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Promoting Energy-Conservation Behavior in a Smart Home App: Kano Analysis of User Satisfaction with Feedback Nudges

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Abstract

Smart home technologies and apps are on a rise. This allows to implement digital nudging elements to foster energy-conservation behavior and, thus, contribute to mitigating climate change. Digital nudging via feedback can be effective in improving energy-conservation behavior, as substantial prior research has shown. However, the investigation of users' preferences concerning feedback nudges is missing. This lack of knowledge is crucial, as user satisfaction influences their continuous app usage, a precondition for achieving positive effects. To close this gap, we perform a structured literature review, categorize the feedback nudge features from extant research, and conduct an online survey. Based on survey data and the Kano model, we analyze the effect of feedback nudge features on user satisfaction. Our study complements the traditional focus on the effectiveness of these nudges with a perspective on user satisfaction. The combination of both perspectives suggests which feedback nudge features should be considered for implementation.

Keywords: Digital Nudging, Feedback, Smart Home Application, Energy Conservation Behavior, User Satisfaction

Introduction

Due to the increasing availability and usage of smart home technologies (He et al., 2021), individuals can connect and intelligently control various household devices, exemplarily the heating system or lighting, by using a smart home application (app). Next to the simple control of various household devices, smart home apps allow for tracking and comparing an individual's energy consumption to others, hence offering the potential to facilitate and motivate users to save more energy. Awareness and reduction of energy consumption are necessary to counteract the challenges of climate change as well as to address political dependencies (International Energy Agency, 2022). While efficient technologies such as energy-efficient heating systems spread in the market, the efficiency gains are out-levered by growing consumption — marking a rebound effect (Sorrell, 2015). This can be because individuals underestimate their energy consumption (Bonan et al., 2021), for example, because of missing information (Callery et al., 2021). As a result, behavioral interventions are needed to influence each individual’s energy consumption.

Prior research focused on the implementation of nudging elements (NEs) in physical environments (e.g., sending energy reports comparing energy consumption to peer groups (Crago et al., 2020)) and digital environments (e.g., the implementation in smart home apps (M. Berger et al., 2022)). Digital nudging elements (DNEs) are seen as a promising type of behavioral intervention (Hummel & Maedche, 2019; Mirsch et al., 2017; Weinmann et al., 2016). (D)NEs aim to improve decision-making without changing economic incentives or restricting individuals’ freedom of choice. In the context of influencing individuals’ energy consumption, smart home apps integrating behavioral interventions bear a great potential to foster energy-conservation behavior (ECB). Prior research on (D)NEs influencing ECB primarily focuses on *feedback nudges* and found overall promising results (e.g., a reduction of energy consumption by 8 to 12% (Karlin et al., 2015)). When investigating *feedback nudges* to foster ECB, prior research configurated the *feedback nudge* differently, for example, by investigating different types of update frequencies (real-time vs. weekly) or different types of energy consumption measurement (e.g., kWh, costs, environmental impact).

While promising insights into the effectiveness of specific *feedback nudge features* (FNFs) already exist, little attention has been paid to the users’ satisfaction and acceptability of these FNFs (Fleury et al., 2018; Gu et al., 2019). The investigation of user satisfaction is essential as it positively influences continuous Information Systems (IS) usage (Bhattacherjee, 2001; Gu et al., 2019; Thong et al., 2006). Beyond, continuous use of smart home apps, in which FNFs are implemented to increase ECB, is crucial to profit from lower energy consumption in the long term. While it is confirmed that user satisfaction contributes to continuance use (e.g., Bhattacherjee, 2001), it is not analyzed how FNFs in a smart home app must be designed to achieve this satisfaction. Therefore, linking the FNFs to user satisfaction is still missing to support continuous smart home app use, hence ECB. Thus, we aim to answer the following research question: *How do potential smart home app users evaluate a broad set of feedback nudge features designed for nudging towards energy conservation behavior?*

To answer this research question, we first perform a structured literature review and develop an overview of FNFs in smart home apps. To categorize the findings, we develop dimensions and verify them via card sorting. Second, using the Kano model, we evaluate users’ perception of these FNFs, that is, whether different FNFs are considered as “must-be,” “one-dimensional,” or “attractive,” or whether users are “indifferent.” We do so via an online survey (n = 188). The paper has several theoretical implications relating to *feedback nudging* in promoting ECB, for example, showing that user satisfaction is important to consider besides effectiveness. Further, this study contributes to which FNFs need to be implemented in smart home apps to encourage individuals to change their ECB. The remainder of this paper is structured as follows: First, we describe the theoretical background, followed by the research process. Then, we present and discuss the results. After outlining the contribution of our work, implications for future research are given.

Theoretical Background

Rising Relevance of Smart Home Apps

Nowadays, households use smart home technologies more commonly; e.g., in the US 35% of the population had already done so in 2021 (He et al. 2021). According to the definition by Gram-Hanssen and Darby (2018, p. 96) a “smart home is one in which a communications network links sensors, appliances, controls, and other devices to allow for remote monitoring and control [...] to provide frequent and regular services to occupants and to the electricity system." In a smart home, users can control and monitor their household appliances through an app which has the potential to facilitate saving energy. This implies a promising response to mitigate the ongoing climate change and reduce political dependencies (International Energy Agency, 2022), especially as households account for a large share of energy consumption.

Technological progress contributes to increasing energy efficiency; an example is household appliances requiring less energy for the same process (Schleich, 2019). However, increasing consumption often exceeds these improvements, leading to the fact that no energy reduction is achieved (rebound effect) (Sorrell, 2015). Therefore, over-reliance on these technologies may bring undesired effects to pro-environmental behavior and reduce the personal responsibility for action because individuals are prone to underestimate their energy consumption (Bonan et al., 2021; Casado-Mansilla et al., 2020). In this context, households' energy consumption is interesting to take a look at, because of the environmental impact and the difficulty of evaluating own behavior due to missing information and feedback (Callery et al., 2021). In this vein, the use of smart home apps can – besides a more pleasant user experience – help to create awareness and to enable the reduction of energy consumption.

