	6-14%
	Zhou et al., 2017	E	USA	8.6%
	Minchala-Avila et al., 2016	L	N/A	10-15%
	Charles River Associates, 2005	E-A	USA	12.1-14.1%
	Bartusch et al., 2011	E	Sweden	10.7-19.2%
	Nicolson et al., 2017	E-S	UK	Positive
	Faruqui and Wood, 2008	E	USA	20%
	Filippini, 2011	E	Switzerland	Positive Flexibility

Among the studies examining the application of tariffs with hourly discrimination, the pilot project analysing the impact of dynamic price rates in California between 2003 and 2004 stands out. It was conducted in the wake of serious supply problems in 2001 and 2002 (Charles River Associates, 2005) and although the average reduction in peak-period energy use on critical days was between 12.1 and 14.1%, the results were heavily dependent on the peak-period considered: critical days (when the highest prices are in effect), normal weekdays (when lower peak prices are in effect) and weekends (which have the same prices as off-peak weekday periods). The impact of dynamic tariffs, therefore, does not only depend on the price differential between peak and non-peak periods but also on the day of the week or the time of the day they are applied, or even on current weather conditions. Similarly, Zhang et al. (2016) demonstrated that load reduction was greatest during extreme temperatures and Zhou et al. (2017) found that the largest reductions occurred in the early afternoon and early evening, while there was a positive correlation with ambient air temperature. Impacts also differ across climate zones and are heavily dependent on energy appliances. For example, households with central air conditioning are more price responsive and produce greater absolute percentage reductions in peak-period energy use than households without air conditioning.

Faruqui and Sergici (2009) also present a comprehensive review of 15 pilot projects in the United States using dynamic electricity pricing. The authors report conclusive evidence that residential customers respond to higher prices by lowering consumption. The size of the price response (ranging from 2 to 51%) depends on several factors, including the magnitude of the price increase, the presence of central air conditioning and the availability of enabling technologies such as two-way programmable communicating thermostats. Across the pilots studied, TOU pricing and critical-peak pricing tariffs induced falls in peak demand that ranged between 3 and 6% and 13 and 20%, respectively. When accompanied with enabling technologies, this second set of tariffs led to a fall in peak demand that ranged between 27 and 44%.

In Europe, pilot projects (Di Cosmo et al., 2014; Bartusch et al., 2011; Filippini, 2011) have examined the impact of the introduction of a demand-based TOU tariff on a pilot or trial basis to a group of households in Ireland, Sweden and Switzerland, respectively. In the first of these, Di Cosmo et al. (2014) demonstrate that, more than the quantitative impact of TOU tariffs, clear feedback is a necessary element in learning how to control energy use more effectively over a long period and that instantaneous direct feedback in combination with frequent, accurate billing (a form of indirect feedback) is needed as a basis for sustained demand reduction.

Other papers analysing the impact of dynamic tariffs (Faruqui and Sergici, 2009; Spurlock, 2015) have focused on consumer behaviour when faced with a tariff characterized by the inclusion of critical peak pricing (CPP) schemes, in which commercial companies include the option to charge a very high rate for peak consumption for a limited number of days or critical hours for the electrical grid. In contrast to other studies that discuss the impact on tariffs with hourly price discrimination, these approaches incorporate issues related to the theory of loss aversion, a key concept in other areas of behavioural economics which find that consumers consider losses to be more important than potential profits. Spurlock (2015), in a study conducted in California, found that the magnitude of the additional reduction in peak consumption relative to the counterfactual group was between 1.20 and 4.37% of daily peak electricity consumption, depending on the positive shock to the probability of a loss and the counterfactual group used. This is a particularly relevant contribution because, although the role of loss aversion has been explored in other economic settings, it has never before been considered for household electricity consumption behaviour and time-differentiated pricing. However, these are modest results compared to those obtained by Faruqui and Sergici (2009).

