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Big data and behavioral policies for the decarbonisation of energy consumption

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List of Acronyms

ALPRs	Automatic License Plate Readers
AMI	Advanced Metering Infrastructure
BDR	Big Data Readiness
BOLD	Big and Open Linked Data
CCUS	Carbon Capture, Utilization and Storage
COP	Coefficient of Performance
CO2	Carbon Dioxide
DEFRA	UK Department for Environment, Food and Rural Affairs
DEG	Digital-era Governance
DR	Demand Response
DSM	Demand Side Management
ESG	Environmental, Social, and Governance
ESI	Energy Social Informatics
EV	Electric Vehicle
GDP	Gross Domestic Product
GHGs	Green-house Gases
GPS	Global Positioning System
GRI	Global Reporting Initiative
ICE	Internal Combustion Engine
ICTs	Information and Communication Technologies
IEA	International Energy Agency
IoT	Internet of Things
IPCC	International Panel on Climate Change
KPI	Key Performance Indicators
LAPD	Los Angeles Police Department
LED	Light Emitting Diode
NAM	Norm Activation Model
NASA	National Aeronautics and Space Administration
NDC	National Determined Contributions
NPM	New Public Management
NZE	Net Zero Emissions
PDCA	Plan, Do, Check, Act
PV	Photovoltaic
R&D	Research and Development
RCT	Randomized control trials
SME	Small and Medium-sized Enterprises
TPB	Theory of Planned Behavior
UNFCCC	United Nations Framework Convention on Climate Change

Introduction

In its recent special report, the Intergovernmental Panel on Climate Change (IPCC) clearly states that human-induced global warming already reached approximately 1°C above pre-industrial levels and that ambitious mitigation policy interventions are indispensable to limit warming to 1.5°C. In this regard, the European Union has recently adopted a binding target to cut greenhouse gas (GHG) emissions by at least 55% below 1990 levels by 2030. Furthermore, for achieving the goal set by the Paris Agreement, the EU is planning to reach carbon neutrality by 2050. The use of technological lever is not sufficient to achieve these targets, as they depend also on how individuals, households and communities will re-orientate their daily consumption, lifestyle, and investment decisions. Indeed, studies that model the feasibility of the 1.5 °C target, reveal behavioural changes and the rapid adoption of low-carbon lifestyles as critical enabling factors.

On the policy side, the ratification of the Paris Agreement has been followed in Europe with ambitious policies such as the EC Green Deal, reinforced after the COVID-19 pandemic by Next Generation EU strategy. The Russian-Ukrainian conflict has boosted to the top of the political agenda, the issue of energy security, reinforcing and accelerating the low-carbon energy transition, as demonstrated by the recent European strategy RE Power EU.

On the side of civil society, a huge global mobilisation led mainly by young people has also risen and put climate change at the centre of the political agenda, claiming the declaration of a state of "climate emergency", and evoking the need for radical changes in peoples' lifestyles.

Understanding how lifestyle changes can be promoted, and early identifying lifestyle-related factors which may accelerate the decarbonisation process will be pivotal for informing the policies that are expected to lead us to the medium and long term GHGs mitigation goals.

With its Long Term Strategy, the EU aims at becoming climate-neutral by 2050, by assigning a role also to citizens in reaching this target. The contribution of all parts of society and economic sectors will be crucial, from the power sector to industry, mobility, buildings, agriculture and forestry.

Citizens lifestyle changes in the main spheres of daily action, namely food choices, mobility and smart energy use at home, will lead to a progressive decarbonisation of the economy. Also, the recent consumption trends preferring re-use and recycling practices, as well as the gradual transition from the ownership to a usership economy, will result in a more efficient use of resources and a lifestyle decarbonisation.

The main purpose of this thesis is to analyse the role of social norms and behavioral science in the definition of behavioral policies aiming at fostering individual lifestyle decarbonisation.

An essential support could derive from the use of big data, an important tool used for years in marketing, but still very few in the public policy processes.

The power of social networks in influencing behaviors can be seen clearly in the political sphere. The most striking example come from the data analytics of Brexit referendum, looking at the interactions that took place on social media.

It is a domain of research at the crossroad of cognitive psychology, social psychology and information and communication technologies.

The thesis will explore the role of behavioral policies for an efficient use of resources and the related decarbonisation of lifestyles, specifically the use of energy in the residential sector.

The first chapter will explore the main drivers to get a net zero emissions by 2050, at a global level. The GHGs reduction targets, assigned to each energy end-use sector, will be examined distinguishing the role of technologies and the role of behavioral changes. A part of the chapter will be dedicated to the theoretical basis of the role of social norms in the adoption of pro-environmental lifestyles changes.

The second chapter will deal with the use of big data to support public policy processes and to the definition of behavioral energy policies in the residential sector.

The third chapter will analyze the contribution that behavioral policies could give to the reduction of GHGs in Italy, through a more efficient use of energy in the residential sector. The methodology presented will be applied to a big data-set collected through the "Beyond Energy app" from Sorgenia Group, used by 43.802 customers, with an average of 6.700 monthly accesses.

CHAPTER	RESEARCH QUESTION	CONTRIBUTION
1	*Is it possible to get net zero emissions in power sector, recurring to technologies only?*	- Assessment of quantitative contribution of behavioral changes in reaching net zero emissions in the power sector by 2050, at global level. - Social norms and behavioral policies in the decarbonisation of power sector
2	*Can the use of big data be a support for the definition of behavioral policies, at public and firm level?*	- Use of big data in the different phases of public policy process. - Role of behavioral policies to increase energy savings in the residential sector
3	*What is the GHGs reduction potential of behavioral energy measures in Italy? Can an energy "app" help in the adoption of behavioral changes?*	- Assessment of GHGs reduction potential of behavioral measures in the residential sector in Italy and related economic savings at current energy prices. - Assessment of GHGs reduction and economic savings for Sorgenia customers through the use of "Beyond Energy App"

1. Role of behavioral policies in the power sector decarbonisation at global level

1.1 Introduction

We are approaching a decisive moment for international efforts to tackle the climate crisis, which is the great challenge of our times. The number of countries that have pledged to reach net-zero emissions by mid-century or soon after continues to grow, but so do global greenhouse gas emissions. This gap between rhetoric and action needs to close if we are to have a fighting chance of reaching net zero by 2050 and limiting the rise in global temperatures to 1.5 °C.

The energy sector is the source of around three-quarters of greenhouse gas emissions so, to averting the worst effects of climate change, a total transformation of the energy systems underpinning our economies is required, with the deep involvement of all stakeholders –governments, businesses, investors and citizens.

After the Paris Agreement, the number of countries that have pledged to achieve net-zero emissions has grown rapidly and now covers around 70% of global emissions of CO_2. This represent a huge step forward, even if most pledges are not yet underpinned by near-term policies and measures. Moreover, even if successfully fulfilled, the pledges to date would still leave around 22 billion tonnes of CO_2 emissions worldwide in 2050.

Staying on the path to net-zero emissions requires massive deployment of all available clean and efficient energy technologies. However, a transition of the scale and speed needed to reach net zero emissions by 2050 cannot be achieved without sustained support and participation from citizens. The changes will affect multiple aspects of people's lives – from transport, heating and cooking to urban planning and jobs.

Around 55% of the cumulative emissions reductions in the net zero emissions scenario are linked to consumer choices such as purchasing an electric vehicle, retrofitting a house with energy efficient technologies or installing a heat pump. Behavioural changes, particularly in advanced economies – such as replacing car trips with walking, cycling or public transport, or foregoing a long-haul flight – also provide around 4% of the cumulative emissions reductions.

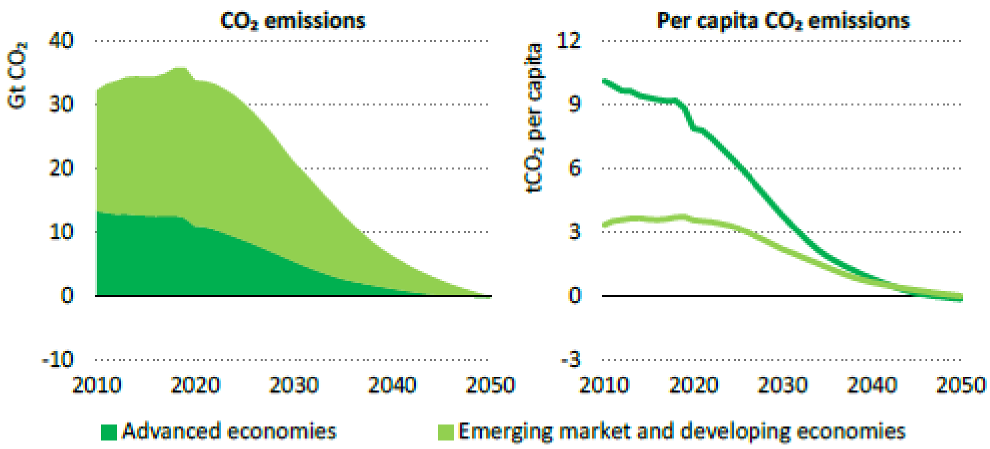
1.2 Net zero emissions target in the energy sector

Under the Paris Agreement, Parties are required to submit Nationally Determined Contributions (NDCs) to the UNFCCC and to implement policies with the aim of achieving their stated objectives. It is a dynamic process, to be updated every five years in a progressive manner to reflect the highest possible ambition. The first round of NDCs, submitted by 191 countries, covers more than 90% of global energy-related and industrial process CO_2 emissions.

In addition, 27 countries and the European Union have communicated *long-term* low GHG emissions development strategies to the UNFCCC. Some of these strategies incorporate a net zero pledge, as requested in IPCC Special Report on Global Warming of 1.5 °C where it is highlighted the importance of reaching net-zero CO_2 emissions globally by mid-century or sooner to avoid the worst impacts of climate change (IPCC, 2018).

The power sector is responsible for around three-quarters of global GHG emissions. The total decarbonisation of the sector by 2050 assigns a key role to: efficiency measures, behavioural change, electrification, renewables, hydrogen and hydrogen-based fuels, bioenergy, and CCUS (carbon capture, utilisation and storage). In the following figure is shown the trend of total and per capita CO_2 emissions according to the net zero emissions scenario of IEA (2021).

Fig. n. 1 – Global net CO_2 emissions in the net zero scenario



Source: IEA (2021)

By 2050, almost 90% of electricity generation comes from renewable sources, with wind and solar PV together accounting for nearly 70%. Most of the remainder comes from nuclear (IEA, 2021).

According to the scenario, emissions from the buildings sector fall by 40% between 2020 and 2030 thanks to a shift away from the use of fossil fuel boilers, and retrofitting the existing building stock to improve its energy performance. The energy intensity (the amount of energy used to generate a unit of GDP) will fall by 4% on average each year between 2020 and 2030.

Energy efficiency measures and electrification are the two main contributing factors, followed by behavioural changes and materials efficiency.

In transport, there is a rapid transition away from oil, which provided more than 90% of fuel use in 2020. In road transport, electricity comes to dominate the sector, providing more than 60% of energy use in 2050, while hydrogen and hydrogen-based fuels will play a smaller role, mainly in fuelling long-haul heavy-duty trucks.

Electricity becomes the dominant fuel in the transport sector globally by the early 2040s, and it accounts for around 45% of energy consumption in the sector in 2050 (compared with 1.5% in 2020).

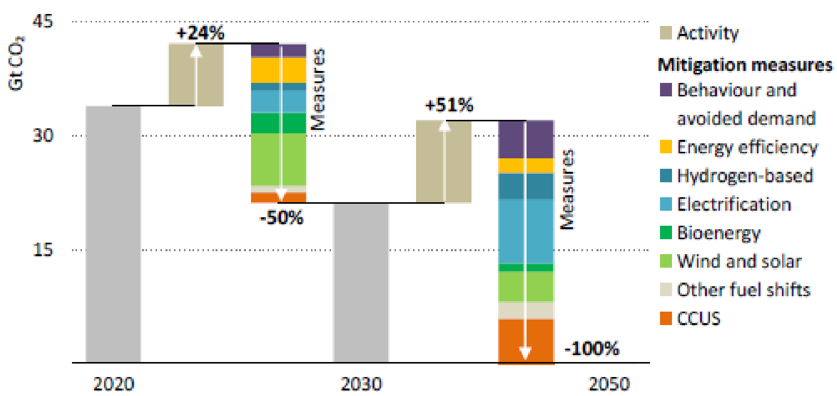
In buildings, the electrification of end-uses including heating leads to demand for electricity increasing by around 35% between 2020 and 2050 accounting for two-thirds of total buildings sector energy consumption. By 2050, two-thirds of residential buildings in advanced economies and around 40% of residential buildings in emerging market and developing economies are fitted with a heat pump. Onsite renewables-based energy systems such as solar water heaters and biomass boilers provide a further quarter of final energy use in the buildings sector in 2050 (up from 6% in 2020). Low-emissions district heating and hydrogen provide only 7% of energy use, but play a significant role in some regions.

Energy consumption in the buildings sector contracts by around 15% between 2030 and 2050 given continued efficiency improvements and electrification. By 2050, energy use in buildings is 35% lower than in 2020. Energy efficiency measures, including improving building envelopes and ensuring that all new appliances brought to market are the most efficient models available, play a key role in limiting the rise in electricity demand. Without these measures, electricity demand in buildings would be around 10.000 TWh higher in 2050, or around 70% higher than the level in the net zero emissions scenario.

1.3 Key pillars of decarbonisation

Achieving the rapid reduction in CO_2 emissions over the next 30 years in the net zero emissions scenario requires a broad range of policy approaches and technologies (Figure 2). The key pillars of decarbonisation of the global energy system are energy efficiency, behavioural changes, electrification, renewables, hydrogen and hydrogen-based fuels, bioenergy and CCUS.

Fig. n. 2 – Emissions reductions by mitigation measure in the net zero scenario, 2020 - 2050



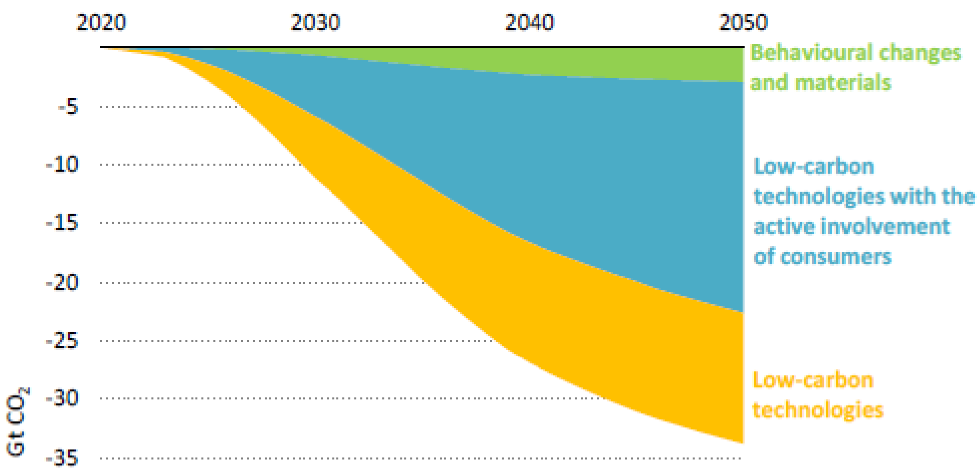
Source: IEA (2021)

Solar, wind and energy efficiency deliver around half of emissions reductions to 2030, while electrification, CCUS and hydrogen ramp up thereafter. Histograms in grey represent the energy service demand due to economic and population growth.

In the buildings sector, many efficiency measures yield financial savings as well as reducing energy use and emissions.

The wholescale transformation of the energy sector cannot be achieved without the active and willing participation of citizens. It is ultimately people who drive demand for energy-related goods and services, and societal norms and personal choices will play a pivotal role in steering the energy system onto a sustainable path. Just under 40% of emissions reductions in the net zero scenario result from the adoption of low-carbon technologies that require massive policy support and investment but little direct engagement from citizens or consumers, e.g. technologies in electricity generation or steel production. A further 55% of emissions reductions require a mixture of the deployment of low-carbon technologies and the active involvement or engagement of citizens and consumers, e.g. installing a solar water heater or buying an electric vehicle. A final 8% of emissions reductions stem from behavioural changes and materials efficiency gains that reduce energy demand, e.g. flying less for business purposes (Figure 3). Consumer attitudes can also impact investment decisions by businesses concerned about public image.