Continuous Use of Smart Home Apps that Promote Energy-Conservation Behavior

Existing research has shown using *feedback nudges* in smart home apps promotes ECB (Karlin et al., 2015). To profit from these results in the long term and on a large scale, users must continuously use smart home apps in which feedback is implemented for conserving energy. IS continuance and the intention that users will continue to use these apps and not switch to another control option for smart home technologies (e.g., another app) are influenced by user satisfaction (Bhattacherjee, 2001; Gu et al., 2019; Thong et al., 2006).

Feedback Nudges in a Smart Home App to Promote Energy-Conservation Behavior

Nudging refers to methods of influencing people's behaviors predictably by changing the environment in which they make decisions without limiting their freedom of choice or increasing the cost of alternatives in terms of effort, time, and other factors (Hansen & Jespersen, 2013; Thaler & Sunstein, 2008). Behavior is the result of conscious and unconscious decisions (Kahneman, 2011), also known as Wason and Evans' (1974) dual-process theory. Heuristics and cognitive biases can affect both unconscious, automatic everyday routines and non-automatic, complex decisions. While heuristics aid in quick decision-making, they also make decisions prone to error, resulting in decisions that are disadvantageous to the individual. Nudging leverages knowledge of heuristics and biases to build decision environments that guide behavior (Thaler & Sunstein, 2008). An example of nudging addressing unconscious, automatic decisions is reducing the plate size to decrease calorie intake, whereas nudging addressing reflective thinking includes energy bills with social comparisons (Hansen & Jespersen, 2013). As a result, nudges are likely appropriate for both routine behavior and deliberate, rather complex decisions.

Weinmann et al. (2016) applied these behavioral insights to digital environments, defining digital nudging as the "use of user-interface design elements to guide people's choices or influence users' inputs in online decision environments" (p. 433). The significant advantage of DNEs is that they can be implemented, evaluated, and even personalized quickly and rather cheaply (Weinmann et al., 2016). Furthermore, their efficacy appears promising because, compared to NEs in physical environments (e.g., *feedback* via letter), when using digital screens people spend less time concentrating while reading, are subjected to choice overload, and have shorter periods of sustained attention (Liu, 2005). This lower concentration of reading on digital screens enables to better influence decisions taken in an online environment, hence gives rise to the implementation of DNEs. This is also discussed in persuasive technology literature. Casado-Mansilla et al. (2020) describe the use of DNEs "as a means to persuade or change the overall behavior [of end-users]" (p.2). Meske and Amojo (2020) classify digital nudging as a subcategory of persuasion because both act on influencing users' minds. Research on persuasive technology precedes research on digital nudging. Thus, all DNEs can be seen as persuasion mechanisms, while this is not true vice versa. We take persuasive technology research into account not to miss any DNEs appearing in this research stream that may not explicitly be designated as a subcategory of digital nudging. With the ongoing shift of individuals' decisions towards digital environments, such as managing a heating system via digital control systems (Li et al., 2021), digital nudging proposes a promising possibility of changing behavior. Prior research demonstrates the promising effectiveness of DNEs in changing behavior toward ecological sustainability (Lehner et al. 2016).

There are several DNE conceptualizations in the literature (Weinmann et al. 2016; Mirsch et al. 2017; Lehner et al. 2016). One conceptualization is the *feedback nudge* which is the focus of this paper. The *feedback nudge* is defined as encouraging people to consider whether their behavior was good or could be improved by highlighting the consequences of the individual's decisions (Cappa et al., 2020). Thus, *feedback* overcomes inertia or procrastination and, therefore, can be used to motivate people (Sunstein, 2014). Examples include *feedback* of the own energy consumption presented on smart home displays (Schultz et al., 2015) or energy consumption of similar consumers displayed in a web portal (Loock et al., 2012). The *feedback nudge* has been intensively studied in the last decades for promoting ECB and received increasing attention because of improving sensing technology and energy infrastructure that better allows collecting and proceeding data and quickly sending it to the user (Karlin et al., 2015; Loock et al., 2012). The work of Karlin et al. (2015) presents the effects of *feedback* on ECB by conducting a meta-analysis and found overall promising results with an average energy saving of 8% to 12%. When conducting the meta-analysis, Karlin et al. (2015) summarize that studies differ in FNFs, for example, in the frequency of updated and pushed information on energy consumption or the type of energy measurement. Empirical evidence on single FNFs exists; still, research misses an overarching overview of FNFs to promote ECB and an understanding of the effect of FNFs on user satisfaction.

User Satisfaction to Increase Smart Home App Continuous Use

User satisfaction plays a central role in customer retention and continuous IS use (Bhattacherjee 2001; Thong et al. 2006). Continuous IS use is critical for many businesses (Bhattacherjee, 2001). In the context of smart home, the costs of acquiring new customers vs. retaining existing ones might play a smaller role. But the potential of increasing ECB through the continued use of a smart home app (e.g., through the DNE *feedback*) becomes central as the user can thus contribute to climate change mitigation as well as save money on heating costs, for example. This can even be used for advertising purposes and lead to competitive advantages due to increasing environmental awareness of individuals. This emphasizes the importance of customer retention in a smart home app context. Next to IS specific research focusing on smart home technologies, Gu et al. (2019) found that user satisfaction significantly and positively influences the intention to continue using a smart home, including smart home apps. Accordingly, an aim is to maximize user satisfaction of smart home app users, which influences continuous smart home app usage that includes features incentivizing ECB (Bhattacherjee, 2001; Chun-Hua et al., 2016; Gu et al., 2019). However, so far, it remains unclear which FNFs contribute to user satisfaction.

