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Tackling Energy Poverty Through Behavioral Change: A Pilot Study on Social Comparison Interventions in Social Housing Districts

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Behavioral Economics has in recent years played a key role in informing the design of non-price interventions aimed at promoting energy conservation behaviors in residential housing. Some of the most influential contributions of the discipline in an applied setting have centered around the development of norm-based interventions. The success that these interventions have had in specific contexts presents an opportunity to exploit them as tools for tackling a prevalent type of poverty at the EU level: energy poverty. Recent contributions to the literature highlight the role of inefficient energy behavior as a significant driver of this particular type of poverty, which is characterized by an inability to afford the basic energy services necessary to guarantee a decent standard of living. Therefore, the effectiveness of norm-based interventions in vulnerable populations merits further investigation to determine whether this approach can suitably address the behavioral components of energy poverty by promoting efficient energy consumption and conservation efforts. This study reports on a pilot conducted in an exemplary social housing context (located in Bolzano, Italy) with the aim to assess the effectiveness of social comparison interventions in energy vulnerable groups. Our investigated cohort covers an initial small sample of apartments with a large representatives of elderly individuals and other energy-vulnerable groups. Using a design that combines appeals to injunctive and descriptive norms embedded within In-Home Devices (IHD) in recently retrofitted homes, our objective is to set a basis for the assessment of effectiveness of these types of interventions in social housing populations. Our study seeks to provide useful methodological insights to policy makers on how to effectively design behaviorally informed interventions aimed at tackling energy poverty. Despite the current data limitations, our results do seem to suggest that uniformly applied norm-based interventions may have potentially backfiring effects in small-scale implementations. Therefore, they suggest that attention needs to be paid to household composition and pre-existing levels of consumption, when designing behavior-change interventions in these groups.

JEL Classification: C93; D03; D04; D12; D19; D91; Q40.

Keywords: energy efficiency, energy justice, behavioral economic, energy poverty, behavior change

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1. INTRODUCTION

The field of Behavioral Economics has contributed greatly to informing the design of non-price interventions aimed at promoting energy conservation behaviors in residential housing (Andor and Fels, 2018). Increasingly more applied research has focused on uncovering the effectiveness of the provision of feedback in promoting energy conservation efforts by household occupants. The main methodological contribution of the discipline in this regard has been in expanding the use of Randomized Controlled Trials (RCTs) (Banerjee and Duflo, 2009) to identify causal links between feedback intervention and reduced energy consumption. In addition, behavioral economics has expanded the implementation of feedback interventions by integrating appeals to social norms, that is by designing norm-based interventions that rely on social comparisons to encourage energy conservation.

Norm-based interventions in the energy domain refers to the provision of information to households about how their individual levels of energy consumption compare to that of a reference group of comparable households (Andor and Fels, 2018) (who ideally should be chosen to have lower levels of consumption, signaling to the target household a pre-existing societal norm toward lower levels of consumption). The specific strand of norm-based interventions based on leveraging social comparisons are known in the literature as *social comparison* interventions.

The main objective of social comparison interventions in the energy domain is to promote energy conservation, reducing therefore our dependence on CO_2 emissions. Given our urgent need as world citizens to take action on climate change, as highlighted by the recent IPCC special report (IPCC, 2018), all efforts promoting conservation and decarbonization are of paramount importance. Evidence suggests that behavioral components are key drivers of variation in household energy use (Chen et al., 2015; Huebner et al., 2016), and behavior is more adaptable in the short-run than the appliance stock or building efficiency. Because of these reasons, adopting sustainable energy consumption habits must be a key component in our efforts to mitigate climate change. Furthermore, behavioral interventions of this kind can help reduce the *energy performance gap* (Galvin, 2014), described as the difference between expected energy savings and actual energy savings. Particularly in what concerns retrofitted apartments, these interventions can help align behavior with the technological innovation in order to achieve greater levels of energy savings.

Despite the existence of a large literature testing norm-based interventions in the field, little attention has been given to understanding the effects of these interventions on specific demographics. Evidence by Khosrowpour et al. (2016) suggests the need for tailored interventions for households with different energy consumption patterns, highlighting the fact that different populations may react in different ways to the provision of social information. The issue of intervention success on target demographics is of crucial importance when testing interventions that could be especially beneficial to the energy vulnerable, a group characterized by specific energy needs and potentially sub-optimal energy behaviors (Kearns et al., 2019). This study aims at addressing this gap in the literature, setting a basis for the evaluation of norm-based intervention effectiveness in a *social housing context*.

We present a methodology to study the effects of providing social information through In-Home Devices (IHDs) installed in recently retrofitted social houses, on energy consumption behaviors. More generally, we set the methodological basis for a more extensive evaluation of these interventions in a specific context of vulnerability. We begin to uncover how context-dependent the success of these interventions may be by adopting an experimental approach that allows us to make causal inferences. Finally, we make the case for a wider implementation of this methodology in social housing demographics to advise policy-making.

Previous research on this specific case studies' cohort (DellaValle et al., 2018) uncovered context-specific factors that affect the energy consumption patterns of the sample. These include the high proportion of retirees and older individuals in our sample who are amongst the most energy vulnerable. Furthermore, conditions of resource scarcity have proven to exacerbate behavioral biases such as myopia (Shah et al., 2012), and other context-specific factors, like stigma, play a crucial role in the development of inefficient energy behaviors within the most vulnerable populations (Hall et al., 2014; DellaValle, 2019). For these reasons, studying the effectiveness of a well-known behavioral intervention on the energy behavior of this specific population is of particular interest.

Our study also adds to the literature on interventions aimed at tackling energy poverty. Recent research (DellaValle, 2019; Kearns et al., 2019) has begun to pay attention to energy behaviors as an additional driver of energy poverty, recognizing factors such as use of household spaces and failure to adopt "adaptive thermal comfort" as significant determinants. Our study is unique in its emphasis on using behavior-change strategies to tackle energy poverty by encouraging the adoption of more efficient behaviors and, as a result, improving access to basic capabilities that derive from an efficient use of energy, such as good physical and mental health, education, and social integration (Day et al., 2016).

Our pilot is embedded within a wider EU project called Sinfonia, ran in social housing districts in Bolzano, South Tyrol (Italy). Consenting tenants were provided with IHDs to monitor and better control their energy use, and it is within this technology that we embed the intervention. In this paper, we focus exclusively on the effects of providing social information, not the effects of providing the IHD technology in general.

At the moment, we report preliminary results from the intervention in a subset of 12 apartments within one of the investigated districts. These were the first wave of apartments to receive the intervention. We plan to investigate the effects of the intervention in more districts and over a wider period of time in a follow-up study. While acknowledging the data limitations of our pilot application at the present time (which limits our ability to draw generalisable conclusions), our focus with this study is to provide useful methodological insights to policy makers on how to design successful behavior-change interventions in vulnerable contexts, with the ultimate aim of addressing the behavioral aspects of energy poverty.

The remainder of the paper is structured as follows: section 2 details the theoretical framework we position our pilot study in, with particular emphasis on why social housing tenants make for an interesting and important target group to investigate in the context of energy behavior-change interventions. Section 3 introduces a methodology for the application of social comparison interventions in social housing districts and explains the context and application of our pilot intervention. Section 4 presents the results from our pilot intervention, with a particular focus on the adoption of a suitable analytical accounts for important household characteristics and preferences. Section 5 discusses the results, limitations of the study as well as directions for future research. Finally, section 6 provides preliminary conclusions.

2. THEORETICAL BACKGROUND

2.1. Norm-Based Interventions

Norm-based interventions[1] have proven amongst the most successful non-price interventions to achieve behavior change in applied settings[2]. In a variety of pro-environmental domains, the provision of social information has proved an effective tool in shifting preferences toward more sustainable behaviors. In the domain of recycling (Schultz, 1999), towel reuse (Schultz et al., 2008), household water use (Ferraro et al., 2011), and crucially energy use (Allcott, 2011), norm-based interventions have been shown to affect both intention and actual behavior in the field.

The psychological processes by which the provision of social information affects individual behavior is still a matter of debate in the literature, but prevailing research seems to emphasize the role that normative appeals play is shaping our empirical expectations[3]. When these expectations on other people's behavior condition our own behavior, the resulting behavioral pattern is described as a "descriptive norm" (Bicchieri, 2005). As noted by Bicchieri and Dimant (2019), while the term "descriptive norm" is widely used in the psychological literature to mean a perception of what is commonly done, it is important to clarify that descriptive norms relate to interdependent behaviors, or those behaviors where motivation to undertake is dependent on a person's beliefs of what is commonly done. Our expectations based on unconditional (shared) behavior, therefore, are distinct from descriptive norms (such as our expectation that people will use an umbrella when it is raining). According to these expectations, people may wish to stick to descriptive norms for fear of social disapproval, or seeking social esteem (Farrow et al., 2017a). Eventually, they condition their own behavior based on the empirical observations of other's behavior (Bicchieri, 2005).

It is also important to discern between descriptive norms and injunctive norms. While descriptive norms relate to behavior motivated by empirical expectations on how people behave, injunctive norms are behavioral patterns that are conditional on our perceptions of what is perceived to be desirable or approved from our peers (therefore, like in the case of descriptive norms, also being interdependent behaviors). The key difference are the relevant underlying expectations, whether they are related to what other people are doing or what other people believe "ought" to be done (Bicchieri and Dimant, 2019).