Figure 3 – Role of technology and behavioral change in emissions reductions in the net zero scenario



Source: IEA (2021)

There are three main types of behavioural change included in the net zero scenario.

- *Reducing excessive or wasteful energy use*. This includes reducing energy use in buildings and on roads, e.g. by reducing indoor temperature settings, adopting energy saving practices in homes and limiting driving speeds on motorways to 100 kilometres per hour.

- *Transport mode switching*. This includes a shift to cycling, walking, ridesharing or taking buses for trips in cities that would otherwise be made by car, as well as replacing regional air travel by high-speed rail in regions where this is feasible. Many of these types of behavioural changes would represent a break in familiar or habitual ways of life and as such would require a degree of public acceptance and even enthusiasm. Many would also require new infrastructure, such as cycle lanes and high-speed rail networks, clear policy support and high quality urban planning.
- *Materials efficiency gains*. This includes reduced demand for materials, e.g. higher rates of recycling, and improved design and construction of buildings and vehicles.

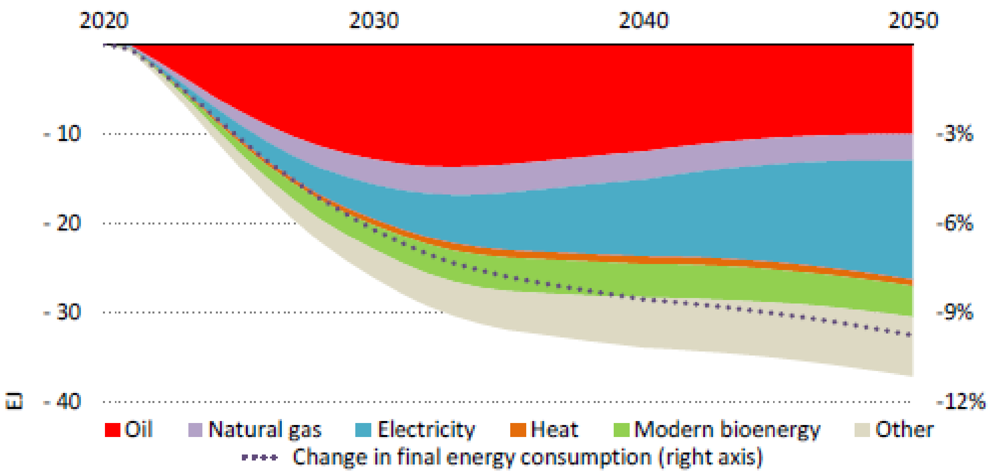
Gains in materials efficiency depend on a mixture of technical innovation in manufacturing and buildings construction, standards and regulations to support best-practice and ensure universal adoption of these innovations, and increased recycling in society at large.

Public awareness campaigns can help shape day-to-day choices about how consumers use energy.

Behavioural changes reduce energy-related activity by around 10-15% on average over the period to 2050 in the net zero scenario, reducing overall global energy demand by over 37 EJ in 2050. In 2030, around 1.7 Gt CO_2 emissions are avoided, 45% of which come from transport, notably through measures to phase out car use in cities and to improve fuel economy. For example, reducing speed limits on motorways to 100 km/h reduces emissions from road transport by 3% or 140 Mt CO_2 in 2030. A shift away from single occupancy car use towards ridesharing or cycling and walking in large cities saves a further 185 Mt CO_2.

Changes in the behaviour reduce a 10% in global energy demand at 2050, and without them cumulative emissions between 2021 and 2050 would be around 10% higher (Figure 4).

Figure 4 – Reduction in total final consumption due to behavioral changes by fuel in the net zero scenario



Source: IEA (2021)

In any case, the road to net-zero emissions is uncertain due to multiple factors: we cannot be sure how underlying economic conditions will change, which policies will be most effective, how people and businesses will respond to market and policy signals, or how technologies and their costs will evolve from within or outside the energy sector.

1.4 Behavioral policies and measures for decarbonisation

A wide range of government interventions could be used to motivate citizens in the adoption of behavioural changes to foster the decarbonisation of lifestyle.

Regulations and mandates could enable roughly 70% of the emissions saved by behavioural changes in the net zero scenario. Examples include:

- Upper speed limits, from their current levels to 100 km/h, cutting emissions from road vehicles by 3% in 2050.
- Appliance standards, which maximise energy efficiency in the buildings sector.
- Regulations covering heating temperatures in offices and default cooling temperatures for air conditioning units, which reduce excessive thermal demand.
- Changes initially tackled by market-based mechanisms, e.g. swapping regional flights for high-speed rail, which can be addressed by regulation over time to mirror changes in public sentiment and consumer norms, as recently adopted by France.

Market-based instruments use a mix of financial incentives and disincentives to influence decision making. They could enable around two-thirds of the emissions saved by behavioural changes in the net zero scenario. Examples include:

- Congestion pricing and targeted interventions differentiated by vehicle type, such as charges for most polluting vehicles, or preferential parking for clean cars.
- Transport demand measures that reduce travel, such as fuel taxes and distance-based vehicle insurance and registration fees (Byars, Wei and Handy, 2017).
- Information measures that help consumers to drive change, such as mandatory labelling of embodied or lifecycle emissions in manufacturing and a requirement for companies to disclose their carbon emissions.

Information and awareness measures could enable around 30% of the emissions saved by behavioural changes in the net zero scenario. Examples include:

- Personalised and real-time travel planning information, which facilitates a switch to walking, cycling and public transport.
- Product labelling and public awareness campaigns in combination, which help make recycling widespread and habitual.

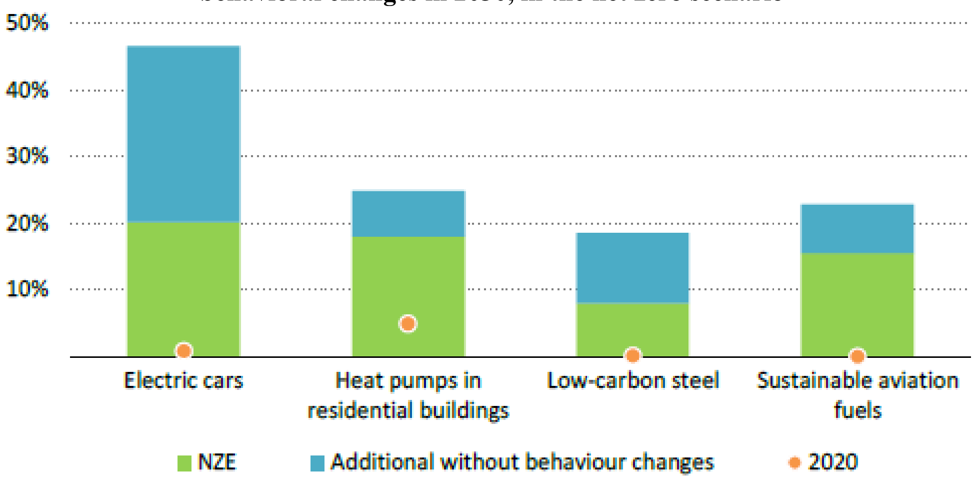
- Comparisons with consumption patterns of similar households, which can reduce wasteful energy use by up to 20% (Aydin, Brounen and Kok, 2018).

Not all the behavioural changes would be equally easy to achieve everywhere, and policy interventions would need to draw on insights from behavioural science and take into account existing behavioural norms and cultural preferences. Some behavioural changes may be more socially acceptable than others. Citizen assemblies in the United Kingdom and France indicate a large level of support for taxes on frequent and long-distance flyers and for banning polluting vehicles from city centres; conversely, measures that limit car ownership or reduce speed limits have gained less acceptance (Convention Citoyenne pour le Climat, 2021; Climate Assembly UK, 2020). Behavioural changes which reduce energy use in homes may be particularly well supported: a recent survey showed 85% support for line-drying clothes and switching off appliances, and only 20% of people felt that reducing temperature settings in homes was undesirable (Newgate Research and Cambridge Zero, 2021).

The behavioural changes in the net zero scenario would bring wider benefits in terms of air pollution in cities, road safety, noise pollution, congestion and health (Table 1). Attitudes to policy interventions can change quickly when co-benefits become apparent. For example, support for congestion charging in Stockholm jumped from less than 40% when the scheme was introduced to around 70% three years later; a similar trend was seen in Singapore, London and other cities, all of which experienced declines in air pollution after the introduction of charging (Tools of Change, 2014; DEFRA, 2012).

If the behavioural changes and the gains in materials efficiency described in the net zero scenario were not to materialise, final energy use and emissions will be higher in 2030 and 2050. In particular, it would further increase the already unprecedented ramp-up needed in low-carbon technologies to ensure the same level of emissions reductions (Figure 5). For example, achieving the same reduction in emissions in homes would require electric heat pumps sales to reach 680 million in 2030 (compared with 440 million in the net zero scenario).

Figure 5 – Share of low-carbon technologies and fuels with and without behavioral changes in 2030, in the net zero scenario



Source: IEA (2021)

Table 1 – Key behavioral changes in net zero scenario

	POLICY OPTIONS	CO-BENEFITS
Low-car cities - *Phase out ICE cars from large cities* - *Rideshare all urban car trips*	- *Low-emissions zones* - *Access restrictions* - *Parking restrictions* - *Registration caps* - *Parking pricing* - *Congestion charges* - *Investment in cycling lanes and public transportation*	- Air pollution mitigation - Public health - Reduced congestion - Urban space - Beautification and liveability
Fuel-efficient driving - *Reduce motorway speeds to less than 100 km/h* - *Eco-driving* - *Raise air conditioning temperature in cars by 3° C*	- *Speed limits* - *Real-time fuel efficiency displays* - *Awareness campaigns*	- Road safety - Reduced noise pollution
Reduce regional flights - *Replace all flights <1h where high-speed rail is a feasible alternative*	- *High-speed rail investment* - *Subsidies for high-speed rail travel* - *Price premiums*	- Lower air pollution - Lower noise pollution
Reduce international flights - *Keep air travel for business purposes at 2019 levels* - *Keep long-haul flights for leisure at 2019 levels*	- *Awareness campaigns* - *Price premiums* - *Corporate targets* - *Frequent-flyer levies*	- Lower air pollution - Lower noise pollution
Space heating - *Target average set-point temperatures of 19-20°C*	- *Awareness campaigns* - *Consumption feedback* - *Corporate targets*	- Public health - Energy affordability
Space cooling - *Target average set-point temperatures of 24-25°C*	- *Awareness campaigns* - *Consumption feedback* - *Corporate targets*	- Public health - Energy affordability

Source: Own elaboration from IEA (2021)

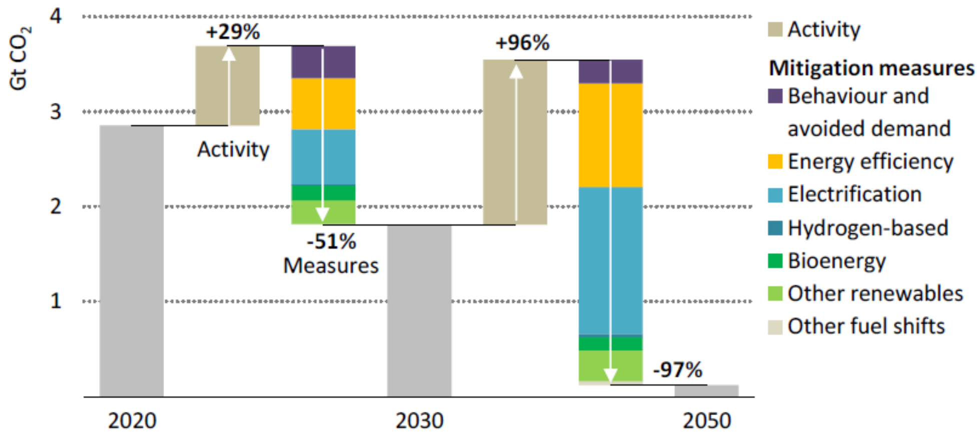
1.4.1. Net zero emissions in the building sector

Energy efficiency and electrification are the two main drivers of decarbonisation in the buildings sector (Figure 6). This transformation relies primarily on technologies already available on the market, including improved envelopes for new and existing buildings, heat pumps, energy-efficient appliances, and bioclimatic and material-efficient building design. Digitalisation and smart controls enable efficiency gains that reduce emissions from the buildings sector by 350 Mt CO_2 by 2050, in the net zero scenario. Behaviour changes are also important, with a reduction of almost 250 Mt CO_2 in 2030 reflecting changes in temperature settings for space heating or reducing excessive hot water temperatures.

Additional behaviour changes such as greater use of cold temperature clothes washing and line drying, facilitate the decarbonisation of electricity supply. These reductions could be achieved rapidly and at no cost.

Rapid shifts to zero-carbon-ready technologies see the share of fossil fuels in energy demand in the buildings sector drop to 30% by 2030, and to 2% by 2050 in the net zero scenario. The share of electricity in the energy mix reaches almost 50% by 2030 and 66% by 2050, up from 33% in 2020. All end-uses today dominated by fossil fuels are increasingly electrified in the net zero scenario, with the share of electricity in space heating, water heating and cooking increasing from less than 20% today to more than 40% in 2050. Energy district networks and low-carbon gases, including hydrogen-based fuels, remain significant in 2050 in regions with high heating needs, dense urban populations and existing gas or district heat networks. Space heating demand drops by two-thirds between 2020 and 2050, driven by improvement in energy efficiency and behavioural changes such as the adjustment of temperature set points.

Figure 6 – Global direct CO_2 emissions reductions by mitigation measure in buildings, in the net zero scenario



Notes: Activity = change in energy service demand related to rising population, increased floor area and income per capita. Behaviour = change in energy service demand from user decisions, e.g. changing heating temperatures. Avoided demand = change in energy service demand from technology developments, e.g. digitalisation

Source: IEA (2021)

Mandatory zero-carbon-ready building energy codes for all new buildings need to be introduced by 2030, and that retrofits need to be carried out in most existing buildings by 2050 to enable them to meet zero carbon-ready building energy codes. Retrofit rates would increase from less than 1% per year today to about 2.5% per year by 2030 in advanced economies. High efficiency electric heat pumps will become the primary technology choice for space heating. Concerning the lighting, the scenario foresees the progressive substitution of incandescent, halogen and compact fluorescent lamps with light-emitting diode (LED) lamps.

The share of electricity in energy consumption in buildings rises from 33% in 2020 to around two-thirds in 2050, with many buildings incorporating decentralised electricity generation using local solar PV panels, battery storage and EV chargers. The number of residential buildings with solar PV panels increases from 25 million to 240 million over the same period. Smart control systems shift flexible uses of electricity in time to correspond with generation from local renewables, or to provide flexibility services to the power system, while optimised home battery and EV charging allow households to interact with the grid. These developments help improve electricity supply security and lower the cost of the energy transition by making it easier and cheaper to integrate renewables into the system.

Strategies and policies for buildings will work best if they are aligned with those being adopted for power systems, urban planning and mobility. This would help to ensure the successful scaling up of building-integrated PV technologies, battery storage and smart controls to make buildings active service providers to grids. It would also help to foster the deployment of smart EV charging infrastructure. Policies incentivising dense and mixed-use urban planning coupled with easy access to local services and public transport could reduce reliance on personal vehicles. There are also links between buildings strategies and measures to reduce the embodied carbon emissions of new construction.

1.5 Social norms to foster sustainable behaviours

This paragraph will deal with behavioral economics which has revealed that individual choices are not fully rational or selfish. People, indeed, systematically go wrong, and this makes them human beings rather than *oeconomicus* beings (Thaler and Sunstein, 2008).

This human characteristic enable the use of behavioral policies to foster sustainability. Evidence has revealed that people are willing to sacrifice their own self-interest in favor of fairer choices. They tend to reciprocate equitable actions and punish inequitable actions of others. Also, people are loss averse and attached to their habits, hence they greatly evaluate the utility loss to give up than the utility loss to receive. Sometimes, human beings discount the utility from present to future and make choices that are not in their long run interest. Furthermore, people are not able to assess risks correctly and tend to be unrealistically optimistic.

According to the traditional interpretation of efficient resources allocation, these behaviors reduce individual welfare.