Simply fulfilling users' expectations does not necessarily lead to user satisfaction. The different users' expectations influence the perceived service or product evaluation and thus the respective user satisfaction (Matzler et al., 1996). As a result, research has offered method-independent empirical evidence for the assumption that the user satisfaction construct is multi-factorial (Hölzing, 2008). Bartikowski and Llosa (2004) examine methods for capturing user satisfaction with specific product or service attributes, including the Kano theory of user satisfaction (Kano model). Kano (1984) developed the Kano model, which has been discussed and applied in several theoretical and empirical research projects (Füller & Matzler, 2008; Löfgren & Witell, 2008). We chose the Kano model because it offers a comprehensive method for analyzing the impact of product or service attributes (i.e., features) on user satisfaction. The Kano model provides a straightforward categorization that can be appropriately used in both theoretical and practical contexts. Furthermore, using the Kano model to evaluate user satisfaction with digital products or services such as mobile applications can already be considered a common practice (e.g., see Gimpel et al. (2021) for an application to a mobile health application and Gimpel et al. (2018) for an application to data privacy measures). The Kano model describes user satisfaction in terms of the degree to which specific product or service features are implemented or available (Kano, 1984). The model distinguishes four main categories of features: attractive quality (delighter), one-dimensional quality (performance need), must-be quality (basic need), and indifferent quality (Matzler et al., 1996). Attractive qualities can inspire users, but as they are not expected, a lack of attractive qualities does not create dissatisfaction while their existence increases satisfaction. One-dimensional qualities are explicitly demanded by users and influence satisfaction in both ways. Must-be qualities are taken for granted and the user only becomes aware of them once they are missing. While they cannot increase satisfaction, users get dissatisfied if must-be qualities are missing.

Lastly, indifferent qualities do not lead to satisfaction or dissatisfaction, whether they are present or not. In Table 1 we list these four categories of features, and Supplemental Material A[1] describes their nature.

Categorization	Users' expectations	Effect on satisfaction	
		if implemented	if not implemented
Attractive quality (delighter)	Users do not expect implementation of feature	positive	none
One-dimensional quality (performance need)	Users explicitly demand implementation of feature	positive	negative
Must-be quality (basic need)	Users implicitly demand implementation of feature	none	negative
Indifferent quality	Users are indifferent to implementation of feature	none	none

Table 1. List of the Kano model factors as described by Matzler et al. (1996)

Research Process

To answer our research question, we first conduct a structured literature review to identify different FNFs. Next, we develop dimensions for the identified FNFs and verify their validity via card sorting. Each FNF can be described in a differentiated manner, making the Kano model the tool of choice for the evaluation of user satisfaction with each of the FNFs individually. To determine whether FNFs are considered "must-be," "one-dimensional," or "attractive" qualities, or whether users are "indifferent", we conduct an online survey.

Identification of Feedback Nudge Features

Structured Literature Review

We conducted a structured literature review following Webster and Watson (2002) and vom Brocke et al. (2015) to gain insights about *feedback* as a NE applied to the context of ECB. The process consists of three phases: (1) literature search, (2) selection, and (3) synthesis (vom Brocke et al., 2015).

(1) We chose a broad search string to get an overview of existing research on the usage of *feedback nudges* to promote ECB, but also to gain insights about all NEs used to promote ECB (Figure 1). This was done to assess whether *feedback nudges* are the most relevant NEs in the specific context, which was assumed, but not verified so far. In addition, this approach made sure that NEs not termed *feedback* in the extant literature, but falling under our definition of *feedback nudge*, are not missed. Even though we focus on IS research, we searched in all research fields in the databases *AISeL*, *Web of Science,* and *EBSCO Host* as the research topic is interdisciplinary. The search string's first part *nudg* OR persuasive* considers NEs and persuasive systems as these concepts are similar and NEs may occur in persuasive technology literature without being denominated as such. For example, one persuasion strategy to promote ECB defined by Casado-Mansilla et al. (2020) is the comparison of the own ECB with the respective performance of peers, which is analyzed under the term of DNE in other studies (e.g., Crago et al., 2020). Thus, we consider the literature on persuasive technology as an important thread for our research. The second part, *energy OR electricity* limits potentially relevant articles to the area of application in the energy domain. The third part *conserv* OR sav* OR use OR consum* OR efficien** integrates the notion of conservation behavior (based on Karlin et al. (2015)). The search string was applied to topics, abstracts, titles, and keywords. We put filters for peer-reviewed full research articles in the English language published in the last five years (2017-2021) to focus on the most relevant recent studies in addition to established meta-analysis and literature reviews considering literature prior to our time span (e.g., Karlin et al., 2015). In total, the search yielded 606 hits.

(2) After removing duplicates, a three-step selection process comprising title and abstract screening and full reading was conducted (Figure 1) based on the following priorly determined inclusion criteria (Webster &

[1] https://bit.ly/38DWZCH

Watson, 2002): (1) the focus lies on promoting ECB of individuals, (2) the paper researches at least one nudging or persuasive system design element, (3) both analog and digital environments of implementation are relevant, as we wanted to include all forms of nudging currently researched in the field, and (4) an application to a smart home app in the energy-conservation context is conceivable. Defined exclusion criteria are: (1) the paper focuses on gamification elements and (2) the paper's main goal is to discuss the ethical justifiability of nudging. Afterward, we complemented the results by backward and forward searches performed for identified seminal papers. Thus, we considered meta-analyses and systematic literature reviews in the domain (vom Brocke et al., 2015) (Figure 1). This approach ensures that the state-of-the-art prior to the time span of the literature review is also considered and reflected in the review's results.

(3) Out of the final 58 articles, only six did not focus on *feedback* or a combination of *feedback* with other NEs. This leads to the observation, that *feedback* is the most researched NE in the ECB context. Supplemental Material B and Supplemental Material C give an overview of the FNFs elaborated through this systematic literature review. Some appeared with high frequency, such as whether *feedback* was given in real-time or visualized over time, and others were less frequent, as is the case for the visualization in comparison to the previous year's energy consumption. We evaluated the list of FNFs derived from the literature regarding the proposed evaluation criteria by Sonnenberg and vom Brocke (2012) within the author team and with an industry expert of smart home apps. We concluded that the initial list was not complete and added two more FNFs (D3 and F2 in Supplemental Material C). The final list has 25 FNFs.