4.2. Load Shifting (LS)

Empirical studies of load shifting schemes were conducted in a range of countries and examined outcomes for different seasons, appliance uses, and market arrangements. Table 3 **Table**

2identifies the studies focusing on LS. Most of the studies focused their attention on monetary incentives based on the analysis of pricing effects, including TOU tariffs, while others focused on the effects of non-monetary signals, including the provision of feedback information. A few studies, in fact, combined analyses of the use of both feedback and pricing incentives to encourage load shifting behaviour. The willingness to change consumer behaviour was found to vary according to the demographic group, the energy characteristics of the home and the degree of environmental concern and attachment (Nicolson et al., 2017).

Table 3. Empirical works on Load Shifting. Note: A, Analytic; E, Experiment; L, Simulation; S, Survey; (*) 1.5 Peak-to-off-peak price ratio. Source: Own elaboration.

Study objectives	Reference	Methodological approaches in the applied order	Country	Result
Impact of Feedback	Fenn et al., 2012	E-L	Germany	15%
	Asensio and Delmas, 2015	E	USA	Positive
	Barnicoat and Danson, 2015	E-S	Scotland	Positive
	Kendel et al., 2017	E-S	France	Positive
	Löfström, 2014	S	Norway	Positive
	D'hulst et al., 2015	E	Belgium	Positive Flexibility
Impact of Pricing	Jessoe and Rapson, 2014	E	USA	0-7%
	Bartusch et al., 2011	E	Sweden	0.8-1.2%
	Di Cosmo et al., 2014	E-S	Ireland	2.2-37.1%
	Element Energy et al., 2014	E	UK	5-10%
	Roldán Fernández et al., 2017	A-L	Spain	6-24%
	NV Energy, 2015	E-S	USA	7-39%
	Jessoe and Rapson, 2014	E	USA	8-22%
	Kahn and Wolak, 2013	E	USA	Peak-off: +3% / Peak: -5%
	Lessem et al., 2017	E-A	Canada	(-0.1) - (-0.15)(*)
	Thorsnes et al., 2012	E-S	New Zealand	10%
	Charles River Associates, 2005	E-A	USA	12.1-14.1%
	Torriti, 2012	E	Italy	13.69% (Increase)
	Woo et al., 2016	E	Canada	15%
	Faruqui and Wood, 2008	E	USA	20%
	Larsen et al., 2017	E-L-A	N/A	27%
	Faruqui et al., 2013	E	USA	Positive
	Fell et al., 2015	E-S	UK	Positive
	Hartway et al., 1999	E-S	USA	Positive
	Nicolson et al., 2017	E-S	UK	Positive
	Sun, 2014	L	N/A	Positive
	Le Ray et al., 2018	E	EU	Positive Flexibility
	Vallés et al., 2018	L	Spain	Positive Flexibility
	Filippini, 2011	E	Switzerland	Positive Flexibility

In most cases, empirical works centred on the effects of feedback incentives provided information on energy use and energy costs exclusively (e.g. Barnicoat and Danson, 2015; Jessoe and Rapson, 2014; Löfström, 2014) or in combination with conservation incentives (Asensio and Delmas, 2015; D'hulst et al., 2015; Kahn and Wolak, 2013; Kendel et al., 2017), while one study (Fenn et al., 2012) relied solely on visual feedback (colours, graphic indicators, etc.). The latter is in fact the only study using feedback incentive for load shifting to provide a quantitative outcome, reporting a shift of approximately 15% of the daily load. The rest of these studies report qualitative results, and in all but one they find that the use of feedback stimulates load shifting. Finally, one study reports a non-significant effect from feedback (Jessoe and Rapson, 2014).

Information travels from the source to the consumer via some means of feedback. In the studies of load shifting surveyed, the most frequently used means is the IHD, present in 50% of the empirical works. The traditional electric bill is used in 25% of the studies, and the remaining 25% use portal web feedback alone or combined with this bill and the mobile phone or tablet.

In line with the studies examining feedback effects, the most frequently used information types in the pricing effects evaluations were energy use and energy cost (90% of the sample), and in 45% of these, additional price information was provided to consumers.