However, this represents simply a natural attitude, as human behaviour diverts from selfish and rational decision-making being immersed in social and cognitive factors that the traditional economic framework is unable to consider. Behavioural studies have proven that people are also motivated by others' well-being, fairness, social norms, living context, and limited rationality. Individuals' cognitive ability constrains human problem solving and human actions are associated with moral costs. People are indeed intrinsically motivated to achieve a good self-image and extrinsically motivated to receive a social appraisal.

According to the theory of social influence, the way people conceive the context in which they live affects their behaviour, and often this perception originates from how people compare to others. This conception finds its origins in the theory of social comparison in Festinger (1954) according to which individuals tend to evaluate the correctness or incorrectness of their abilities and beliefs by comparing them with those of others, and in particular with others that are not very divergent from them. This happens because, besides wealth maximization, people derive utility also from doing the right thing or complying with moral. The fact that an action is not commonly accepted or practiced may inflict additional costs for undertaking such behaviour (Levitt and List, 2007). People care about their reputation and self-image, hence they will interpret the external environment and behave in order to pursue or reinforce a good social status (Johansson-Stenman and Martinsson, 2006). It follows that a social normative influence can be identified behind human behaviour: humans are influenced by other humans, and, as reported in Thaler and Sunstein (2008) this occurs in two different ways. On the one side, people learn from others, therefore, if the majority acts or thinks in a specific way this suggests what is the right way to behave or believe. People may follow a practice without conscious reason, except that most people do it. According with Cialdini et al. (1990), this tendency refers to the descriptive meaning of the social norm, which indicates what the majority does, and therefore what is perceived as "normal". In this way, subjects by recognizing and imitating the emergent conduct can «usually choose efficiently and well» especially in unfamiliar situations. This may happen even when a norm is not current yet, but it is emerging, as Sunstein (2020) reports «when people learn that other people are increasingly engaging in certain behavior, they are more likely to do it, even if it has not yet attracted majority support" (Sunstein, 2020 p.21). On the other side, Thaler and Sustain (2008) recognize that individuals feel the pressure of their peers. People care about what other people think about them, and therefore they act to conform with the group, in order to avoid disapproval. This exemplifies the injunctive meaning of the social norm, hence what is morally acceptable, which motivates the individual to act in order to avoid social sanction.

These traits affect both human decisions and market outcomes, and due to their predictability they can be exploited to correct market failures as in the case of environmental protection. The environment is a public good, governed by the principles of non-rivalry and non-excludability. As such, selfish and rational people are led to free ride when they benefit from an environmental service, and monetary incentives can correct this behaviour. However, the failure of homo oeconomicus assumptions opens to the possibility of exploiting individual non-selfish and non-rational motivation to foster pro-environmental conducts. Knowing the factors that influence certain behaviours, it is possible to condition human choices (Thaler and Sunstein, 2008).

Since individuals decide and conform to their conduct by using peer norms as standards, policymakers can exploit instruments such as social norm information and social comparison to increase the effectiveness of traditional market levers and direct individuals' choices towards more beneficial social behaviours. The positive impact of these non-pecuniary interventions, recognised as nudges, has been confirmed in many fields such as organ donation, charitable actions, and environmental preservation. Nudges represent one of the main tools used among the behavioural toolbox (Sustein, 2020), and as defined by Thaler and Sustein (2008), a nudge is «any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid. Putting the fruit at eye level counts as a nudge. Banning junk food does not» (Thaler and Sustein, 2008).

In the environmental domain, studies on the use of nudges i.e. pro-conservation messages, social norm information, and comparison have successfully demonstrated to promote consumers' environmental conservation. "Nudges" are able to change people's attitudes by simply making them aware of what other people are doing in similar situations (Costa and Kahn, 2013). Evidence of the efficacy of descriptive norm information can be found in (Goldstein et al., 2008) according to which hotel guests are encouraged to reuse their towels when they learned that most people participate in the water conservation program, and adherence is reinforced in accordance with the increase of the level of perceived similarity with other guests and their identification in a reference group. The effect of inter-group solidarity and intra-group competition have been specifically emphasised in Nomura et al. (2011) which found out how providing feedback to households about their street recycling rates (the reference group) compared to others produces a sense of identity and positively impacts recycling behaviours. Sometimes the power of information disclosure and feedback has been found greater than market mechanisms, such as in Allcott et al. (2010) who demonstrated how informing households about their energy use compared to that of similar neighbours and that of efficient users not only induces energy conservation but also leads greater energy reduction compared to traditional tools. Nudges based on social comparison have been found to be effective also in the case of water conservation, as pointed out in Ferraro and Price (2013). In addition, given the apparent short-run effect of non-pecuniary strategies, in Bernedo et al., (2014) has been provided empirical evidence on the persistence of social comparison effects after years. These studies highlight that nudges, providing information on own and peers' consumption behaviours, are therefore able to change people's welfare because they influence individuals' moral payoff. (Allcott and Kessler, 2019).

Individuals want to conform to social norms not simply when their actions are visible (reputation motivation) but also when their behaviour is not observed by others, in order to maintain a positive self-image (Johansson-Stenman and Martinsson, 2006). Delmas and Lessem (2014) distinguish, indeed, among an intrinsic motivation behind conservation behaviors and reputation reasons. The authors investigate the effect of private and public information disclosure. While in the first instance, giving information about others' energy use modifies people perception of what is moral (e.g. people feel guilty when they know their usages deviate above from the average), public information makes behaviour visible hence, in this case, energy conservation will be motivated to gather green reputation benefits.

1.6 Conclusions

In this chapter has been outlined the contribution that behavioral policies could bring to the decarbonisation of the energy sector, with a special focus on building sector, which will be treated in the third chapter of the thesis, with reference to the Italian residential sector.

The data utilized in this chapter derived mostly from the "Net Zero by 2050", a scenario roadmap of IEA, which is based on IEA's research work on energy data modelling, where are weld for the first time the complex models underlying the World Energy Outlook and Energy Technology Perspectives series.

This scenario represents the most technically feasible, cost-effective and socially acceptable pathway to reach net zero emissions by 2050. It outlines more than 400 milestones, spanning all sectors and technologies, to transform the global economy from one dominated by fossil fuels into one powered predominantly by renewable energy like solar and wind.

Even if the pathway is global in scope, it represents a framework within each country can outline its own strategy, taking into account its specific circumstances, according to its different stage of economic development.

Citizens must be active participants in the entire process of decarbonisation, making them feel part of the transition and not simply subject to it. The Covid-19 pandemic has increased general awareness of the potential effectiveness of behavioral changes, such as mask-wearing, and working and schooling at home. The crisis demonstrated that people can make behavioural changes at significant speed and scale if they understand the changes to be justified. It is necessary that governments provide clear guidance about what changes are needed and why they are needed.

After this introductory framework, where major spheres of action of behavioral policies have been highlighted, the thesis will investigate the role of big data in supporting the definition of behavioral policies aiming at the decarbonisation of energy use. A focus about the characteristics of the residential energy demand in Italy will be carried out, as well as the suitability of an energy App, issued by an energy market operator, as a tool to foster behavioral changes in the use of energy.

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2. Using big data to support behavioral policies

2.1. Introduction

In the digital era, almost any action leaves a digital trail and the electronic data being generated in the world is increasing as people's lives become more digitalized. Devices that are always connected to Internet (e.g. smartphones, sensors, IoT systems, analytics software, cameras with image recognition, etc.) produce huge amounts of different types of electronic data. Also, the development of new possibilities of information collection, storage, and processing, increase the data's availability and usability. These phenomena create new opportunities for accessing to extraordinary quantities of data about citizens (and vice versa), which offer the potential for vast improvements of public policies and services (Clarke & Margetts, 2014).

The current literature on big data suggests many ways in which big data can be used to improve public sector efficiency, effectiveness and transparency. Governments can use new forms of big data analysis to understand citizens' behavior and to improve public programs (Mergel, Rethemeyer & Isett, 2016), allowing the provision of better services based on enhanced insight into citizens' needs and demands, and more informed policymaking (Klievink et al., 2017). There is a vast potential of the use of big data in different policy areas, such as health care, economy, environment or transport (Maciejewski, 2017; Jarmin & O'Hara, 2016; Schintler & Kulkarni, 2014). However, the limits and potential of big data are still unanswered (Desouza and Jacob, 2017), although big data solutions are promoted as a way to address public issues. Also, the actual use of big data in the public sector is still very limited. Most big data projects are still being planned for future implementation or are in an early stage of development (Kim et al., 2014).

The literature on big data in the policy process is still too scarce. The use of big data in the policy process builds on the research stream of evidence-based policymaking and it is increasingly studied in relation with the policy cycle "Plan, Do, Check, Act" (PDCA) (De Marchi et al., 2016; Giest, 2017; Höchtl, Parycek & Schöllhammer, 2016).

The second part of the chapter will be dedicated to energy big data, as with the increasing penetration of conventional and emerging information and communication technologies (ICTs), traditional energy systems are being digitized. The energy big data provides a new way to analyze and understand individuals' energy consumption behavior, and thus to improve energy efficiency and promote energy conservation.

Energy big data has a high degree of variety. It is a mix of structured (e.g., the energy consumption data), semi structured (e.g., data exchanged between smart energy management platform and third-party data aggregators using XML, Web services), and unstructured data (e.g., email or SMS notification about energy use, interactions of consumers on social media about their energy use). In addition, there are also some interindustry data (e.g., electric vehicle-related data) and outside-industry data (e.g., weather data) in the energy big data. It will be proposed a framework of the interdisciplinary research of energy, social and information science, which includes energy social science, social informatics and energy informatics. Then, different dimensions and different research paradigms of household energy consumption behavior will be presented.

2.2 Big Data definition and characteristics

There is no agreed-upon the definition on big data. It is characterized by a variety of factors, primarily the three dimensions of volume, velocity and variety (Laney, 2001). It has been expanded by various authors to include further dimensions, such as veracity, volatility, complexity, etc. (Desouza and Jacob, 2017; Malomo & Sena, 2017; Mayer-Schönberger & Cukier, 2017; Kim et al., 2014; Boyd & Crawford, 2012). Big data has many different definitions in different contexts. Also, as it is constantly changing due to the high speed of technology advances, making it challenging to express it in specific and measurable terms (Klievink et al., 2017).

Big data can be structured, with an organized structure clearly identifiable, such as a database with specific information stored in columns and rows or unstructured which cannot be stored in traditional databases without data transformations, such as texts, photos, videos and audio files (Daniell et al., 2016). Unstructured data is much better suited to store knowledge (Höchtl et al., 2016). Also, the effort for a computer system to analyse and derive meaningful insights from unstructured data types is much higher and requires a framework to manage computations over large data quantities.

Another characteristic discussed in the literature is the data source. Big data extends the sources of data traditionally used in policymaking, such as census, tax collection or governmental surveys. Today, it coexist with other sources of big data that can be useful for various government departments (e.g. electronic medical records, meteorological data, data from surveillance cameras, social media, GPS tracking, etc.) (Daniell et al., 2016, p. 7; Ruggeri et al., 2017). Dunleavy (2016) distinguishes between *administrative data* and the *digital residues* as the two main sources of new information for policy-makers. *Administrative data* is collected for transactional purposes, rather than being designed as a dataset for analysis or as part of the national statistics reporting. It typically records objective behaviors, not opinions. *Digital residues* allow government agencies to collect digital data series that resemble administrative data but contain a great deal of potentially useful text, image or sound information if decoded (Dunleavy, 2016).

Data access is a third characteristic of big data found in the literature. Heitmueller et al. (2014) distinguish among different data types in terms of who controls access to them:

• *Personal and proprietary data* is controlled by individual or commercial entities, which typically have the right to restrict access to the data, e.g. personal health records or credit card information.

• *Government-controlled data* is data to which a government can restrict access, e.g. census data or personal tax or health records.

• *Open data commons* are data available to all. The data may be private, commercial or government controlled.

Open data commons are usually kept up-to-date and provided in accessible format, e.g. for geographic, climate, census or financial data.

Finally, data size is a fourth characteristic of big data. The size does not refer only to *volume*, but also includes *variety, velocity*, and *complexity*. While *volume* is a function of the capacity of an organization to collect, store and analyze its data, *velocity* is the speed at which data are created, stored and retrieved. *Variety* refers to the various structures of big data outlined above and *complexity* is the degree to which data are interconnected. Many insights that emerge from big data applications are the result of connecting previously unrelated datasets (Desouza & Jacob, 2017).

2.3 Support of Big Data in Policymaking

Big data in public policy can be analyzed using the current data-based theories of Digital-era Governance (DEG) (Clarke & Margetts, 2014), the Big Data Readiness concept (Klievink, et al., 2017), and the concept of Big and Open Linked Data (BOLD) (Janssen, et al., 2017).

These three theoretical concepts build on e-government and New Public Management (NPM) research and tie in with the broader concept of evidence-based policymaking (Giest, 2017).

The *Digital-era Governance (DEG) concept* is a successor of the NPM concept. According to the DEG research stream, governments lag behind the private sector in the development of technology and digitization in public services, which leads to low levels of literacy regarding new technologies. Therefore, governments need to acquire new skills and develop the capacity to process information and realize desired outcomes (Giest, 2017). DEG is characterized by the complete digitalization of paper and phone based systems and places digital technologies at the center of bureaucracy. The use of big data in the public policy process contributes to the ideal type of DEG, by making the process more transparent, efficient, and citizen-focused.

The *Big Data Readiness concept* raises complementary points to DEG. It assesses public capacities by looking at the big data readiness of public organizations (Giest, 2017). In order to evaluate big data readiness, Klievink et al. (2017) introduce an assessment framework, which rests on three component parts:

• *Organizational alignment* concerns an organization's current structure, main activities and strategy and whether big data use can be reconciled with them.

• *Organizational maturity* indicates how far an organization has developed towards better collaboration with other public organizations and the provision of more citizen-oriented services and demand driven policies.

• *Organizational capabilities* address whether an organization possesses the required capacities to use and create value from big data and to avoid negative consequences from its use.

According to Klievink et al. (2017), much work is still to be done to unlock the full potential of big data in the public sector. Therefore, public organizations should assess what the use of big data will require and what specific added value it could bring.

Janssen, et al. (2017) identify *Big and Open Linked Data (BOLD)* as a driver of innovation in government.

The concept of BOLD can be described as the integration of three major developments that affect our society (Janssen & van den Hoven):

• Big data involves large volumes of data from various sources that need to be processed – value is created by combining different data sources.

• Open data enables access to data without any restrictions or usage conditions. The opening of data can lead to efficiency improvements, innovation, and more transparency.

• Linked data involves connecting structured and machine-readable data.

According to Janssen, et al. (2017), *policymaking innovation* is the idea that government and the public can use big data to model and understand policy implications and to support policy decisions. The use of BOLD is often linked to enhancing evidence-based policymaking as it subjects policies and models to rigorous testing of their underlying assumptions and predictions and is less dependent on subjective assessment and opinions.

According to Howlett et al. (2009), evidence-based policymaking "represents an effort to reform or restructure policy processes by prioritizing data-based evidentiary decision-making criteria over less formal or more 'intuitive' or experiential policy assessments in order to avoid or minimize policy failures caused by a mismatch between government expectations and actual, on-the-ground conditions".

Evidence-based policymaking is a relatively new topic, consistent with NPM and the public sector's increased interest in efficiency and effectiveness (Head, 2008).

Proponents of evidence-based policymaking believe that it offers to the decision-makers the opportunity for continuous improvement in policy settings and performance, based on rational evaluation and a well informed debate of options. Furthermore, governments can better learn from experience, avoid repeating past errors, and apply new techniques to old and new problems (Howlett et al., 2009). Critics emphasize different forms of information competing in the policy process, which "further require the capacity of decision-makers to comprehend it" (Giest, 2017).

De Marchi et al. (2016) suggest that evidence-based policymaking fails to address certain challenges: as evidence does not exist independently from policies, it does not "objectively" drive the policy process.

The growing demand for using analytic information to support policymaking has lead to the new concept of *policy analytics*.

According to De Marchi et al. (2016) *policy analytics* is the development and application of "skills, methodologies, methods and technologies, aiming at supporting relevant stakeholders engaged at any stage of a policy cycle, with the aim of facilitating meaningful and informative hindsight, insight and foresight".