(nudg* OR persuasive) AND (energy OR electricity) AND (conserv* OR sav* OR use OR consum* OR efficien*)		
Application to Databases	Web of Science: 532, EBSCO Host: 72, AISeL: 2	= 606 articles
Removal of Duplicates	- 52 duplicates	= 554 articles
Title & Abstract Screening	Inclusion and exclusion criteria, - 476 articles	= 78 articles
Backward/ Forward Search	For seminal papers, + 33 articles	= 111 articles
Full Text Screening	- 59 articles	= 58 articles
Only feedback NEs	- 6 articles (other NEs only)	= 52 articles

Figure 1. Structured literature review

Categorization and Card Sorting

We defined overarching dimensions (Supplemental Material C) to cluster the FNFs for preparing the survey (based on Schaffer and Fang (2018)). Card sorting was executed to validate the categorization by eight fellow IS researchers. To develop a dimension, we focused on the FNFs' main characteristic and clustered them based on similarity. For example, dimension A (*update frequency*) consists of the two FNFs *near real-time* (A1) and *periodically* (A2), where the focus clearly lies on the frequency the feedback is updated. We only asked the IS researchers to assign 16 out of 25 FNFs to an overarching dimension via card sorting as the dimension of the remaining 9 FNFs is already predefined in prior literature: *social comparison*. The FNFs in this dimension compare the user's energy consumption to a specific peer group. Even though only 16 out of the 25 FNFs were included in the card sorting procedure, all 25 FNFs are considered for the following survey. We defined overarching dimensions for the 16 FNFs where no dimension was stated in literature so far. We verified the validity of our determined dimensions with the help of closed card sorting, a setup in which it is not possible for the participant to add new dimensions other than the predetermined ones. Card sorting unhides hierarchies, allowing for the adjustment of predetermined dimensions (Capra, 2005; Maida et al., 2012). Following the approach of Capra (2005) and Maida et al. (2012), we based the FNFs' assignment on a dimension of relatedness. Therefore, names and short clarifying descriptions for each dimension were elaborated grasping its main concept. The IS researchers were asked to assign the randomly ordered FNFs to one of the dimensions with the related description. Following the approach of Schaffer and Fang (2018), an option with the name "I cannot assign this feature to any of the other dimensions" was added, so that participants were not forced to categorize FNFs into the predetermined dimensions when they did not see any fit or when they couldn't decide between the given options.

The strength of agreement between the participants is moderate, as indicated by a Fleiss' Kappa of 0.57 (Landis & Koch, 1977). Most FNFs were assigned to our predefined dimensions. Nevertheless, the results indicate that the difference between the dimensions *visualization* and *display unit* was not clear enough.

FNFs from both dimensions were frequently assigned to the respective other. Thus, the card sorting shows our intended dimensions need to be revised. As a result, the dimensions *visualization* and *display unit* were merged to one dimension *visualization and display unit* which corresponds to dimension B in our list (see Supplemental Material C). Finally, we have six dimensions instead of the previously conceived seven where each of our 25 FNFs can be clearly assigned. After the merge, Fleiss' Kappa was 0,61, indicating substantial agreement (Landis & Koch, 1977).

Evaluation of Users' Satisfaction of Feedback Nudge Features

Implementation of the Kano Model

When applying the Kano model, it is most common to use a two-question approach, consisting of a functional and a dysfunctional question (Löfgren & Witell, 2008). Survey participants are first asked about their evaluation of the hypothetical case in which a specific FNF is implemented (functional question) and a case in which it is not (dysfunctional question). Each time, they can choose one of five possible answers (see Table 2). These answers do not represent a level of acceptance and are not scaled ordinal. The classification of the FNFs into the above-mentioned categories (see Table 1) depends on the users' answers to both questions (see Table 2). As proposed by Matzler et al. (1996), we stem the final classification of a FNF based on the respective most frequent individual result. To avoid unjust representations in case the shares of the most frequently chosen categories are close together (Schaule, 2014), we determine the categorization significance (Gimpel et al., 2018; Schaule, 2014). Lee and Newcomb (1997) propose the use of the variable category strength, which is determined by subtracting the share of the second most frequently chosen category from the share of the most frequently chosen one. With a category strength greater than 6%, the classification to only one category is justified. To determine significance more accurately, we complement the use of the category strength with the approach of Fong (1996). The Fong test calculates a reference value based on observed frequencies and the sample size and assumes significance in case the category strength is higher. If the Fong test does not prove significance, C. Berger et al. (1993) propose to apply the (A, O, M) < > (I, R, Q) rule. The first group consists of the categorizations A (attractive), O (one-dimensional), and M (must-be) having the power to influence user satisfaction. The second group consists of the categorizations I (indifferent), R (reverse), and Q (questionable) not influencing user satisfaction. The rule can be applied if one of the two most frequently mentioned categorizations belongs to one group and the second one belongs to the other group. In case the rule is applicable, the most frequently chosen categorization within the dominant group (>50%) is selected. For the cases where category strength is not significant at the ten-percent level according to the Fong test (Gimpel et al., 2021), and the (A, O, M) < > (I, R, Q) rule is not applicable, the feature will be assigned to a mixed category following Lee and Newcomb (1997). A mixed category includes all categories that do not significantly differ compared to the most frequently chosen category according to the Fong test (Gimpel et al., 2021). To further analyze a mixed category, Hölzing (2008) uses its total strength to influence user satisfaction (A+O+M). A dynamic view of the qualities is recommended: What the user might be indifferent to today, may soon be a must-be quality (Hölzing, 2008).

		Dysfunctional answer						Legend
		(1)	(2)	(3)	(4)	(5)		O = One-dimensional quality
Functional answer	I like it that way. (1)	Q	A	A	A	O		A = Attractive quality
	It must be that way. (2)	R	I	I	I	M		M = Must-be quality
	I am neutral. (3)	R	I	I	I	M		I = Indifferent quality
	I can live with it that way. (4)	R	I	I	I	M		R = Reverse quality
	I dislike it that way. (5)	R	R	R	R	Q		Q = Questionable result

Table 2. Derivation of Kano model factors based on Matzler et al. (1996)

For better visualization and verification of the survey results, we take a second, continuous approach by calculating the satisfaction and dissatisfaction coefficients (C. Berger et al., 1993; Schaule, 2014). The satisfaction coefficient (value between 0 and 1) is calculated by the sum of all participants that categorized a feature as a factor able to increase their satisfaction (i.e., attractive and one-dimensional quality) divided by the sum of all participants that categorized a feature as attractive, one-dimensional, must-be or indifferent. The dissatisfaction coefficient (value between -1 and 0) differs in that it takes the factors that can decrease satisfaction, thus of must-be and one-dimensional quality, into the numerator. The explanatory power of these coefficients is the mean importance of features over all participants for both improving satisfaction and avoiding dissatisfaction. We provide the results in Supplemental Material B.

