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Can feedback nudges enhance user satisfaction? Kano analysis for different eco-feedback nudge features in a smart home app

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Abstract

Digital nudging in smart home apps promotes energy conservation behavior in everyday life, helping to mitigate climate change. Prior research demonstrates the promising effect of the digital nudging element eco-feedback supporting behavioral change. However, the effect depends on adopting and using smart home apps with eco-feedback integrated. Hence, investigating user preferences concerning eco-feedback nudges is crucial in developing smart home apps that satisfy users. Considering the eco-feedback nudge features derived from a structured literature review, we conducted two user surveys approximately one year apart and assessed user satisfaction using the Kano model. The Kano model categorizes these features according to whether the user expects the feature or not, and whether the feature has a positive effect on user satisfaction when implemented or a negative effect when not implemented. As a result, we examine the impact of different eco-feedback nudge features on user satisfaction. Our study evaluates the robustness of user satisfaction over time and thereby adds another perspective to the traditional focus on the effectiveness of these nudges. Combining both perspectives – effectiveness and user satisfaction – is valuable for developers and providers of smart home apps to suggest which eco-feedback nudge features to incorporate.

Keywords Digital nudging · Feedback · Smart home app · Energy conservation behavior · User satisfaction

JEL Classification C83 · D12 · D91 · Q01 · Q40

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Introduction

Minimizing energy consumption is an imperative step to mitigate the challenges of climate change and alleviate political dependencies (International Energy Agency, 2022). Because households account for a substantial share of final energy consumption (e.g., more than a quarter in Germany (AGEB, 2023)), they represent a significant area for improvement. Technological advancements have made household appliances more energy-efficient (Schleich, 2019). However, the use of these technologies often leads to higher overall energy consumption due to the rebound effect, where efficiency gains result in increased usage (Sorrell, 2015). This issue is exacerbated by individuals underestimating their energy consumption due to a lack of comprehensive information (Callery et al., 2021). To address this, behavioral change is essential. Integrating conscious consumption practices is crucial for ensuring that efficiency improvements lead to genuine reductions in energy usage, effectively addressing both environmental and socio-political challenges. Smart

home technologies present a promising approach to facilitate this transformation by providing real-time feedback and enabling better energy management.

Smart homes that enable, for instance, to steer heating or household devices like washing machines are already widely available, and their use is increasing (Statista Inc., 2023). The penetration rate of the global smart home market increased by 53% from 2019 (9.3%) to 2022 (14.2%), and according to forecasts, the penetration rate will grow with an increasingly steep curve toward 33.2% in 2028 (Statista Inc., 2023). Nowadays, smart home devices are often expected as standard equipment in new buildings and, as such, are a basic digital technology that can and should be a lever for energy conservation behavior (Hakimi & Hasankhani, 2020; Hirt & Allen, 2021; Pohl et al., 2021). As defined 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.” Smart home apps facilitate efficient energy management by enabling information exchange between energy providers and consumers, optimizing device usage for renewable energy utilization or cost reduction (Hakimi & Hasankhani, 2020; Pohl et al., 2021). Furthermore, users can monitor and manage their household appliances via a dedicated app (smart home app), potentially encouraging energy conservation behavior. In the context of rising energy consumption and simultaneously rising costs, it is increasingly important to study behavioral interventions over time to shape and influence individuals’ energy consumption patterns in the long-term, for which smart home apps provide a good interface between the information system (IS) and the user.

(Digital) Nudging elements hold great promise as a behavioral intervention to positively influence user behavior, e.g., by reframing the decision environment or giving feedback regarding the decision. These elements aim to enhance decision-making without altering economic incentives or limiting individuals’ freedom of choice (Hansen & Jespersen, 2013; Thaler & Sunstein, 2008). Prior studies demonstrated the effective integration of nudging elements to promote energy conservation behavior in physical settings, such as delivering energy reports via postal services (Crago et al., 2020) and in digital environments, e.g., smart home apps (Berger et al., 2022b). Smart home systems can positively influence sustainable behavior by integrating nudging elements in their apps (Kürschner et al., 2024). Previous studies show that especially feedback nudges can reduce energy consumption by 8 to 12% (Karlin et al., 2015). However, the configuration of eco-feedback nudge features, which we will refer to as “features” in this paper, varies. Research has looked at features like update

frequency (real-time vs. weekly) and measuring units (kWh vs. costs).

While certain features have proven effective, there has been limited research on user satisfaction and acceptance of these features (Fleury et al., 2018; Gu et al., 2019), neither by actual nor by potential users of smart home apps. IS adoption and use can be distinguished in different phases across time: adoption phase and continued use phase (also termed post-adoption use) (Karahanna et al., 1999). Distinguishing between these phases is essential for understanding and managing the process of IS adoption and use over time. In both phases, behavior depends on attitudes and subjective norms (Karahanna et al., 1999). In the adoption phase, the potential users are influenced by normative pressures and innovation characteristics (Karahanna et al., 1999). In the continued use phase, the confirmation or disconfirmation of user expectations is particularly important for user satisfaction and continuance intention (Bhattacharjee, 2001). Focusing on both potential users and actual users is crucial, as potential users (especially younger ones) also have growing expectations of a smart home app’s features based on their experiences in digital environments (Tam et al., 2020). Thus, user satisfaction impacts the long-term success of apps (Bhattacharjee, 2001; Gu et al., 2019; Thong et al., 2006). Both the initial adoption by prior non-users, and thereafter the sustained use of smart home apps incorporating features is essential for long-term energy savings. Therefore, it is crucial to analyze the configuration of these features in smart home apps to ensure they satisfy both potential users in the adoption phase and users in the continued use phase. Thus, our first research question is:

RQ1: How do potential and actual smart home app users evaluate a broad set of eco-feedback nudge features designed for nudging towards energy conservation behavior?