They therefore suggest the concept policy analytics to support policy makers in a way that is: meaningful – relevant and adding value to the process; operational –practically feasible; legitimating – ensuring transparency and accountability.

2.4 Use of Big Data in the Public Policy Process

In this paragraph it is analysed the use of big data in the different phases of the policy process; planning, design, delivery, and evaluation phase.

Overall, many of the analyzed works outline the potential of using big data to improve the entire policy process. According to Maciejewski (2017), big data supports better policy development and execution *"by strengthening the information input for evidence-based decision-making and provides more immediate feedback on policy and its impacts"*. According to Schintler and Kulkarni (2014), big data has great potential as a resource for helping to inform different points in the policy analysis process *"from problem conceptualization to ongoing evaluation of existing policies, and even empowering and engaging citizens and stakeholders in the process"*.

2.4.1 Planning Phase

The use of big data in the planning phase deals with agenda-setting, problem definition, policy discussion, and participation. Agenda-setting is concerned with the way problems are recognized as requiring government attention. According to Longo et al. (2017), big data can serve as an input for "framing a policy problem before it is apprehended as such, indicating where a need is being unmet or where an emerging problem might be countered early". It has long been recognized that media play a central role in agenda-setting by framing issues and spreading relevant information (McCombs & Shaw, 1972). According to Höchtl et al. (2016), digital media increase complexity to the dynamics of agenda-setting.

Through the use of social media, any audience member can easily initiate new discussions, and responses to existing discussions can take various forms, such as text, audio, video or images. Therefore, one way for governments to identify emergent topics early and to create relevant agenda points is "to collect data from social networks with high degrees of participation and try to identify citizens' policy preferences, which can then be taken into account by the government in setting the agenda" (Höchtl et al., 2016).

Big data can play a significant role regarding set policy priorities, such as infrastructure, security, education etc. An example is Boston's *Street Bump Application*, which measures the smoothness of car rides based on movements of cell phones, thereby identifying the areas that should be prioritized for infrastructure improvements (Höchtl et al., 2016). This information can be used in open policy discussions by helping to find the most efficient starting point for implementation. *Sentiment analysis* and *opinion mining* can also be used to identify opinion streams linked to any topic of interest in public policy, mentioned in textual messages (Alfaro et al., 2016). The following two examples show in more detail how Internet-based big data can inform agenda-setting and policy discussion.

Whitman Cobb (2015) analyses Google Trends and social media sources for tracking public opinion of U.S. space policy. Public opinion plays an important role in setting the direction for U.S. space exploration. Google Trends offers a wide range of potential data sources, broken down by country, state, region, and time.

While Google Trends offers a longer-term view, Twitter provides policymakers with information on what people are interested in at particular points in time. Together, they provide a flexible tool, through which policy analysts can measure public interest. "Policy entrepreneurs in both the space community and political community could find this type of data valuable as they endeavor to lobby Congress and the executive branch to support further activities or spending for NASA" (Whitman Cobb, 2015).

Panagiotopoulos et al. (2017) examine the value of social media data as part of the policymaking cycle and evidence-based policymaking. They conducted an exploratory study with the UK Department for Environment, Food and Rural Affairs (DEFRA), focusing on farming and agricultural policy. The goal was to explore how collective input by farmers on Twitter could be useful as input in policy activities.

Communities have formed on Twitter around influential accounts and hashtags (e.g. #AgriChatUK, @FarmersGuardian or @NFUTweets). The cluster technique was used to summarize and visualize the large exploratory Twitter dataset and discover how conversations evolve.

Two separate farming-relevant branches were identified, dairy farming and arable farming. Terms clustering around dairy farming were often connected to topics concerning renewable energy, showing a mutually connected relevance, which provided interesting insights for policymakers. Terms clustering around arable farming were often associated to terms like "economy", "government" or "support", showing that the issues of government funding is interconnected with arable farming.

2.4.2 Design Phase

The concept of policy design is linked to the idea that governments want to implement goals effectively and efficiently and are interested in using knowledge and experience about policy issues (Giest, 2017). Once a public problem has entered onto the formal agenda of government, policy makers can formulate specific courses of action. *Policy formulation* involves the development of alternative courses of action for dealing with a public problem (Anderson, 2014). According to Giest (2017), most of the design activities come into play at the formulation stage. “The policy design concept looks at these considerations in policy formulation and the outcomes in implementation”.

This perspective pays special attention to policy instruments. When exploring policy options, policy makers consider not only what to do but also how to do it. Giest (2017) links these concepts to big data and argues that the increased use of big data is shaping policy instruments. “The vast amount of administrative data collected at various governmental levels and in different domains, such as health records, social programs, tax systems and the like can, with their digitization, be used for decision-making in areas of education, economics, health and social policy” (Giest, 2017). The different information-based policy tools used by governments illustrate the various ways in which big data can be used for pursuing specific policy outcomes. *Procedural* informational instruments describe government activities to regulate information. They are “designed to affect policy processes in a way consistent with government aims and ambitions through the control and selective provision of information” (Howlett, 2009). Some efforts aiming at promoting information release (e.g. freedom of information legislation) while others aiming at preventing it (e.g. censorship).

Open data policy frameworks or the release of government data are examples of how big data can be used as procedural policy instruments (Giest, 2017). Substantive informational instruments “describe government collecting data to enhance evidence-based policymaking” (Giest, 2017), such as judicial inquiries, executive commissions, national statistical agencies, surveys and polling (Howlett, 2009). Governments increasingly complement these more traditional data with (real-time) big data based on social media input, cameras and sensors (Giest, 2017).

The education sector is an example where real-time big data techniques are increasingly used as policy instruments. According to Williamson (2016), they provide up-to-date information on the education system for policymakers, e.g. by creating digital and interactive data visualizations. Learning analytics platforms are able to capture data from children’s educational activities to track and assess their development and attainment and to algorithmically optimize and customize their future educational experience. For policy-makers, this provides fine-grained knowledge, which can be used to formulate policy options (Giest, 2017).

Stakeholder participation can also play an important role when using big data in the design phase, particularly regarding substantive information-based policy tools. In the transport sector, big data can also be used for decision-making, with an app-based data collection process. In the city of Leuven the app *Routecoach* enables citizens to voluntarily contribute their mobility data. Using a machine leaning based approach, the results of more than 8,300 participants could be used to derive insights on various sustainable mobility indicators, such as CO_2 emissions or cost per trip. Due to the acceleration of data collection and processing as well as the improved relevance of the data, policymakers receive imminent feedback on implemented measures, e.g. the construction of a new bike line, speeding up the decision-making process (Semanjski, et al. 2016).

2.4.3 Delivery Phase

Big data can influence the implementation phase of the policies, due to the real-time availability of data that can be used to evaluate the effectiveness of policies and improving the future implementation processes. Although the means to pursue a policy goal are mostly identified in the policy decision, subsequent choices are inevitably required to make a policy work, such as allocating funds, assigning personnel and developing rules of procedure (Howlett et al., 2009).

Testing a new policy in real time can provide insights whether it has the desired effect or requires modification. This leads to increased autonomy for public administrations, which are enabled to react quickly to evaluation results (Höchtl et al., 2016). Governments can use real-time micro-experimentation to test policies by manipulating input variables in law, markets, architecture, social norms, and information. The impacts that correlate with these changed variables can be measured with great accuracy in order to propose, test, evaluate, and redesign policy intervention (Longo et al., 2017).

Dunleavy (2016) shows the potential of using big data for behavioral insights. *Online randomized control trials* (online RCTs) enable the evaluation of small-scale effects using the availability of huge datasets. They can often be undertaken at low cost and in real time by government agencies or businesses. For example, the UK is getting 1.9 million people a year to pay court fines – the government is chasing unpaid debts using contractors, which involves great costs. However, people's willingness to pay may be influenced by very small factors, e.g. the design of reminder letters. Using an online RCT, a re-designed letter can be sent to large, randomly assigned treatment groups that are compared with a control group. Finding out which treatment works best can generate great saving for government finances.

Predictive policing programs are another example of using big data in the delivery phase. The Los Angeles Police Department (LAPD) is at the forefront of data analytics and invests heavily in its data collection, analysis, and deployment capacities, in order to harness big data (Dunleavy, 2016). It uses big data systems and predictive analytics for a wide variety of law enforcement-related activities, such as algorithms predicting where and when future crimes are most likely to happen or risk models that identify officers most likely to engage in at-risk behavior (Brayne, 2017). The LAPD uses *Palantir*, one of the leading analytic platforms for law enforcement and intelligence agencies to compile and analyze massive data. One of the most fundamental transformations is that the police increasingly utilizes data on individuals who have not had any police contact before. For example, *Automatic License Plate Readers* (ALPRs) take readings on everyone and create data that can be used in several ways. Cameras on police cars and static ALPRs at intersections take two photos of every car and record the time, date, as well as GPS coordinates. The ALPR data can then be compared against a "heat list" of outstanding warrants or stolen cars, a geo-fence can be placed around a location to track cars near the location or the data can be stored for potential use in future investigations (Brayne, 2017).

2.4.4 Evaluation Phase

The concept of policy evaluation refers to the means being employed and the objectives being served (Anderson, 2014; Howlett et al., 2009). It is the stage of the policy process at which it is determined how a public policy has performed in action, its consequences, whether it was effective, and why or why not. After a policy has been evaluated, it may be reconceptualised or the *status quo* may be maintained. Reconceptualization can happen at the planning or any other phase of the policy process and may consist of minor changes or fundamental reformulation of the problem, including a termination of the policy. The use of big data in this phase of the policy process was least frequently described in the literature.

Traditionally, evaluation happened at the end of the policy process. Big data enables fast policy evaluation, which allows the policymakers to find out whether policies have the desired effect in a short time (Höchtl et al., 2016). Also, big data can be used for continuous evaluation of policies, instead of merely as a last phase of the policy cycle. Höchtl et al. (2016) suggest a redesigned policy cycle, in which "evaluation does not happen at the end of the process but continuously, opening permanent possibilities of reiteration, reassessment, and consideration". Schintler and Kulkarni (2014) also describe ongoing evaluation of existing policies as one of the great potentials of big data to inform the policy analysis process, which can even empower and engage citizens and stakeholders in the process.

2.5 Big data for understand and change household energy consumption behavior

This paragraph deals with the use of big data to understand residential energy consumption behavior. Residential energy consumption accounts for an important part of total energy consumption worldwide. In Italy the share of residential energy use in total final energy consumption is approximately 30% (ISPRA, 2022).

The energy consumption patterns of households show high variance, due to different factors, but has a large saving potential. It is estimated that up to 27% of current households' energy use can be saved through more efficient energy use (EC, 2006). A case study of households in EU countries showed that each household can achieve annual savings of 1.300 kWh through a combination of technological and behavioral changes (de Almeida et al., 2011). Therefore, understanding and changing the energy consumption behavior of households are considered a way to improve energy efficiency, energy savings and the related GHGs reduction.

A substantial contribution to the energy transition and the penetration of renewables in the electricity generation mix is expected to come from distributed, small-scale installations at end-consumers' premises. In such cases, consumers turn into 'prosumers', i.e. consumers which produce part or all of the electricity they consume, and sell the excess electricity.

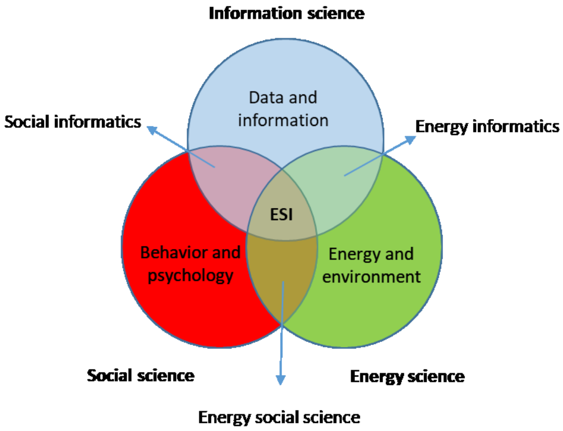
Renewable self-consumption, in addition to savings in the energy bill of consumers, also unlocks a variety of benefits such as the reduction of CO_2 emissions and electrical power losses in the transmission network, as well as the reduction of electricity price in the wholesale market.

Improving energy efficiency and reducing energy demand are widely considered as the most promising, fastest, cheapest and safest ways to reduce GHGs emissions (Sorrell S, 2015). This is why substantial research and development (R&D) efforts on energy efficient technologies have been carried out (Allcott et al., 2010). Though technological improvements and strict regulations are important ways for promoting energy efficiency (Steg et al, 2005), behavioral factors also are of great importance in achieving the goal (Dietz et al, 2009). It has been suggested that behavioral changes can be just as important as technological changes (Prindle et al., 2011). In the past decades, many behavioural and psychological models of consumers have been developed and adopted in exploring householders' energy consumption behaviour and the influencing factors (Jackson T, 2005). Then, different types of intervention strategies were developed, aiming at stimulating or encouraging changes of people's energy use behaviour to achieve energy efficiency and GHGs reduction (Poortinga et al, 2003).

Due to the increasing penetration of sensing and measurement technology, communication network technology, as well as cloud computing and big data storage and analytics, traditional energy systems are being digitized. Large amounts of energy production and consumption data are generated, collected and stored. This provides the possibility to implement energy big data mining and analysis. Decision support systems are playing an increasingly important role in the operation and management of energy systems, driving the formation of smart energy systems. Smart grid is a specific application form of smart energy system (Lund et al, 2012; Zhou et al, 2014), in which energy flow, information flow and business flow are integrated (Zhang et al, 2009). The smart power grid mainly includes six aspects, namely smart power generation, smart power transmission, smart power distribution, smart power transformation, smart scheduling, and smart power consumption. As an important part of smart grid, smart power consumption aims at the realization of flexible, efficient and tailor-made electricity consumption, using advanced data acquisition equipment and data analysis techniques. Through the smart meters deployed at the user side, large scale electricity consumption data of residential users can be collected in near real time. Through the analysis of electricity consumption data collected by smart meters and other data acquisition terminals, daily or monthly electricity consumption patterns of different users can be discovered (Zhou et al, 2013). Understanding the electricity consumption behavioral characteristics of different users is important for both power companies and consumers. Power companies can develop more flexible and personalized marketing strategies or demand side management measures (Moghaddam et al, 2011). Consumers can adjust and optimize their electricity consumption behaviours, thus reducing their energy costs. The large amounts of available energy consumption data and advanced big data analysis techniques have combined to trigger the formation of a new interdisciplinary research area at the crossroad of energy science, social science and information science. (Zhou, 2016), as illustrated in the Figure 7.

Research on the energy consumption behavior of consumers is an important way to improve energy efficiency and to seek effective energy conservation (Allcott et al, 2010) and GHGs reduction. The objective of energy social science is to establish behavioral or psychological models to understand energy consumption behaviors and find effective ways to achieve energy efficiency and environmental targets.

Figure n. 7 – Interdisciplinary research areas of energy, social and information science



Source: own elaboration

Traditionally, social science has played an important role in energy field studies. Social science methodologies and models have been successfully applied in solving many energy and environmental problems. Energy consumption and saving are important behavioral and psychological research areas (Abrahamse et al, 2005) in energy social science. The research works of energy consumption in energy social science deal mainly with the following aspects:

- *Behavioral and psychological factors*. Individual's energy consumption behavior is affected by many kinds of factors, including both objective and subjective ones (Branco et al, 2004). Objective factors depend on income levels, housing characteristics, family size, as well as energy prices, climatic conditions and energy policies. Subjective factors are those related to individuals' intention and awareness. The effects of subjective factors on households' energy consumption behavior are important research questions of energy social science.

- *Intervention strategies* (e.g., feedback, goal-setting, information and prompts) aiming at influencing people's energy use behavior and encouraging energy saving (Abrahamse et al, 2005). Generally, there are three types of interventions, namely structural ones (e.g., price policies and subsidies), antecedence ones (e.g., goalsetting, information, and commitment), and consequence ones (e.g., feedback and rewards) (Nilsson et al, 2014).

Social informatics is a crossed research area "focusing on the relationships between information and communications technologies (ICTs) and the larger social context in which these ICTs exist" (Sawyer S., 2005). The objective of social informatics research is to deal with social and behavioral issues with data and information. In the age of big data, the large amount of multi-source data provides new research opportunities for social science. Big data analytics can reveal many hidden behavioral patterns of both individuals and groups (Lazer et al, 2009).

