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Research Paper

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Abstract

Increasingly, new energy-efficient technologies connected to smart home arise and bear great potential of influencing user's decisions. Thereby, behavioral interventions like digital nudging are promising to influence behavior. While nudging has been investigated in several contexts to promote sustainable behavior, little is known about its effectiveness in digital choice environments promoting daily energy conservation behavior, especially through mobile applications. As private households account for a large share of total energy consumption, which needs to be reduced to counteract climate change, we conducted an online survey to test the nudging elements framing and default rules, as well as their combination. We surveyed 231 participants and found a large effect of framing and an even larger effect for the combination. This paper contributes by exploring these digital nudges, which received little attention in prior research, and by providing insights on the design of smart home applications to reduce energy consumption.

Keywords: Digital Nudging, Smart Home Application, Energy Conservation Behavior, Sustainability.

1 Introduction

Driven by smart home technologies, which enable individuals to connect and intelligently control household devices, the digital environment has reached our homes and thus affects our daily decisions and habits massively. Such smart home technologies (e.g., smart lighting and heating systems) can be controlled by individuals via a smart home application (app). Therefore, these smart home apps bear a great potential of influencing the user's decisions, for example, on energy consumption. Within these apps, the use of behavioral interventions can additionally help to influence energy conservation behavior. Behavioral interventions using different nudging elements (NE) applied in the physical as well as in the digital environment - which defines the term digital nudging element (DNE) - are already an essential part of the scientific discourse (e.g., Mirsch et al. (2017), Thaler and Sunstein (2009), and Weinmann et al. (2016)). In contrast to restricting the number of options available by rules, regulations, or fiscal measures, (D)NEs intend to support better decision-making by modifying the so-called choice architecture: the shape of the context and environment in which people make decisions (Thaler and Sunstein, 2009).

As human activities, including private energy consumption behavior, are responsible for a substantial share of climate change, a comprehensive reform of our global energy consumption is unavoidable (United Nations Climate Change, 2021). In the context of private energy consumption, the everincreasing efficiency of digital technologies like energy-efficient heating systems or household devices nurtured hopes to cut down energy consumption and are already part of the scientific discourse (Mills and Schleich, 2012; Schleich, 2019). However, the energy consumption by private households in Germany in 2020 is higher than in 1990 (Federal Environmental Agency of Germany, 2019). That efficiency gains are out-levered by increasing consumption and demand, also known as the rebound effect (Sorrell, 2015). Thus, besides technological progress, behavioral interventions like DNEs in smart home apps can represent an effective way to encounter climate change and therefore need to be analyzed in more detail in the scientific discourse.

Lehner et al. (2016) found four NEs to be effective in encouraging sustainable behavior in energy consumption, personal transportation, and food: *default rules*, *simplification* or *framing*, *social norms*, and *adjustments to the physical environment* (which is not applicable as a DNE). In the context of energy consumption, most of the prior studies focus on the implementation of *social norms* (Loock et al., 2012; Graml et al., 2011; Tussyadiah and Miller, 2019; Schultz et al., 2015) and *feedback* (Cappa et al., 2020; Schultz et al., 2015; Tussyadiah and Miller, 2019; Abrahamse et al., 2007). Little to no attention has been paid to *default rules* (i.e., changing the default, e.g., pre-selecting the most sustainable option) and *framing* (i.e., simplifying complex information, e.g., by using labels or icons such as green leaves) (Lehner et al., 2016). These DNEs show already encouraging results in other sustainability-related contexts, for example, *default rules* when promoting sustainable food choices (Berger et al., 2020) or *framing* to promote electronic cars in car rental processes (Schrills et al., 2020). However, research lacks the investigation of these DNEs in the increasingly important context of smart home apps. Prior research shows that the effectiveness of DNEs highly depends on the underlying context. For example, while Berger et al. (2020) did not find significant results of *social norms* to promote sustainable food choices, Kroll et al. (2019) found significant results in the context of daily energy consumption behavior. Next to the missing investigation of the (D)NEs *default rules* and *framing*, studies fall short on investigating the impact of DNE in a digital behavior environment (e.g., smart home apps), while being on the rise (Ali and Yusuf, 2018; Statista, 2021). Consumers can now actively regulate their energy consumption in the same environment, in which the DNE is implemented instead of being nudged in a digital environment (e.g., in-home displays) but taking decisions in a different, physical environment (e.g., physically turning down the heating). Humans behave differently in a digital environment (Liu, 2005), which is why we argue that a separate consideration of the effectiveness of DNEs in a digital behavior environment (i.e., smart home app) is important. Kroll et al. (2019) were the first and so far the only ones who studied the DNEs *social norms* and *self-commitment* in mobile smart home apps and provided the basis for further research on the use of further DNEs in this context. As next to *social norms*, the two NEs of *default rules* and *framing* are promising when promoting sustainable behavior; we aim to fill this research gap by addressing the following research question:

Do the digital nudging elements – framing and default rules – promote energy conservation behavior of individuals in mobile smart home apps?

To answer this research question, we designed a smart home app and conducted an online experiment in which participants were asked to control four smart home devices through the app. We implemented the DNEs *framing* and *default rules* in different treatment groups. We additionally investigated the combination of both nudges, which may result in stronger effects by combining their advances as prior studies suggested (e.g., Kroll et al. (2019), Loock et al. (2012), Andor and Fels (2018)). Afterward, we analyzed the effectiveness of the DNEs using parametric and nonparametric statistics and analyzes. Next to several theoretical implications in digital nudging to promote sustainable behavior, this study contributes to how smart home apps need to be designed to encourage individuals to change their energy conservation behavior.