Throughout a product’s or service’s life cycle, user satisfaction with certain features can change; the longer a service exists, the less attractive its features may become (Kano, 2001). We live in a rapidly changing world, including a transformation of energy supply and consumption – with rising energy prices, increasing pressure to reduce CO₂ emissions quickly, and political dependencies impacting energy supply. These issues often confront (potential) smart home app users via daily news. As a result, news can influence our attitudes toward technologies that help us managing our own energy behaviors. Therefore, we need to know whether user satisfaction regarding these technologies may change over a short period of time, for example, due to various external influences. A rapid shift in user satisfaction would pose a challenge for app developers, as this approach may not support medium-term product strategies for app development. Thus, we aim to answer our second research question by collecting and comparing data at different points in time:

RQ2: Is the evaluation of different eco-feedback nudge features of potential and actual smart home app users robust over time?

An overview of features in smart home apps from a structured literature review is the basis for answering the research questions. We supplement this with a brief qualitative analysis of the use of features in selected smart home apps that are currently in use. We employ the Kano model to assess users' perceptions of these features, determining whether various features are "must-be," "one-dimensional," or "attractive," or if users remain "indifferent." We do this by surveying potential and actual users of smart home apps at two points in time, approximately one year apart, to confirm results over time and across different groups of people (users vs. non-users). With the findings from both studies, the paper holds theoretical implications concerning eco-feedback nudging. It highlights the significance of considering user satisfaction alongside effectiveness in configuring and implementing eco-feedback nudges. This study provides valuable insights into which features promote user satisfaction and, therefore, may contribute to energy conservation behavior within smart home apps.¹

Related work

The research field of smart home apps

The rapid advancement of smart home technologies and apps has led to a dynamic and fast-evolving field, with new possibilities emerging constantly (Kürschner et al., 2024). These technological innovations have prompted significant research interest, especially in the last five years, as scholars seek to explore smart home technology from various perspectives. Recent studies cover diverse aspects such as the classification of smart home technology (e.g., Huber et al., 2024), IS security (e.g., Nehme & George, 2022) and data privacy (e.g., Gerlach et al., 2022), user behavior (e.g., Hubert et al., 2020), and the design of smart home technology (e.g., Tiefenbeck et al., 2019). The classification of smart home technologies within the "smartness" contexts relates to the understanding of how smart home systems are categorized based on their intelligence and capabilities (Huber et al., 2024). Smartness in the smart home context can be defined by the capability of smart devices (e.g., devices like washing machines or heating systems) to interact with individuals and accommodate their preferences (Huber et al., 2024). This classification emphasizes the importance of the smart home app user and his or her preferences, which is central to our research endeavor.

Research on IS security and data privacy consistently highlights the threats posed to users by smart home

technologies, which collect and process significant amounts of personal data. Ensuring the security of these technologies and protecting user privacy are, therefore, widely recognized as critical concerns. While our work does not directly focus on security and privacy issues, it acknowledges that collecting energy consumption data – a premise of giving feedback on energy consumption behavior – raises privacy considerations. Common across the literature is the finding that users who experience fear or perceive threats to their data privacy may avoid using smart home devices (Bhati et al., 2017; Nehme & George, 2022). However, there are differences in the proposed solutions: while some studies emphasize privacy-friendly design requirements (Chhetri & Genaro Motti, 2022), others focus on principles tailored specifically for personal data processing in smart energy services (Gerlach et al., 2022). These insights underline the importance of addressing privacy concerns to ensure user trust. For our research, this highlights the need to consider how user perceptions of IS security and data privacy may affect their satisfaction with app features, such as those requiring detailed energy consumption data. For example, privacy concerns could lead to dissatisfaction with features that users perceive as intrusive.

Researchers have extensively examined user behavior and the effects of smart home technology usage. Common across the literature is the identification of factors such as the user's motivation for system engagement, perceived benefits, and nudges that potentially have an impact on the use of smart home technology (Kürschner et al., 2024). A key similarity across these studies is their focus on how well-configured app features can support user goals. For instance, framing nudges have consistently been shown to effectively help users reduce energy consumption (Berger et al., 2022b; Ghesla et al., 2019; Kim & Kaemingk, 2021). Our work builds on these findings by exploring not only the effectiveness of such features but also their impact on user satisfaction, contributing to a deeper understanding of how different configurations influences user experience. Additionally, research emphasizes the role of personalization in smart home apps as a key factor for enhancing perceived value and fostering acceptance of smart home ecosystems (Hagejård et al., 2023; Hubert et al., 2020). These insights highlight the significance of personalization and well-configured features for ensuring sustained use of IS, reinforcing the importance of studying various configurations of app features in smart home applications.

Promoting sustainable behavior, such as reducing energy consumption, is another area where research has demonstrated the effectiveness of persuasive systems and digital nudging (e.g., Shevchuk et al., 2019; Tiefenbeck et al., 2019). In an experiment employing real-time feedback on resource consumption during showering by Tiefenbeck et al. (2019), a treatment effect of 11.4% in reducing energy

¹ This paper builds on the work by Berger et al. (2022a).

consumption showcases how impactful well-configured features can be in fostering energy conservation. Similarly, Cellina et al. (2024) conducted a one-year app-based electricity-saving intervention in 55 Swiss households, achieving an average treatment effect of 4.95% during the treatment period. However, while Tiefenbeck et al. (2019) highlight short-term gains, Cellina et al. (2024) emphasize the challenges of maintaining behavioral change over longer periods. Furthermore, in line with Kürschner et al. (2024), we found that studies on the effectiveness of design elements for promoting sustainable behavior in smart home contexts vary greatly in their setups. For instance, studies have been carried out in different world regions (e.g., Post-Soviet Eastern Europe (Kim & Kaemingk, 2021); Switzerland (Cellina et al., 2024); Japan (Kim et al., 2020)), living environments (e.g., households (Kim et al., 2020); student dorms (Myers & Souza, 2020)), and vary in the length (e.g., three months (Myers & Souza, 2020) vs. three-year-long intervention (Ruokamo et al., 2022)) and their closeness to real-world conditions (e.g., actual usage of a smart home app in own living environment (Hagejård et al., 2023); online experiment with simulated environment (Fanghella et al., 2021)). These differences provide valuable insights into the design and implementation of interventions, reinforcing the importance of studying various configurations of app features to maximize their impact on sustainable behavior.