In the context of norm-based interventions therefore, at least two things need to be clearly outlined before designing an intervention. First, we need to diagnose the targeted behavior, whether it is conditional on our expectations of others or not (interdependent or independent) (Bicchieri and Dimant, 2019). Assuming the targeted behavior is interdependent, we then need to define what expectations to target in order to achieve the desired behavioral change, whether expectations on what people do or expectations on what people think is right, therefore appealing to descriptive norms or injunctive norms, respectively (Bicchieri and Dimant, 2019). Here, the answer is likely to be highly dependent on context, but at least in the energy domain there is extensive research that supports appealing to both of these norms simultaneously when designing an intervention, as explained in the following section.

2.2. Norm-Based Interventions in the Energy Domain

Norm-based interventions in the energy domain for the most part rely on allowing energy users to compare their consumption levels with other users, therefore they can be classified as social comparison interventions. Some ambiguity in terminology exists in the literature regarding the use of the term social comparison interventions compared to norm-based interventions. For the purposes of our paper, social comparison interventions are taken to be a subset of applications within a wider set of norm-based interventions.

Social comparison interventions in the energy domain refer to the provision of information to households about how their individual levels of energy consumption compare to that of a reference group of comparable households (Andor and Fels, 2018). This approach is intrinsically linked to the provision of feedback on one's consumption, and, at the same time, also introduces appeals to norms through the provision of social information. As outlined above, the application of a norm-based intervention to target energy behaviors assumes that at least part of people's decisions regarding energy consumption are interdependent with how others behave. This is intuitive (while a certain level of energy consumption is required to meet our needs, a large portion of our daily energy behaviors depend on what we believe to be socially acceptable, as well as the behavior of our peers, Wolske et al., 2020), and further backed by a wealth of empirical research on successful interventions that leverage social norms (Andor and Fels, 2018). Moreover, using the framework of Bicchieri and Dimant (2019), we recognize that a large part of the literature is primarily concerned on appealing to descriptive norms by altering empirical expectations on social behaviors.

The most heavily researched social comparison interventions have been ran by the US utility company OPower, where

[1] i.e., interventions relying on social influence.

[2] For a recent review of the literature (Farrow et al., 2017a; Andor and Fels, 2018).

[3] i.e., how we expect other people to behave.

consumers were sent Home Energy Reports (HERs) through the mail with varying levels of frequency (Allcott, 2011). More recently, digital devices such as "smart meters" and other In-Home Displays (IHDs) have allowed for more flexibility and a higher frequency in the delivery of social information, as well as for the combination of several types of interventions to study their aggregate and interactive effects (Schultz et al., 2015). Our methodology uses IHDs as feedback mechanisms that integrate appeals to social norms in order to obtain a desired behavioral change (i.e., reduction in energy consumption). Despite the great potential offered by IHDs for the implementation of behavioral interventions, their effectiveness as delivery modes in social comparison interventions is still under-researched.

Despite differences in feedback frequency and delivery mode (Farrow et al., 2017a), implementations of norm-based interventions in the energy domain share several commonalities. One common attribute of these interventions is the combination of appeals to injunctive norms and descriptive norms. Evidence suggests that descriptive norms are more effective in encouraging behavior change than injunctive norms, however appeals to descriptive norms in isolation can lead to what is known as a *boomerang effect* (Clee and Wicklund, 1980). The boomerang effect in this context refers to an increase in energy consumption from households initially consuming less than the norm once they have access to the social information. This risks backfiring on the intervention's desired effect, and can have consequences on the net results of the intervention. However, when descriptive norms are used in conjunction with injunctive norms, the boomerang effect has been shown to disappear (Schultz et al., 2007).

Another common aspect is the target demographics that these interventions are aimed at. For the most part, these interventions have been limited to residential energy use, primarily in the private sphere. Their effectiveness on energy use in the public sphere has been largely ignored. In this paper, we start to contribute to this line of research by studying the effectiveness of social comparison interventions in social housing.

There is no general consensus in the literature as to the success of social comparison interventions in the energy domain, but estimates from applications in private households seem to suggest the interventions lead to reduced energy consumption anywhere between 1.2 and 30% compared to a non-intervened control group (Andor and Fels, 2018). However, very few of these studies use IHD devices in their delivery. In comparison, Schultz et al. (2015) finds a reduction of approximately 7% in energy consumption from households receiving norm messages integrated in IHD devices. However, this can vary widely on a case-to-case basis, with some backfiring effects observed in some contexts (Farrow et al., 2017b), particularly with low energy users (Schultz et al., 2007). Furthermore, some evidence from Germany (Andor et al., 2017) seems to suggest these interventions are less effective with European populations, who typically consume less energy on average than the general US population targeted in the OPower trials.

The ambiguity of the existing evidence suggests that these norm-based interventions should be designed carefully, with a clear understanding of what discreetly defined behavior we aim to achieve, what are the underlying expectations we want to affect in order to do this and, most importantly, who we are targeting and how they take energy decisions. For example, some households (particularly those with lower incomes or more restrictive budgets) have been shown to exhibit a "prebound effect" (Sunikka-Blank and Galvin, 2012) wherein they consume less energy pre-retrofitting than expected from techno-centric estimates, at cost to basic quality of life given that they usually live in energy-inefficient buildings. Behavioral patters such as the prebound effect constitute a challenge for behavior-change interventions, but also illustrate why it is so important that technical innovations making the housing stock more efficient are accompanied by a good understanding of pre-intervention behavior.

2.3. Conceptualization of Energy Poverty

By focusing on the specific context of retrofitted social housing our study adds to the literature on energy poverty, particularly in relation to behavioral-change interventions that tackle the issue (DellaValle, 2019). While currently there is no academic or policy consensus regarding the definition of energy poverty, a leading conceptualization that we will adopt for the remainder of this study is the capabilities approach, first applied to the energy domain by Day et al. (2016). In particular, energy poverty is conceptualized as an "inability to realize essential capabilities as a direct or indirect result of insufficient access to affordable, reliable, and safe energy services, and taking into account available reasonable alternative means of realizing these capabilities" (p. 260).

The theoretical basis of this approach is grounded in the link between energy and well-being by explicitly acknowledging the relationship between energy services and the realization of basic capabilities (good mental and physical health, social acceptance, access to education, etc.), more so than other measures discussed in the literature. This is particularly important when considering the social housing context of our study, a demographic typically characterized by vulnerable conditions in socio-economic terms (low-income households, aging populations, large families) and a high level of energy vulnerability (high number of hours at home, troubles in paying energy bills, etc). In these contexts, basic capabilities are not always realized, making it of paramount importance to acknowledge their connection with energy services.

Our study takes the view of recent studies recognizing behavior as a driver of energy poverty. A number of papers have suggested that a key factor determining energy poverty is the interaction between low household incomes and thermally inefficient homes (Bouzarovski, 2014). However, recent literature (Kearns et al., 2019) has begun to pay attention to energy behaviors as an additional driver of energy poverty, recognizing factors such as use of household spaces and failure to adopt "adaptive thermal comfort" as potentially lowering behavioral efficiency in interactions with the dwelling stock. The consequences of reduced behavioral efficiency can have detrimental effects on physical and mental health, which could further contribute to the worsening of energy poverty conditions (poor mental health can lead to the adoption of poor heating regimes, and increasing challenge in a households ability to keep warm/cool).

2.4. Energy Behaviors in a Social Housing Context

A notable feature of our study is the choice of the specific target group for intervention. Social housing tenants are a demographic that is often overlooked in energy behavior-change research (Hafner et al., 2020), yet they present a particularly interesting and important group to study for a number of reasons.

Firstly, due to the very aim of social housing being to provide affordable housing for all, there is usually a high representativeness of vulnerable demographics in social housing populations. This includes low-income households, unemployed individuals, retirees, disabled individuals, and large families. These groups are exposed to a number of energy vulnerabilities, for example low-income groups spend a larger share of their income on energy costs than high-income households (Schaffrin and Reibling, 2015). In some cases tenants may need to make energy-consuming adjustments to the dwelling, or add consumptive appliances for health-related reasons (keeping house warm, medical equipment, etc.). Additionally, social housing is typically energy-inefficient, and even in recently retrofitted housing (as is the case in our pilot study), empirical evidence highlights critical behavioral responses that limit the effectiveness of efficiency upgrades (Sorrell et al., 2007). This all suggests that the failure to adopt efficient energy behaviors can have substantial negative distributional or health-related consequences for social housing tenants. Subsequently, these tenants have the most to gain from an intervention that leverages their behavior to achieve energy savings, while also possessing unique energy needs that have to be considered by policymakers and practitioners. Research carried out on this specific cohort of tenants in Bolzano confirms that vulnerable situations are also apparent in the investigated Sinfonia districts (DellaValle et al., 2018), where the majority of individuals are identified as low educated or retired.

Secondly, there exists a large literature on the psychology of scarcity that points at the potential impacts that living in precarious conditions may have on energy decision-making. For example, scarcity has been shown to focus attention on the most immediate concerns (for the vulnerable this may be paying rent and bills, improving health, caring for children or the elderly), while significantly depleting attention for decisions that are not considered of immediate importance (Shah et al., 2012). Paradoxically, research also shows that this attention depletion leads to sub-optimal decision-making in some domains that would have helped individual combat their existing conditions of scarcity (Tomm and Zhao, 2016). This large body of evidence could also be applied to energy decision-making in vulnerable demographics. In particular, the psychology of scarcity could lead to the adoption of sub-optimal energy behaviors and the lack of interaction with behavior-change interventions, that actually contribute to helping reduce scarcity in the form of lower energy costs.

We should also expect that resource scarcity will worsen the individual tendency toward myopia in the energy domain (DellaValle, 2019). This refers to the over-weighting of present costs and benefits, and the under-weighing of future ones in a time-inconsistent fashion (Loewenstein and Prelec, 1992), leading to sub-optimal choices in the long-run. In the energy domain, such myopic behavior results in the undervaluing of future benefits associated with adopting energy efficient behaviors (Hershfield, 2011). Overall, the literature gives us ample reason to believe that the specific vulnerable conditions that social housing tenants are exposed to will cognitively impact them, leading to the adoption of sub-optimal energy behaviors.