The paper is structured as follows: We introduce the research design after reviewing the theoretical background on (D)NEs, especially in the context of energy conservation behavior. Subsequently, we present the results. We conclude by discussing the results, pointing out implications, limitations, and further research proposals.

2 Theoretical Background

2.1 The Need for Energy Conservation Behavior and the Relevance of Smart Home Apps in that Regard

Improving energy efficiency is widely seen as the most promising response to mitigate climate change. The German Federal Ministry of Economics and Technology identifies advancing energy efficiency in the building sector and increasing personal responsibility for energy efficiency as the most important fields of action for energy efficiency policy (Federal Ministry for Economic Affairs and Energy).

Driven by technological advances and innovations, energy efficiency has steadily increased in recent decades, indicating that less energy is needed for the same purposes. However, these improvements do not necessarily lead to reductions in energy demand. Instead, they are frequently accompanied by an increase in energy demand, described by the rebound effect (Sorrell). This effect states that after an increase in efficiency, additional demand for the more efficient product or service may occur, reducing the actual savings (Federal Ministry for Economic Affairs and Energy). To back this up with numbers, while the global energy efficiency increased by 1.2% in 2018, the demand grew by 2.2% (International Energy Agency; International Energy Agency, 2022). Considering the context of energy consumption in private households, which accounts for about 29% of the total energy consumption taking Germany as an example (Federal Environmental Agency of Germany, 2019), innovations such as more energy-efficient technologies like washing machines and dishwashers with environmentally friendly programs or light that can be dimmed in its brightness can enable energy savings. In this context, smart home is an overarching term for various automation processes for connecting and intelligently controlling all kinds of these technical devices in buildings. Driven by increasingly more connected products and the Internet of Things (IoT), this concept is becoming more widespread and aims to focus the opportunities of technological progress on private households (Ali and Yusuf, 2018; Statista, 2021). With a smart home app, individuals can control the smart home devices (e.g., in the selection of the wanted IoT-enabled dishwasher program or controlling the IoT-enabled heating system) by themselves, keep an overview as well as track, and better control their energy consumption. Due to their technological possibilities and easy accessibility, they are an important instrument for improving overall energy reduction (Strese et al., 2010). Moreover, the implementation of smart homes will continue steadily in the coming years due to technological advances like IoT (Statista, 2021).

However, as stated above, the simple existence of innovative technologies like smart home is not enough to reduce energy consumption at home; personal responsibility for energy conservation and, consequently, consumer behavior plays an equally important role in using the technologies effectively. As a result, action needs to be taken to change the energy conservation behavior of individuals. Behavioral research has shown that targeted behavioral interventions, referred to as nudges (Thaler and Sunstein, 2009) and their digital counterpart, digital nudges (Weinmann et al., 2016), can effectively influence human behavior. These could establish themselves as an essential component for better consumption decisions and thus climate protection (Allcott, 2011). As the ideal intermediary for such nudges in private households could be smart home technology, behavioral measures like digital nudging seem to be promising to achieve this goal (Lehner et al., 2016; Loock et al., 2013; Asensio and Delmas, 2016).

2.2 The Concept of (Digital) Nudging

Nudging describes ways to predictably impact individuals' behaviors by altering the environment in which decisions are made without restricting the freedom of choice or raising the cost of alternatives in terms of effort, time, and other factors (Hansen and Jespersen, 2013; Hausmann and Welch, 2009; Thaler and Sunstein, 2009). Behavior results from decisions made consciously and unconsciously (Kahneman, 2011), also known as the dual-process theory of Wason and Evans (1974). For both unconscious, automatic everyday decisions but also non-automatic, complex routines, shortcuts can be taken like gut feelings or listening to social conformity, also known as heuristics or cognitive biases (Kahneman, 2011;

Tversky and Kahneman, 1974). While, on the one hand, heuristics support quick decision-making, they also make decisions prone to error, leading to decisions to the individual's own detriment. The concept of nudging is intended to counteract this and aims to influence psychological effects so that the decision outcome becomes predictable (Thaler and Sunstein, 2009). Examples for nudging unconscious, automatic decisions include a change of printer defaults to reduce paper or fake speedbumps painted on the streets as visual illusions to slow down the speed, while examples for nudges addressing rather reflective thinking include calorie postings on menus or energy bills with social comparison (Hansen and Jespersen, 2013). Hence, nudges are likely to be suitable for both routine behavior and consciously made, rather complex decisions.

As decisions are increasingly made in a digital or online behavior environment (e.g., in apps or browsers), Weinmann et al. (2016) transferred the behavioral insights tested in the physical world to digital environments and defined digital nudging as the "use of user-interface design elements to guide people's choices or influence users' inputs in online decision environments" (Weinmann et al., 2016, p. 433). The significant advantage of DNEs is that they can be implemented, evaluated, and even personalized quickly and without high costs (Weinmann et al., 2016). Also, their effectiveness seems promising because individuals spend less time being concentrated while reading on digital screens and suffer from choice overloads and decreasing time spans of sustained attention (Liu, 2005). Lembcke et al. (2019) introduced the concept of "blended environment" and stated that future research should consider the targeted behavior environment to develop a full picture of digital nudging. The authors, therefore, differentiated between the targeted behavior environment (physical vs. digital, e.g., turning on the heating on-site vs. turning on the heating in an app) and the intervention being analog (physical nudge (here: NE), e.g., printed label on the heating reminding you to reduce heating when opening the window) or digital (digital nudge (here: DNE), e.g., *framing* in the form of logos or highlighting by color marking in an app) (Lembcke et al., 2019).