The amount of empirical research analysing monetary incentives (pricing effects) for load shifting is more than double that focusing on information incentives. Sixty-five percent of the studies surveyed reported the quantitative outcomes of pricing incentives on consumers' load shifting behaviour. Although all the studies report positive and significant effects, their magnitude is highly heterogeneous both between and within some papers.

Between papers, this heterogeneity manifests itself with load shifting magnitudes ranging from non-significant effects in some groups reported by Jessoe and Rapson (2014) and Larsen et al. (2017) to a maximum of 39% in NV Energy (2015). While Larsen et al. (2017) focused on automated devices reacting to five-minute electricity pricing, Jessoe and Rapson (2014) explored consumer reactions by combining extreme pricing settings with quantity and price feedback and NV Energy (2015) analysed household behaviour under TOU and CPP, with and without feedback, and with and without a programmable thermostat. The latter study found that during summer months, participants shifted their electricity use out of more expensive periods, which delivered load-shifting benefits of up to 39%. The poor response in Jessoe and Rapson (2014) is attributed by the authors to the short-notice (30 minutes) of pricing events, whereas in NV Energy (2015) the extreme price warning was announced one day beforehand.

Within papers, the differences relate mostly to the variety of pricing schemes tested in each study. In Di Cosmo et al. (2014) different peak-to-off-peak TOU ratios led to different load shifting outcomes. Measured in terms of substitution elasticities (i.e. the percent change in the ratio of peak-to-off-peak consumption due to a 1% change in the peak-to-off-peak price ratio), load shifting results were found to vary between -2.2 and -37.1%. Likewise, Larsen et al. (2017) reported load shifting effects ranging from the non-significant up to 27% in the best case scenarios.

In contrast to the above, the results from some empirical analyses were relatively uniform in terms of the loading shifting effect reported both within and between papers. This is the case of both Kahn and Wolak (2013), who report load savings linked to peak vs. off-peak prices of between 8 and 15%, and Element Energy et al. (2014), who report savings between 5 and 10%. Likewise, Lessem et al. (2017) report substitution elasticities lying between -1 and -1.5%, which is very similar to the elasticities observed in other studies.

Some studies report load shifting outcomes in terms of the spread in response to peak and off-peak prices, depending on the length of critical days. Charles River Associates (2005) find a load shifting spread of 2.9% on the first day of the critical event, 5.3% on the second and 3.42% on the third. The increasing short-term effect is confirmed, while persistency is rejected.

Element Energy et al. (2014) draw on data from a number of UK domestic TOU trials (conducted between 2003 and 2014) to examine how much actual household demand is shifted out of the evening peak period for various TOU. A highly relevant finding is that, in most cases, UK households engage well with TOU and are even willing to shift loads that involve some element of lifestyle change. Overall, the implication is that, in addition to washing, drying and water-heating loads (which can be shifted with minimal impact to lifestyle by using timers, for instance), other loads more closely linked to lifestyle patterns (e.g. cooking consumption) are being shifted in response to TOU.

Interestingly, all the studies in our systematic survey reporting qualitative results, both as regards information feedback and pricing schemes, confirm a positive effect of these incentives on consumers' load shifting behaviour.

In short, the main insights gained from analyses of the effects of feedback and pricing schemes on load shifting in the studies examined herein are:

- Energy use and energy costs are the most frequently used information type.
- Timing is relevant: information given beforehand needs to be delivered at just the right moment. If the period is too short, a response may not be viable. In contrast, if the

period is too long, a consumer may forget or consider the future event to be of little importance.

- Half of the studies use IHD as a means of providing information feedback.

Additional insights from the studies surveyed can be extracted from an analysis of both their findings and limitations. For example, it would be interesting to gather further data on the types of lifestyle change – especially those associated with cooking appliances – that consumers are willing to make under modern TOU interventions, and which would ultimately lead to load shifting behaviours. Finally, the amount of information accompanying the TOU incentives needs to be limited to a level that can be processed and retained for consumer decision-making proposes (Element Energy et al., 2014).