The surge in academic attention highlights the importance of addressing remaining questions to ensure that the full potential of smart home apps is realized and embraced by users. For this research endeavor, the scientific discourse on the configuration of smart home technologies and user behavior is particularly important, as they provide a valuable foundation. Prior work focused on the effectiveness of digital nudging elements in promoting sustainable behavior and highlighted the importance of personalization and the careful configuration of features in smart home apps. We complement this by analyzing whether specific smart home app features may delight or may even be demanded by (potential) smart home app users to support adoption and continuous use of smart home apps promoting energy conservation behavior.

Adoption and continuous use of smart home apps promoting energy conservation behavior

IS adoption

Adoption “refers to the stage before and right after a target technology implementation/introduction” (Venkatesh et al., 2016, p. 345). During the adoption phase, user satisfaction is not yet a focus, as potential users must initially try and then continuously use the technology to become actual users of,

for example, a smart home app (Venkatesh et al., 2016). In the adoption phase, expectations are created and then tested during the post-adoption phase. As users begin to interact with the smart home app, they compare their initial expectations with their actual experiences, leading to (dis-)satisfaction, affecting continuous use.

Potential adopters form expectations about smart home apps based on their previous behavior regarding energy consumption as well as experiences with systems in other domains (e.g., Tam et al., 2020), stories from friends, social media influencers, users, and providers (e.g., Karahanna et al., 1999; Kim et al., 2016). Additionally, their attitudes are shaped by a broad range of innovative characteristics, such as perceived usefulness, ease of use, result demonstrability, visibility, and trialability. These factors collectively form their expectations and influence their decision to adopt the app (Karahanna et al., 1999).

These different phases of adoption are important to our research, as the research questions consider both potential users and actual users. For these groups, the assessment of app features either depends on expectations or experiences. Hence, the assessment of different features and their impact on satisfaction might differ.

User satisfaction in continued IS use

After the IS adoption, a user’s attitude is strongly influenced by the app’s perceived usefulness and the social image it conveys (Karahanna et al., 1999). For example, once the smart home app is adopted, the user might focus on how effectively the app helps them achieve their energy conservation goals (usefulness) and how using the app enhances their image as an energy-conscious individual (image enhancement). User satisfaction is pivotal in continuous IS use (Bhattacharjee, 2001; Thong et al., 2006). The significance of increasing energy conservation behavior through the continued use of a smart home app (e.g., facilitated by the digital nudging element *feedback*) becomes paramount as the user can actively contribute to mitigating climate change. Furthermore, leveraging these strategies for advertising can result in competitive advantages, especially considering the growing environmental awareness among individuals. Gu et al. (2019) found that user satisfaction exerts a considerable and beneficial influence on the inclination to continue using smart home apps. Therefore, maximizing user satisfaction should be a goal (Bhattacharjee, 2001; Chun-Hua et al., 2016; Gu et al., 2019). This relevance of user satisfaction is a key motivation for our study. However, it is unclear which features contribute to or hinder user satisfaction.

Merely meeting users’ expectations does not guarantee user satisfaction. User satisfaction is influenced by varying expectations, which shape the perceived evaluation

of a service or product (Matzler et al., 1996). We use the Kano theory of user satisfaction² (Kano, 1984), which helps researchers and businesses understand how different product or service features affect user satisfaction in different ways, and was since then extensively examined and implemented in various theoretical and empirical investigations (Füller & Matzler, 2008; Löfgren & Witell, 2008). Moreover, the Kano model has been used to assess user satisfaction with digital products or services, such as mobile apps for diverse purposes of use. For instance, Gimpel et al. (2018) used the Kano model to evaluate data privacy measures according to their implementation needs and Wenninger et al. (2022) used the Kano model, among others, to more precisely classify and prioritize features for proactive services to match them to the predominant personality trait of a customer. Putra and Priyanto (2021) explore users' preferences for an app designed to help teachers select learning media for their courses. In the domain of health and fitness apps where maintaining healthy behavior is both crucial and challenging, research about app features (Gimpel et al., 2021), app quality principles (Malinka et al., 2022), and gamification elements (Yin et al., 2022; Yuan & Guo, 2021) used the Kano model to enhance user satisfaction and support individuals in managing their health and fitness. In times of an aging society, user satisfaction becomes increasingly important for encouraging the adoption and continued use of IS by older adults whose needs are typically not the focus of app developers (Ho & Tzeng, 2021; Yuan & Guo, 2021). Therefore, Ho and Tzeng (2021) investigated the features of 14 mobile reading apps in a survey for participants aged 45 years or older employing the Kano model. Concerning this paper's smart home technology context, Li et al. (2024) used a questionnaire based on the Kano model with the functional attributes of a smart home to find out which attributes may offer comfort to the elderly aged 60 to 70 and above. Furthermore, Xiong and Xiao (2021) studied the functional requirements of smart door locks with the help of the Kano model to provide design guidelines for smart door locks and other smart products.

The Kano model comes along with a comprehensive method for analyzing the impact of product or service features on user satisfaction. It provides a procedure for categorization applicable to theoretical and practical contexts. The Kano model explicates user satisfaction based on the implementation or availability of product or service features (Kano, 1984). The model distinguishes five main categories (Matzler et al., 1996; Sharif Ullah & Tamaki, 2011):

- *indifferent* with no substantial effect on user satisfaction if the feature is implemented or not (i.e., users are indifferent regarding the implementation of the feature),
- *attractive* with a positive effect on user satisfaction if the feature is implemented and no substantial effect if it is not implemented (i.e., users do not expect the implementation of the feature),
- *one-dimensional* with a positive effect if the feature is implemented and a negative effect if it is not implemented (i.e., users explicitly demand the implementation of the feature),
- *must-be* with no substantial effect if the feature is implemented, but a negative effect if it is not implemented (i.e., users implicitly demand the implementation of the feature),
- *reverse* with a negative effect on user satisfaction if the feature is implemented and a positive effect if it is not implemented (i.e., users are averse to the implementation of the feature).