Different lists and definitions of DNEs exist (Mirsch et al., 2017; Lehner et al., 2016; Weinmann et al., 2016), including, among others; *default rules*, *social norms*, *framing*, *feedback*, *priming*, *simplification*, and *goal setting* (also referred to as *self-commitment*). As we focus on *default rules* and *framing*, we define both elements in the following: *Default rules* refer to situations where the preferred choice is pre-selected (Thaler and Sunstein, 2009) and are defined as "standard choices that determine the result in case people take no action" (Lehner et al., 2016, p. 169). The NE is based on the need to procrastinate due to the time and effort required (Sunstein, 2014) and preserving the status quo (Kahneman, 2011). Examples include default smaller plate sizes that avoid food waste (Vandenbroele et al., 2018) or the configuration of eco-friendly search engines as default (Henkel et al., 2019). The NE *framing* uses the "anchoring bias", which states that by presenting the same information in multiple ways/"frames", individuals tend to make different decisions (Thaler and Sunstein, 2009). The NE *framing* often comes along with the NE *simplification* as it aims at transporting condensed information about complex constructs or by framing specific characteristics more noticeably (e.g., by using logos) (Sunstein, 2014). Examples include using emission labels for burgers to increase customers' choice of Burgers with a lower-carbon footprint (Van Gilder Cooke, 2012) or providing energy-efficient scores in e-commerce for electronic products like washing machines (Arquit Niederberger and Champniss, 2018).

2.3 (Digital) Nudging to Promote Energy Conservation Behavior

Lehner et al. (2016) found *default rules*, *simplification* or *framing*, *social norms*, and *adjustments to the physical environment* (which is not applicable as a DNE) to be effective in encouraging sustainable behavior in energy consumption, personal transportation, and food. Little to no attention has been paid to *default rules* and *framing* in the context of daily energy consumer behavior, even though they show encouraging results in related energy-saving contexts. Examples include using *default rules* for energy-saving choices in a web-based configurator for TVs (Hankammer et al., 2021) or choosing renewable energy contracts (Momsen and Stoerk, 2014; Pichert and Katsikopoulos, 2008). The investigation of *framing* also showed meaningful results in sustainable daily behavior contexts, mainly shopping-related, like the choice of sustainable food products in an online supermarket (Berger et al., 2020) or choosing the most sustainable product in fast-moving-consumer products (Antonides and Welvaarts, 2020). At least to our knowledge, these promising NEs have not been studied in the context of daily energy consumer behavior neither their combination.

Next to the fact that little to no research exists applying *default rules* and *framing* to promote energy conservation behavior; little research focused on using DNEs in a digital targeted behavior environment (e.g., a smart home app) but mainly focused on physical behavior environments even though when applying DNEs instead of analog NEs (please refer to "blended environments" (Lembcke et al., 2019) introduced in Section 2.2). Examples of studies analyzing analog NEs targeting a physical behavior environment include Allcott (2011), who mailed letters containing home energy reports to residential customers comparing their energy consumption with their neighbors. By implementing the NE *social norms*, the study succeeded in reducing energy consumption by an average of 2% (participants N=600,000). Regarding rather DNEs, the study of Abrahamse et al. (2007) created a webpage with an energy report to promote energy conservation behavior. Applying the DNEs *priming*, *goal setting*, and *feedback* decreased the energy consumption in the observation period of 5 months of N=189 by 5%. Implementing *feedback* and *goal setting* in a similar setting but on a larger scale with N=1,789, Loock et al. (2013) reduced the energy consumption by 2.3%. Also, in a similar setting using a website that calculated the energy consumption, Graml et al. (2011) analyzed the DNE *social norm* and found positive results.

While existing studies show promising results for the use of DNEs (e.g., websites, in-home displays) and analog NEs (e.g., letters) to promote energy conservation behavior, the studies focused on a physical targeted behavior environment (i.e., energy consumption is determined by, for example, managing the heating system or light switch analog in the physical world). Focusing on digital targeted behavior environments like smart home apps, in which consumers actively regulate their energy consumption in a digital environment, Kroll et al. (2019) test the effectiveness of the DNEs *self-commitment* and *social norms* to influence consumers' energy conservation behavior in a smart home app. Although the results of the author's pre-study were not significant, they demonstrated that the experimental approach works and present possible modifications. The present study extends the efforts of Kroll et al. (2019) and transposes the approach for examining the promising NEs of *default rules, framing,* and their combination in a similar setting.

3 Hypothesis Development

Prior studies demonstrated the promising effects of different DNEs to promote sustainable individual behavior. But the diversity of use cases and studied elements emphasize that their effect highly depends on the underlying context (e.g., food vs. mobility vs. energy) and its decision environment regardless of where the DNE is implemented (i.e., physical, for example, by turning on the heating on-site while the DNE is implemented in a web-based tool vs. digital, for example, by turning on the heating in an app in which the DNE is implemented). As humans behave differently in a digital environment (Liu, 2005), a separate investigation of DNE in a digital behavior environment (e.g., smart home apps) is justifiable. We state that especially decisions being made in a digital behavior targeted environment in which the DNE is implemented seem promising to positively influence decision behavior since there is no interruption in the media between the situation that has been nudged (e.g., a website displaying energy consumption) and the actual decision (e.g., turning on or off the lightening or heating). So far, though, research in the context of energy consumption has focused on physical behavior targeted environments (e.g., Abrahamse et al. (2007)). Whilst the use of smart home apps is on the rise (Ali and Yusuf, 2018; Statista, 2021), so far, only Kroll et al. (2019) have investigated the effectiveness of two different DNEs (*social norms* and *self-commitment*) to promote daily energy conservation behavior when managing smart home devices through the app, hence in a digital behavior environment. Next to *social norms*, the use of *default rules* and *framing/simplification* of information (here: *framing*) are useful DNEs when promoting sustainable behavior (Lehner et al., 2016). These DNEs have not been studied in the context of daily energy conservation behavior, especially not in a smart home app.