Finally, the cognitive impact of stigmatization, deeply linked with social housing residency, poses barriers to the achievement of several benefits accrued by the adoption of energy efficient behaviors. Stigmatization has been shown to be linked to under-performance (Mani et al., 2013), due to the depletion of executive resources deriving from efforts to suppress negative thoughts and emotions in the service of self-regulation (Hall et al., 2014). Furthermore, stigmatization has also been shown to result in social distancing, whereby individuals distance themselves from a prescribed social identity (Horan and Austin, 2014). These factors pose important barriers to the adoption of energy efficient behaviors.

2.5. Sources of Heterogeneity in Energy Conservation

In order to disentangle the effect of the intervention from other motivations to conserve energy, we need to understand the decision-making process of energy conservation and, subject to data availability, control for ulterior factors that may affect the underlying choice of conserving energy.

Energy conservation can be interpreted as a pro-environmental behavior (Brekke and Johansson-Stenman, 2008). Accordingly, we need to account for heterogeneity of factors underlying the decision-making process to act pro-environmentally. For example, a tenant's decision to act more pro-environmentally by consuming less energy could be motivated by (i) a desire to act in accordance to empirical and normative expectations (targeted by the intervention) (Bicchieri, 2005), (ii) possessing a high-degree of intrinsic pro-environmental self-identity (Whitmarsh and O'Neill, 2010) or (iii) possessing an intrinsic motivation to contribute to a public good (Bénabou and Tirole, 2006); being the environment the most prominent public good (Brekke and Johansson-Stenman, 2008). We thus measure and control for pro-environmental self-identity and a number of primary predictors of contribution to a public good: trust, altruism, and reciprocity (Kollock, 1998), in order to allow us to more closely understand the effects of the intervention.

The decision to conserve energy can be also understood as an economic behavior. Tenants respond to certain market incentives by reasonably adjusting their behavior (retail energy prices, energy bill subsidies, etc.). Lacking data on the specific economic incentives facing each individual tenant, we do not control for these factors econometrically, however we can reasonably assume that they all face the same economic conditions.

Additionally, conservation can be seen as an inter-temporal utility trade-off between present consumption and future financial benefits (in the form of a lower energy bill). A proportion of our population may be intrinsically very patient and willing to sacrifice some consumption now to benefit from lower energy-related expenses in the future. Therefore, the decision to conserve less energy, similarly to the decision to invest in energy-efficient appliances (Newell and Siikamäki, 2015), can be motivated by an intrinsic preference for delayed returns. In our analysis we therefore elicit and control for time preferences.

Finally, the decision to conserve more energy may simply be due to a better understanding on how energy behaviors relate to environmental and financial outcomes. For example, even if an occupant self-identifies as environmentally-friendly, she may not adjust to more conservatory behavior if she fails to recognize the link between her energy behaviors and environmental outcomes. Therefore, following (Blasch et al., 2017), we control for a general level of energy literacy in our analysis.

2.6. Pilot Application Aims

The pilot experiment has been designed to address two main research questions:

1. What are the effects of social comparison interventions, integrated within IHDs, in a social housing context?
2. Can a social comparison intervention applied to a target demographic comprised primarily of vulnerable individuals, help alleviate energy poverty?

To tackle these questions with the accessible set of data, we make a simplifying assumption on the drivers of energy vulnerability in our target demographic, which allows us to study differences in the evolution of energy consumption between groups. In particular, we assume pre-existing energy behaviors are sub-optimal and exacerbating a household's position of energy vulnerability (Kearns et al., 2019). Therefore, if we observe a larger reduction in energy consumption during the investigated period in our treatment group than in our control group, we can take this result as signaling that the intervention was successful in optimizing energy behaviors, and in turn in reducing the energy vulnerability of households. For example, if we assume a negative rebound effect post-intervention which reduced the potential energy savings from the retrofit, a reduction in consumption following our *behavioral* intervention can be interpreted as aligning the technological and behavioral components of energy efficiency.

Of course, these assumptions are limiting and a closer study on energy poverty conditions (whether through indoor temperature monitoring or self-reported measures) would have allowed us to tackle the second question more carefully. Obtaining this data however is impossible in practice at this stage of the project as self-reported measures on the occupant's energy experience are yet to be collected. For the scope of this paper, the assumptions are instrumental to study the impact of the intervention on energy poverty by looking at electricity consumption only.

The success of the intervention faces several barriers deriving from the specific context of social housing, such as a high level of energy vulnerability, and the cognitive impacts of scarcity and stigmatization. On the other hand, it is also because of these contextual reasons that understanding the effects of this widespread behavioral intervention is of paramount importance. It can highlight pathways to the successful implementation of energy efficiency investments that account for and target social aspects by promoting the adoption of more virtuous energy behaviors, thus contributing to drawing social housing tenants out of a situation of energy poverty. If the intervention is unambiguously successful, it can further promote the roll-out of these uniform normative appeals in the context of social housing retrofits. Alternatively, if we find substantial resistance in the intervention success, or encounter unique difficulties that limit the intervention's effectiveness, our results may suggest the importance of targeted feedback programs (Khosrowpour et al., 2016) that address the particular needs and characteristics of the most vulnerable.

Our results unveil practical recommendations for policy makers who wish to maximize the impact of retrofit interventions in social housing settings, mindful of contextual influence. Specifically, behavioral policies in vulnerable demographics should be financially assessed vis-a-vis price interventions in order to choose the most efficient policy instrument to achieve the desired social and environmental objectives. Our focus at this time is not to present generalisable results, but rather provide a practical example of a behavioral approach to tackling energy poverty, underlining advantages and limitations of this approach with respect to context, data availability, and assumptions on pre-existing consumption, and finally proposing a quantitative analytical approach for the creation of more general conclusions.

3. MATERIALS AND METHODS

3.1. Context and Pilot Design

The Sinfonia Smart city project, born from the cooperation between Bolzano and Innsbruck, aims at finding integrated solutions to achieve significant levels of energy savings in social housing districts[4]. As part of this project's activities, a number of apartment buildings in different districts throughout Bolzano were retrofitted to make them more energy efficient. The retrofitting activities took place between July 2017 and May 2019. One of the key aspects of the technical renovation was that they were designed to be completed without the need to temporarily relocate occupants. For this reason, the majority of the work involved external activities: constructing an envelope for the energy improvement of the building by installing prefabricated panels on the external walls, creating a centralized heating system with geothermal heating pump, and installing a solar thermal field, a controlled mechanical ventilation system, and a 20 kWp photo-voltaic system on the rooftop. As the retrofitting was part of a large-scale EU project, the works were financed by the project budget, with the municipality of Bolzano also providing part of the financing. Importantly, the tenants did not personally

[4]Sinfonia website, http://www.sinfonia-smartcities.eu/.

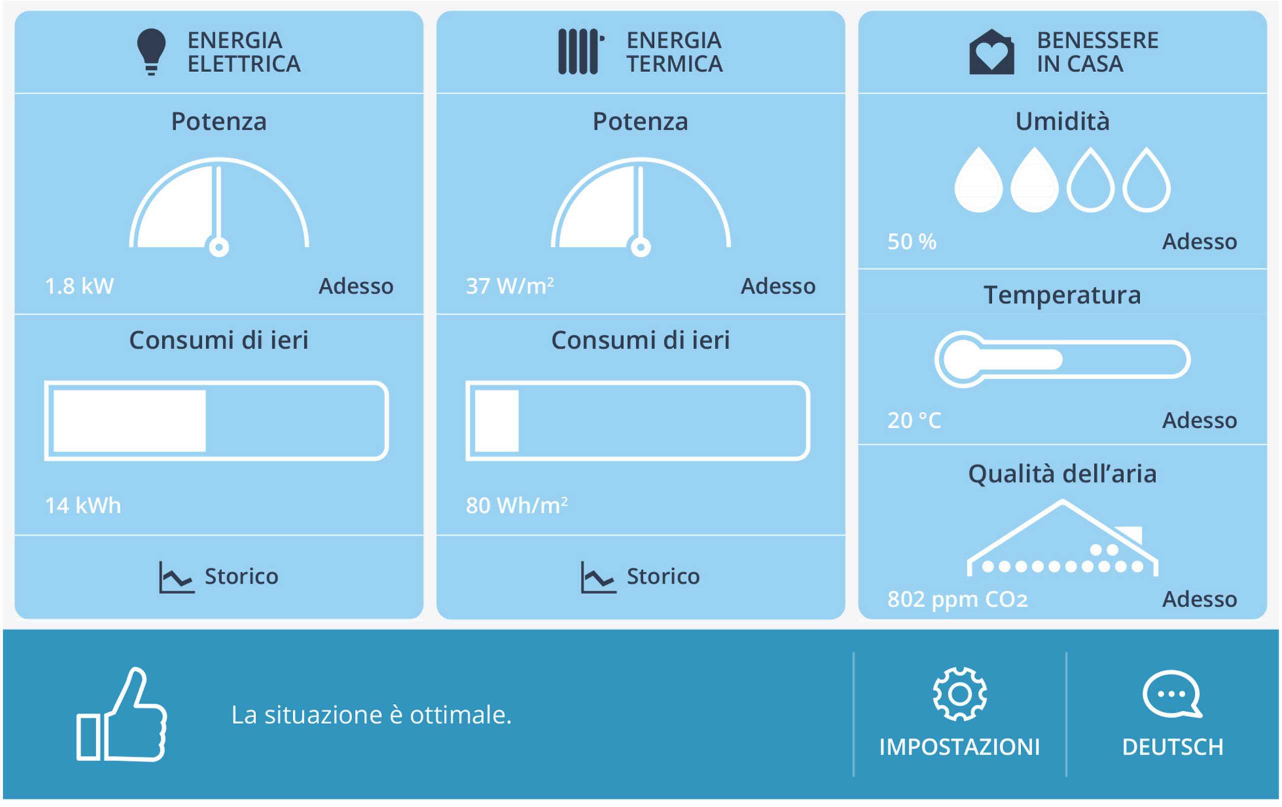

FIGURE 1 | Control group home display.

pay for any of the retrofitting activities. This also meant that the retrofitting decision was imposed in a top-down manner, tenants did not have a say on whether or not they wanted their apartment retrofitted.