Figure 1 graphically depicts the influence of the five categories on user satisfaction.

While the Kano model is useful for understanding user satisfaction, it has notable criticisms. First, it relies on survey data, which may not reflect participants' actual behavior. Users' responses in surveys often differ from their real-world actions, and the model does not account for unconscious preferences. Another issue is its rigid categorization into five discrete groups, leaving no room for subtle gradations between features (Yang, 2005). Fellow researchers also criticize the ambiguous wording used for the categories and the respective questions (Song, 2018). With a high number of features, it is cumbersome for survey participants to fill in a Kano questionnaire (Matzler et al., 2004), leading to potential distraction. Furthermore, the model focuses on the majority opinion, potentially overlooking individual differences and unique customer needs. Additionally, it considers features in isolation, ignoring interdependencies where features may only become attractive when combined. Finally, it does not factor in the implementation cost or customers' willingness to pay, which are crucial in real-world product development decisions.

Despite these critics, we opted for using the Kano model, as it is a well-established approach that provides a comprehensive method and reveals users' satisfaction with product or service features in a straightforward manner (Gimpel et al., 2021; Koomsap et al., 2023; Li et al., 2024). Furthermore, the Kano model allows for analysis at the feature level, directly aligning with the critical decisions app developers need to make during the development process (e.g., Yin et al., 2022). The model not only offers guidance on which features drive user satisfaction but also identifies features that contribute to user dissatisfaction,

² Market research usually refers to customer satisfaction. Following Gimpel et al. (2021) and considering that this work examines a smart home app, we use the term user satisfaction.

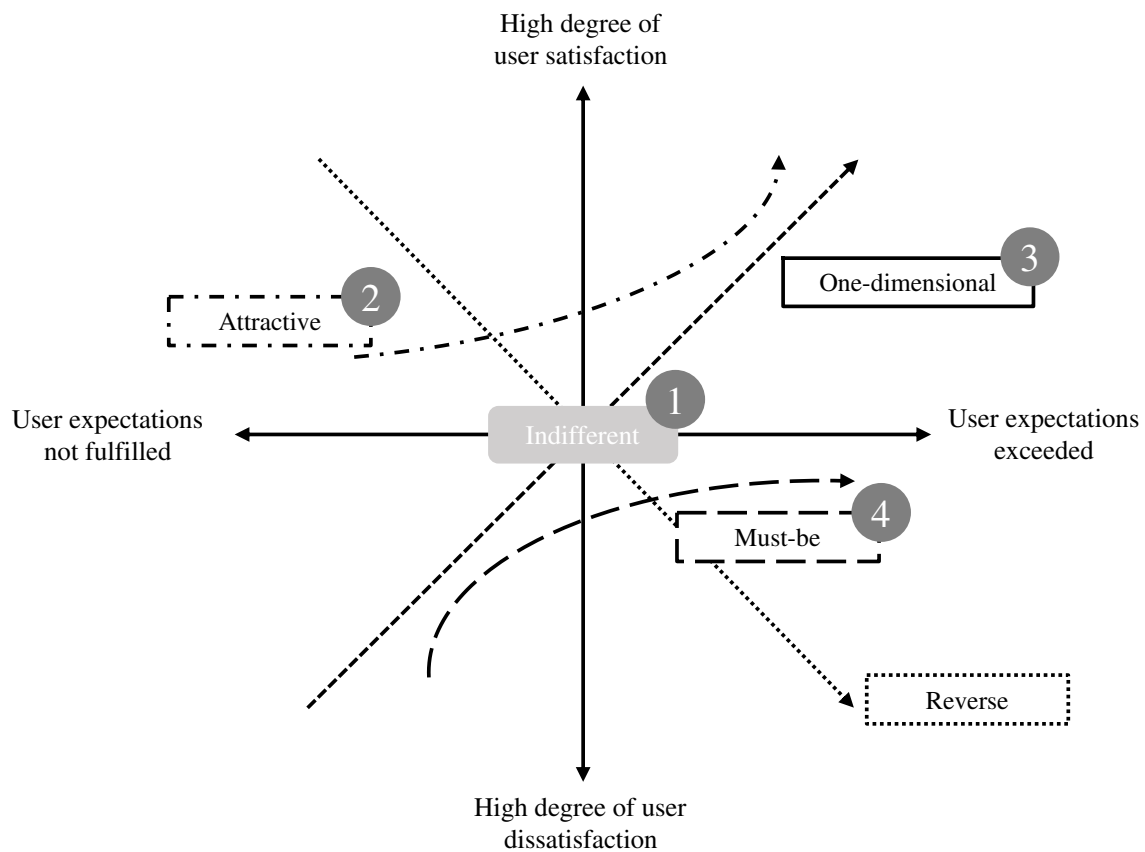


Fig. 1 Graphical depiction of the five Kano model categories based on Sharif Ullah and Tamaki (2011) (own representation). Note: The numbers represent the change in categorization according to the Kano lifecycle theory (Kano, 2001)

highlighting those that may be superfluous or even counterproductive to the app's success (e.g., Malinka et al., 2022; Putra & Priyanto, 2021). It has proven highly useful in other contexts for deriving implementation decisions (e.g., Gimpel et al., 2021; Ho & Tzeng, 2021; Yin et al., 2022). The critique of potentially distracted respondents due to lengthy questionnaires can be countered with attention check questions.