Default rules have been successfully studied in diverse contexts promoting general energy-saving behavior (e.g., Hankammer et al. (2021), Momsen and Stoerk (2014), or Pichert and Katsikopoulos (2008)) and environmentally-friendly everyday behavior (e.g., Henkel et al. (2019), Berger et al. (2020), Antonides and Welvaarts (2020)). So far, *default rules* have not been investigated in the context of daily energy usage. But *default rules* are known to bridge the behavior-intention gap, such as living more energy conservatively, which is preferred by far more individuals than those who actually choose energy-saving options (Münscher et al., 2016). To take advantage of a smart home app in which the barrier between intention and behavior is already lower due to the non-existent media break, we, state that by changing the default, more people will choose more energy-conserving options in their daily life when using a smart home app. Hence, we hypothesize the following:

Hypothesis 1 (H1): *Default rules in a smart home app result in more energy-conserving selections than without any behavioral interventions.*

Next to *default rules*, *framing* is a promising DNE for promoting sustainable consumption behavior (Lehner et al., 2016). Especially for daily, rather unconscious decisions, the intense and straightforward presentation of information revealed promising results for promoting sustainable decisions (e.g., in the context of impulsive food decisions in an online supermarket (Berger et al., 2020)). We state that daily energy consumption decisions like choosing a dishwasher program or turning on/off the lights are similar unconscious decisions. Users might not be aware of the environmental consequences of daily choices regarding their energy consumption as food choices in the online supermarket. Hence, breaking down the complex information concerning the energy impact when unconsciously operating household appliances might be helpful to decrease energy consumption. Accordingly, we hypothesize:

Hypothesis 2 (H2): *Framing nudges in a smart home app result in more energy-conserving selections than without any behavioral interventions.*

Nevertheless, the use of single NEs is less common than the combination of several, which strengthens their effects and combines their advantages (Andor and Fels, 2018). For example, *default rules* were successfully combined with *priming* in the context of sustainable investments (Gajewski et al., 2021) or in promoting the usage of electric vehicles (Stryja et al., 2017). In general, studies on DNEs to promote sustainable behavior have analyzed a combination of different NEs (Abrahamse et al., 2007; Fanghella et al., 2019; Gajewski et al., 2021; Stryja et al., 2017). Therefore, we hypothesize:

Hypothesis 3a (H3a): *The combination of default rules and framing in a smart home app results in more energy-conserving selections than without any behavioral interventions.*

As we combine *default rules* with *framing*, we state that the combination of both elements leads to higher energy conservation decisions than the use of *default rules* alone by arguing that framing increases the effect of *default rules* by increasing the user's understanding and comprehensibility of the pre-selected option. This leads to the following hypothesis:

Hypothesis 3b (H3b): *The combination of default rules and framing in a smart home app results in more energy-conserving selections than the single usage of default rules.*

In the sense of completeness and to gain more insights into the effectiveness of the single DNEs, we are also interested in studying the adverse effect of whether the combination of *default rules* and *framing* leads to higher energy savings compared to the single usage of *framing*. Hence, we hypothesize:

Hypothesis 3c (H3c): *The combination of default rules and framing in a smart home app results in more energy-conserving selections than the single usage of framing.*

4 Research Process

We perform a randomized control trial to test the relationship between the between-subjects independent variables (implementation of the DNEs *default rules*, *framing*, and their combination) and the dependent variable (energy conservation behavior) (Gravetter and Forzano, 2016). First, we design and implement the two DNEs *default rules* and *framing* and their combination in a smart home app to control four smart home devices: light, washing machine, dishwasher, and heater. Consequently, we evaluate the DNEs' effectiveness below.

4.1 Design and Implementation of the Experiment

We designed a complete set of screen designs simulating a working smart home app and chose suitable smart home devices, which had to be controlled by the participants. Next, we implemented the screen designs in an online experiment, following Kroll et al. (2019). Our experiment consisted of a brief introduction to the concept of the smart home app before the participants were randomly assigned to one of four groups (A, B, C, D). We asked them to control all four specified devices using different DNEs for each group. Lastly, we collected demographic data.

4.1.1 Design of Default Rules and Framing in a Smart Home App

We followed the proposals of Fan et al. (2017) in designing the smart home app. To create a modern and realistic app environment, we respected the design guidelines of Neil (2014). Consequently, we integrated a tab bar with a home button, an account avatar, a settings icon, and overview navigation. To ensure a realistic user experience, we constructed a welcome, an overview, and a home screen.

Next, we chose suitable connected devices. The prerequisite was that the selected devices are not merely easy and intuitive to use but also compatible with a smart home system. Following Krishnamurti et al. (2012) and Kroll et al. (2019), lights, washing machines, dishwashers, and heaters seemed appropriate. In this study, we elaborated on the programs and settings of the focal devices by studying the user manuals, their stated energy consumption, and considering the recommendations of how to save energy as mentioned in Eiselt (2013). Due to their smart home capabilities, we chose the Bosch WAV28G40 as our washing machine and the Bosch SBV4HCX48E as our dishwasher to define the energy consumption for each program. For a broad and valid scale, each device has five selectable options. As a basis for the subsequent analysis, each option implies a different energy conservation level from 1 to 5; where 1 is the lowest and 5 is the highest. Each level serves as a polytomous measuring point. Table 1 presents an overview of the devices and their related programs; each device appears in its row.