4.3. Strategic Conservation (SC)

Table 4 identifies the studies focusing on strategic conservation as a DSR. According to the outcomes reported therein, households tend to respond to the provision of energy feedback information and dynamic pricing schemes by using less electricity. Unlike studies of PC and LS, the study of load curve variation associated with SC is carried out in complete periods of months or years, so that the methodological design of these empirical works is not constrained by time variables. Generally speaking, this facilitates the calculation of the reduction in energy consumption. As a result, a larger number of empirical studies have been carried out in relation to this DSR, while some interventions that study PC and LS also study the effects of SC.

In the study of the reduction of electricity consumption, traditional public information campaigns, i.e. without smart meters, are less effective. However, social marketing methods, feedback and the higher data resolution provided by smart meters offer greater potential for such studies because they allow the information to be adapted to the needs of specific individuals or groups of consumers with different demographic and housing characteristics (Naus and Van Der Horst, 2017). In this sense, information about energy costs provides consumers with personalized details that can influence their daily use of electricity more strongly and persistently (Asensio and Delmas, 2015).

In the case of energy information feedback, nearly 60% of these papers present quantitative outcomes, the rest presenting qualitative results. The energy savings reported in the former range from 2 to 32%. The latter, their results based mainly on surveys, report the likelihood of their samples reducing energy consumption in response to energy information feedback: 24 report a positive outcome, 5 indeterminate, and 2 negative.

In studies providing quantitative results, 79% examine the effects of direct feedback. Indeed, the study reporting the greatest savings (32%) is of this kind (Petersen et al., 2007). Within this group of studies, the works of Alahmad et al. (2012), Chen et al. (2015), Gosnell et al. (2019), Nye et al. (2010), Shimada et al. (2014), Stinson et al. (2015) and Xu et al. (2015) study the impact on energy savings that can be achieved using different types of technology to provide feedback. Fenn et al. (2012), Maan et al. (2011), Quintal et al. (2013), Rettie et al. (2014), Spagnolli et al. (2011) and Wood and Newborough (2003) analyse the use of visual feedback as an additional aid combined with the technological possibilities afforded by IHD. Likewise, Erickson et al. (2013), Houde et al. (2012); Jessoe and Rapson (2014), Petersen et al. (2007), Schleich et al. (2012) and Sun et al. (2015) do not just study the effect of feedback technologies but extend their analyses to include the impact of different types of information and save-energy campaigns.

Among the studies of the effects of direct feedback, Grønhøj and Thøgersen (2011) and Laicane et al. (2015) focus on the impact of socioeconomic variables. Likewise, to examine the social variables related to energy consumption, Anderson et al. (2017), Chen et al. (2014), Jain et al. (2013a), Peschiera and Taylor (2012), Reeves et al. (2015) and Schultz et al. (2015) study the response in consumption of the intervention groups in comparison with that of other consumers. Bager and Mundaca (2017), Poznaka et al. (2015) and Schleich et al. (2011) go one step further and analyse economic aspects of energy saving. Finally, Bager and Mundaca (2017), Delmas and Lessem (2014), Schleich et al. (2017) and van Dam et al. (2010) analyse the persistence of energy savings.

Among the studies of the impact of indirect feedback, Bariss et al. (2014) report the positive effect of persisting energy savings due to the deployment of smart meters. Studies in this category analyse in the main the different types of information provided to consumers. Allcott (2011), Anderson and Lee (2016), Ayres et al. (2009) and Gans et al. (2013) follow this research approach, while Schwartz et al. (2013) test for the Hawthorne effect.

In studies providing qualitative results, the majority (77.5%) are concerned with the effects of direct feedback. In most of these studies, the possibility of obtaining energy savings is evaluated in relation to consumer preferences for a certain type of information when seeking to determine their level of consumption, as well as for a certain type of technology via which to receive this feedback (see Kowalska-Pyzalska and Byrka, 2019; Mogles et al., 2017; Schwartz et al., 2015; Strengers, 2011). Taking one step further in their analyses of energy information feedback, Brewer et al. (2011), Foster et al. (2010), Lossin et al. (2016), Oltra et al. (2013), Peschiera et al. (2010) and Petkov et al. (2012) undertake social comparisons of consumption results; Ek and Söderholm (2010) and Kang et al. (2012) study the effect of consumers' environmental awareness; and Bager and Mundaca (2015), Loock and Staake (2013) and Pereira et al. (2013) examine socioeconomic variables and the cost reductions achieved thanks to energy efficient behaviour.