Eco-feedback nudges

Nudging involves predictably influencing people's behaviors by altering their decision environment without restricting their freedom of choice or increasing the costs of alternatives – in terms of effort or time (Hansen & Jespersen, 2013; Thaler & Sunstein, 2008). Human behavior is either intuitive or reflective (Evans & Stanovich, 2013), often referred to as Wason and Evans' (1974) dual-process theory. Heuristics (e.g., rule of thumb) and cognitive biases (e.g., loss aversion) can impact autonomous, intuitive routines and non-autonomous, reflective decisions that require working memory. Although heuristics facilitate rapid decision-making, they can introduce errors, leading to decisions that may disadvantage

the individual or society. Nudging utilizes an understanding of heuristics and biases to construct decision environments that steer behavior in desired directions (Thaler & Sunstein, 2008). An instance of nudging targeting autonomous, intuitive decisions involves reducing plate sizes to lower calorie intake. In contrast, nudging addresses reflective thinking by presenting energy bills with social comparisons (Hansen & Jespersen, 2013). Consequently, nudges are suitable for shaping routine behaviors and deliberate, intricate decisions.

Weinmann et al. (2016) introduced the concept of digital nudging, defining it as the use of "user-interface design elements to guide people's choices or influence users' inputs in online decision environments" (p. 433). The advantages of digital nudging elements are their ability to be swiftly implemented, evaluated, and personalized at a relatively low cost (Weinmann et al., 2016). Furthermore, given the growing prevalence of individual decisions in digital settings, exemplified by the rising relevance of smart home apps, digital nudging holds promise for influencing behavioral change. Previous research showcases the encouraging effectiveness of digital nudging elements in altering behavior toward ecological sustainability (Berger et al., 2022b, 2022c; Demarque et al., 2015; Lehner et al., 2016; Zimmermann et al., 2021).

Various digital nudging element conceptualizations are discussed in scientific literature (Lehner et al., 2016; Mirsch et al., 2017; Weinmann et al., 2016). Among these, feedback nudges have been shown to be particularly effective in promoting energy conservation behavior (Table 4 in the supplementary material). In this work, we focus on feedback nudges due to their proven effectiveness in enhancing energy conservation behavior (Berger et al., 2022c) as well as in other contexts (e.g., Hribernik et al., 2022; Lechermeier et al., 2020). In their meta-analysis on feedback to promote energy conservation, Karlin et al. (2015) find effects between 8 and 12%. This is in line with studies like Cappa et al. (2020), Emeakaroha et al. (2014), and Grønhøj and Thøgersen (2011) who showcase the effectiveness of feedback in their experiments for the energy consumption of residential buildings. However, effectiveness depends on the configuration of the feedback nudge, i.e., different features (Brandsma & Blasch, 2019; Schultz et al., 2015). Feedback providing normative information and social comparison was found to be effective (e.g., Tussyadiah & Miller, 2019; Wemyss et al., 2019), whereby the importance of configuration could also be measured (e.g., Loock et al., 2013; Schultz et al., 2015).

A feedback nudge provides individuals with information about their behavior, such as their energy consumption, enabling them to reflect on and potentially adjust that behavior (Cappa et al., 2020; Khanna et al., 2021). Therefore, feedback surmounts inertia and procrastination, making it a valuable tool for motivating individuals (Sunstein, 2014). Examples include displaying individuals' energy consumption on smart home displays (Schultz et al., 2015) or presenting the energy consumption of similar consumers on a web portal (Loock et al., 2012). Feedback nudges to promote energy conservation behavior (eco-feedback nudges) have been extensively studied due to advancements in sensing technology and energy infrastructure, enabling data collection, processing, and rapid dissemination to users (Karlin et al., 2015; Loock et al., 2012). Karlin et al. (2015) noted variations in feedback nudge studies, such as differences in the frequency of updated information on energy consumption or the energy measurement method. While there is empirical evidence on the effectiveness of individual features (Table 4 in the supplementary material), research is lacking in understanding the impact of an extensive set of features on user satisfaction. By evaluating whether features may lead to user satisfaction, we add a new perspective to the current focus on the measurement of feedback nudges' effectiveness. By identifying features that are seen as must-be or as attractive by (potential) smart home app users, we assume that a user-centric development of smart home apps combining effectiveness in promoting energy conservation behavior (e.g., Brandsma & Blasch, 2019; Schultz et al., 2015) and promoting continuous use through user satisfaction can be enabled.

Changes in user behavior and attitudes over time

Kano lifecycle theory

The Kano lifecycle theory specifies that the categorizations change over time following a lifecycle (Kano, 2001). Users' experiences and changing expectations induce categorization change from indifferent (1) to attractive (2) to one-dimensional (3) to must-be (4) (see numbering in Fig. 1). New or previously unknown features are typically categorized as indifferent (1) or attractive (2), as users did not form expectations without prior use experience. Categorization changes when users gain experience; features become part of users' expectations and negatively influence user satisfaction if not implemented (i.e., one-dimensional (3)). In the end, features become prerequisites (i.e., must-be (4)) because they no longer have the potential to delight but must be implemented (Kano, 2001). Researchers confirmed Kano lifecycle theory in their studies. Nilsson-Witell & Fundin (2005) used the Kano model to evaluate an e-service and found that customers considered service attributes differently depending on their experience level. In their study, early adopters already regarded e-services as one-dimensional or must-be, while overall, users categorized them as attractive. This finding is backed by Gimpel et al. (2021), who used the Kano model to evaluate mobile health app features by Germans and Danes. The features' categorizations of the Danish sample were more mature than those of the German sample, presumably as mobile health apps were introduced earlier in Denmark, and, thus, Danes already gained more experience. Nilsson-Witell & Fundin (2005) point out the value of Kano lifecycle theory in helping organizations estimate how far a service has proceeded in its lifecycle and when it will no longer be able to delight customers indicating the need for organizations to offer new services or service attributes to further succeed in the market. With RQ2, we investigate if and how fast the features move along Kano's predicted lifecycle.

Service quality model

A smart home app is a service that provides convenience and automation for users in managing their homes (Kürschner et al., 2024). As with any service, users have certain expectations regarding performance and capabilities. However, discrepancies may arise between perceived service quality and actual performance, resulting in user dissatisfaction. Hence, the primary objective is to provide a service that fulfills and surpasses user expectations, culminating in heightened user satisfaction. These arising discrepancies are addressed in the gap theory of the well-established service quality model "SERVQUAL" (Parasuraman et al., 1985, 1988). The gap theory conceptualizes service quality as the difference between customers' expectations and customers' perception

of the actual performance of the service, which is compatible with the Kano theory and highlights the importance of perceived quality (and not the objective quality) measured through the extent to which the offered service performance fulfills customer expectations. Parasuraman et al. (1985) outline customer expectations as moderated by personal needs, word of mouth, and past experiences.