Device	Energy conservation level				
	1	**2**	**3**	**4**	**5**
Lights [Brightness in %]	100%	80%	60%	40%	20%
Washing machine [Duration]	Cotton 60 °C 3:20 h:min	Cotton 40 °C 3:20 h:min	Cotton 40 °C 3:20 h:min	Cotton 20 °C 3:05 h:min	Eco 40 – 60 3:40 h:min
Dish washer [Duration & temperature]	Intensive 2:15 h:min & 70 °C	1h 1:00 h:min & 65 °C	Auto 1:40-2:45 h:min & 45-65°C	Silence 4:00 h:min & 50 °C	Eco 4:55 h:min & 50 °C
Heater [Room temperature]	25°C	23°C	21°C	19°C	17°C

Table 1. Overview of smart home devices and related energy conservation level

To present the five selectable options per device to the user, we allocated each device its own screen. While the upper bar displays the device menu, the center of the screen allows the user to choose between five brightness levels, programs, or room temperature (Figure 1). To implement the focal DNEs appropriately, we adopted the approach of Karlsen and Andersen (2019) and the suggestions of Münscher et al. (2016) and Schneider et al. (2018). We defined a pre-selected option according to the definition of *default rules*. In this case, to conserve energy, the option with the lowest energy consumption for all four devices is pre-selected. We illustrated this with a blue line around the least energy-consuming option and the inverted colored arrow for the washing machine and dishwasher. For light and heating, the blue line ends with a selection point at the least energy-consuming option. With the power switch already on, we also clarified that these options are already set. To further clarify the implemented default rule, we added the information "already pre-selected" for the option we set as default in the survey. For the DNE *framing*, we implemented a green leaf to highlight the option with the lowest energy consumption for all four devices. In addition, we colored the associated font green instead of blue (similar to prior studies in this context (e.g., Roozen et al. (2021)). The green leaf was supposed to symbolize environmental friendliness (Pancer et al., 2015). Thus, the participants should become aware of the consequences associated with their decisions. In the context of this study, we assume that the survey participant perceives the additional design elements as just described. These options were highlighted thus, but not overly obtrusive. Combining the implementation of the two individual nudges resulted in the combination nudge, where the least energy-consuming option was pre-selected and highlighted in each case. Figure 1 depicts the applied DNEs for all four devices: screen 1 (light) shows the *default rules* seting, screen 2 (washing machine) displays the *framing* condition, screen 3 (dishwasher) combines both nudges, and screen 4 (heater) displays none DNE used for the control group.

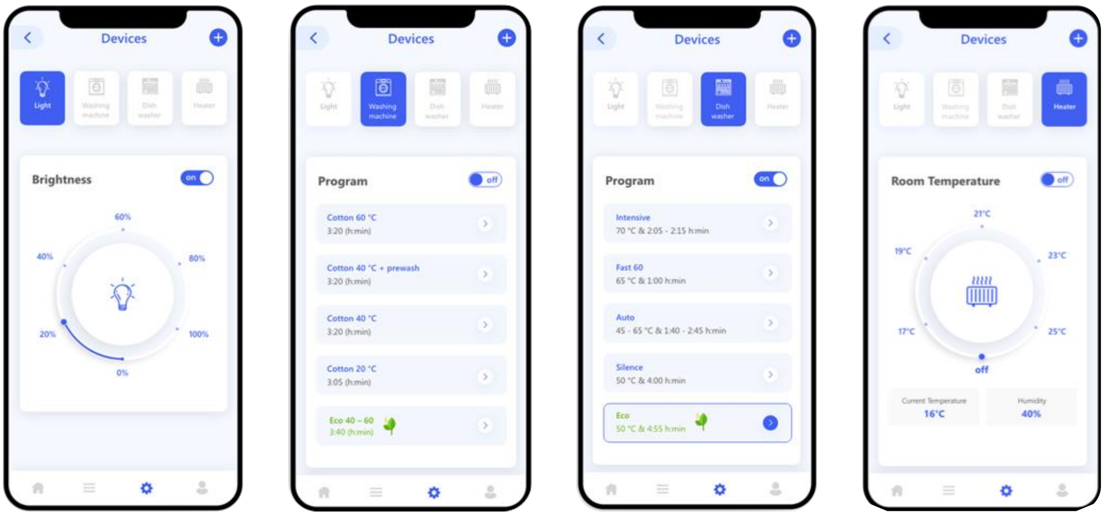

Figure 1. *Screens for each device (light, washing machine, dishwasher, and heater) with their five programs. To exemplify the DNEs, each screen shows different DNEs.*

4.1.2 Design and Implementation of the Online Experiment

Through an initial introduction to smart home and accurately explained scenarios of using the devices, we intended to guide each participant through the survey without the need for prior knowledge. After the welcome slide and the brief primer, the participants were randomly allocated to four groups (A, B, C, D). Every participant saw the same four smart home scenarios and the underlying questions concerning which option they wanted to select (i.e., the different room temperatures for the heating scenario). But the presented screen designs were slightly different – dependent on the groups assigned DNE. All participants in the control group (A) received the screen designs of the device menus without a nudge. Participants belonging to the *default rules* (B), *framing* (C), or combination (D) groups saw the corresponding screen designs shown and discussed in Section 4.1.1 (see also Figure 1). Considering the smart home scenarios, the participants were then asked to control all four devices mentioned above through the screen designs. Each participant was shown only the screen design of the four devices, with the nudge assigned to their group. After utilizing the smart home app, the survey requested the demographics. Figure 2 displays the flow of the experiment. To better understand the subsequent analysis, Figure 2 illustrates the variables under investigation (where 1 represents the implementation in this group and 0 represents non-implementation). For simplicity, we refer to the combination group when we focus on group D, in which both nudges, and thus both independent variables (*default rules* as well as *framing* is marked with 1), were implemented.