Among the qualitative studies, Gölz and Hahnel (2016), Hargreaves et al. (2013), Herrmann et al. (2018), Naus and Van Der Horst (2017) and Pereira et al. (2013) present indeterminate results. These authors failed to find a positive effect of energy information feedback on the reduction of a household's energy consumption either because of the limits imposed by their sample size or the non-negotiability of energy consumption activities. In their analysis of socioeconomic variables, Pereira et al. (2013) determine a minimum point of energy consumption that cannot be modified given the volume of household activities. Finally, Barreto et al. (2013) and Kowalska-Pyzalska and Byrka (2019) report negative results due to the fact that consumers fail to understand how to employ the technological devices for visualising energy information.

Another set of studies are concerned with the reduction in consumption that can be achieved using price schemes. Within this category of empirical study, CER (2011) and NV Energy (2015) include in their methodological approaches analyses of incentive campaigns to save energy. Here, the eventual focus on SC may be the result of studying other demand responses – for example, the outcomes reported by CER (2011) and Minchala-Avila et al. (2016) are obtained as a result of studying PC responses. Likewise, the SC outcomes of Jessoe and Rapson (2014), Lessem et al. (2017), NV Energy (2015), Roldán Fernández et al. (2017) and Torriti (2012) are obtained from their study of LS response. As can be seen in NV Energy (2015) and Torriti (2012), the variation in energy consumption between the peak and valley periods in response to price schemes does not necessarily imply a reduction in energy consumption in global terms.

Table 4. Empirical works on Strategic Conservation. Note: A, Analytic; E, Experiment; L, Simulation; S, Survey; (*) Positive but not constant, 24% Increase after treatment. Source: Own elaboration.

Study objectives	Reference	Methodological approaches in the applied order	Country	Result
Impact of Feedback	Allcott, 2011	E-A	USA	2.0%

	Quintal et al., 2013	E-S	(N/A) Southern Europe	2.0%
	Reeves et al., 2015	E-S	USA	2.0%
	Ayres et al., 2009	E	USA	2.1%
	Anderson and Lee, 2016	E-L	USA	2.2%
	Schwartz et al., 2013	E-S	USA	2.7%
	Allcott and Rogers, 2012a	E-L	USA	2.6%; 2.9%
	Fenn et al., 2012	E-L	Germany	3.0%
	Rettie et al., 2014	E-S	UK	3.0%
	Schleich et al., 2011	E-S	Germany and Austria	3.7%
	Erickson et al., 2013	E-S	USA	3.7%
	Schleich et al., 2012	E-S	Austria	4.5%
	Spagnolli et al., 2011	E	Europe	5.0%
	Schleich et al., 2017	E	Austria	5.0%
	Houde et al., 2012	S-E-S	USA	5.7%
	Bager and Mundaca, 2017	E	Denmark	5-7%
	Stinson et al., 2015	E-S	Scotland	7.0%
	Shimada et al., 2014	E	Japan	7.6%
	van Dam et al., 2010	S-E-S	Netherlands	7.8%
	Grønhøj and Thøgersen, 2011	S-E-S	Denmark	8.1%
	Peschiera and Taylor, 2012	E	USA	8.8%
	Schultz et al., 2015	E	USA	7-9%
	Xu et al., 2015	E	China	9.1%
	Jain et al., 2013a	E-L	USA	10.0%
	Nye et al., 2010	E-S	UK	5-10%
	Chen et al., 2015	E	USA	11.0%
	Gosnell et al., 2019	E	UK	4-12%
	Alahmad et al., 2012	E-S	USA	12.0%
	Anderson et al., 2017	E	South Korea	14.0%
	Wood and Newborough, 2003	E	UK	15.0%
	Gans et al., 2013	E	N. Ireland	11-17%
	Asensio and Delmas, 2015	E	USA	8-19%
	Bariss et al., 2014	E	Latvia	20.0%
	Chen et al., 2014	E-S	USA	20.0%
	Delmas and Lessem, 2014	E	USA	20.0%
	Maan et al., 2011	E	Netherlands	21.0%
	Jessoe and Rapson, 2014b	E	USA	8-22%
	Laicane et al., 2015	E-L	Latvian	6-23%
	Poznaka et al., 2015	E-S	Latvian	23.0%
	Adnane Kendel, 2015	E-S	France	13.3-23.3%
	Bager and Mundaca, 2017	E	Denmark	7-25%
	Costanza et al., 2012	E-S	UK	5-32%
	Petersen et al., 2007	E-S	USA	32.0%
	Peschiera et al., 2010	S-E-S	USA	Positive
	Foster et al., 2010	E-S	UK	Positive(*)
	Ek and Söderholm, 2010	S	Sweden	Positive
	Strengers, 2011	E-S	Australia	Positive
	Karjalainen, 2011	S	Finland	Positive
	Brewer et al., 2011	S-E-S	USA	Positive
	Ellegård and Palm, 2011	E-S	Sweden	Positive
	Petkov et al., 2012	S	Australia	Positive