After the works finished, a number of consenting apartments were installed sensors and "smart meter" (IHD) technology providing timely feedback about several household characteristics relating to energy efficiency and comfort. These characteristics include humidity, temperature, air quality and, notably, electrical and thermal energy consumption (in terms of kWh and Wh/m^2). Notably, tenants did face a decision here about whether or not to allow for the display's installation, potentially introducing some self-selection bias in our analysis of intervention effects (discussed in section 5).

The home page of the smart meter display can be seen in **Figure 1**. These displays were shown on a tablet installed near the tenants front door, which is being transmitted the information recorded by the sensors. The reason for installation near the front door was technical: the tablets were to be powered by the building electrical grid which is distinct from the apartment electrical grid. In order to connect to the building grid therefore, the displays had to be positioned close to the entrance. While this placement ensures the display is in an area of frequent movement for tenants where it is likely to be seen with some regularity, placement in a m of the intervention.

The sensor technology employed to record this information (installed after the retrofitting works) allows us to collect information and provide feedback with high-level granularity. Users have access to electricity consumption through both the home page of the display, and an additional "consumption history" page which they can access via the home page. In the home page, they receive information on previous-day consumption, as well as information on current consumption levels which is updated with a frequency of 5-min. Once they click the "consumption history" tab, users are brought to a separate page as seen in **Figure 2**. Users can then navigate this page to find information on their past energy consumption aggregated at different levels (daily, weekly, monthly), and they can visualize the evolution of their consumption levels.

3.2. Pilot Study Design

Households with installed IHDs are then randomized into two different groups, the control group and the norm group. The control group receives feedback on their own energy consumption through the home and history pages as described above. The layout of the pages in their display is identical to that shown in **Figures 1**, **2**.

The norm group receives identical information on their own consumption as the control group, but their level of energy consumption is also compared in their display to that of a

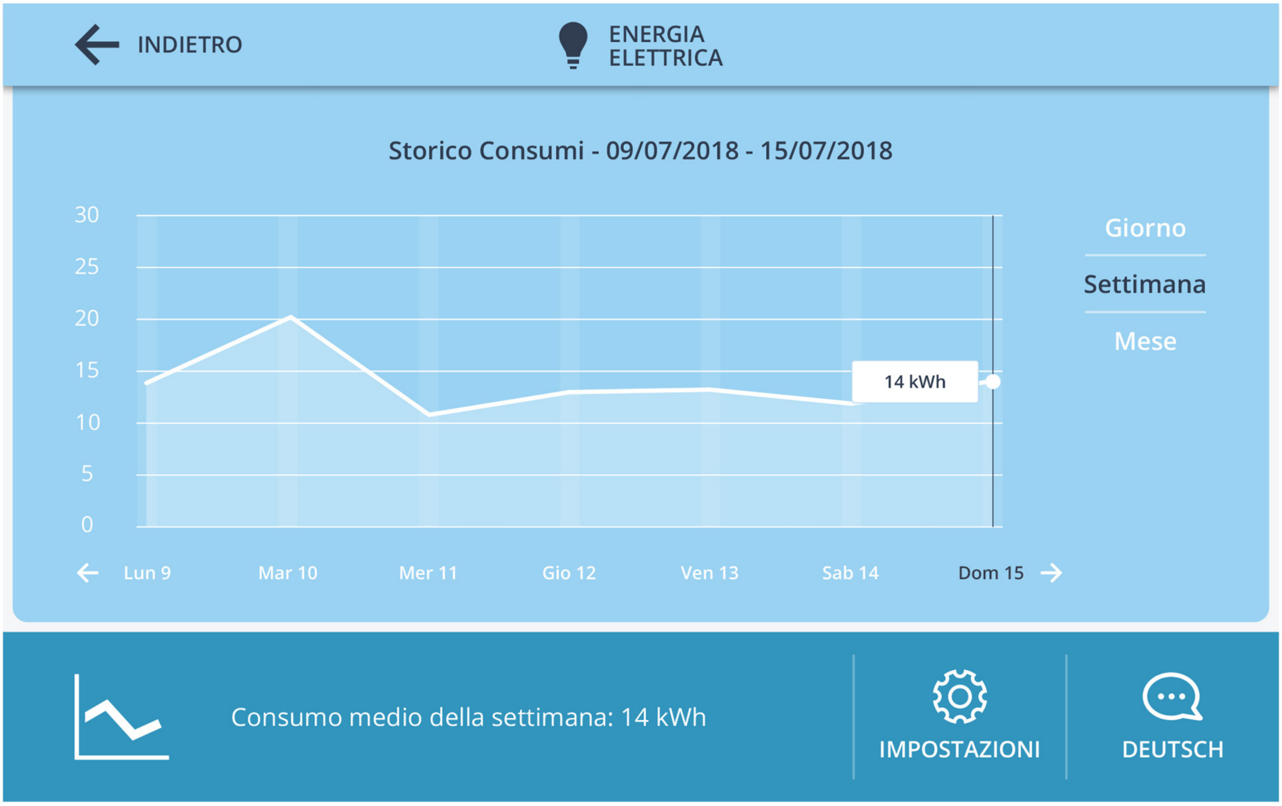

FIGURE 2 | Control group history display.

reference group of neighbors. This comparison is represented both in terms of last-day averages (as shown in **Figure 3**) and in different formats through the "history" tab (shown in **Figure 4**). In short, tenants in the control group receive only information on their own electric and thermal consumption, whereas tenants in the norm group receive own-information as well as social information.

Close attention was paid to the selection of the reference groups from which to generate the displayed social information for apartments in the norm group. Evidence suggests that the choice of reference group is crucial for the effectiveness of norm-based interventions (Abrahamse et al., 2005; Bicchieri and Dimant, 2019). Toward this end, we use a restrictive similarity criterion to cluster households into different reference groups on the basis of observable characteristics which reflect actual energy use. These are: number of household occupants and average number of hours spent at home by household members. This means that two apartments may well be both in the norm group yet receive different social information if they have a household composition which allocates them in different reference groups based on the employed clustering technique.

Furthermore, in line with previous literature (Alberts et al., 2016; Anderson et al., 2017), we choose to compare individual household behavior not to an average of other households in the reference group, but rather the behavior of top performers within the reference group to provide a virtuous example to follow. We were able to create comparable groups comprising of 3-4 households in our investigated apartments, and picked the average energy consumption of the top two highest performers in that group as the shared social information to display to those households in the same reference group who were under the norm treatment.

The high feedback frequency of consumption information is a notable contribution of our study to the overarching literature on norm-based interventions using IHDs. There has been mixed evidence on how the frequency of feedback affects energy conservation efforts. Fischer (2008) argued that frequent feedback on energy consumption was more effective than infrequent feedback due to the closer link it creates between actions and consequences, but later empirical evidence has refuted this claim (Ehrhardt-Martinez et al., 2010), finding real time feedback to result in lower conservation efforts than weekly/daily feedback. In an experimental environment, Casal et al. (2017) also find that the frequency of feedback does not impact individual performance.

For our purposes, the frequency of feedback is only relevant insofar as all tenants have access to information on their consumption (and others' consumption in the case of the norm group) at the same frequency. This is the case in our pilot study. Future research could focus on the effects of increased feedback

FIGURE 3 | Norms group home display.

frequency on energy conservation with a particular focus on social housing.

In our norm-based intervention we appeal to both descriptive and injunctive norms. We employ "smiley face" emoticons similar to those used in the HERs in Allcott (2011). These emoticons are meant to appeal to injunctive norms by suggesting the social desirability of a behavior. If a specific household were currently consuming less than their reference group of neighbors, they would be presented with a smiling face together with the social information, while if the household was currently consuming more than the reference group of neighbors, they would receive a red frowning face.

Our experiment also draws from previous evidence highlighting that social comparison interventions are more effective when complemented with actionable tips (Dolan and Metcalfe, 2013). The technology of the IHDs allows us to suggest targeted actions to reduce consumption of energy in households while maintaining a suitable level of comfort (such as opening a window and turning down heating when the outside temperature is greater than the inside temperature). These tips are available to households both in the control and treatment groups, meaning that in our analysis we only isolate for the effect of exposure to social information, and not the inclusion of the tips.

In conclusion, all consenting apartments were installed with IHD technology. These apartments were then randomized into 2 groups (Control and Norm) with the only difference between the groups being the provision of descriptive and injunctive norm appeals in the form of social information on energy consumption. The social information was generated by clustering households into reference groups based on two observable characteristics (number of tenants, hours spent at home), and choosing the level of energy consumption equivalent to the average of the two best performing households in each reference group to display to the norm group households within each reference group. All other aspects of the display (targeted actionable tips, frequency of feedback, other design features) were kept constant between groups.