As the usage of smart home apps increases and technology advances, expectations for these technologies constantly evolve. It is essential to consider the dynamic nature of personal needs, word of mouth, and past experiences for measuring the potential changes in expectations over a short time. Individuals' perceptions and requirements may shift as they interact with smart home apps and encounter new experiences. For example, someone who used to care about convenience and automation may value energy efficiency and sustainability more because of external factors such as the shift to renewable energy sources, global warming, and rising energy costs. Such external factors can affect personal needs and priorities. Prior studies showed that personal experience significantly impacts energy conservation behavior (e.g., Xu et al., 2021).

Therefore, it is crucial to assess and evaluate whether and how expectations for smart home apps change in a relatively short period of time. By considering possible changes we can gain insights into the dynamic nature of expectations and better understand the evolving demands of users. This understanding will be valuable for developers and providers of smart home apps to adapt their offerings to users' changing expectations and requirements. If it was the case that current external factors, such as ongoing discussions about the energy transition, climate change, and rising energy prices, could cause substantial and rapid changes in the Kano categorizations, knowing the categorization would not be helpful to smart home app providers because they would have to change their feature set frequently. However, if the categorizations were relatively stable over time, developers could build an app according to these categorizations to appeal to users. Therefore, we intend to address robustness of Kano categorizations over time with our second research question.

Research process

Identification of eco-feedback nudge features

Structured literature review

The relevant features result from a structured literature review. This structured literature review adhered to the guidelines by Webster and Watson (2002) and vom Brocke

et al. (2015), involving three phases: (1) literature search, including the search string and databases utilized, (2) selection, and (3) synthesis.

The search string was deliberately broad to provide a comprehensive overview of existing research on eco-feedback nudges and gather insights about all nudging elements employed for promoting energy conservation behavior (Fig. 2). This structured literature review confirmed that feedback nudges were the most relevant type of nudging elements for altering behavior toward ecological sustainability, an assumption not verified before (Table 4 in the supplementary material). Among the 58 articles analyzing nudging elements, only six did not concentrate on eco-feedback nudges or their combination with other nudging elements. Therefore, eco-feedback nudges emerge as the most researched nudging elements for energy conservation behavior, making them highly relevant for analyzing user satisfaction.

The search process resulted in 52 articles (Fig. 2) that contained 25 features. The features and the scientific studies that examined each feature are listed in Table 5 in the supplementary material. Following the approach proposed by Schaffer & Fang (2018), these features were clustered into overarching dimensions. To create a dimension, we concentrated on the primary characteristics of features and grouped them according to their similarities. The validity of the identified dimensions was confirmed using closed card sorting, a method allowing adjustments to predetermined dimensions but not adding new ones (Maida et al., 2012). As a result, we identified six distinct dimensions, allowing each of our 25 features to be categorized. For further details on the literature review, the categorization, and the card sorting, see Berger et al. (2022a). Table 5 in the supplementary material gives an overview of the 25 features identified, including a definition, as well as an overview which papers present which feature in the scientific discourse, categorized into the six dimensions A–F. Generally, features are not mutually exclusive and can be implemented in combination.

Analysis of contemporary smart home apps

To verify the relevance of the features presented in this paper, we analyzed contemporary smart home apps on the market. We combined questionnaires and interviews with users, joint analysis of app features with users, and a review of online documentation for six smart home apps. It is important to note that the available features in smart home apps strongly depend on the connected devices and historic data. Consequently, engaging users to test the apps was necessary, as analyzing them without corresponding connected devices and historic data only shows a subset of features. This also explains the substantial variation in features offered across apps, depending on not only the indented purpose

(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
Feedback Nudging Elements	- 6 articles (other nudging elements only)	= 52 articles

Fig. 2 Overview of the structured literature review

and user experience but also the devices with which the app is compatible. We asked six users of smart home apps to complete a questionnaire regarding the presence of the 25 features and then conducted semi-structured interviews with a time frame of 30 to 60 min. In the interviews, we queried the presence of the 25 features, and we jointly analyzed where and how the features were implemented within the app, particularly in cases where it was unclear whether users had already engaged deeply with their smart home app. We recruited the interviewees from our immediate social environment (family, friends, and colleagues) to ensure a high level of motivation and trust, fostering thorough analysis of the apps. The choice of apps resulted from which apps the interviewees use. The list is provided in Table 5 in the supplementary material. Additionally, we reviewed user figures to ensure that we considered apps that are successful in the market. Five of the six apps are widely used, each having more than 500,000 downloads in Google Play Store (where data on downloads is available). The Smapee App has only more than 50,000 downloads. We considered it anyways, as it functions as the energy management system of the widely used Home Connect App (> 1 million downloads) and the corresponding Home Connect devices. To fully understand these apps' features, we additionally reviewed their online documentation. The last column in Table 5 in the supplementary material shows the presence of features in the six smart home apps analyzed. The overview represents a status quo as both apps and compatible devices continue to evolve. The summary of the frequency of a feature across the six apps analyzed in September 2024 shows how commonly a feature was available at that time.