Survey

To evaluate users' satisfaction with FNFs, we conducted an online survey using Lime Survey. To ensure high-quality results, we first ran a pretest with four IS researchers and one industry expert followed by the main survey. Using the insights of the pretest, we modified the survey by giving further explanations, deleting redundant information, and rephrasing unclear questions.

After welcoming the participants, we explained smart home and presented screenshots of a fictional smart home app to ensure that all participants have the same understanding of the context (M. Berger et al., 2022). In the main part, participants were put into the situation to evaluate the potential FNFs concerning their ECB. For each of the 25 FNFs, the participants answered the pair of functional and dysfunctional questions (Supplemental Material C). As we conducted the survey in German, the translation of the five answer options previously presented by Hölzing (2008) was used. Between the questions for FNFs F7 and F8, we integrated a trap question to see whether participants complete the survey attentively. In the last part, we queried sociodemographic background.

We recruited via social media and e-mail. The survey was completed by 206 German-speaking participants. After filtering for participants, that correctly answered the trap question, the final sample consists of 188 participants. The sample consists of students (28.7%), employees (56.4%), retirees and people that are unable to work (4.3%), civil servants (3.7%), and others (6.9%). The participants' age ranges from 18 to 72 years with an average of 33.2 years. Men (46.3%), women (53.2%) and non-binary people (0.5%) completed the survey. The share of participants, who already use a smart home app, is 31.4%.

Results

Feedback Nudge Features

Table 3 gives an overview of the 25 identified FNFs (primarily from the structured literature review), categorized into six dimensions A-F (please find a detailed description of each dimension in Supplemental Material C). For each FNF, a description is provided. Generally, FNFs are not mutually excluding and can be implemented together. Thus, when using them in smart home app design, any number of FNFs can be chosen for implementation and every possible combination of FNFs is conceivable. The only exception is dimension A (*update frequency*), where the implementation of only one FNF is more useful to keep the implementation effort low. For dimension F (*social comparison*) it seems most convenient to implement only one or two FNFs to avoid overwhelming the user with information.

In bold: Dimension, in plain font: FNFs		Description of FNFs
A. Update frequency		
A1	Near real-time	Energy consumption is updated at short time intervals (e.g., every 30 minutes).
A2	Periodically	Energy consumption is updated on a weekly basis.
B. Visualization and display unit		
B1	Over time	Energy consumption is visualized in a graph over a certain period of time, e.g., over the last months/ weeks/ days/ hours.
B2	Previous year's energy consumption	The monthly energy consumption is compared to the energy consumption in the same month exactly one year ago.
B3	Comparison with similar housing situation	Energy consumption is compared to the standard and visualized based on input parameters, e.g., household size or occupied square meters.
B4	Display in kWh	Energy consumption is displayed in kilowatt-hours.

B5	Display in Euro	Energy consumption is displayed in costs incurred for the app user.
B6	Display of the environmental impact	Energy consumption is displayed in CO_2 emissions.
C. Level of coverage/granularity		
C1	Overview of all devices	An overview value for all appliances indicates energy consumption.
C2	Appliance-specific	Energy consumption is measured and indicated for each appliance individually, e.g., lighting, dishwasher, washing machine, heating.
D. Push notifications		
D1	High energy consumption	Push notifications alert to current high energy consumption.
D2	Peak energy consumption period	Push notifications alert to peak energy consumption periods.
D3	High proportion of green electricity in the energy grid	Push notifications alert to times when a lot of electricity from renewable sources is available in the energy grid.
E. Saving opportunities		
E1	Technical advice	Technical advice for a more energy-efficient use of appliances is given.
E2	Financial savings	Possible financial savings from reducing energy consumption are given.
E3	Environmental contribution	The possible environmental contribution of reducing energy consumption is shown in corresponding CO_2 emissions.
F. Social comparison		
F1	Average - all	Energy consumption is compared with the average of all app users.
F2	Most efficient - all	Energy consumption is compared with that of the most efficient app users (e.g., the upper 15%).
F3	Average - similar housing situation	Energy consumption is compared with the average of other app users with similar input parameters, e.g., household size, occupied square meters.
F4	Most efficient - similar housing situation	Energy consumption is compared with that of the most efficient app users (e.g., the upper 15%) with similar input parameters (e.g., household size, occupied square meters).
F5	Average - neighborhood	Energy consumption is compared with the average of app users in the neighborhood.
F6	Most efficient - neighborhood	Energy consumption is compared with the most efficient app users (e.g., the upper 15%) in the neighborhood.
F7	Average - network	Energy consumption is compared to the average of app users in a network (e.g., friends or relatives).
F8	Most efficient - network	Energy consumption is compared with that of the most efficient app users (e.g., the upper 15%) in a network (e.g., friends or relatives).
F9	Ranking	Energy consumption is given in the form of a ranking of app users.

Table 3. The elaborated FNFs assigned to the dimensions (A-F) including descriptions

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The results of our analysis based on the Kano model are shown in Table 4. For each FNF, we present the category strength and the final categorization as one of the Kano model factors. We illustrate the process of finding the final categorization for FNF B1. Its category strength (subtracting the sum of the second most frequently chosen categorization M from the most frequently chosen categorization O) is merely 1%. This category strength is not significant according to the Fong test (Fong, 1996). In the next step, we check whether the (A,O,M) < > (I,R,Q) rule can be applied. It is not applicable as both, the most and the second most frequently chosen factor, belong to the (A,O,M) group. Consequently, the FNF is assigned to a mixed group and all four categorizations are listed in the order of descending frequency of occurrence.