	Kang et al., 2012	S	Korea	Positive
	Allcott and Rogers, 2012b	E	USA	Positive
	Chiang et al., 2012	E	UK	Positive
	Chen et al., 2012	E-L	USA	Positive
	Laicane et al., 2013	S	Latvia	Positive
	Oltra et al., 2013	E-S	Spain	Positive
	Chen et al., 2013	E-L	USA	Positive
	Jain et al., 2013a	E-L	USA	Positive
	Loock and Staake, 2013	E	Zurich	Positive
	Buchanan et al., 2014	S	UK	Positive
	Schwartz et al., 2015	E-S	UK	Positive
	Bager and Mundaca, 2015	E	Denmark	Positive
	Lossin et al., 2016	E-S	Switzerland	Positive
	Qingbin Wang, 2016	S	USA	Positive
	Mogles et al., 2017	E-S	USA	Positive
	Rausser et al., 2018	S	Ireland	Positive
	Pereira et al., 2013	E-S	Portugal	Indeterminate
	Naus and Van Der Horst, 2017	S	Netherlands	Indeterminate
	Herrmann et al., 2018	E-S	UK	Indeterminate
	Hargreaves et al., 2013	S	UK	Indeterminate
	Gölz and Hahnel, 2016	S	Germany	Indeterminate
	Barreto et al., 2013	S	Portugal	Negative
	Kowalska-Pyzalska and Byrka, 2019	S	Poland	Negative
Impact of Pricing	Gilbert and Graff, 2014	E	USA	0.6-1%
	CER, 2011	E-S	Ireland	0.3-2.2%
	Lessem et al., 2017	E-A	Canada	1.53-2.55%
	Roldán Fernández et al., 2017	A-L	Spain	1.5-6%
	Jessoe and Rapson, 2014	E	USA	0-7%
	Laicane et al., 2015	E-L	Latvian	13.0%
	Torriti, 2012	E	Italy	13.69% (Increase)
	Bartusch et al., 2011	E	Sweden	11.1-14.2%
	Minchala-Avila et al., 2016	L	Ecuador	10-15%
	Shimada et al., 2015	E	Japan	22.0%
	Buchanan et al., 2016	E	UK	Positive
	Campillo et al., 2016	E	Sweden	Positive
	Tiefenbeck et al., 2016	E	Switzerland	Persistence Positive
	NV Energy, 2015	E-S	USA	Negative

5. Conclusions and policy implications

Active participation in demand response is undoubtedly a critical element in helping achieve a more efficient operation of the electrical system, a process in which the rollout of smart meters is creating new opportunities and new areas of action. However, success in this process is not only conditioned by considerations of a technical nature, but also by a range of aspects related to consumer behaviour, which, ultimately determine the willingness and interest of consumers to engage in a more active participation and, therefore, to exploit to the full the capabilities of smart equipment.