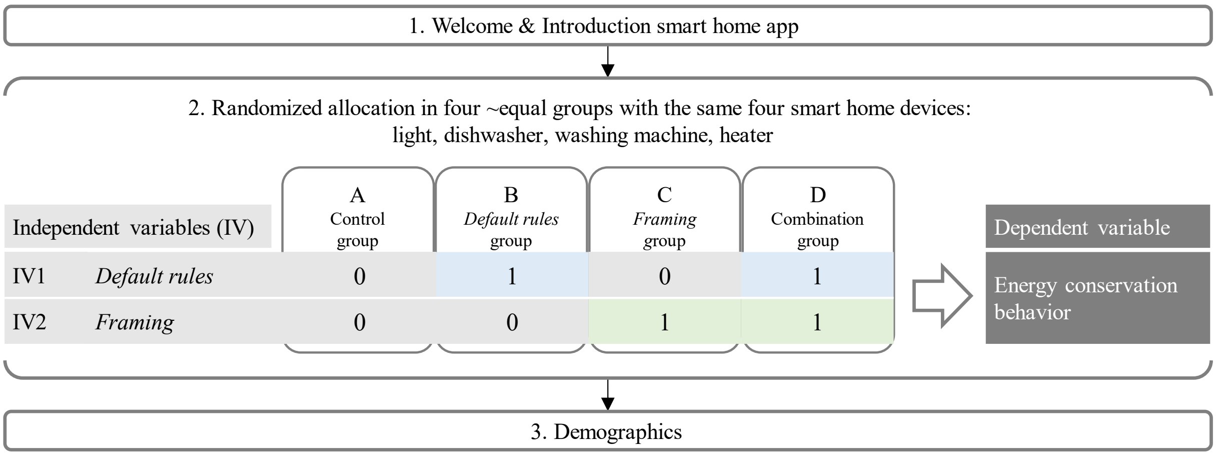

Figure 2. The procedure of the online experiment and information on the variables (based on Kroll et al. (2019))

Consecutive to a pretest with 20 participants in the first cycle and a revision of the experiment design according to the comments from this pretest, we implemented the questionnaire via the online survey tool of easyfeedback.de. 231 participants completed the online experiment and answered both included control questions correctly. 43.0% of participants were female, 56.5% male and 0.5% identified as diverse. Most of them (55%) were in employment, and about one-third (37%) were students and trainees. The median age of participants was 30, while all age groups from younger than 18 to older than 65 were represented.

4.2 Data Analysis

The focus of the present study was to test the hypotheses concerning the effectiveness of the applied DNEs - *default rules* and *framing* and their combination - on energy conservation behavior. To answer the research question, a measure of the energy conservation behavior in the prevailing use case of the smart home app needed to be defined first. For this purpose, we assigned each selected program within the smart home app to a different energy conservation level (as described in section 4.1.1, see Table 1). As the classification relies on the stated energy consumption, each of the five options per device is rated between 1 (least environmentally sustainable choice), 2, 3, 4, or 5 (highest energy conservation level). Subsequently, we combined the ratings of all four devices that had to be controlled by the participant in the field experiment into a measure called the energy conservation score (ECS). The ECS thus represents the overall degree of energy conservation of the decisions taken by one participant in the online experiment.

To answer our research question, which of the studied DNEs and their combination promote daily energy conservation behavior, we conduct the nonparametric Kruskal-Wallis test to compare the means between the focused groups. Additionally, we conduct pairwise comparisons using the Dunn-Bonferroni test. Normally distributed data must be assumed when calculating the parametric counterpart to the

Kruskal-Wallis test, the Analysis of Variance (ANOVA) (Howell, 2012). Since our dependent variable (ECS) is not normally distributed, calculating the ANOVA is only possible to a limited extent, specifically assuming normally distributed data for treatment groups with more than 30 participants, according to the Central Limit Theorem (Lumley et al., 2002). Because of this limitation and the higher power associated with the rank analyzing Kruskal-Wallis tests for distribution-free groups (Kirk, 2012; Wickens and Keppel, 2004), we perform the parametric ANOVA and the associated contrast tests only second to validate the results.

5 Results

According to Kolmogorov Smirnov and Shapiro-Wilk tests, the variables of the treatment groups (A) and (B) are normally distributed, while the groups (C) and (D) are not. Therefore, we first perform the nonparametric analyses and then, according to the Central Limit Theorem, the parametric ANOVA (Lumley et al., 2002). The Levene-Test indicates variance homogeneity ($F(3, 231) = 1.326$, $p = 0.267$). Considering a significance level of 5%, the Kruskal Wallis test rejects the null hypothesis that there are no mean differences between the groups ($p = .000$). This is confirmed by the ANOVA ($p = .000$). Table 2 shows the descriptive statistics of the ECS, assigned to the four treatment groups, as well as the Kruskal Wallis and the ANOVA test statistics.

To allocate the origin of these differences, we proceed with pairwise comparisons (based on the Kruskal Wallis) and contrast tests (based on the ANOVA) of the individual groups. Each null hypothesis states that there is no difference between the groups within each paired comparison. For both calculations, the contrast pairs 1, 2, 3, and 4 reveal statistically significant differences and thus reject the hypotheses $H1_0$, $H2_0$, $H3a_0$, and $H3b_0$. $H3c_0$ indicates a relevant significance only in the contrast test after the ANOVA (pair 5) (see Table 3). This is consistent with the elaborated alternative hypotheses H1, H2, H3a, and H3b, while the H3c is only consistent following the ANOVA. Hence, there are effects of all the various implemented DNEs on promoting energy conservation behavior.