The emerging information technologies (e.g. internet of things, cloud computing and data analytics), are penetrated into the energy sector from production to consumption (Zhou et al, 2015), thus forming the smart energy system. All the data generated in the energy system represent valuable resources to support smart energy management. For example, the near real-time collection and analysis of individuals' electricity consumption data in smart grid can support the behavioral changes of consumers (Loock et al, 2011).

Information science is integrated with energy science giving rise to an interdisciplinary research field called energy informatics. According to Watson et al. (2010), energy informatics applies data and information thinking and skills to increase the efficiency of energy demand and supply systems and optimize the energy distribution and consumption networks, through energy data collection, analysis, as well as system designing and implementation.

Moreover, energy social informatics (ESI) is a new interdisciplinary research area of energy science, social science and information science. It can be considered as a research field aiming at improving energy efficiency and environmental sustainability using advanced ICTs techniques and behavioral models, from the psychological and social perspectives.

2.6 Research paradigms of household energy consumption behavior

The energy consumption behavior of households can be described in time, user and spatial dimension (Fig. 8). With the deployment of smart meters in the demand side of smart grid, householder' electricity consumption data can be collected in near real time in different time granularity, from an hour to a year.

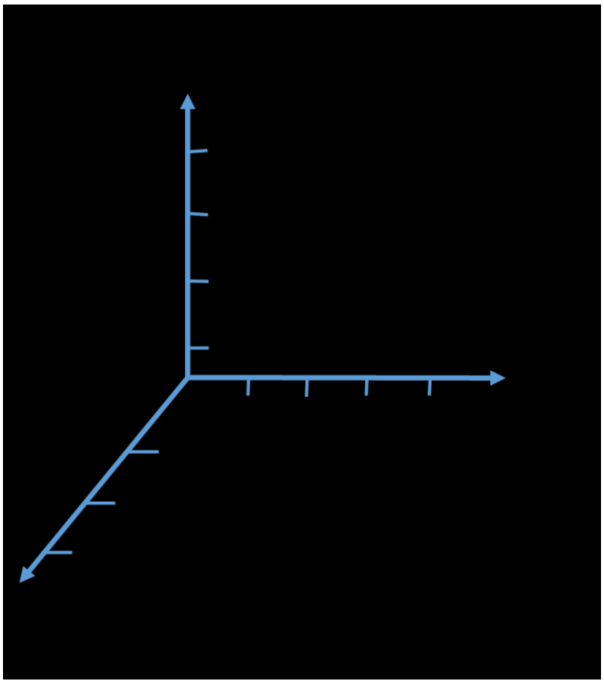
In the user dimension, the energy consumption behaviors of different households vary according to internal and external factors. Internal factors are the subjective intentions, such as habit and environmental awareness. External factors mainly include housing and demographic characteristics, way of working, and other factors.

In addition, the energy consumption behavior of households in spatial dimension deals with the geographical environment, the level of economic development, climate characteristics and other factors. In a smaller spatial range, household energy use behaviors can differ due to the impact of regional location, building structure and other spatial differences in different residential districts, or even different buildings.

In the past decades, the energy consumption behavior has been analysed from different research perspectives, including behavioral economics (Fredericks et al, 2015), environmental psychology (Bamberg et al, 2007), behavioral and experimental economics (Sapci et al, 2014), and ecological economics (Wicker et al, 2013). The research paradigms of energy consumption behavior can be divided into two major categories: the economic paradigm and the behavior-oriented paradigm (Loock et al, 2013).

The basic principle underlying the economic paradigm is the rational choice theory, which suggests that people with rationality are able to obtain the maximum benefit with minimum cost such that to maximize their utility.

In the energy sector, the rational energy consumers make decisions of energy consumption based on the costs, benefits and all of the available information. From this view, early studies suggested that users would take actions to conserve energy if sufficient information were provided. However, the cognitive burden of information processing always weakens the ability of consumers to take deliberative actions, so that they are bounded in the rationality (Simon HA, 1955). Currently, a lot of research efforts have demonstrated that many social and psychological factors like norms, habits and emotions may reduce the cognitive deliberation, thus undermining the assumptions of rational choice theory (Loock et al, 2013).



From the perspective of economic paradigm, demand side management (DSM), is an effective way to promote energy consumption behavioral changes of households through price or incentive-based strategies. DSM includes actions ranging from the replacement of less energy-efficient appliances, to the reduction of energy consumption and the shifting of time when electricity is used, to the implementation of pricing mechanisms (Zhou et al, 2015).

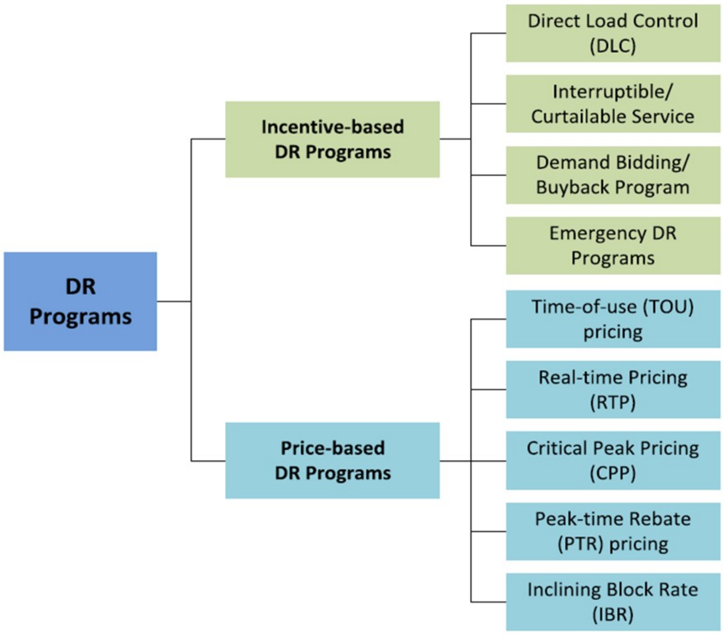
These changes in the time pattern and magnitude of the network load lead to the desired changes in their load shapes. The six major types of DSM objectives and tasks are peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shape (Qureshi et al, 2011). DSM programs can be divided into two categories, namely price-based demand responds (DR) programs and incentive-based DR programs. Price-based DR programs aim at changing the energy consumption patterns of consumers by different electricity pricing mechanisms (Aalami et al, 2010), while incentive-based DR programs mean the planned changes in electricity consumption that customers have agreed to response to requests from the operators (Zhong et al, 2013). Some of the major DR strategies are shown Figure 9.

To implement effective DR programs, the collected energy consumption big data are important resources. By the efficient analysis of the energy use data, different energy consumption patterns of different households can be discovered, and the corresponding energy use behavioral characteristics can be identified.

The assumption of behavior-oriented paradigm is that consumers' energy consumption behaviors are usually determined by the complex interplay of intrapersonal factors, interpersonal factors and external factors (Gifford et al, 2011), as shown in Figure 10.

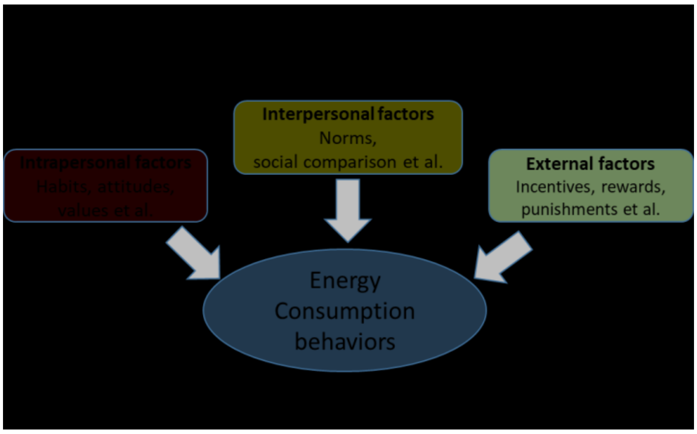
Some different behavioral models have been proposed (Jackson T, 2005), including the theory of planned behavior (TPB) (Ajzen I, 1991) and the improved models (Perugini et al, 2004), the norm activation model (NAM) (Schwartz SH, 1977), as well as the combinational model (Abrahamse et al, 2007). The TPB incorporates individual level variables as predictors of behavior. It posits that the behavioral changes of individuals are determined by three major predictors, namely attitudes toward the behavior, perceived behavioral control, and perceptions of subjective norms (Fishbein et al, 2009). These variables together predict behavioral intentions, which in turn predict actual behavior (Dixon et al, 2015). The NAM suggests that normative considerations play important roles in affecting energy consumption behaviors. Namely, people are more likely to reduce their energy consumption when they feel morally obliged to do so. Van der Werff and Steg (van der Werff et al, 2015) pointed out that a general conceptualization of the NAM that focus on energy use in general predict a range of different energy behaviors.

Figure n. 9 – Some Demand Response strategies



Source: Zhou K, Yang S. (2015)

Based on these behavioral models, there are also some studies that focused on the intervention strategies for energy consumption behavior, including goal-setting, feedback, information and prompts (Abrahamse et al, 2005). The objective of these interventions is to promote energy conservation through the provision of rewards that render pro-environmental decisions more attractive (Steg et al, 2009) or targeting an individual's perceptions, preferences, and abilities in order to induce eco-friendly behavior (Steg L, 2008). According to the goalsetting theory (Harding et al, 2014), the energy consumption behavior of individuals is directed by goals that are difficult yet realistic. At the same time, the anticipation of attaining a goal has a motivating effect. Feedback is based on the idea that feedback can influence behavior since it provides information about some given performance that people have undertaken (Kluger et al, 1996). Feedback information is mainly the households' energy consumption in terms of energy units and/or monetary values (Abrahamse et al, 2005). Based on the frequency of information, feedback can be divided into continuous feedback that using a user interface showing the current energy consumption, and non-continuous feedback that providing daily, weekly or monthly information of energy consumption via mail or internet. Existing studies have demonstrated that continuous feedback is more effective than non-continuous one in achieving energy conservation (Grønhøj et al, 2011). Information aims at providing people with sufficient understanding of how to achieve a certain objective, thus motivating them to change behaviors (Schultz PW, 2002). However, it has been found that information is not necessarily in changing householders' energy consumption behavior and promoting energy conservation, though it can result in higher knowledge levels. The objective of prompts is to give a reminder or encouragement to consumers for changing their energy consumption behavior. For non-complex behaviors, particularly the well-placed and well-timed ones, prompting is considered as the most effective intervention strategy.



The various intervention strategies, aiming at improving energy efficiency and stimulating energy saving, can be categorized into three major types, namely structural, antecedent, and consequence ones, as shown in Fig. 11 (Han et al, 2013).

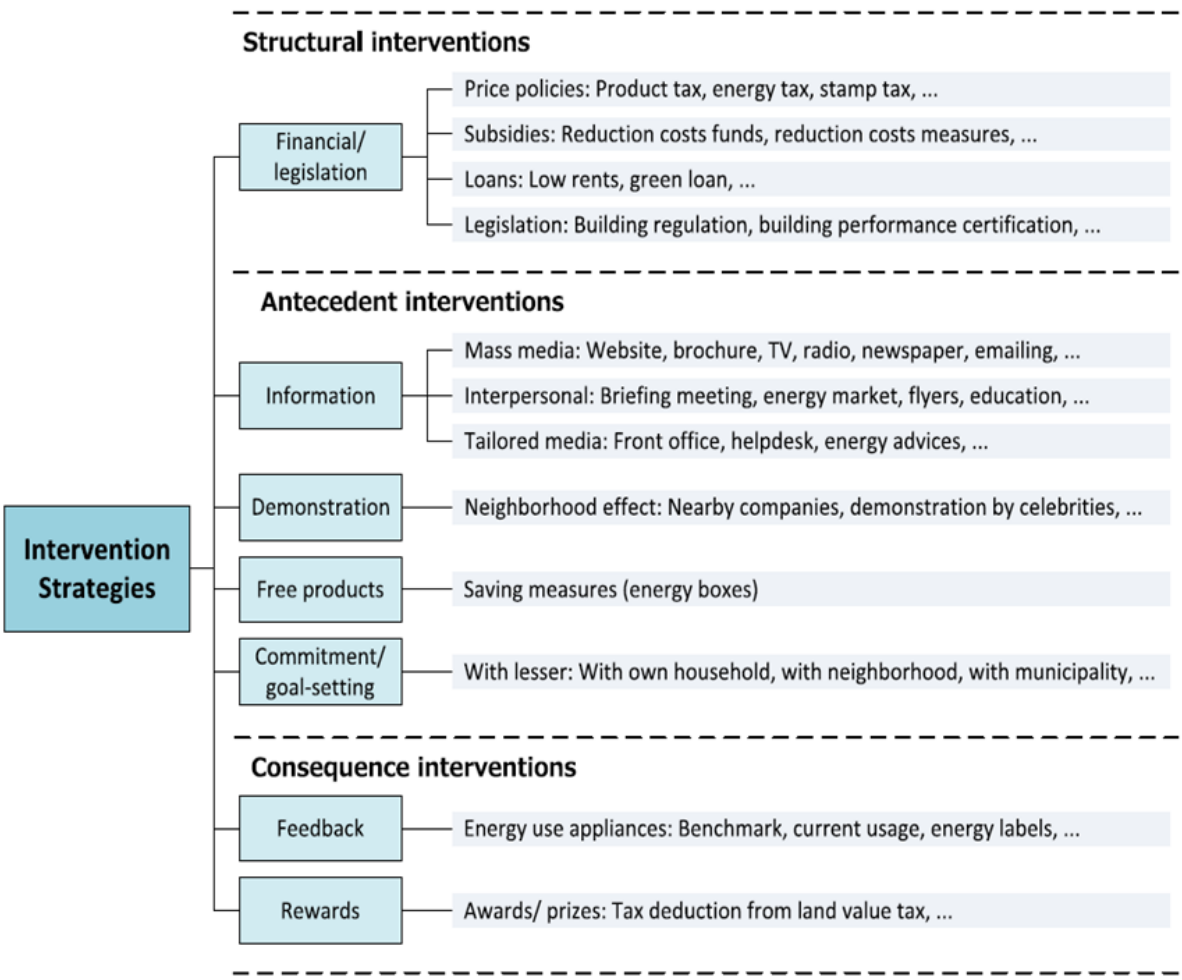
Different types of factors including intrapersonal, interpersonal and external ones influence household energy consumption behavior. Intrapersonal factors are the internal factors from their own of households, such as attitude, awareness and habit. Interpersonal factors are the social factors come from interpersonal interaction. External factors are the external economic, technological or environmental factors. Geographical location is an important regional factor that could have a significant effect on household energy consumption behavior.

The data sample sizes of most existing studies were not big enough, which were usually less than 1000. Also, many of the experimental data were survey data collected via face-to-face interviews/communications, or questionnaires based on email, telephone and Internet. Therefore, these traditional research works that have taken very few data into consideration were insufficient in scalability. Due to the widespread deployment of advanced metering infrastructure in energy system and the increasing availability of energy consumption data, energy big data analytics provides a new direction for the future research on household energy consumption behavior. In the next chapter an energy app experiment, involving more than 43.800 customers, will be presented.

Existing studies have demonstrated that behavioral factors have significant effects on household energy use. However, effective intervention strategies aiming at stimulating behavioural changes of households can promote great improvement in energy efficiency and reduction in energy consumption. For example, compared with other attitudes, the attitudes of households towards comfort and finances always correlate most with their energy use (Yang et al, 2015). In addition, due to the fact that people usually have little knowledge about their indirect energy use (Pedersen LH, 2000), the extent to which they are aware of the environmental problems and the extent to which they perceive they can contribute to solving the problems can strengthen their feelings of moral obligation to solve these problems in turn promoting behavioral changes (Steg et al, 2010). By changing the energy consumption behaviors of households, domestic energy consumption can be reduced by 10–30% (Yoanis et al, 2008; Aldossary et al, 2014).