3.3. Data Description

To study whether changes in behavior have taken place in the short-term, we studied the effect of the intervention during the first 3 months of implementation. The project has been ongoing past these first 3 months, but to enhance project accountability, it is important to highlight immediate results of the intervention. In a later study, we will analyse also the long-term effects of the intervention for households in the remaining districts. It is also important to note that this study is part of an overarching complex project including dwellings with different technical characteristics and different

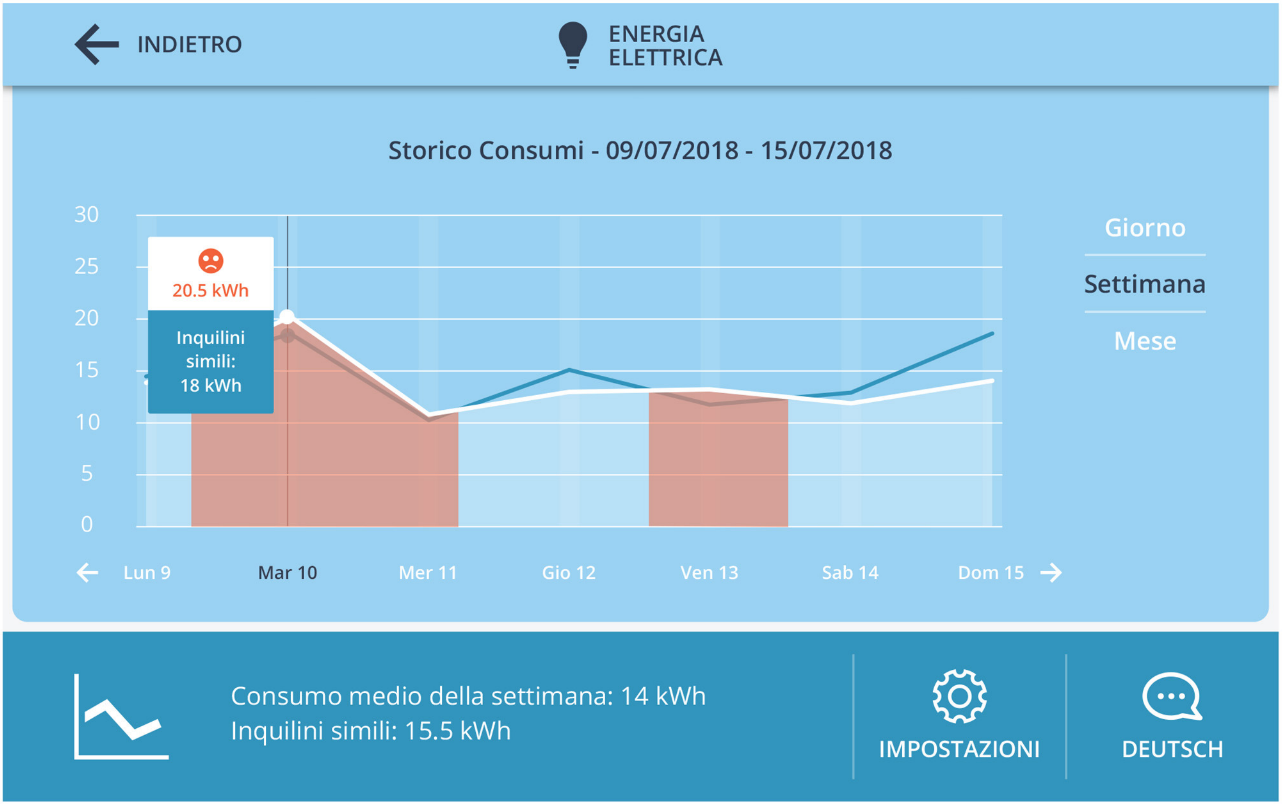

FIGURE 4 | Norms history display.

sets of interventions being implemented across districts. In this study, we are solely interested in studying the effects of the social comparison intervention, and adopt our analytical approach accordingly.

3.3.1. Sample Characteristics

This initial analysis includes only the first consenting apartments to have their displays activated in one of the project districts. The households included in the sample all had their displays activated at the same moment, meaning they were exposed to the intervention for an equal time period. This included 13 apartments initially. Subsequently, one of the tenants asked to have the sensor uninstalled and was removed from the sample. This left us with 12 apartments across 2 groups (Control and Norm group; 6 apartments in each group) analyzed over a period of 3 months, from November 22nd to February 23rd. This included 27 enants.

A descriptive analysis on the observable characteristics of the sample population is summarized in **Table 1**. This data was based on self-reported individual-level characteristics compiled by the occupants present at time of installation of the display. From this data, a number of aggregate household characteristics were measured. The first five rows of **Table 1** describe the distribution of individual categorical characteristics in the sample (defined as dummy variables that take the value of 1 if the individual is part of the defined category, and 0 otherwise) while the last four rows describe the distribution of the aggregated household characteristics.

These descriptive statistics reveal some key points. Firstly, a significant proportion of the tenants in the sample are

TABLE 1 | Descriptive characteristics of sample.

Variables	*N*	Mean	St. Dev.	Min	Max
Female dummy	27	0.518	0.509	0	1
Retired dummy	27	0.259	0.446	0	1
> 65 years dummy	27	0.259	0.446	0	1
40–59 years dummy	27	0.481	0.509	0	1
Children dummy	27	0.0740	0.267	0	1
N. children	12	0.167	0.389	0	1
N. > 65	12	0.583	0.793	0	2
N. retired	12	0.583	0.793	0	2
N. members spending > 12 h at home	12	0.833	0.389	0	1

The first five rows describe the distribution of individual-level characteristics in our sample. These are defined as dummy variables that take the value of 1 if the individual is part of the defined category, and 0 otherwise. The final four rows describe the distribution of apartment-level aggregate characteristics, including Number of Children, Number of over 65 year old, number of retired individuals, and number of members spending more than 12 h at home per day.

retired and over 65 years of age (26% of individuals in the sample for both categories). Subsequently, the majority of the households have one member that stays at home more than 12 h each day. This confirms that the sample prominently features vulnerable individuals, such as the elderly and retired, and that the general energy needs of the our sample might be high.

The sample does not feature a large number of children, meaning the large prevalence of individuals staying long hours at home is not primarily driven by adults staying home with their children. Rather this is likely driven by retirees, or potentially the unemployed.

3.3.2. Energy Consumption Data

Using the sensor technology installed after the retrofitting works, we gathered data on hourly energy consumption for each of the 12 apartments. Taking advantage of both the longitudinal and cross-sectional nature of the data, we created a panel dataset that collected highly granular information on energy consumption across the 12 households. This granular data was aggregated at the hourly level for the sake of tractability.

In this study, we focus only on electrical energy consumption, which was measured in kWh. As anticipated, thermal energy consumption will be investigated in a follow-up study.

It is worth mentioning that we encountered some technical difficulties during the data collection process that resulted in receiving distorted hourly data on electricity consumption. Due to the nature of the sensing technology and a margin of error, for a small proportion of hours and in a limited number of apartments, consumption was recorded but not reported immediately. Instead, the recording system aggregated the results from multiple hours of consumption into the observation for a single hour. This led to some incorrect observations in the dataset, in 4 of the 12 apartments in the sample, which could bias our results. We decided to drop these biased observations (the individual hours with recorded errors) from the dataset before estimating our regression models: whenever there was a gap in reporting of more than 1 h for any apartment, the following observation was dropped. While this makes it so that we lose a small number of observations (hence ending up with an unbalanced panel), it allows the analysis to be unaffected by technical difficulties in the sensor and recording technology, ensuring that every observation in the dataset is indeed collecting consumption during the span of a single hour. It is important to note however that, as the incidence of these errors disappeared when aggregating consumption at the daily level, these observations were not dropped when completing the Difference-in-Differences (DID) analysis.

A notable limitation of the dataset is the inability to access long-term pre-intervention data on energy consumption. This did not allow us to complete a comprehensive DID Analysis. Therefore, a proxy DID approach was adopted, following Bager and Mundaca (2017), as will be explained in the following section.

Summary statistics for this variable can be found in the **Appendix**. The mean hourly level of energy consumption in the overall sample and control group is 0.248 (St. Dev = 0.294).

TABLE 2 | Summary statistics of hourly energy consumption of sample (kWh).

Group	*N*	Mean	Std. Dev.	Variance
Control	13,190	0.248	0.290	0.084
Norm	13,386	0.249	0.298	0.089

3.3.3. Household Preferences

In addition to data on household characteristics and energy consumption, we collected data on a number of household preferences using surveys administered at the time of installing the smart meter. The objective of the survey is to collect valuable information on the individual preferences of occupants in order to control for factors that may affect the underlying decision-making process of conserving electricity, in absence of the intervention. By controlling for these potential sources of heterogeneity in the analysis, we can determine how much of the resulting change in behavior can be attributed to the intervention. The survey-elicited measures are therefore integrated into the estimated regression models as additional explanatory variables.

The survey-elicited data included measures on energy literacy (Blasch et al., 2017), pro-environmental self-identity, altruism, trust, reciprocity, group identity and inter-temporal preferences. The survey items, based on Luhtanen and Crocker (1992) and the experimentally-validated items developed by Falk et al. (2018), were a combination of Likert scales and multiple-choice questions.

It is important to note that many of the items in the survey elicit information on individual characteristic of the respondent, not necessarily the household as a whole. As the survey was conducted on only the one household member present at the time of installation, the collected measures are likely affected by an individual bias and can at best be used as proxies of general household characteristics. This is a limitation of the collected data, that can lead some of the relevant variables to have an individual-level bias.

4. RESULTS

4.1. Descriptive Analysis

Studying differences in overall average energy consumption between the two groups in the short-term (**Table 2**) there appear to be no significant differences at the average level amongst groups, with the control group consuming 0.248 (St. Dev = 2.90) as opposed to the norms group consuming 0.249 (St. Dev = 0.298).