Group		ECS		Kruskal Wallis		ANOVA	
	N	Mean	Std. deviation	H	p-value	F	p-value
Control (A)	54	3.028	.808	42.217	.000***	18.139	.000***
Default rules (B)	58	3.500	.628				
Framing (C)	60	3.650	.706				
Combination (D)	59	3.996	.681				
Total	231	3.555	.789				

*Table 2. Descriptive statistics of the ECS and Kruskal Wallis and ANOVA test statistics p-value significance codes: *** for < 0.001, ** for < 0.01, * for < 0.05*

	Pair			Pairwise comparisons			Contrast tests		
H	Pair	Contrast		p-value	Effect size r	Effect size d	p-value	Effect size r	Effect size d
$H1_0$	1	A	B	.035*	small	medium	.000***	-	-
$H2_0$	2	A	C	.000***	medium	large	.000***	-	-
$H3a_0$	3	A	D	.000***	large	large	.000***	small	small
$H3b_0$	4	B	D	.001**	medium	medium	.000***	-	-
$H3c_0$	5	C	D	.078	-	-	.008**	-	-

Table 3. Test statistics of the pairwise comparison and the contrast tests

Subsequent to the pairwise comparison, following the effect sizes "d" by Cohen (1992) as well as the "r" by Gignac and Szodorai (2016) (Table 3), there is a small to medium effect size for the *default rules* (pair 1), a medium to large effect size for the *framing* (pair 2), a large effect size for the combination of *default rules* and *framing* (pair 3), and a medium effect size for $H3b_0$ (pair 4). Regarding the contrast tests, there only exists a small effect size for pair 3. Even though there are differences in the effect sizes, the results prove the influence of the DNEs on promoting energy conservation behavior. The combination of the DNEs only indicates a significant effect, considering the *default rules* $H3b_0$/pair 4. No significant difference was identified compared to only *framing* $H3c_0$/pair 5 (Table 3).

6 Discussion

The present study explored the effectiveness of the DNEs *default rules*, *framing*, and their combination in promoting energy conservation behavior through a smart home app. Overall, we confirmed the effectiveness of DNEs, as affirmed by Weinmann et al. (2016), Mirsch et al. (2017), and Lehner et al. (2016).

In accordance with hypothesis H1, *default rule*s are associated with a higher energy conservation behavior, with a small to medium effect size. This indicates that *default rules* can promote energy conservation behavior. Accordingly, smart home app users prefer to maintain the status quo of the pre-selected option or simply want to avoid making active and conscious decisions in such rather daily routine tasks (Kahneman, 2011; Sunstein, 2014). The results build on existing evidence of the effectiveness of *default rules* being it in (1) energy-related contexts (e.g., shopping for energy-efficient products (Hankammer et al., 2021) or choosing an energy contract (Momsen and Stoerk, 2014; Pichert and Katsikopoulos, 2008)) or (2) in daily routine tasks like using a search-engine (Henkel et al., 2019) or doing grocery shopping (Berger et al., 2020).

In line with hypothesis H2, *framing* may also promote energy conservation behavior by yielding a medium to large effect size. The green leaf, as an environmentally friendly *framing*, seems to be perceived positively by the participants and encourages them to select more energy-conserving options. Hence, the way the different energy level options are presented seems to influence consumer behavior and the magnitude of the resulting energy efficiency improvements. Our findings are also consistent with the findings of prior studies on using *framing* for relatively unconscious daily shopping behavior (Antonides and Welvaarts, 2020; Berger et al., 2020). Interestingly, the effect of *framing* is larger than the effect of *default rules*. This is surprising as *default rules* seemed much more promising in prior literature and have been investigated several more times and in various contexts (e.g., e-commerce, mobility, food, etc.) compared to *framing.*

Lastly, the combination of *default rules* and *framing* reveals a large effect size (H3a) in promoting energy conservation behavior. When comparing each single DNE with the combination of both, we only found a significant effect comparing the combination with *default rules* (H3b), not when considering the single *framing* compared to both DNEs (H3c). This confirms our assumption that *framing* might help to increase the user's comprehensibility of the pre-selected option by the *default rules*. Similar to Gajewski et al. (2021), who compared *default rules* and *priming*, we strengthen the finding that *default rules* achieve better results if compared with an additional nudge.

Considering the non-significant effect in terms of H3c, apparently, *framing* alone already goes along with a large increase in energy conservation behavior. Hence, the combination did not lead to a significant increase. This again leads to the assumption that in the present study, *framing* overall had a greater impact on the energy conservation behavior than the single DNE *default rules*. However, including *framing* for *default rules* even strengthens its effect.

6.1 Theoretical Contribution

Besides confirming previous research findings on DNEs in the field of the promotion of sustainable behavior and the validation of the efficacy of DNEs in general, this study contributes to the current state of research in several ways. (1) We extend the effort of Kroll et al. (2019), who were the first to test the

DNEs *social norms* and *self-commitment* in a smart home app, hence investigating DNEs to promote daily energy conservation behavior in a digital behavior environment. Compared to the study by Kroll et al. (2019), which did not find any significant effects so far, our study is the first that reveals significant effects of DNEs in smart home apps to promote energy conservation behavior. (2) We analyzed the two missing DNEs out of Lehner et al.'s (2016) list that promotes sustainable behavior by investigating *default rules* and *framing*. We successfully transferred these DNEs into a mobile app domain. The elaborated design of the implementation of the DNEs can serve as a cornerstone for further research. (3) Our results contribute to a clearer understanding of the individual (D)NE and their related effect sizes. We shed light on *framing* as a promising DNE that has received too little attention in prior studies. (4) While the focus of previous studies is predominantly on applying single DNEs, this study performs the first investigation of the combination of *default rules* and *framing*. Consequently, we provide evidence that combining *default rules* with *framing* increases the effect compared to only including *default rules*.