#	**Dimension** and FNF	Category strength	Catego-rization
A	**Update frequency**		
A1	Near real-time	20%*	I
A2	Periodically	8%*	M
B	**Visualization and display unit**		
B1	Over time	1%[2]	O,M,A,I
B2	Previous year's energy consumption	5%[1]	A
B3	Comparison with similar housing situation	3%[1]	A
B4	Display in kWh	18%*	M
B5	Display in Euro	9%*	A
B6	Display of the environmental impact	14%*	M
C	**Level of coverage/granularity**		
C1	Overview of all devices	11%*	A
C2	Appliance-specific	4%[1]	A
D	**Push notifications**		
D1	High energy consumption	2%[1]	A
D2	Peak energy consumption period	6%[1]	I
D3	High proportion of green electricity in the energy grid	17%*	A
E	**Saving opportunities**		
E1	Technical advice	3%[1]	A
E2	Financial savings	8%[1]	A
E3	Environmental contribution	5%[1]	A
F	**Social comparison**		
F1	Average - all	47%*	I
F2	Most efficient - all	60%*	I
F3	Average - similar housing situation	5%[1]	A
F4	Most efficient - similar housing situation	38%*	I
F5	Average - neighborhood	44%*	I
F6	Most efficient - neighborhood	50%*	I
F7	Average - network	28%*	I
F8	Most efficient - network	51%*	I
F9	Ranking	31%*	I

Legend	
* =	Categorization significant at ten-percent level according to Fong test
[1] =	(A,O,M) < > (I,R,Q) rule applicable
[2] =	(A,O,M) < > (I,R,Q) rule not applicable
A =	Attractive quality
O =	One-dimensional quality
M =	Must-be quality
I =	Indifferent quality

Table 4. Empirical results of the FNFs' evaluation via the Kano model

In total, ten FNFs are considered by the participants to be of indifferent quality which means, that no distinctive interpretations toward any direction can be done. Three out of the 25 FNFs are categorized as must-be qualities (i.e., if implemented with no effect, if not implemented with a negative effect on user satisfaction): updated *periodically* (A2), *display in kWh* (B4), and *display of the environmental impact* (B6). No FNF can directly be categorized as one-dimensional quality (i.e., if implemented with a positive, if not implemented with a negative effect on user satisfaction). However, *visualization over time* (B1), the only FNF assigned to the mixed category, is most frequently categorized as one-dimensional quality. Finally, eleven FNFs are categorized as attractive qualities (i.e., if implemented with a positive, if not implemented with no effect on user satisfaction). All FNFs belonging to the dimensions *level of coverage/granularity* (C) and *saving opportunities* (E) can be attractive to users. More attractive FNFs can be found in the dimensions *visualization and display unit* (B), *push notifications* (D), and *social comparison* (F).

To further analyze the survey results, we visualized the FNFs' categorization in a satisfaction-dissatisfaction diagram (Supplemental Material D), indicating a low share of FNFs categorized as must-be and one-dimensional qualities and high shares of FNFs that participants see as indifferent or attractive qualities. Eight out of nine FNFs of the dimension *social comparison* (F) appear in a well-separated cluster, indicating an overall evaluation of indifference by participants. The diagram further shows that FNFs categorized as attractive quality are closer to a value of 0.5 than 1.0 indicating relatively low category strengths. Thus, FNFs of attractive quality were also frequently assigned to other categories by participants.

Consequently, it is considered worth complementing these results with a more detailed look at the categorization of FNFs per participant. Table 5 presents the minimum, median, mean, and maximum count of categorizations as a specific factor of the Kano model on participant-level. For example, participants saw an average of 6.3 out of 25 FNFs as an attractive quality; at least one participant evaluated even 20 FNFs as attractive quality. Furthermore, the shares of participants who categorized zero or at least ten FNFs as one of the six factors are indicated. With 56% of participants who categorized at least ten FNFs as indifferent quality, this factor is strongest. However, only 11% of participants evaluated none of the FNFs as attractive which implies that overall, *feedback nudges* to promote ECB have a significant impact on the satisfaction of a very large share of users: For 89% of participants, the FNFs had the possibility to improve their satisfaction within the smart home app (see Table 5).

	min	med	mean	max	none	>=10
Attractive quality	0	6	6.3	20	11%	25%
One-dimensional quality	0	2	3.0	25	24%	8%
Must-be quality	0	3	3.1	17	15%	2%
Indifferent quality	0	10	10.2	24	1%	56%
Reverse quality	0	1	2.1	15	45%	4%
Questionable result	0	0	0.2	2	84%	0%

Table 5. Statistics of categorizations per Kano model factor and participant

Discussion

The realization of the FNFs categorized as must-be quality may be considered a prerequisite for smart home apps, as they lead to user dissatisfaction if not implemented. Three FNFs were assigned as must-be qualities: updated *periodically* (A2), *display in kWh* (B4), and *display of the environmental impact* (B6). Additionally, the FNF B1 (*visualization over time)* is assigned to both categories, must-be (32.5%) and one-dimensional quality (33%). Both categories lead to user dissatisfaction if not implemented and should therefore be in focus. Hence, we regard all four FNFs (A2, B4, B6, and B1) as FNFs that should be implemented to avoid user dissatisfaction, which negatively influences continuous app usage (Bhattacherjee, 2001). Regarding FNF B1 (*visualization over time*), Karlin et al. (2015) and Chatzigeorgiou and Andreou (2021) state that nowadays, the comparison with historical values is considered a standard for energy-conservation intervention. This goes along with our findings. Additionally, the FNF B6 *(display of the environmental impact)* opens an interesting discussion. The result of being a must-be quality is consistent with the findings of Nolan et al. (2008) who state that users cite concerns about the environment as a key motivator to engage in ECB, hence users expect it as a FNF in a smart home app. Also, Nolan et al. (2008) found that it is less effective in promoting ECB compared to other FNFs. This is an important and interesting finding as it implies that only focusing on FNFs that are efficient in promoting ECB, and therefore disregarding for example F6 *(display of the environmental impact)* jeopardizes user satisfaction, and hence continuous app usage (Bhattacherjee, 2001). It is therefore essential to integrate must-be FNFs next to effective FNFs to enable long-term effects on ECB through continuous app usage.

Next up are FNFs of attractive quality. Users would not miss them but may be delighted by them. Hence, their implementation implies the opportunity to please the user. Attractive quality FNFs are the largest group (11 out of 25) and open the opportunity to individualize the app based on the FNFs that provide user satisfaction for the individual (e.g., implementing a *comparison with similar housing situation* (B3) or *push notification on high energy consumption* (D1)). These FNFs are not expected by users and can therefore be implemented optionally. At this point, our results emphasize individualization and personalization as prior research mentioned (Buckley, 2020). The app can either allow the user to add or delete individual FNFs him- or herself or already make this arrangement based on user information. This is especially relevant for the FNFs categorized as attractive quality as our survey indicates relatively low category strengths which means that participants also assign these FNFs frequently to other categories.