The future research on household energy consumption behavior based on big data analytics, have important practical implications for policies aiming at improving energy efficiency and reduce energy consumption. To reduce energy consumption, mitigate climate change and promote sustainable development, a wide range of energy use behaviors of households need to be changed. The government, local communities and power companies should take more effective measures to encourage householders' behavioral changes, including introducing them more about the relationship between their energy use and carbon emissions (or climate change), providing more specific information about their energy consumption, as well as encouraging them to replace with more efficient appliances. However, the technologies or knowledge provided to households should not be too complex, since people may encounter information overload (Abrahamse et al, 2007) or response fatigue (Kim et al, 2011).

Figure n. 11 - Intervention strategies



Source: Han et al (2013)

When people have problems or difficulties in understanding the intervention strategies or incentive mechanisms, they will lose interest in the information and no longer pay attention to the policies and strategies. Also, people's energy consumption behavior is complex and often deviate from traditional decision-making and economic theories, so psychology and behavioral economics can play important roles in designing and delivering effective intervention measures (Fredericks et al, 2015).

2.7 Conclusions

Evidence-based policymaking favors data-based decision-making criteria over more ‘intuitive’ or experiential policy assessments. The use of big data helps to minimizing policy failures that result from diverging government expectations and actual conditions.

Rational evaluation and a well-informed debate of options offer decision-makers the opportunity for continuous improvement. The use of big data in each of the different phases of the policy process directly contributes to reaching these goals.

The use of big data in the different phases of the policy cycle enables policy analytics – supporting relevant stakeholders engaged at any stage of the policy cycle, aiming at facilitating informative hindsight, insight and foresight. Also, considering the three criteria of policy analytics – meaningful, operational, and legitimating – the results described in this chapter show that the three criteria apply to the use of big data in all phases of the policy process. However, while the use of big data is meaningful in all four phases, the real-time production of data in the delivery phase, which enables continuous evaluation, may be the most meaningful contribution of big data, compared to policymaking in a pre-big data setting. Furthermore, the use of big data is operational and legitimating particularly in the planning phase, as social media data are easily accessible and stakeholder participation is improved.

As the goal of the thesis is to evaluate the support of big data in defining behavioral policies to foster decarbonisation, a focus on the use of big data to understand households energy consumption has been carried out.

With the increasing penetration of sensing and measurement technology, communication network technology, as well as cloud computing and big data analytics, traditional energy systems are being digitized. Thus, increasing amount of energy consumption data is collected. Research and development of energy big data analytics and applications have brought new opportunities for understanding household energy consumption behavior.

The energy consumption behavioral patterns of different households show high variance, due to the fact that their decision makings about energy use are usually affected by various intrapersonal, interpersonal and external factors.

The overall objective of the chapter has been to enhance the understanding of social issues in energy consumption from the data science perspective. Demand response strategies and intervention strategies aiming at stimulating more efficient energy use of households have been presented, in order to allow the achievement of long-term energy conservation and decarbonisation.

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3. Decarbonisation potential of behavioral policies in the residential sector in Italy

3.1 Introduction

The residential sector is currently responsible for about 30% of final energy consumption and 12% of CO_2 emissions in Italy (ISPRA, 2022). This data show a significant potential for reducing energy consumption to comply with the energy efficiency Directives from European Union and to accelerate the decarbonisation process undertaken by Italy to tackle climate change.

Aim of this chapter is the assessment of different measures addressed to the residential sector, aiming at decreasing natural gas consumption in buildings and providing an important contribution to mitigate the effects of current international energy crisis.

Behavioral measures to be used in this sector can be divided into two categories: administrative measures that can be imposed within regulatory framework and changes in habits, related to user behaviour.

Concerning the administrative measures, it has been estimated that they could lead to energy savings for approximately 2,7 billions of Sm^3 of natural gas per year (ENEA, 2022). The administrative measures considered in this analysis are:

- Reduction of the maximum indoor temperature from 20 ° to 19 ° C
- Reduction of one hour a day of heating time
- Reduction of the heating period by 15 days

Measures related to the user behaviour could lead to energy savings for further 4,1 billions of Sm^3 of natural gas per year. These measures can be divided into:

- measures entailing an initial cost;
- no cost measures.

To assess the energy savings achievable in Italy, assumptions related to the diffusion of each measure have been done, considering the number of households in Italy, by applying corrective coefficients according to regulatory and literature data, and keeping a conservative approach.

3.2 Research methodology

To assess the natural gas consumption related to plants and appliances powered by electricity, it has been considered the final consumption (kWh) and the corresponding natural gas consumption (Sm^3), taking into account that approximately 43.2% of the electricity produced in Italy is linked to thermoelectric production from natural gas with a production yield of 56.4%.

The potential of each measure has been assessed, using as starting point the number of Italian households and their average dimension (25.7 million, with an average of 2.3 persons each). The economic savings achievable per measure and per household, have been calculated considering the tariffs of gas and electricity under the protection regime. In the following table are shown the sources of data used to carry out the analysis.

Table n. 3 – Main assumptions of the analysis and data source

HOUSEHOLDS AND BUILDINGS CHARACTERISTICS IN ITALY		
No. of households	25.716.000	ISTAT Annuario statistico italiano_2020
Average dimension of household	2,3	ISTAT Annuario statistico italiano_2020
No. of dwellings equipped with gas supply	20.200.000	6° Rapporto congiunturale e previsionale: il mercato dell'installazione degli impianti negli edifici in Italia 2020-2022 (CRESME)
Average dimension of dwellings	81 m^2	RUR – Rete Urbana delle Rappresentanze. http://www.rur.it
No. of single-household buildings	9.298.410	ENEA, RAEE 2021
No. of dwellings in Italy	31.208.161	ISTAT – Censimento della popolazione
No. of single-households dwellings	30%	
ENERGY CONSUMPTION DATA		
Annual electricity consumption in Italy	283.815 GWh	Terna, Consumi 2020
	300.887 GWh	Terna, Consumi 2021
Households electricity consumption	66.212 GWh	Terna, Consumi 2020
	67.052 GWh	Terna, Consumi 2021
Households natural gas consumption per year	19.500.000.000 Sm^3	SNAM, elaborazione dati SII, 2020
	21.700.000.000 Sm^3	SNAM, elaborazione dati SII, 2021
Natural gas consumption for households heating per year	15.200.000.000 Sm^3	SNAM, elaborazione dati SII, 2020
	15.400.000.000 Sm^3	SNAM, elaborazione dati SII, 2021
Electricity price – IV Quarter 2021	0,29700 €/kWh	ARERA
Electricity price – II Quarter 2022	0,41340 €/kWh	ARERA
Natural gas price – IV Quarter 2021	0,96850 €/Sm^3	ARERA
	0,09889 €/kWh	ARERA
Natural gas price – II Quarter 2022	1,33780 €/Sm^3	ARERA
	0,13659 €/kWh	ARERA
THERMOELECTRIC PRODUCTION DATA		
Thermoelectric production from natural gas	43,2%	https://www.gse.it/servizi-perte/news/fuel-mix-determinazione-del-mixenergetico-per-gli-anni-2019-2020
Methane consumption for electricity production	24.689.000.000 Sm^3	Terna, statistiche energia elettrica 2020
Thermoelectric production from natural gas efficiency	56,4%	https://www.isprambiente.gov.it/files2021/pubblicazioni/rapporti/r343-2021.pdf

Source: Own elaboration on ENEA (2022)

As shown in the table above, there has been a sharp increase in gas prices between 2021 and 2022, mainly due to a speculative finance phenomenon.

The overall consumption of natural gas at national level in the industrial sector, the civil sector (including residential and tertiary sectors) and the thermoelectric sector, is around 70 billion m^3.
Considering the consumption of natural gas for households (total and for heating only) and the consumption for thermoelectric production, it is estimated that:

Natural gas consumption for electricity production is	24,689,000,000 Sm^3 / year
Natural gas consumption for domestic use is	21,700,000,000 Sm^3 / year
Natural gas consumption for domestic heating is	15,400,000,000 Sm^3 / year

The natural gas consumption for heating purposes (15.4 billion Sm^3) has been divided per climatic zone.

Table n. 4 – Heating consumption in residential sector per climatic zone in Italy

Climatic zone	Natural gas consumption (MSm^3)	%
A	0	0,0
B	150	1,0
C	970	6,3
D	2.814	18,3
E	11.082	72,0
F	384	2,5

Source: ENEA (2022)

3.3 Behavioral measures entailing an initial cost

- Substitution of existing air conditioners with new high efficiency models (for heating)

To assess the energy savings connected with the replacement of a heat pump with a new high efficiency one, it has been considered a shift from a Class D energy label (972 kWh) to A+++ (686 kWh) of 2.5 kW. The annual energy consumption indicated on the energy label relates to 1400 hours of operation in heating mode to which is added the energy consumption in other modes such as standby.
To calculate energy savings at national level, it has been assumed that 5% of total households would adhere to the measure, equal to 1,285,800.

- Installation of new electric heat pumps to replace the old boilers

In accordance with the forecasts of the relative market, approximately 246,050 heat pumps will be installed in the next year to replace existing boilers (CRESME, 2022). The replacement involves a reduction in consumption linked to greater efficiency of the new heat pumps (COP equal to 4) compared to traditional natural gas boilers.
Achievable savings have been evaluated considering an average annual consumption of methane gas per household and an average boiler efficiency of 0.8, in order to reach the energy thermal demand for heating in kWh/y.

Once calculated the thermal energy demand for heating per year (5,973 kWht), passing through the COP, the electricity consumption of heat pumps used instead of the natural gas heating system has been obtained. Finally, it has been converted into equivalent natural gas for electricity production, taking into account the national energy mix and the performance of production plants.
The households concerned with this measure, would stop using natural gas for heating (100% savings) and use electricity. A change of energy carrier that would result in an economic savings for the household.

Measures for energy savings, entailing an initial cost, for residential cooling are:

- *Substitution of existing air conditioners with new high efficiency models (for cooling)*

To assess the energy savings connected with the replacement of a heat pump with a new high efficiency one, it has been considered a shift from a Class D energy label (243 kWh) to A+++ (103 kWh) of 2.5 kW. The annual energy consumption indicated on the energy label relates to 350 hours of operation in cooling mode to which is added the energy consumption in other modes such as standby. To calculate energy savings at national level, it has been assumed that 5% of total households would adhere to the measure, equal to 1,285,800.

Substitution of appliances

- *Substitution of a washing machine*

To assess the energy savings connected with the replacement of a washing machine with a capacity of 8 kg, it has been considered a shift from a Class G energy label to A and an energy consumption in kWh_e for 100 washing cycles, corresponding to 92 kWhe for G energy label and 47 kWhe for A energy label. Considering an average of one washing cycle per day, this substitution allow savings approximately of 48.9% and about 164 kWh per year. To calculate energy savings at national level, it has been assumed that 10% of total households would adhere to the measure, equal to 2,571,600.

- *Substitution of a dishwasher*

To assess the energy savings connected with the replacement of a dishwasher (12 covers), it has been considered a shift from a Class G energy label to A and an energy consumption in kWh_e for 100 washing cycles, corresponding to 65 kWhe for G energy label and 34 kWhe for A energy label. Considering an average of one dishwasher cycle per day, this substitution allow savings approximately of 47.7% and about 113 kWh per year. To calculate energy savings at national level, it has been assumed that 5% of total households would adhere to the measure, equal to 1,285,800.

- *Substitution of a refrigerator*

To assess the energy savings connected with the replacement of a refrigerator (size 300 l), it has been considered a shift from a Class G energy label to A and an energy consumption of 303 kWhe for G energy label and 100 kWhe for A energy label. This substitution would allow savings approximately of 67% and about

203 kWh per year. To calculate energy savings at national level, it has been assumed that 10% of total households would adhere to the measure, equal to 2,571,600.

- *Substitution of an oven*

To assess the energy savings connected with the replacement of an oven (size 100 l), it has been considered a shift from a Class D energy label (154,3 kWhe) to A+++ (43,7 kWhe). Considering an average of 100 functioning cycles per year, this substitution would allow savings approximately of 71,7% and about 111 kWh per year. To calculate energy savings at national level, it has been assumed that 10% of total households would adhere to the measure, equal to 2,571,600.

- *Replacement of incandescent and fluorescent bulbs at the end of life with LEDs*

To evaluate the effects of energy savings related to the replacement of incandescent and fluorescent light bulbs with LED, assumptions have been made according to the current diffusion of lighting technologies in Italy and the annual replacement rate of bulbs. Starting from the average surface area of dwellings in Italy (81 m^2), the required luminous flux has been calculated according to the technical standards, in order to define the minimum installed power required, considering the use of lighting devices per 6 hours/day and a contemporaneity factor of 0.3. As the replacement of bulbs occurs only at end of life it has been assumed that this measure could be referred to 100% of households.

Here is a synoptic table on the behavioral measures entailing an initial cost showing: electricity and natural gas savings, economic savings, both at household and national level.

Table n. 5 – Behavioral measures entailing an initial cost

Measure	At household level				At national level		
	Electric savings (kWh/y)	Savings (%)	Economic savings Prices 2021 (€/y)	Economic savings Prices 2022 (€/y)	Electric savings (kWh/y)	Natural gas saving (Sm3/y)	% of house holds
Substitution of existing air conditioners with new high efficiency models (for heating)	286,00	29,4%	84,94	118,23	367.738.800	28.759.677	5%
Installation of new electric heat pumps to replace old boilers			294,84	402,56		158.846.604	1%
Substitution of existing air conditioners with new high efficiency models (for cooling)	140,00	57,6%	41,58	57,88	180.012.000	14.078.163	5%
Substitution of washing machine (from G to A energy label)	164,25	48,9%	48,78	67,9	422.385.300	33.033.405	10%
Substitution of dishwasher (from G to A energy label)	113,15	47,7%	33,61	46,78	145.488.270	11.378.173	5%
Substitution of refrigerator (from G to A energy label)	203,00	67,0%	60,29	83,92	522.034.800	40.826.674	10%
Substitution of oven (from D to A+++ energy label)	110,6	71,7%	32,85	45,72	284.418.960	22.243.498	10%
Replacement of incandescent and fluorescent bulbs at the end of life with LEDs	43,31	15,0%	12,86	17,9	1.113.689.241	87.098.498	100%

Source: Own elaboration on ENEA (2022)

3.4 No cost behavioral measures

These measures, if adopted from a large number of households, could bring a huge energy savings. Among them:

- *Using heat pumps both for cooling and heating;*

Using heat pumps both for cooling and heating involves a reduction in energy consumption linked to the greater efficiency of heat pumps compared to traditional natural gas boilers. In this estimation, the average efficiency (COP) considered for existing heat pumps is equal to 3, while the efficiency considered for traditional boilers is equal to 0.8. According to the current market data, only 5% of Italian households holds a heat pump for cooling, suitable to be used also for heating, but in order to estimate the energy savings at national level, a wider audience of users has been considered. Households concerned with this measure, would stop using natural gas for heating (100% savings) and would use only electricity. This change of energy carrier would result in an economic savings for households.

Other behavioral measures able to limit energy consumption for heating, but difficult to translate into numerical terms are:
- Limiting windows opening when the heating system is on;
- Leaving areas adjacent to the radiators clear;
- Insulating radiators from the external walls;
- Lowering shutters during the night to limit heat loss.

- *Use of natural gas in kitchen*

Many tricks could be used in kitchen to save natural gas consumption. For example, if a gas burner of 3 kW is turned down to half of the initial power, from the boiling point to the end of cooking, it would be achievable a 25.7% saving of the gas required for cooking pasta. To assess the savings at national level, it has been assumed a quantity of 100 g of pasta per person and per litre of water, an average dimension household of 2.3 persons and 365 first dishes per year. As it is an easy-to-implement measure, it has been assumed that it can be followed by 50% of households.

- *Use of natural gas for hot sanitary water production*

Shower duration reduction

Considering an average duration of a shower of 7 minutes and a boiler set at 33°C with an efficiency of 80%, a water flow rate of 12 l/min, the basic consumption is approximately 0.78 Sm^3 per shower. Reducing the duration of the shower from 7 to 5 minutes could allow a saving of 0.223 Sm^3, equal to approximately 29% of initial gas consumption, as well as water savings. To assess the annual savings per household, it has been considered a number of 300 showers per year for each member of an household composed by an average of 2.3 persons. To estimate the natural gas savings at national level, it has been assumed that the measure could be followed by 40% of households.