This is confirmed by a cross-sectional Mann–Whitney *U*-test at the household level that fails to reject the null of equal distributions across groups ($p = 0.6310$).

4.2. Difference-In-Differences

Following Bager and Mundaca (2017), we employ a DID approach by measuring relative change in daily electricity consumption from the first to the last week of intervention for both groups, and comparing the changes between

TABLE 3 | Daily average hourly electricity use for households by groups.

Group	First week average (kWh)	Mid-period week average (kWh)	Last week average (kWh)	Change in consumption (δ%)
Control	6.179	6.446	5.176	–16.232
Norm	6.145	5.866	5.588	–9.064

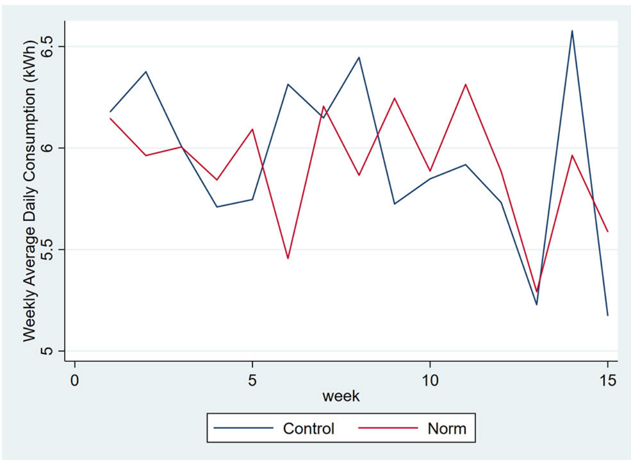

FIGURE 5 | Weekly average daily energy use for households by groups.

groups. The variable of interest is weekly average daily electricity consumption[5].

The results for the weekly DID analysis can be found in **Table 3**, and a graphical representation of the weekly evolution of daily consumption can be found in **Figure 5**.

As is clear from the table, over the relevant period of intervention both groups experience a reduction in their daily electricity consumption. However, there is a larger reduction in the energy consumption of the control group, rather than the norms group (a differential effect of 7.168%), suggesting a backfiring role of the intervention. From **Figure 5** however, we can see there are no marked differences between daily consumption of the two groups throughout the weeks.

It can also be seen from **Table 3** and **Figure 5** that both groups reduced their weekly average daily energy consumption overall in the investigated period. More detailed analysis, taking into account weather effects, is needed to understand why both groups go through a reduction in electricity consumption. We can speculate, based on previous research on the effects of increased feedback on consumption (Faruqui et al., 2010), that the display installation did have an effect in reducing overall electricity consumption, but that the normative appeals were unable to promote further reductions for the treatment group.

[5]This was measured by aggregating hourly energy consumption over a single day. This daily energy consumption measure was then averaged at a weekly-level.

4.3. Regression Analysis

The regression analysis method we present here is intended as a methodological starting point for the complete analysis that will be conducted once data from further districts is collected. It is important to note however that due to the currently low number of households included in the analysis, indications of statistical significance should be considered with caution.

We start by defining a bivariate model to analyse the impact of treatment assignment on hourly electricity consumption levels of individual households:

$$electricity_{it} = c + \beta social_i + \epsilon_{it}$$

The dependent variable is kWh of electricity consumed by household i during hour t in the panel data-set (t = 1–2233). *Social* is a treatment dummy variable that takes the value of 1 if the household is in the norm group, and 0 if the household is in the control group. ϵ is a randomly distributed error term.

We further enrich our model (following Schleich et al., 2017) by adding hourly and monthly dummies in order to control for variations in electricity demand across months (i.e., due to weather conditions) and across hours of the day (i.e., due to variations in household occupancy and activities). The purpose of controlling for these parameters is to study how the intervention performs when this variability is taken into account.

$$electricity_{it} = c + \beta social_{it} + \sum_{m=1}^{4} M + \sum_{h=1}^{24} H + \epsilon_{it}$$

Finally, we define two multivariate models [MV(1) and MV(2)] that separately control for household structural characteristics, as well as the survey-elicited preferences. The two multivariate models are defined separately in order to circumvent potential biases in the results deriving from analyzing data collected at two different levels (household structural variables represent household level characteristics, while survey-elicited preferences represent individually-collected preferences). In defining MV(2), we use the individual preferences as household-level proxies for overall preferences, in order to control to some extent with potential sources of heterogeneity in energy consumption deriving from individual preferences. This approach however suggests treatment effects derived from estimation of our MV(2) model are to be considered carefully, acknowledging this aggregation of preferences.

The two multivariate models then become:

$$electricity_{it} = c + \beta social_i + \alpha latermovein_i + \mu Z_i + \epsilon_{it}$$

and

$$\begin{aligned} electricity_{it} = c + \beta social_i + \sigma\, TimePref_i + \zeta\, ReciprocityPref_i \\ + \rho AltruismPref_i + \delta GroupId_i + \lambda EnvSelfId_i \\ + \gamma\, TrustPref_i + \theta EnerLit_i + \epsilon_{it} \end{aligned}$$

latermovein is a dummy variable that accounts for when the tenants moved into the apartment in the timeline of the retrofitting project. Z_i is a matrix of variables measuring different household characteristics, including number of children, number of males and females, number of people over 65, number of occupants in the household, and average number of hours spent indoors by occupants. We exclude data on dwelling size for this part of the analysis, as it is not expected to be strictly relevant for electricity consumption, but rather will be included in the follow-up study when investigating the effects of the intervention on thermal energy consumption. For the sake of completeness however, we also run all our regressions with the variable of dwelling size (in M^2) included and report the results in the **Appendix** (obtaining qualitatively similar results). We should note that the decision of parameters to include in our estimation was also made on the basis of allowing for replication across different districts, and hence we omitted aspects which would not be replicable in other districts (such as specific geographical or locational characteristics).

Turning to the variables obtained by survey answers, *TimePref*, *TrustPref*, and *ReciprocityPref* are ordinal variables that capture individual-level intertemporal preferences and preferences on trust and reciprocity, respectively, on a scale of 1–7. *AltruismPref* is a normalized variable that captures individual level altruistic preferences from 0 (extremely non-altruistic) to 1 (extremely altruistic). *GroupId* is a measure that captures degree of cohesion to social groups which proxies social distance which, as previously explained, can be a predictor to willingness to contribute to public good. This measure is defined as an average to the answers to four questions relating to the level of identification with specific social groups. Finally, *EnvSelfId* is a measure of pro-environmental self-identity and *EnerLit* is a normalized variable measuring the amount of correct answers out of 4 in a series of questions carefully designed to test the general level of energy literacy of the individual.

All models are estimated via the GLS panel random-effects estimator. In order to understand whether or not there are differences in intervention efficacy during weekends and weekdays, we also estimate all models separately for weekends and weekdays.

The results from the estimated model can be seen in **Table 4**. These results confirm the limited, potentially backfiring role of the intervention. The estimated coefficient in the two bivariate models is positive, confirming that subjects in the treatment group consumed on average more than those in the control group. As expected by the small sample, the results do not reach statistical significance. Estimates of the average treatment effect in the bivariate model range from a positive effect of 0.03–0.07%, with the inclusion of monthly and hourly dummies diluting the positive effect.

TABLE 4 | Results from GLS random effects regression.

Variables	(1) BV(1)	(2) BV(2)	(3) MV(1)	(4) MV(2)
Social	0.000688	0.000331	0.124***	−0.0476***
	(0.0613)	(0.0740)	(0.00587)	(0.00852)
EnvSelfId				0.0205
				(0.0134)
TrustPref				0.0263***
				(0.00347)
ReciprocityPref				−0.0790***
				(0.00455)
AltruismPref				−0.0626***
				(0.00835)
TimePref				0.0506***
				(0.00232)
EnerLit				−0.0520***
				(0.00339)
GroupId				0.0162***
				(0.00293)
latermovein			−0.183***	
			(0.00628)	
OccupantNumber			−0.215***	
			(0.0124)	
HoursAtHome			0.0113***	
			(0.00115)	
MeanAge			−0.00855***	
			(0.000476)	
N children			−0.00759	
			(0.0109)	
N > 65			0.155***	
			(0.00837)	
*N*female			0.238***	
			(0.00849)	
Constant	0.248***	0.160***	0.639***	0.178***
	(0.0433)	(0.0531)	(0.0308)	(0.0655)
Observations	26,576	26,576	26,576	22,160
Number of apartments	12	12	12	10

Standard errors in parentheses.
****p < 0.01, **p < 0.05, *p < 0.1.*
Dependent variable is energy consumption of apartment i at hour t (t = 1–2233). BV(2), MV(1), and MV(2) control also for hourly and monthly variations by including hour and month dummies in the regression (suppressed in output). MV(2) drops observations from two apartments from which we do not have survey data.

Turning to the multivariate models, controlling for household characteristics, we again estimate a positive coefficient for our treatment dummy, but this time the effect of the intervention is statistically significant. On the other hand, when controlling for individual characteristics, not only do the coefficients associated to some individual characteristics (namely trust, reciprocity, altruism, time discounting, and level of energy literacy) turn significant, but also the coefficient of the treatment dummy turns negative. This suggests that heterogeneity in unobserved household preferences might play a crucial role in affecting the efficacy of the intervention.

During weekdays the effects of the intervention are not qualitatively different from the effects we observe using the entire range of data (reported in **Appendix**).

Different results emerge when estimating the model using only weekend data (**Table 5**). The estimated coefficient of the treatment dummy for MV(1) is still positive, further suggesting that socio-demographic characteristics are important determinants of the effectiveness of social comparison interventions in this context. However, the estimated coefficient for the treatment dummy is negative in both our bivariate models, despite being statistically insignificant.