Finally, ten FNFs being of indifferent quality do not influence user satisfaction. This means that the user is not interested in including these FNFs, for example, in a personalized set of FNFs in a smart home app. But our results provide important insights into which FNFs should be focused on if it influences ECB and is additionally easy to implement. Out of the ten indifferent FNFs, eight belong to dimension F (*social comparison*). In academic literature, the effect of FNFs belonging to the dimension *social comparison* (F) is discussed controversially. Karlin et al. (2015) as well as the literature review of Fischer (2008) point out that no effect could be found regarding the effect of *social comparison* on ECB. In contrast, in our literature review, we identified studies that measured effect sizes for different FNFs of the dimension *social comparison*, for example, Brülisauer et al. (2020) and Nemati and Penn (2020). As the second-mentioned studies have been published recently, the observation that features may change the categorization throughout time (Hölzing, 2008) should be considered. Additionally, academic research is — to the best of our knowledge — still missing to compare the effect size of different *social comparison* FNFs. Therefore, further investigation is needed here if conclusions are to be drawn about the implementation of *social comparison* FNFs. Another FNF of indifferent quality is whether *feedback* is updated in *near real-time* (A1). As this FNF has no impact on user satisfaction, it may or may not be implemented depending on the implementation effort (e.g., availability of real-time data, continuous connection to the network). The last FNF which is categorized indifferent is a push notification that alerts the user *peak energy consumption periods* (D2). However, the literature indicates that push notifications for peak load times can contribute to users' ECB (Di Cosmo & O'Hora, 2017; Jorgensen et al., 2021). In this context, especially the period in which the push notification is displayed to the user is decisive (Jorgensen et al., 2021).

Focusing on the results of FNFs in each dimension, we found that concerning the *update frequency* (dimension A), users only expect the app to deliver feedback *periodically* (A2, must-be quality) while being indifferent about *near real-time feedback* (A1, indifferent quality). As pointed out by Karlin et al. (2015), it is important to note that researchers differ in their definition of how often the feedback is updated vs. how often users receive the feedback. As dimension A refers to the former, the results implicate that users do not expect to always see real-time data on their energy consumption, which should simplify the app development and overall set-up of the smart home as continuous real-time data availability is not necessary.

The dimension *visualization and display unit* (B) is of specific importance to users as every FNF influences user satisfaction. The FNFs *display in kWh* (B4) and *display of the environmental impact* (B6) considered as must-be qualities as well as the FNF *visualization over time* (B1) considered in a mixed category (must-be and one-dimensional) are all recommended for implementation as it is expected as a standard in this context (Chatzigeorgiou & Andreou, 2021; Karlin et al., 2015) while not necessarily affecting ECB. Karlin et al. (2015) found that the comparison with historical values, in our case FNFs B1 and B2, does not impact feedback effectiveness. The remaining FNFs of this category (*previous year's energy consumption* (B2), *comparison with similar housing situation* (B3), and *display in Euro* (B5)) are evaluated as attractive qualities, which have the potential to increase user satisfaction and should therefore be configurated individually if the user is interested in these *visualization and display* options.

Both FNFs of the dimension *level of coverage/granularity* (C), namely *overview of all appliances* (C1) and *appliance-specific feedback* (C2) are viewed by the participants as attractive qualities, while none of them is categorized as must-be quality. Karlin et al. (2015) study the same levels of granularity and found that more granular feedback for specific appliances rather than on the whole-home level did not have a positive effect on ECB. They argue that this might be due to lacking knowledge of what to do with the granular information and that it is only relevant to them at particular points in time and not generally. Our data, therefore, rather suggest implementing FNF C1 as the effort of providing more granular appliance feedback does not pay off positively in terms of user satisfaction or environmental benefit (ECB).

Push notifications (D) consist of the indifferent FNF *peak energy consumption period* (D2) and two FNFs considered as attractive qualities: *high energy consumption* (D1) and *high proportion of green electricity in the grid* (D3). The implementation of *push notifications* is therefore optional. But considering the two attractive FNFs, we observe that the latter was the FNF with the highest share of participants seeing it as attractive quality (41.5%) throughout the whole set of the 25 FNFs. Thus, its implementation might delight a large share of users.

Similar accounts for *saving opportunities* (E) as all FNFs are categorized as attractive qualities, the implementation is optional without risking user dissatisfaction. Prior research provides different outcomes so far on the effect of messaging on *saving opportunities* (E). In their meta-analysis, Karlin et al. (2015) found that price messaging did not lead to ECB, but the combination with external incentives or goal-setting did increase ECB. In a more recent study, Mi et al. (2020) found a 14% increase in household energy saving of cost-benefit feedback (E2) compared to the control group. Therefore, implementing these FNFs in a smart home app additionally to FNFs that generate user satisfaction seems promising. In addition, these FNFs can be connected to external incentives or goal-setting nudging to reach even more promising results.

Lastly, the dimension *social comparison* (F) is mostly categorized as indifferent quality, therefore its FNFs' implementation should depend on the promising effect on ECB (as discussed above). Only the FNF F3 (*average - similar housing situation*) is categorized as attractive quality, hence bearing the potential to increase user satisfaction. Prior studies found positive effects on implementing F3 to increase ECB (Mukai et al., 2022; Sudarshan, 2017), emphasizing the possibility, that the user can optionally add this FNF.

Theoretical Contributions

This paper contributes to the body of knowledge about digital nudging to promote ECB. Specifically, it focuses on FNFs in a smart home app. In academic and practitioner-oriented literature, the promotion of ECB by using different DNEs as well as nudges in analog settings has been studied in depth. Until now, little research has been done using smart home apps as the digital interface (M. Berger et al., 2022). Yet, this specific interface is important as it is increasingly used, relates to major energy-related decisions (esp. heating, air conditioning, electricity), and cannot be assumed to be perceived like other interfaces. We shed light on the upside of nudging through *feedback* beyond its mere informative value. Our paper consists of four main contributions.