If none of our features were used, this would challenge the relevance of studying features in smart home apps (we term this *case A*). If most apps would implement most of the features, one could reason that implementation is so simple that it is done anyways (*case B*). Otherwise, the analysis would support the relevance of features in smart home apps and suggest a decision to be taken by providers on which features to implement (*case C*). Only in *case C*, our study is meaningful. Five out of six current smart home apps analyzed employ at least one feature. The maximum we have found is an app having ten features. Jointly, the five apps

using features implement fifteen different features. Details are in Table 5 in the supplementary material. We interpret this as evidence for *case C*. We continue with analyzing the 25 features and refrain from limiting the set to the ones used in practice for two reasons: First, our sample in this qualitative review is sufficient to demonstrate practical relevance but is too small to assume an exhaustive list of features used in smart home apps today. This is because smart home apps and connected devices are constantly evolving. Also, we encountered a variety of devices where the focus is on controlling them with smart home apps, e.g., Philips Hue, which can be used to control the lights (by voice), set a color scheme or automatically turn off the lights when you leave the house, but does not include energy consumption related features. Second, scientific literature might be ahead of practical app implementations in identifying relevant features.

Evaluation of users' satisfaction with eco-feedback nudge features

Kano model

Applying the Kano model for evaluating user satisfaction with each feature individually involves a two-question approach, comprising a functional and a dysfunctional question (Löfgren & Witell, 2008). Participants evaluate hypothetical scenarios in which a feature is implemented (functional question) or not (dysfunctional question). For each scenario, participants can choose one of five possible answers (Table 6 in the supplementary material). The classification of the features into the categorizations (Fig. 1) relies on the participants' responses to both questions. As proposed by Matzler et al. (1996), we derive the final classification of a feature based on the respective result that occurs most frequently among individuals. To avoid unjust representations when the shares of the most frequently chosen categories are closely matched, we assess the categorization significance (Gimpel et al., 2018). Lee and Newcomb (1997) introduce the variable category strength as the difference between the proportions of the most and second most frequently chosen categories. For precise significance determination, we employ Fong's (1996) test, which computes a reference

value by considering observed frequencies and the sample size, and assesses the significance of the observed differences. Should the Fong test indicate no significant difference, Berger et al. (1993) propose to apply the $(A, O, M) < > (I, R, Q)$ rule for further evaluation. The first group comprises categorizations *A* (attractive), *O* (one-dimensional), and *M* (must-be), which possess the potential to impact user satisfaction. The second group comprises categorizations *I* (indifferent), *R* (reverse), and *Q* (questionable), which do not influence user satisfaction. The rule can be applied when the two most frequently mentioned categorizations belong to separate groups. If the rule is applicable, the categorization most frequently chosen within the dominant group ($> 50\%$) is selected. In instances 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 (Lee & Newcomb, 1997). A mixed category names the most frequently chosen category along with all categories that, based on Fong's approach, do not differ significantly when compared to the most frequently chosen category (Gimpel et al., 2021). The sequence of categories in a mixed category begins with the most frequently chosen category, followed by the other categories in descending order of selection frequency. The mixed category ends with the last category without significant difference to the most frequently chosen category.

User surveys

Upon welcoming the participants, we explained smart home. We displayed screenshots of a hypothetical smart home app to ensure all participants shared a common understanding of the context (Berger et al., 2022b). To apply the Kano Model, participants responded to functional and dysfunctional questions for each of the 25 features. The "Description of eco-feedback nudge features" column in Table 5 in the supplementary material shows the functional questions. An example of a dysfunctional question is presented in Table 7 in the supplementary material. In contrast to a functional question, which asks whether the feature has been implemented, a dysfunctional question asks whether the feature has *not* been implemented. We used the German translation of the five answer options proposed by Hölzing (2008) and incorporated an attention check.

Additionally, we queried sociodemographic background and used the Affinity for Technology Interaction (ATI) scale by Franke et al. (2019) as an approximation for the usage of similar services for measuring past experiences. Next, we asked about prior smart home app usage. For personal needs (see the [Changes in user behavior and attitudes over time](#) section), we measured the attitude toward pro-ecological behavior with the help of Bidwell's (2013) revised version

of the New Ecological Paradigm (NEP) by Dunlap et al. (2000). The scales used in the user survey to measure Affinity for Technology (ATI) and the New Ecological Paradigm (NEP) are presented in Table 7 in the supplementary material. For high-quality results, we made a pretest with four IS researchers and an industry expert.

We used the same questionnaire in two surveys about a year apart (Table 1) to determine how actual and potential smart home app users evaluate a broad set of features. A single survey for users and non-users of smart home apps suffices for RQ1. The second survey in comparison to the first aims for answering RQ2. For both studies, we used LinkedIn, Instagram, and Facebook, our research network, and personal contacts (via email and WhatsApp) as recruitment channels. We asked study 2 participants whether they had already participated in study 1. We took this into account in the analysis. Our results do not observe within-person changes over time, but differences between two cross-sectional surveys. Table 1 describes the samples of both studies.

Results

Table 2 presents the category strength and the final categorization of each feature according to the Kano model for both studies separately (study 1: $n = 188$; study 2: $n = 178$) as well as an overall evaluation ($n = 326$).³ For each feature, we assessed whether there is a substantial and/or significant change between study 1 and study 2. A substantial change is a change in categorization between the two studies as we see it for two features; *near real-time update frequency* (*A1*) and *visualization over time* (*B1*). Regarding significance, for each feature individually, we performed a χ^2 test on the frequencies of categorizations in the two studies (after dropping categories not selected in either study and with simulated *p* values). We apply a 10% significance level. Interpreting results from inferential statistics typically focuses on results which are both significant and have a meaningful effect size. In that line of thought, we interpret a significant change in the frequency of individual categorizations that results in a change in the overall category as an important change.

³ Robustness check: When the participants that already took part in study 1 are excluded from the analysis of study 2, the results are almost identical. Only B1 would be categorized as a mixed category (*M, O, A*) instead of clearly being categorized as must-be. This would slightly increase consistency of results from the two studies. Having more mixed categories is not surprising, as a lower sample size reduces the likelihood of the Fong test being significant and, thus, the likelihood of a mixed categorization increases. Given that including repeat participants does not artificially increase consistency of results (but rather slightly decreases it), we opt for presenting the results from the larger sample.