Shower temperature reduction

Reducing the shower temperature by 3°C leads to a 9% saving on natural gas consumption. To assess this measure, the same assumptions as for the previous measure have been considered (average duration of the shower of 7 minutes, a gas boiler with an efficiency of 80%, water flow rate of 12 l/min, 300 showers per year for each member of the household). In this case the thermostat of the boiler is set at 30°C. To assess the natural gas savings at national level, it has been considered that 10% of households would adhere to the measure.

- *Reducing the use of washing machine*

To assess energy savings related to the reduction of a washing machine use, an average between G (92 kWh per 100 washing cycles) and A (47 kWh per 100 washing cycles) energy labels has been considered and a washing machine of 8 kg of capacity. The reduction of washing cycles from one per day to one every two days, could result in savings for around 126 kWh/y. Given the widespread use of washing machines, it is assumed that this measure could be extended to 100% of households.

- *Reducing the use of dishwasher*

To evaluate energy savings related to a reduction of dishwasher use, an average between G (65 kWh per 100 washing cycles) and A (34 kWh per 100 washing cycles) energy labels has been considered, and a dishwasher of 12 covers. The reduction of washing cycles from two per day to one per day, could result in savings for around 180 kWh/y. To assess the energy savings at national level, it has been assumed that 50% of households could adhere to the measure.

- *Unplug the washing machine when not in use*

A medium-sized washing machine absorbs a power of 0.5 W, even not in use. Therefore, unplugging allows to save energy in all the hours in which the washing machine is not in use. To evaluate the energy savings of this measure, the unplugged hours of a washing machine have been estimated starting from the average operating hours (one washing cycle every day) and considering a duration of 3h per cycle.

To assess the annual consumption, an average between G (92 kWh per 100 washing cycles) and A (47 kWh per 100 cycles) energy labels has been considered, and one washing cycle per day for a total of 254 kWh/year. This measure allows for a 1.5% reduction in annual energy consumption and a saving of 3.83 kWh per year. It is assumed that this measure could be extended to 100% of households.

- *Unplug the refrigerator during the holidays*

To assess the impact of this practice in reducing energy consumption, a medium-sized refrigerator of 300 litres of capacity has been considered, with an average consumption between energy class A and G (201.5

kWh/year), and an average period of 15 days per year. This measure allows for a 4.1% reduction in annual consumption and a saving of 8.28 kWh. To assess the energy savings at national level, it has been assumed that 50% of households could adhere to the measure.

- *Set the refrigerator in eco mode during holidays*

This represent an alternative to the previous measure. A refrigerator of 300 litres of capacity, set in eco mode for 15 days per year, provide 2.5% energy savings equal to 4.97 kWh. To assess the energy savings at national level, it has been assumed that 50% of households could adhere to the measure.

- *Unplug TV and entertainment devices*

A stand-by TV absorbs a power of 0.5 W, even not in use. To evaluate the energy savings of this measure, the unplugged hours of a TV have been estimated starting from an average of 4 operating hours per day. If we assume, for each TV, the presence of at least two other connected devices (such as DVD player, decoder…) the power consumption in stand-by reaches 1.5 W and the annual consumption reaches 10.95 kWh. It is assumed that this measure could be extended to 100% of households.

- *Reduce the duration of oven use*

A trick for reducing oven energy consumption is to turn it off during the last few minutes of cooking. In fact, as the oven chamber is thermally insulated from the outside it is possible to keep its temperature for a certain amount of time, if remains strictly closed. To evaluate this measure, a basic consumption corresponding to an oven operating cycle of 60 minutes, 20 for reaching the temperature and 40 for cooking has been assumed, where the duration of cooking has been reduced by 10 minutes. Assuming 200 operating cycles per year, the annual energy saving associated is about 11.4% corresponding to 33.3 kWh/year. To assess the energy savings at national level, it has been assumed that 50% of households could adhere to the measure.

- *Reducing the hours the bulbs are switched on*

To evaluate the energy saving due to the reduction of lighting hours, three main types of luminaire have been taken into consideration (incandescent light bulbs, fluorescent light bulb, LED). Reducing the switching on of a single light bulb by one hour a day for each household (not by decreasing the visual comfort but using more carefully the lighting) leads to an energy saving of 13%, corresponding to 21.9 kWh/y for a traditional bulb, 4.02 kWh/y for a fluorescent bulb and 2 .92 kWh/y for a LED. To calculate energy savings at national level, it has been considered the current diffusion of different lighting technologies in Italy: it is estimated that 40% of households still own incandescent lamps, 35% fluorescent lamps and the remaining 25% LED lamps, for a total of 100% of households involved.

Here is a synoptic table of no cost behavioral measures showing natural gas and economic savings, both at household and national level.

Table n. 6 - No cost behavioral measures

Measure	At household level				At national level		
	Natural gas savings (Sm3/y)	Savings (%)	Economic savings Prices 2021 (€/y)	Economic savings Prices 2022 (€/y)	Electric savings (kWh/y)	Natural gas saving (Sm3/y)	% of households
Using heat pumps both for cooling and heating	606,66		147	196,78		824.599.502	5%
Improving natural gas use in kitchen	9,32	25,7%	9,02	12,46		119.797.070	50%
Reduction of shower duration	153,63	28,6%	148,79	205,52		1.580.276.481	40%
Reduction of shower temperature	48,88	9,0%	47,34	65,39		125.703.811	10%
	Electric savings (kWh/y)						
Reduction of washing machine use	126,49	50,0%	37,57	52,29	3.252.816.840	254.392.412	100%
Reduction of dishwasher use	180,68	50,0%	53,66	74,69	2.323.119.150	181.683.726	50%
Unplug the washing machine when not in use	3,83	1,5%	1,14	1,58	98.556.570	7.707.794	100%
Unplug the refrigerator during holidays	8,28	4,1%	2,46	3,42	106.474.808	8.327.055	50%
Set the refrigerator in eco mode during holidays	4,97	2,5%	1,48	2,05	63.884.885	4.996.233	50%
Unplug TV and entertainment devices	10,95		3,25	4,53	281.590.200	22.022.270	100%
Reducing the duration of oven use	33,3	11,4%	9,9	13,78	428.600.000	33.519.437	50%
Reducing the use of incandescent bulbs	21,9		6,5	9,05	225.272.160	17.617.816	40%
Reducing the use of fluorescent bulbs	4,02		1,19	1,21	36.137.409	2.826.191	35%
Reducing the use of LED	2,92		0,87	1,21	18.772.680	1.468.151	25%

Source: Own elaboration on ENEA (2022)

In the following table are shown the natural gas savings and the tCO2eq avoided, yearly achievable with behavioral measures at national level.

Table n. 7 - Total natural gas savings and tCO_2eq emissions avoided at national level per year

	Behavioral measures entailing an initial cost (Sm^3/y)	No cost behavioral measures (Sm^3/y)	Total behavioral measures (Sm^3/y)	Emissions avoided (tCO_2eq/y)
Savings for direct use of natural gas	158.846.604	3.135.234.420	3.294.081.024	6.258.754
Savings of natural gas for electricity production	237.417.667	534.561.084	771.978.751	1.466.760
Total natural gas savings	**396.264.271**	**3.669.795.504**	**4.066.059.775**	**7.725.514**

Source: Own elaboration on ENEA (2022)

Four billions of natural gas savings represents an important part of the Italian natural gas demand. Before the Russian-Ukrainian conflict, imports of natural gas from Russia were about 30 billions m^3. Thanks to the recent diversification of suppliers, imports from Russia have dropped to about 14 billions m^3. Hence, the potential of natural gas savings of behavioral measures represents 28% of current natural gas imports from Russia. Concerning the GHGs potential reduction, 7,7 $MtCO_2eq$ represent 17% of residential sector emissions and 2% of GHGs emissions at national level.

3.5 Overview of Sorgenia Group

Sorgenia SpA is a leading company in the free market for electricity and natural gas in Italy. In 2021 it has sold 2,7 billion kWh of electricity and managed 188 million m^3 of gas, with a portfolio of 445,000 customers, in the households and SMEs segments.

The company operates in the electricity generation, import of electricity and gas, wholesale markets and sales to end-users customers. Since 2020 Sorgenia has also entered the ultra-fast fiber market for internet connection.

The company holds electricity generation plants for approximately 4,700 MW of installed capacity, distributed as follows:

- four Combined Cycle Gas Turbine power plants, providing 3,170 MW in Termoli (CB), Modugno (BA), Bertonico-Turano Lodigiano and Aprilia (LT).
- 50% share of Tirreno Power spa with 3 natural gas plants and various hydroelectric plants for a total of approximately 2,500 MW.
- one biomass energy production company with a capacity of 68 MW and 7 wind farms for further 282 MW.

The path towards decarbonisation and energy transition of Sorgenia is based, in addition to the gradual increase in renewable power generation capacity, on the following initiatives:

- Integration in the business plan of environmental, social and governance key performance indicators (ESG KPIs) linked with Sorgenia activities;
- Preparation of a Sorgenia Sustainability Report identifying the materials matrix of Sorgenia, relevant for its stakeholders. The Sustainability Report also include the Sorgenia ESG performance, reported according to the principles and standards defined by GRI (Global Reporting Initiative);
- Definition of a Sustainability Plan starting from the issues identified in the materials matrix, in order to build a roadmap and define the commitments in the environmental, social and governance (ESG) fields in the medium and long term.

The strategy towards the decarbonisation foresees also the direct involvement of customers, through the main instrument of MySorgenia App.

Through the App, the customers can monitor their energy consumption and bills in a simple and intuitive manner, by getting ideas and tips for energy saving and a sustainable lifestyle.

Sorgenia is the first Italian digital energy company, managing its customers through digital channels exclusively. Restricted web area and MySorgenia App represent the milestones of the customer interaction with Sorgenia and are continuously updated according to Design Thinking and Human Centered Design paths, in order to optimize the customer experience and increase the number of accesses. The App is also the privileged channel for the interactions with the *Greeners community*, which is a loyalty program born in 2020, where customers are involved in "missions" on environmental and social issues, where they can win green coins to be spent on a catalog of eco-sustainable products or use them in solidarity actions. Sorgenia also offers to its customers interactive services and tools for assessing their environmental impact, such as the Carbon Footprint calculator.

A recent survey conducted by SWG, a research and market trend company, dealing with the services assessment level of major competitors and digital players from Booking, Amazon, Netflix, Vodafone, AXA and Fineco, has judged the level of Sorgenia services better than the competitors in the energy sector and similar to the best operators in the digital field.

This is why Sorgenia has been selected as case-study to answer to the research question “Can an energy app help in the adoption of behavioral changes?”

The next paragraph will be dedicated to “Beyond Energy” initiative from Sorgenia.

3.6 Beyond Energy initiative

Beyond energy is a mobile and web App released by Sorgenia Group on August 2020. It is an application targeting residential customers aiming at an in-depth analysis of energy consumption behaviour of the customer. The App is linked to the other sustainability initiatives of Sorgenia, like the carbon footprint calculator and the *Greeners community program* aiming at accompanying the customer on his path towards a sustainable lifestyle. The App consists of 5 sections, namely: “Overview”, “Analisi dei tuoi consumi”, “La tua casa”, “Riduci i tuoi consumi”, “FAQ”. **All the screenshots of the App are available in the Appendix A**.

In “Overview”, the first section of the app, the customer could find the main information of his energy consumption behaviour, namely: bill projection (only for customers with a smart meter - AMI); detail of consumption in the bill; environmental impact related to the consumption; monthly trends consumption, and finally suggestions for adopting more efficient behaviors.

Customers with smart meters (AMI) can know the consumption forecast by the end of the month and the daily energy consumption trend. In this case, data collected in the dwellings are processed with machine learning and artificial intelligence algorithms, which are able to recognize typical signals of the different devices installed in the dwelling.

Monthly electricity consumption is broken down into 12 items respectively: Standby; Pool; Heating; Cooling; Lighting; Refrigerators/Freezers; Hot sanitary water system; Electric vehicle; Kitchen (hob, oven); Laundry; Entertainment; Other.

A cluster analysis of the customers have been done in order to find typical patterns of energy consumption. The profile of the App user is characterized by:

Gender:	mostly male (68% vs 60%) and younger (mean age 44 vs 50);
Geographic area:	mainly living in the North-West area (44% vs 40%), with a high concentration in Lombardy and Piedmont
Meter:	most users’ dwellings (66% vs 34%) are equipped with a smart meter (AMI).

Beyond Energy allows to Sorgenia to deepen the knowledge of the customers and in particular of their dwellings through the collection of *first-party* data.

The architecture of the App reflects the theoretical criteria at the basis of behavioral economics and social norms, in fact the user has the possibility to do a “peer comparison” of his trend of energy consumption with the most efficient or “average” dwelling of his cluster.

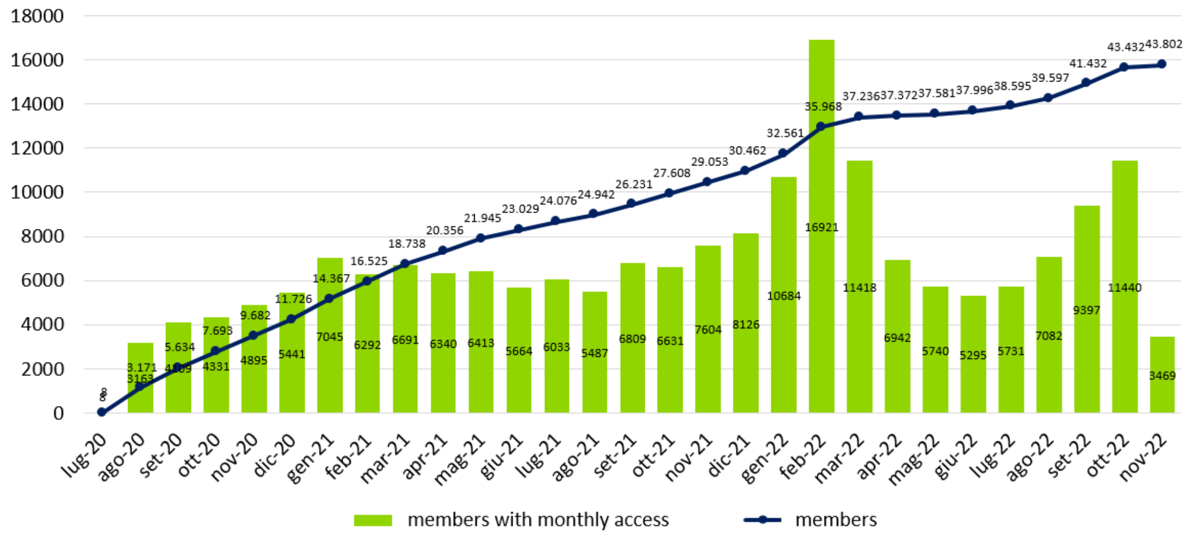
The section "Riduci i tuoi consumi" provides the customer with personalized suggestions based on his major consumption items. The customer can save energy by adopting more efficient behaviors and purchasing the latest energy technologies available on the market. Since 2022, the devices recommended can be purchased directly from “Myshop” of Sorgenia.

The customer has the opportunity to make a deeper analysis of his energy consumption by answering to a survey, via App, to analyse the energy consumption characteristics of the dwelling. The survey is about:

Heating system; Hot sanitary water system; Hob; Oven; Washing appliances; Cooling; Pool; Entertainment devices; Electric vehicle; EV charging station; Refrigerator; Led lamps; Dwelling typology; Dwelling Ownership; Photovoltaic system.