First, we provide insights into different FNFs that have been investigated in relation to ECB. We consolidate existing knowledge and provide an overview of dimensions with FNFs that can be regarded when investigating *feedback nudges* in smart home apps. Second, we link different FNFs to user satisfaction, which we state to support continuous usage based on known IS literature (Bhattacherjee, 2001; Thong et al., 2006). By conducting a survey based on the Kano model, we shed light on different users' expectations and their influence on user satisfaction. We especially point out, that next to the focus on FNFs that were shown to have significant positive effects on ECB, it is important to also implement FNFs that are considered as must-be qualities by users. Neglecting them due to a lack of efficiency in improving behavior would reduce user satisfaction. Must-be qualities support continuous smart home app usage, which in the long run, can lead to ECB. Third, by pointing out FNFs that belong to attractive qualities, being optional FNFs that can be personalized by each individual user, we offer possibilities to integrate personalization and individualization in a smart home app. Lastly, having FNFs that are categorized as indifferent qualities, we point out further investigation to focus on these FNFs that provide the largest effect on ECB, as they do not impact user satisfaction at all.

In summary, besides the effectiveness of nudges in steering behavior, their effect on user satisfaction is important. Our work complements the traditional focus on DNEs' effectiveness with a perspective on user satisfaction. Users' evaluation of FNFs as presented in this paper is a point of orientation for researchers who study *feedback* for ECB in smart home apps, but also in the broader context of digital interfaces.

Practical Implications

As smart home technologies are already widely used in many households, the use of smart home apps controlling these technologies to influence ECB is nearby. With the findings of this paper, we provide practitioners with an overview of which FNFs may be implemented in a smart home app to generate user satisfaction and thereby support the continuous use of smart home apps. Since FNFs can have a large implementation overhead, especially regarding the temporal resolution and data privacy issues, for example when comparing individuals' values with comparative values from neighbors, it is very helpful to know which FNFs really contribute to user satisfaction. As smart home apps should not be overloaded with FNFs, our findings also present a selection of FNFs that are best implemented optionally in a personalized area so that users can personally decide to activate them (FNFs with attractive qualities). To define which FNFs should be available for this personalized area our results in combination with the literature regarding effectiveness should be analyzed (see the Discussion section).

Limitations and Future Research

Researchers and practitioners should be aware of the following limitations. The presented FNFs were derived from a systematic literature review that considered publications in academic literature throughout the past five years (2017-2021), combined with a forward and backward search to access established FNFs. We discuss the findings in terms of completeness with an industry expert. Yet, the findings could be further complemented by practical insights. Additionally, according to the Kano model survey procedure participants answered a functional and a dysfunctional question for each of the 25 FNFs which is quite lengthy. This may have influenced the concentration of participants and might partially explain the high dropout rate (out of 328 participants, 122 (37%) dropped out throughout the process). Additionally, the effect of the FNF B1 (*visualization over time*) on user satisfaction is not clear since B1 is the only FNF in a mixed category. In our study we made no distinction between the time horizon in which the visualization is displayed, we only asked about a "visualization over time" and named the examples months, weeks, days, or hours. To make a more precise analysis, differentiation between various time horizons is necessary, which might resolve the mixed categorization of B1. Lastly, the approach lacks real-world consequences. When going through the survey, participants had to imagine how each FNF could look like and might understand the given descriptions of the FNFs differently. In our setup, participants only had to evaluate each FNF once. In real-life situations when they are nudged by the FNFs every time they open the app, the results might differ. Lastly, when interpreting the survey results it is important to have in mind that they reflect the categorization only for a given point in time. Consistent with the observation that in general, features go through a lifecycle and may change the categorization throughout time (Hölzing, 2008), we found that those FNFs considered as basic needs are relatively well studied. We expect FNFs that are assigned to the indifferent or attractive quality to possibly eventually be classified as must-be quality.

For further research, we emphasize four endeavors. First, we measured aggregated user satisfaction of a set of 25 FNFs. Thereby we do not consider differences dependent on participants' individuality. As our results show that individual perceptions differ, research can be taken a step further by looking at different subgroups. In the given context, it might be interesting to analyze the impact of the environmental attitude, for example by using the New Ecological Paradigm, or of the technological affinity of participants. Additionally, the current sample of the survey done in Germany cannot be considered representative, as the mean age is 33.2 years and thus significantly lower than the mean age of the German population (44.6 years (Statistische Ämter des Bundes und der Länder, 2021)). Even though we argue that older age groups may not be the most important target group for smart home apps, due to the promising findings we are planning to expand the survey to consider a balanced sample for additional findings. Next, in this paper, we synthesized our results of users' expectations by applying the Kano model for certain FNFs with effect strengths on those measured by prior research on ECB. Measuring the whole set of FNFs for isolated effect sizes on ECB would contribute to the regarded user preferences. Thus, taking on another research focus, our findings on user satisfaction could be complemented by interpreting whether the implementation of the FNFs assigned to the attractive or indifferent quality is worth it from the point of view of promoting ECB.

Conclusion

The need for behavior changes towards ECB becomes increasingly urgent. The increasing availability and usage of smart home technologies provide a promising opportunity for implementing DNEs as a behavioral intervention in a smart home app to foster ECB. Prior research focused on the promising DNE *feedback* to decrease energy consumption and tested different FNFs. While valuable knowledge on the effectiveness of specific FNFs exists, the investigation of the users' expectations and preferences concerning these FNFs is missing. This is crucial to support user satisfaction, influencing continuous app usage. We aim to close this gap and created a set of 25 FNFs categorized into six dimensions, that were verified via a card sorting with IS researchers. To empirically investigate users' preferences, we conducted a survey with 188 participants based on the Kano model and measured the users' perceptions of the identified FNFs as must-be, one-dimensional, attractive, or indifferent qualities. We illustrate essential and optional FNFs that can increase user satisfaction and avoid user dissatisfaction, hence enabling continuous app usage. We call attention to the fact, that when implementing a smart home app to enable ECB, the focus should not only be on effectiveness but also on user satisfaction, as these two do not necessarily correspond. By pointing out FNFs that belong to attractive qualities, we offer a possibility to enable personalized app design by each individual user. Lastly, identifying FNFs categorized as indifferent qualities, we point out to focus on these indifferent FNFs that provide the largest effect on ECB, as they do not impact user satisfaction at all. Our findings expand the understanding of implementing behavioral interventions in terms of *feedback* when designing smart home technologies to encourage ECB directly through the ongoing trend of digitalization. As user satisfaction supports continuous app use, we hope to contribute toward ECB in the long term.

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