6.2 Practical Implications

Smart home apps are on the rise (Ali and Yusuf, 2018; Statista, 2021), gaining more relevance in our everyday lives and having the power to influence our unconscious decision behavior. We shed light on important design (*framing*) and feature (*default rules*) decisions companies and software developers should consider when creating smart home apps. In this way, they could benefit from a "green image" in addition to their ethical and moral obligations. This opens the opportunity to facilitate sustainable behavior when spreading new digital innovations (e.g., smart home technologies). Insights into behavioral science nudging can help to address and reduce the rebound effect, hence avoiding increasing consumption when introducing new, more energy-efficient technologies. Currently, not all household appliances are yet designed in such a way that they can be controlled via a smart home app (digital environment), nor are household appliances from different manufacturers controllable via one smart home app. However, since our results indicate that the application of DNEs via a smart home app can help to improve energy conservation behavior, government regulations and policymaking should provide the basis for promoting and standardizing the possibilities for implementing such apps. To sum it up, our study recommends using DNEs in smart home apps, namely *default rules*, and *framing*, to promote daily energy conservation behavior. As a result of our addressed behavior changes, consumers could profit from cost savings due to smaller energy bills. Moreover, they are supported by following their responsibility in counteracting climate change by conserving more energy and living more sustainably in their daily lives. Overall, in the long run, by incorporating efficient DNEs, behavior changes can help to reduce energy consumption as one of many factors influencing the ongoing climate change.

6.3 Limitations and Further Research

Like any research paper, our study is subject to limitations. First, experimental approaches lack real-world consequences, such as waiting longer for the dishwasher to finish. Moreover, we did not examine direct app use but screen designs via the online survey tool and described only one scenario (e.g., we did not examine a scenario in which the user wants to turn on the light for work, consequently, might rather decide for brighter options). Additionally, because of the A/B testing approach, there was no actual study of behavior change. Therefore, like all experimental studies, the survey responses in this study are subject to numerous respondent biases – such as social desirability (Furnham, 1986). This could be mitigated, for example, by phrasing questions differently or using a social desirability scale to both identify and control for this factor (van de Mortel, 2008). Supplementary, all results are based on only one measurement. Causal conclusions of any kind can therefore only be drawn to a limited extent since temporality cannot be proven with them. A re-examination with measurement over a more extended period could provide insights into the long-term effect of the DNEs and increase the power of the findings. In this study, we conducted the survey in Germany without a representative sample because of an overrepresentation of the age group between 18 and 35 years, while all other age groups were underrepresented. Even though we argue that this age group is especially suitable for using a smart home app, future studies should consider pre-selecting a balanced sample. Despite the limited degree of representativeness, we rely on sufficiently valid data sets to analyze the online experiment. As O'keefe (2007) suggested, we performed an a-priori power analysis before conducting the online experiment. We calculated a required and total sample size of 180. With 231 participants, this quantity is covered by 128%. We used from the recommendations by Lehner et al. (2016) and Kroll et al. (2019) as well as from the weighted average effect sizes of similar types of interventions aggregated by Osbaldiston and Schott (2012) to set the underlying parameters assumed for effect size and power. In addition, to address the declining power of the study due to the division into four different treatment groups, an even larger sample should be drawn if the study is expanded. Considering the survey design, we assume that the user trusts the predefined program sequences and perceives the additional design elements as described. Beyond that, we do not question the psychological background of the perception of the user interface since there is a separate scientific discourse on this, for example, on technological determinism (Dafoe, 2015; Drew, 2016). Lastly, we analyzed the survey results regarding the participants' demographic data to provide an important first insight into whether the selected DNEs impact energy conservation behavior. However, people do not have a common understanding of climate change and sustainability. Therefore, people's attitudes toward climate change and their need to take action can have an influence on the effectiveness of NEs. Therefore, another limitation of this study is that we have not yet surveyed and evaluated the participants' attitudes towards it, for example, by using the New Ecological Paradigm (NEP) scale (Dunlap et al., 2000).

For further research, we see especially three relevant endeavors. First, based on the promising results of our study, future research could address the challenges faced due to the experimental approach by conducting a field experiment. As our results were encouraging, a field experiment would be worthwhile. Next, further research could include cost-benefit analyses, as only a minority of studies to date have analyzed the benefits and costs of the behavioral interventions in-depth, which is certainly the strongest argument in favor of their implementation. Finally, so far, the application of the DNEs in smart home apps is limited to our efforts on *default rules* and *framing* as well as *social norms* and *self-commitment* by Kroll et al. (2019) without considering the effectiveness of the DNEs dependent on participants' characteristics. Both, an examination of all these four DNEs combined in one study, as well as the consideration of specified characteristics (e.g., the NEP (Dunlap et al., 2000)) could provide interesting results. Even though these NEs are most promising when promoting sustainable behavior (Lehner et al., 2016), additional elements exist. Future research should face the challenge of exploring other DNEs (or their combination) in a similar setup.

7 Conclusion

Due to the substantial share of (residential) daily energy consumption in greenhouse gas emissions and the negative consequences of the rebound effect independent of the energy-efficient technological innovations, the need for behavior changes becomes increasingly more urgent. The proliferation of smart home apps offers a great opportunity to foster behavior change towards energy conservation using DNEs. This study goes beyond existing research as we analyze DNEs in a digital behavior environment – a smart home app. We explore the question of whether energy conservation behavior can be promoted through the DNEs *default rules*, *framing*, and their combination and found significant positive results. Especially, we show large positive effects of *framing* and medium effects of the combination of both compared to the single usage of *default rules*. This study contributes to theory in several ways and provides implications for the practical implementation and design of smart home apps. We encourage researchers to engage in the challenge of transferring more NEs to digital environments and to focus on a digital behavior environment, like smart home apps.

Overall, we hope to contribute to the ongoing research efforts concerning the implementation of DNEs to promote sustainable behavior, hence addressing the human-induced environmental deterioration by the behavior of each individual.

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