4.4. Interaction Effects

We conducted a study of conditional marginal effects in the model for a subset of significant variables. This was done in order to better understand the direction of treatment effects at different levels of significant covariates in our model. We completed this study separately for models MV(1) and MV(2).

The results of this analysis for the structural variables (**Table 6** and **Figure 6**) are not surprising given earlier results and much of the literature on socio-demographic determinants of energy use (Šćepanovi et al., 2017). The difference in energy consumption of those households assigned to the control group and those assigned to the treatment group increases as the number of females and mature tenants increases. However, only the results relating to the variable "number of females" are significant. These results suggest that (according to the estimated model) the more females in a household, the wider the positive difference in electricity consumption between treatment and control groups, therefore the less the intervention has been effective. This highlights that household family-composition characteristics may be crucial determinants in how effective these interventions are in a social-housing context, and suggests the need for targeted interventions that take into account household gender composition.

Moving on to studying the marginal conditional effects of some of the survey-elicited variables, we are interested in estimating the conditional marginal effects of reciprocity, energy literacy, and willingness to delay (**Table 7**).

The results for energy literacy and time preferences are not significant. Turning to reciprocity (**Table 7** and **Figure 7**), there seems to be a statistically significant difference in electricity consumption between groups at different levels of this variable. This difference also seems to be increasing at higher levels of reciprocity, which counters the predictions of our theoretical framework. The results seem instead to show a diminishing negative difference, and eventually a positive difference in electricity consumption between groups as reciprocity increases, signaling a reduced effectiveness of the intervention for higher levels of reciprocity. While this result might be an artifact of the limited sample, it might also be driven by the reduced sense of agency from living in sub-optimal contexts that generally leads to a deterioration of social preferences (Becchetti et al., 2013).

TABLE 5 | Results from GLS random effects regression including only weekends.

Variables	(1) BV(1)	(2) BV(2)	(3) MV(1)	(4) MV(2)
Social	−0.0172	−0.0181	0.132***	−0.0275*
	(0.0607)	(0.0662)	(0.0111)	(0.0161)
latermovein			−0.175***	
			(0.0119)	
OccupantNumber			−0.270***	
			(0.0234)	
HoursAtHome			0.0134***	
			(0.00217)	
MeanAge			−0.0101***	
			(0.000899)	
N children			0.0114	
			(0.0206)	
N > 65			0.185***	
			(0.0158)	
N female			0.281***	
			(0.0161)	
EnvSelfId				0.00714
				(0.0255)
TrustPref				0.0207***
				(0.00656)
ReciprocityPref				−0.0940***
				(0.00861)
AltruismPref				−0.0814***
				(0.0157)
TimePref				0.0534***
				(0.00441)
EnerLit				−0.0422***
				(0.00640)
GroupId				0.00380
				(0.00555)
Constant	0.269***	0.179***	0.741***	0.430***
	(0.0429)	(0.0497)	(0.0582)	(0.125)
Observations	7,952	7,952	7,952	6,626
Number of apartments	12	12	12	10

Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Dependent variable is energy consumption of apartment i at hour t (t = 1–2233). BV(2), MV(1), and MV(2) control also for hourly and monthly variations by including hour and month dummies in the regression (suppressed in output). MV(2) drops observations from two apartments from which we do not have survey data.

5. DISCUSSION

5.1. Discussion of Results

The results, while acknowledging significant limitations in the data sample size (from only one district) and scope (electricity consumption only), points to the fact that the application of norm-based interventions in vulnerable contexts may not be as straightforward as may seem from the evidence emerging from larger RCTs in more general residential populations. We fail to

TABLE 6 | Conditional marginal effects of household characteristics.

1.Social	*N* female	*N* > 65
Delta method		
0	−0.099	−0.047
1	0.011	0.037
2	0.121**	0.122
3	0.231**	0.206

Standard errors in parentheses.
****p < 0.01, **p < 0.05, *p < 0.1.*

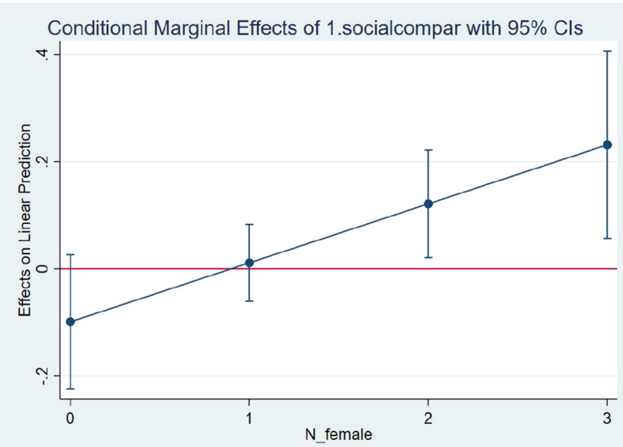

FIGURE 6 | Conditional marginal effects of *N* of females in household.

TABLE 7 | Conditional marginal effects of energy-related preferences.

1. Social	ReciprocityPref	EnerLit	TimePref
Delta method			
1	−0.992**	0.007	0.0555
2	−0.812**	−0.066	0.046
3	−0.633**	−0.139	0.036
4	−0.454**	−0.211	0.026
5	−0.274**	-	0.016
6	−0.094**	-	0.006
7	0.085	-	−0.004

Standard errors in parentheses.
****p < 0.01, **p < 0.05, *p < 0.1.*

identify significant differences in electrical energy consumption between the two groups at the average level, and find statistically insignificant treatment effects in the bivariate regression models. Furthermore, we observe some backfiring effects of the intervention when we control for household characteristics. We do estimate a statistically significant negative coefficient for our treatment effect when controlling separately for survey-elicited characteristics. Given the potential for individual bias however, the estimated results from this model will be corroborated by a future study with data from other districts.

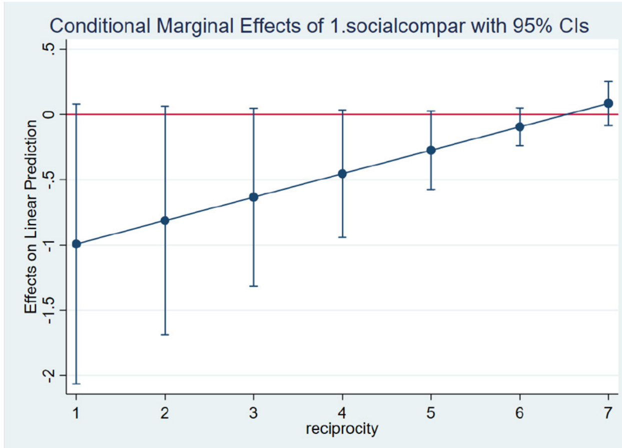

FIGURE 7 | Conditional marginal effects of reciprocity.

A first recommendation emerging from this pilot is that policymakers and practitioners ought to fully consider the characteristics and particular behaviors of the target group before designing an intervention aimed at tackling energy poverty through behavioral change. Even if the low statistical significance and effect size of the intervention is a result of the small sample, the direction of the behavior change suggests that running a small-scale uniform intervention could backfire in vulnerable demographics, particularly if the scope of the intervention is narrow (a small sample limits the capacity to communicate relevant differences in consumption within the sample). It is paramount to take into consideration the specific needs, pre-existing behaviors, motivations, and key reference groups relevant for the demographics being targeted, in order to maximize the effectiveness of the intervention. Drawing on previous findings by Khosrowpour et al. (2016), that highlight the need for targeted feedback mechanisms in behavior-change interventions, similar behavior-change interventions could leverage these contextual features to design more targeted norm-based interventions. Of course, the results do not provide conclusive evidence that these approaches would lead to more successful norm-based interventions, and this remains an empirical question that further research with more targeted approaches should strive to answer.

For this particular demographic, a more holistic behaviorally-informed intervention than one based solely on nudging, might be desirable. As an example, an intervention that provides individuals with basic facts on energy poverty might be implemented to boost skills and knowledge required for identifying and sharing their needs and problems related to home energy comfort and energy consumption (DellaValle and Sareen, 2020). This might not only a way to harness the local experience, thus truly engaging target individuals in the process of betterment of their conditions, but also a way to further increase their capabilities and optimize their energy-use to fit their specific needs. At the stage of analysis furthermore, the integration of more qualitative methods could complement our quantitative approach to better understand experienced conditions of tenants in relation to energy vulnerability and engagement with IHDs (Ambrosio-Albala et al., 2020).

The difference in the direction of the treatment effects between weekdays and weekends is also significant. Given the sample composition being comprised in large part of retirees or other groups that stay a minimum of 12 h at home, we should not observe substantial differences in energy behaviors for these tenants between weekdays and weekends. The fact that the intervention leads to a negative difference in electricity consumption between the treatment and control group when considering only weekend data, could suggest that the composition of occupants in a home at any one time has a moderating effect with the intervention. For example, young adults who are typically away during weekdays might have a higher likelihood to interact with the technology (and therefore see the normative appeals) than some of the older household members who are at home during weekdays. Such an interpretation could support the implementation of remote feedback mechanisms with integrated normative appeals and high granularity information on consumption, such as an app. This more accessible information could lead to the diffusion of more efficient energy behaviors in the home, even when the younger members are away. However, it is important to remark that our findings are not statistically significant, and further research needs to be conducted to support these types of expensive policy propositions.

5.2. Further Research

While our pilot design is not well-suited to identify what specific contextual features limited the effectiveness of the intervention, we propose a number of directions for future research, emerging from patterns in the data and/or supported by preexisting literature, that can further shed some light on the issues we have begun to explore in this study.