In human behaviour, it is given that a range of cognitive, emotional and social factors combine to affect how information is perceived and understood, affecting the economic decision-making process of consumers. If we hope to include the economic dimension of demand management measures in our analyses, further study is needed on such behavioural factors as the rigidity of consumption patterns, the capacity to process information depending on its quality and quantity, the potential and persistence of reaction to price signals, and the degree of environmental awareness. These factors, individually and together, are major determinants of consumer behaviour and, in relation with smart meter use, will determine the benefits that can be reaped from the system's enhanced flexibility, including the integration of non-programmable and highly variable energy sources, the reduction in the system's operating costs and the promotion of a greater awareness of generation costs in periods of peak demand.

Based on the results and associated insights extracted from the preceding review of empirical studies, valuable conclusions can be drawn in relation to the potential of demand side response to endow the system with the necessary flexibility. Indeed, one of the main findings to emerge from this review is that there is a sizeable potential market for smart TOU tariffs amongst consumers following the rollout of the smart meter. Moreover, with different impacts on the load curve, various demand side response types, including peak clipping, load shifting and strategic conservation, lead to an ample range of responses from consumers. However, the greatest effects were found in papers examining load shifting and strategic conservation, while a more homogeneous group of findings was found in studies of peak clipping. Yet in all three kinds of study, some null effects were reported on load curve shaping, while in strategic conservation studies even negative results were reported, confirming rebound effects.

Based on the above analysis, it can be confirmed that the introduction of dynamic pricing schemes would appear essential for taking full advantage of the highly granular data on energy consumption that smart meters are able to offer. However, not all consumers respond in the same way. First, while the business sector is largely driven by financial motives, households are not. Socioeconomic factors, including education, social norms, age and culture, have a marked impact in the case of households. Second, the willingness of consumers to change their behaviour depends on their preferences with regard to such criteria as price risk, volume risk, complexity, and loss of autonomy or privacy. This means that for consumers to be engaged, their preferences must be met by personalised actions in the contract terms.

In addition, to the pricing design, information is a key element when seeking to shape consumer behaviour. More specifically, based on the results of the review, it is apparent that continuous energy information feedback may well be an effective driver of energy-related behaviour change. In this regard, while energy cost information is clearly relevant, providing consumers with specific, tailored, and scientifically verifiable information about the associated environmental and health effects of their energy consumption can have a stronger and more persistent influence on a consumer's daily electricity use.

Furthermore, consumer willingness to change their behaviour varies across demographic groups in response to DSM initiatives. In this regard the elements identified as playing a particularly relevant role are the level of household income, the energy characteristics of the home, the number and composition of the family unit, and the degree of environmental concern and attachment. A specific finding in relation to a home's energy characteristics – in particular in regions with warm summers – is that households with central air conditioning are more price-responsive and produce greater absolute percentage reductions in peak-period energy use than households without air conditioning.

Moreover, it should be stressed that some consumer groups are more likely to want to switch than others. This means an in-depth knowledge of consumption determinants is required to maximise the potential consequences from demand side response actions. Overall, this suggests that behavioural intervention based on information strategies can be an effective complement to price-based policies.

While traditional public information campaigns have proved to be largely ineffective, based on the studies reviewed here it would appear that new information strategies, including social marketing and smart meter feedback, hold greater potential insofar as they allow information to be tailored to the needs of specific individuals or consumer groups.

Finally, one issue that needs to be taken into consideration in future work is the persistence of the effects of consumer guidelines on electricity demand management. As seen here in the analysis of the effects stemming from the implementation of digital counters in combination with dynamic pricing schemes and informative feedback, consumers react to the signals they are fed. Indeed, most studies record how attitudes change over the course of the pilot or experimental project, but to-date we have no subsequent follow-ups that can provide the full picture of long-term changes in consumption patterns and the persistence of these changes. For the sake of a sustainable electricity system, analyses of this type will be needed when it comes to evaluating the long-term efficiency of the different measures implemented.

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