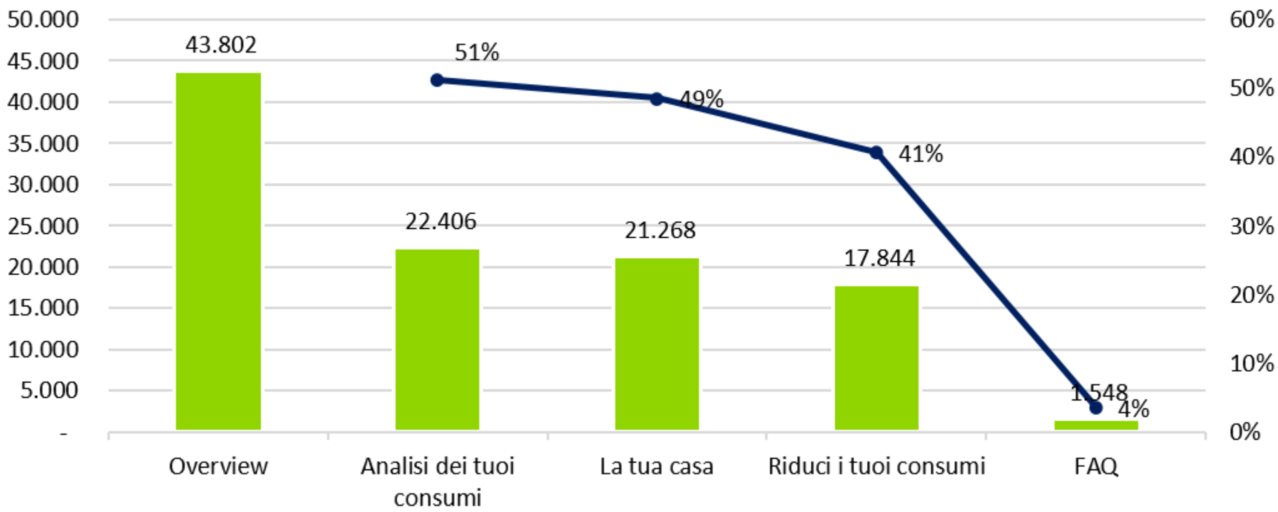
Since Beyond Energy was launched, the users of the App have grown continuously, as shown in Figure n. 12. Today the App is used from about 35% of MySorgenia APP users, which represent 20% of residential customers. The interactions in the APP show an average of 6.7k monthly accesses (Figure n.13).

Figure n. 12 - Trend of app users



Source: Own elaboration of Sorgenia data

Figure n. 13 - no. of accesses per section of the App (Period: August 2020 – November 2022)



Source: Own elaboration of Sorgenia data

To date, the most visited sections are "analisi dei tuoi consumi" and "la tua casa". About 50% of users completed the survey about the characteristics of the dwelling, including the presence of a PV system. The second most visited section is "riduci i tuoi consumi" (41%) with advices and suggestions for an in-depth monitoring of energy consumption.

So far Sorgenia has collected information from about 21k households (equal to 49% of users) that, if adequately explored and mined, support both business decisions and customer services.

For customers, the interaction with the App could bring to energy savings, operational efficiency, and improved visibility into how they are using energy.

The ENEA methodology previously presented has been applied to the Sorgenia' data, in order to assess economic and natural gas savings, as well as the CO_2 eq avoided (Tables nn. 8, 9 and 10).

Table n. 8 – Economic and natural gas savings achievable by Sorgenia customers using Beyond Energy App

Behavioral measures entailing an initial cost	Electric savings per household (kWh/y)	Savings (%)	Economic savings per household Prices 2021 (€/y)	Economic savings per household Prices 2022 (€/y)	Total Electric savings (kWh/y)	Total Natural gas savings (Sm^3/y)	% of house holds
Substitution of existing air conditioners with new high efficiency models (for heating)	286,00	29,4%	84,94	118,23	300.300	23.486	5%
Substitution of existing air conditioners with new high efficiency models (for cooling)	140,00	57,6%	41,58	57,88	147.000	11.496	5%
Substitution of washing machine (from G to A energy label)	164,25	48,9%	48,78	67,9	344.925	26.975	10%
Substitution of dishwasher (from G to A energy label)	113,15	47,7%	33,61	46,78	118.808	9.292	5%
Substitution of refrigerator (from G to A energy label)	203,00	67,0%	60,29	83,92	426.300	33.340	10%
Substitution of oven (from D to A+++ energy label)	110,6	71,7%	32,85	45,72	232.260	18.164	10%
Replacement of incandescent and fluorescent bulbs at the end of life with LEDs	43,31	15,0%	12,86	17,9	909.510	71.130	100%

Source: Own elaboration on ENEA and Sorgenia data (2022)

Table n. 9 – Economic and natural gas savings achievable by Sorgenia customers using Beyond Energy App

No cost behavioral measure	At household level				At national level		
	Natural gas savings (Sm³/y)	Savings (%)	Economic savings Prices 2021 (€/y)	Economic savings Prices 2022 (€/y)	Electric savings (kWh/y)	Natural gas saving (Sm³/y)	% of households
Using heat pumps both for cooling and heating	606,66		147	196,78		636.993	5%
Improving natural gas use in kitchen	9,32	25,7%	9,02	12,46		97.860	50%
Reduction of shower duration	153,63	28,6%	148,79	205,52		1.290.492	40%
Reduction of shower temperature	48,88	9,0%	47,34	65,39		102.648	10%
	Electric savings (kWh/y)						
Reduction of washing machine use	126,49	50,0%	37,57	52,29	2.656.290	207.740	100%
Reduction of dishwasher use	180,68	50,0%	53,66	74,69	1.897.140	148.369	50%
Unplug the washing machine when not in use	3,83	1,5%	1,14	1,58	80.430	6.290	100%
Unplug the refrigerator during holidays	8,28	4,1%	2,46	3,42	86.940	6.799	50%
Set the refrigerator in eco mode during holidays	4,97	2,5%	1,48	2,05	52.185	4.081	50%
Unplug TV and entertainment devices	10,95		3,25	4,53	229.950	17.984	100%
Reducing the duration of oven use	33,3	11,4%	9,9	13,78	349.650	27.345	50%
Reducing the use of incandescent bulbs	21,9		6,5	9,05	183.960	14.387	40%
Reducing the use of fluorescent bulbs	4,02		1,19	1,21	29.547	2.311	35%
Reducing the use of LED	2,92		0,87	1,21	15.330	1.199	25%

Source: Own elaboration on ENEA and Sorgenia data (2022)

Table n. 10 – Assessment of natural gas savings and emissions avoided through Beyond Energy initiative

	Behavioral measures entailing an initial cost (Sm^3/y)	No cost behavioral measures (Sm^3/y)	Total (Sm^3/y)	Emissions avoided (tCO_2eq)
Natural gas savings	193.883	2.564.498	2.758.381	**5.241**

Source: Own elaboration

Conclusions

In this chapter has been presented a methodology to assess the contribution to the decarbonisation from the adoption of behavioral measures in the residential sector in Italy. The same methodology assumptions have been applied to the App big dataset of a private energy company, showing as these initiatives are suitable to get both marketing insights and citizen awareness improvement in the use of energy.

It is not misleading to fully include energy apps in the "toolbox" of behavioral measures to foster decarbonisation, due to their widespread diffusion among energy companies. They represent a useful scalable experiment to collect data in a continuous relationship with customer, a data mining tool unthinkable before the digital era.

The design of these "Applications" is carried out taking into consideration theories and principles of behavioral sciences and social norms, trying to reflect interpersonal, intrapersonal and external factors influencing energy consumption behavior, as in the "peer comparison" section included in the Sorgenia App.

Recently, there is a lot of debate about data democratization, a process that should lead to sharing data collected within the companies, don't leaving them available for marketing and IT sectors only. Data has to become an asset for the whole company.

But, there is still no discussion for a process of data democratization between private companies and public administration.

Within a regulatory framework respecting the privacy implications for users and companies, it would be decisive to use the huge data collected by private sector for academic and policy purposes.

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Appendix A

Screenshots of Beyond Energy App

Torna alla tua fornitura
Beyond Energy
Trend Consumi
Dettaglio
01/02/2020 - 31/01/2021
150 kWh
120 kWh
90 kWh
60 kWh
30 kWh
0 kWh
25 °C
20 °C
15 °C
10 °C
5 °C
0 °C
feb 20
apr 20
giu 20
ago 20
ott 20
dic 20
Cucina
Acqua calda
Standby
Frigoriferi, Fre...
Lavanderia
Intrattenimen...
Illuminazione
Temperatura ...

Suggerimenti e analisi
Analisi
03/03/21
Nel mese di Gennaio ti sei piazzato tra i migliori per quanto riguarda l'efficenza energetica. I tuoi comportamenti nel consumo sono nella fascia del 10% più alto tra tutti i nostri utenti. Fantastico!
Suggerimento
24/02/21
La funzione "risparmio energetico" ti salverà
Imposta nei tuoi dispositivi elettronici la funzione "risparmio energetico": ridurrai i consumi fino al 45%.
Analisi
03/03/21
Nel mese di Gennaio hai consumato di più rispetto alla media dei 5 mesi precedenti.
ALTRI SUGGERIMENTI

Torna alla tua fornitura
Beyond Energy
Dettaglio
Confronto
29/02/20 - 31/01/21
Il tuo consumo confrontato con abitazioni simili
250 kWh
200 kWh
150 kWh
100 kWh
50 kWh
0 kWh
29/02/20
30/04/20
30/06/20
31/08/20
31/10/20
31/12/20
Casa tua
Abitazioni più efficienti
Abitazione media

Torna alla tua fornitura
Beyond Energy
Dettaglio
Confronto
01/01/21 - 31/01/21
Acqua calda
55 kWh
Cucina
22 kWh
Lavanderia
11 kWh
Intrattenimento
5 kWh
Standby
5 kWh
Frigoriferi, Freezer
9 kWh


Passa ai LED
Le lampadine a LED durano fino a tre volte più delle lampadine tradizionali e consumano molta meno energia.
8 'Mi piace'
Controlla la temperatura del frigorifero
La temperatura ideale per il frigorifero è tra i 4 e i 5 °C: impostala correttamente!

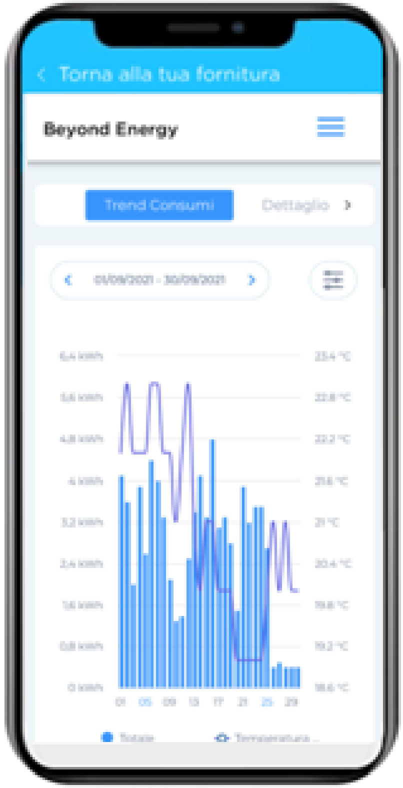

Usa una ciabatta multipresa intelligente!
Lo sapevi che che i dispositivi in stand-by consumano anche se spenti? Prendi in considerazione la sostituzione delle multiprese tradizionali con altre intelligenti, così potrai spegnere completamente tutti i dispositivi collegati.
1
La funzione "risparmio energetico" ti salverà
Imposta nei tuoi dispositivi elettronici la funzione "risparmio energetico": ridurrai i consumi fino al 45%.

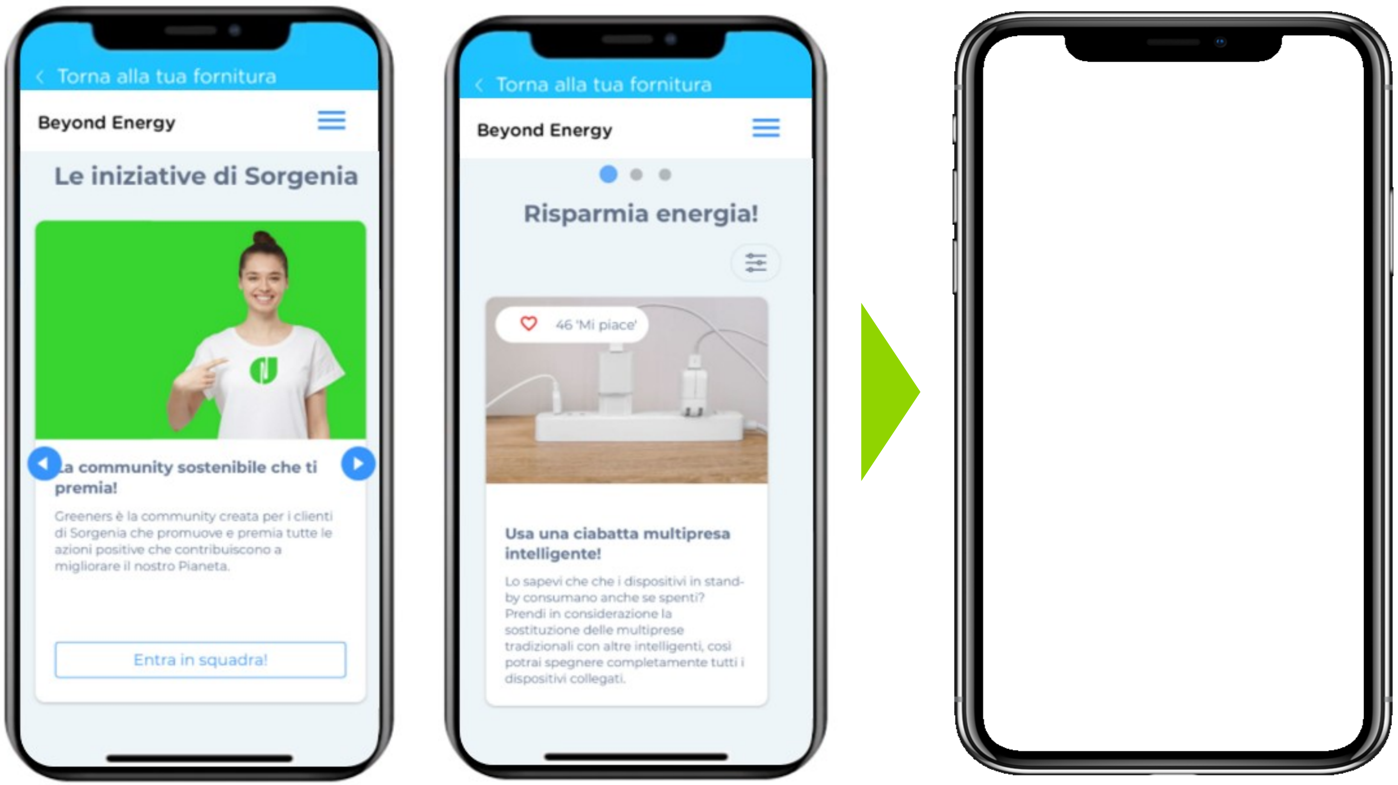

La tua casa
Come riscaldi l'acqua a casa tua?
Seleziona una risposta
Boiler elettrico con accumulo
Scaldacqua istantaneo a gas
Scaldacqua in pompa di calore
Altro


La tua casa
Quali elettrodomestici utilizzi per lavare?
Seleziona una o più risposte
Lavatrice
Asciugatrice
Lavastoviglie
Nessuno


Torna alla tua fornitura
Via Antonio Gramsci 96
2021
Giugno
kWh
83,1
Gen 2021
Feb
Mar
Apr
I tuoi consumi in dettaglio
Accedi al monitoraggio
Bollette recenti
PAGAMENTI REGOLARI
PAGATA
Bolletta
Maggio 2021
€ 27,60


Torna alla tua fornitura
LERICI
6°C in più rispetto al mese precedente
Dettaglio dei tuoi consumi
01/06/21 - 30/06/21 (Ultimo mese)
129 kWh
38 kWh Lavande...
28 kWh Frigorife...
23 kWh Intratten...
40 kWh Altro
Completa il profilo di casa tua e aiutaci a migliorare l'analisi dei tuoi consumi!
La tua casa


Torna alla tua fornitura
Beyond Energy
Trend Consumi
Dettaglio


Torna alla tua fornitura
Beyond Energy
Le iniziative di Sorgenia
La community sostenibile che ti premia!
Greeners è la community creata per i clienti di Sorgenia che promuove e premia tutte le azioni positive che contribuiscono a migliorare il nostro Pianeta.
Entra in squadra!
Torna alla tua fornitura
Beyond Energy
Risparmia energia!
46 'Mi piace'
Usa una ciabatta multipresa intelligente!
Lo sapevi che che i dispositivi in stand-by consumano anche se spenti? Prendi in considerazione la sostituzione delle multiprese tradizionali con altre intelligenti, così potrai spegnere completamente tutti i dispositivi collegati.