Firstly, it could be that the level of cognitive strain associated from being in a condition of income and energy vulnerability is too large to lead to the required level of interaction with the technologies and initiatives designed to achieve behavioral change (due to the contextual-psychological reasons outlined in section 2.4). While this issue is likely to have impacted the effectiveness of the intervention to an extent, it would seem dismissive to assume that it categorically impedes social housing tenants from engaging with a behavior-change strategy. This would also be inconsistent with previous findings that have trialed different forms of behavior change interventions in social housing districts with moderate success (Hafner et al., 2020; Sangalli et al., 2020). It would however be interesting to uncover to what degree different psychological barriers stifle the adoption of more optimal energy decisions, and how each, in turn, could be addressed. A controlled laboratory could prove a suitable environment to provide further knowledge in this direction (Lunn and Ní Choisdealbha, 2018).

Secondly, it is plausible that the lack of effectiveness of the intervention does not derive from the uniform design applied, but rather that tenants are simply not interacting with the IHD technology enough to be exposed to the normative appeals. Certainly increasing the level of interaction with the IHD technology would be unquestionably beneficial, not only to promote energy conservation but also to increase the agency of vulnerable individuals in the control of their energy consumption. The data however does not seem to support this hypothesis as the estimated model fails to identify statistically significant interaction effects when adding Number of clicks as a variable in our Bivariate regression models (**Appendix**). Further researcher on a larger sample would need to be conducted to investigate causality between the level of display interaction and intervention effectiveness. It would also be important to conduct further research that can identify behavioral determinants of interaction with IHDs.

Thirdly, it may be that the integration of the intervention in the context of recently retrofitted homes is affecting its behavior-change potential. Evidence has shown that in social housing districts there exists a particularly high tendency to "take-back" a large proportion on energy savings after efficiency upgrades in the form of increased internal temperatures (Coyne et al., 2018). This behavioral response to retrofitting is likely to be consistent across different forms of energy consumption, including electricity. Taken together with the evidence of a pre-bound effect prevailing in low-income populations (Sunikka-Blank and Galvin, 2012), it seems likely that our group of tenants (who are part of particularly vulnerable demographics and would be consuming below optimal levels of energy pre-retrofitting), increase their consumption post-retrofitting in order to appropriately meet their basic capabilities now that they can financially afford to do so. The impact of this behavioral response to retrofitting on tenants' subsequent willingness to adapt their consumption downwards as a result of normative appeals is hard to measure with the available data (all tenants were subject to retrofits and no pre-retrofit consumption information was available to compare individual apartment behaviors at different stages). However, it seems plausible to assume that tenants who have recently adjusted to a higher levels of consumption thanks to the efficiency upgrades, would be reluctant to then adjust their consumption downwards when presented with social comparison modules, especially if they were previously consuming sub-optimal levels of energy.

To our knowledge, there currently is no literature studying the impact of rebound and pre-bound effects on the effectiveness of subsequent behavior-change interventions, so it is challenging to discern how important these effects are to the observed results. An interesting direction for further research would be to study social comparison interventions in a social housing context not having recently undergone refurbishment, and see if the results differ.

It is important to note that just because the intervention did not lead to statistically significant differences in electricity consumption during the time-period investigated, this does not mean that the households were not consuming energy at an optimal level. Their current consumption levels may well have been conducive to them achieving their basic capabilities. Studying how changes in behavior following the retrofit affected the achievement of basic capabilities would be necessary in order to evaluate the success of the intervention from more of a capabilities perspective. This would require a longer period of observation and a more qualitative study of household outcomes as the optimal levels of energy consumption needed to satisfy basic capabilities are likely to be highly subjective.

5.3. Pilot Study Limitations

Due to the field nature of the pilot study, there were a number of limiting factors during implementation and in the scope of the study which should be addressed in future research. These limitations are worth discussing in order to better interpret the study's outcomes and outline future approaches to more closely determine the effect of social comparison interventions in social housing contexts.

The scope of this study is narrow, as the focus is on electricity consumption only, over a 3 month period and in a limited number apartments. This narrow scope was taken for three reasons: (i) existing data limitations as there was a delay of apartment display installations following COVID-19, (ii) in order to focus on short-term effects as these are the most relevant for behavior change and (iii) to emphasize the methodological and analytical aspects of our study, so as to serve as a reference point for a larger, more extensive analysis once more data is available. While it is plausible that expanding the scope of analysis by including more apartments, studied over a larger period of time, and additionally considering thermal behavior would result in the identification of significant differences in energy consumption between groups, we have no reason apriori to believe that this will be the case. These concerns however are certainly valid from an analytical point of view and a more exhaustive analysis of the available data will be carried out in a forthcoming study in order to draw rigorous conclusions that can direct policy-making. Moreover, further research could look at how similar interventions affect energy profiles throughout the day, as it may be that the intervention does not reduce overall energy consumption but rather shifts energy habits and consumption patterns across the day, which could have associated environmental and financial benefits for a society (especially in the case of variable energy tariffs).

A common implication of field studies such as ours is that participation is voluntary, creating the possibility that our sample is non-representative of the wider population we intend to study as there may be some systematic relationship between participation and some unobservable characteristics, leading to a self-selection bias. The potential for a positive self-selection bias is well-researched in field experiments (Gautier and Klaauw, 2012), as well as in the case of our specific type of intervention (Allcott, 2015).

In our study it is possible that the households which self-select to allow the display installation are particularly prone to have a higher pro-environmental attitude (the mean for the elicited measure of pro-environmental self-identity is 6.58, considerably higher than the median of 4.5) or be more likely to be willing to take control of their energy consumption. This is indeed a limitation of the study as it threatens to reduce the external validity of our findings.

Additionally, the apartment-level randomization that took place within the district has the potential of leading to negative spillover effects, arising from social interaction between tenants, which violate the "stable unit treatment value assumption" (SUTVA), an assumption routinely invoked in order to draw causal inferences from experimental effects (Rubin, 1986). These spillover effects could occur as a result of communication between tenants in different groups. For example, if tenants in the control group become aware that other tenants have displays that show social comparison modules, or even observe each other's displays, this could potentially affect the way they behave, obfuscating the potential causal inferences to be drawn from the results. While a better option would have been to randomize treatment assignment at the building or district-level, the existing timeline of the project as well as other technological considerations made this impossible.

Finally, some issues when running the regression analysis. As previously explained, a number of the variables included in our full regression model are based on individual-level measures obtained from survey responses. This was done because it proved too intrusive and methodologically complex to try and obtain survey answers from all occupants in the dwellings. We opted instead to get answers from one of the occupants present at time of installation. These variables were treated in our analysis as proxies for household-level preferences. This approach is certain to produce household-level measures which are subject to the individual bias in preferences of the occupant answering, introducing this bias to the results. Moreover, despite basing the survey items on experimentally validated items following (Falk et al., 2018), there is still scope for hypothetical bias in our survey answers. Finally, there is little variation in the answers to some of the survey items (ReciprocityPref St. Dev = 0.674, TimePref St. Dev = 1.794, EnerLit St. Dev = 1.128), which together with the relatively small sample, limits the significance of our survey-elicited variables and the results obtained from the corresponding model estimation.

6. CONCLUSIONS

In this study, we have presented a methodology designed to integrate a popular behavior-change intervention in the context of social housing retrofits, with the aim of addressing social and behavioral elements of energy efficiency improvements that are often overlooked in a social housing context. We introduced our pilot field study, based on a wealth of previously successful social comparison interventions in the energy domain, and discussed why social housing tenants make for a particularly interesting and important case study, due in part to their high level of energy vulnerability and potential to fall in energy poverty. Our primary aim throughout has been to uncover whether this intervention could be applied in a standard way within a social housing context, with its unique difficulties and characteristics.

The results suggest prudence on the part of policy-makers when applying these behavior-change interventions in vulnerable demographics. Interventions of this kind, especially if delivered using the IHD technology, can be costly to implement. If their effectiveness in social housing are miscalculated and overstated based on the evidence of RCTs on a more general residential area, the costs of the intervention could far outweigh its actual benefits. This echoes findings from Andor et al. (2017) who find that the benefits of social comparison interventions may be overstated in European populations, making their indiscriminate implementation potentially unfruitful when the costs and benefits are fully accounted for. Policy-makers might alternatively wish to initially implement more cost-effective interventions that are less cognitively taxing for vulnerable demographics to engage with, and instead boost the competencies of vulnerable individuals, so as to empower them to make more optimal energy decisions. Of course there may be benefits related to the use of the display, other than reduced energy consumption caused by social comparison modules, which would make their installation cost-effective. Further research could take a more holistic approach and study the benefits of IHD devices on different dimensions to better evaluate the effectiveness of the display installation as a whole.

Overall, while results at present are somewhat limited from data availability and a narrow research scope, the methodological basis we introduce with this study enriches the emerging field of applied behavior-change interventions in social-housing districts. This field not only has immense practical importance for policy-makers wishing to leverage virtuous behavior in the context of efficiency upgrades of the social housing dwelling stock, but is also deeply important for discussions on energy justice and the tackling of energy poverty. If research in this area can identify ways that behavior-change interventions could be designed to be mindful of the contextual situations of the most vulnerable, we could ensure that behavior is effectively leveraged together with technical upgrades, in order to improve the capabilities of the most vulnerable and tackle energy poverty.

DATA AVAILABILITY STATEMENT

Data generated as part of EU Project Sinfonia, Grant Agreement No. 609019. Requests to access the datasets should be directed to nicolas.caballero@eurac.edu.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Eurac Research. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

Both authors provided input into the draft and final manuscript, including conceptualization, and writing-original draft preparation. NC compiled the literature review and was in charge of the data curation and formal analysis. ND was in charge of overall supervision.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frsc.2020.601095/full#supplementary-material

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.