Table 1 Overview of samples in study 1 and study 2

		Study 1 (<i>n</i> = 188)	Study 2 (<i>n</i> = 178)
Recruiting channels		LinkedIn, Instagram, and Facebook, our research network, and personal contacts (via email and WhatsApp)	
Inclusion criteria		German-speaking, adult, attention check correctly answered	
Period of user survey execution		March to April 2022	January to March 2023
Age range and mean		18–72 years, 33.2 years	18–76 years, 31.5 years
Gender	Male	46.3%	52.2%
	Female	53.2%	47.8%
	Non-binary	0.5%	0%
Occupation	Students	28.7%	38.2%
	Employees	56.4%	51.1%
	Retirees/unable to work	4.3%	0%
	Self-employed	0%	2.2%
	Civil servants	3.7%	4.5%
	Others	6.9%	4.0%
Share of participants who have already used a smart home app		31.4%	28.1%
New Ecological Paradigm (NEP) mean (SD)		3.99 (0.78)	3.92 (0.85)
Affinity for Technology Interaction (ATI) mean (SD)		3.29 (1.15)	3.46 (1.15)
Self-reported prior participation in study 1 (in %)		-	40 (22.5%)

Such a change exists for *near real-time update frequency* (*A1*); for the other 24 features, the changes are either not significant or not relevant in the sense of not changing the overall category, or both.

23 of the 25 features indicate no substantial change in categorization between the two studies (Table 2). Among these 23:

- Nine features are categorized as indifferent, meaning they do not affect user satisfaction.
- Eleven features are categorized as attractive qualities that can delight users when implemented but are not essential as they have no negative effect on user satisfaction if not implemented.
- Two features are categorized as must-be qualities that, if absent, will have a negative effect on user satisfaction.

Neither study includes the one-dimensional category, which would positively affect user satisfaction if implemented and have a negative effect if not implemented. In addition, both studies do not include the reverse category, which would negatively affect user satisfaction if implemented and positively affect it when not implemented.

Two (8%) of the 25 features were categorized differently in the two studies:

- (1) *near real-time update frequency* (*A1*) was categorized as indifferent in study 1 and as attractive in study 2. This change is significant, as indicated by the X^2 test.

- (2) *visualization over time* (*B1*) was first assigned to the mixed category in study 1, where it was most frequently categorized as one-dimensional, and categorized as must-be with a category strength being significant at ten-percent level according to the Fong test in study 2. However, considering the frequency of different categorizations by participants, the difference between the two studies is not statistically significant. Hence, it should not be overinterpreted but might be a marginal difference occurring by chance and slightly affecting the categorization as mixed (*O*, *M*) or must-be (*M*).

We used Cohen's kappa and percent agreement to assess the categorizations' reliability across the two studies. Usually, these metrics are applied to two raters who act as judges who independently categorize a sample of units. In our case, the measures assess the agreement between the two studies. With 23 out of 25 features categorized identically, inter-rater reliability (kappa) is 0.87. The percent agreement of 0.92 indicates almost perfect agreement between the two studies (Landis & Koch, 1977).

With high consistency between the two studies and only one of 25 features showing a substantial and statistically significant change between the studies, the overall evaluation of both datasets yields highly consistent results, leaving little room for unexpected outcomes. Apart from *visualization over time* (*B1*), the categorization of all features in the overall evaluation is the same as in study 1. This consistency is likely due to the greater influence of study 1 on the overall

Table 2 Empirical results of the eco-feedback nudge features' evaluation via the Kano model

#	Dimension and eco-feedback nudge feature Note: Each eco-feedback nudge feature relates to the display of your own energy consumption	Study 1 ($n = 188$)		Study 2 ($n = 178$)		Change? (substantial/ significant)	Overall ^a ($n = 326$)	
		Category Strength	Categorization	Category Strength	Categorization		Category Strength	Categorization
A	Update frequency							
A1	Near real-time	20%	I	6%	A	Yes/Yes	7%	I
A2	Periodical	8%	M	35%	M	No/Yes	20%	M
B	Visualization and display unit							
B1	Over time	1%	O,M	10%	M	Yes/No	3%	M,O
B2	Previous year's energy consumption	5%	A	13%	A	No/No	9%	A
B3	Comparison with similar housing situation	3%	A	5%	A	No/No	5%	A
B4	Display in kWh	18%	M	23%	M	No/No	19%	M
B5	Display in Euro	9%	A	13%	A	No/No	10%	A
B6	Display of the environmental impact	14%	M	21%	M	No/No	17%	M
C	Level of coverage/granularity							
C1	Overview of all devices	11%	A	21%	A	No/No	16%	A
C2	Appliance-specific	4%	A	8%	A	No/Yes	6%	A
D	Push notifications							
D1	High energy consumption	2%	A	9%	A	No/No	4%	A
D2	Peak energy consumption period	6%	I	2%	I	No/No	5%	I
D3	High proportion of green electricity in the energy grid	17%	A	10%	A	No/No	13%	A
E	Saving opportunities							
E1	Technical advice	3%	A	10%	A	No/No	8%	A
E2	Financial savings	8%	A	17%	A	No/No	9%	A
E3	Environmental contribution	5%	A	4%	A	No/No	2%	A
F	Social comparison							
F1	Average	47%	I	31%	I	No/Yes	40%	I
F2	Average	5%	A	5%	A	No/No	1%	A
F3	Average	44%	I	30%	I	No/No	37%	I
F4	Average	28%	I	30%	I	No/No	28%	I
F5	Most efficient	60%	I	35%	I	No/Yes	49%	I
F6	Most efficient	38%	I	26%	I	No/No	32%	I
F7	Most efficient	50%	I	39%	I	No/No	44%	I
F8	Most efficient	51%	I	40%	I	No/No	45%	I
F9	Ranking	31%	I	25%	I	No/No	30%	I

^aStudy 1 + study 2 minus repeat participants; *Categorization significant at a ten-percent level according to the Fong test; ¹(A,O,M) < > (I,R,Q) rule applicable; ²(A,O,M) < > (I,R,Q) rule not applicable; Categorization: A = attractive, O = one-dimensional, M = must-be, I = indifferent

Table 3 Statistics of categorizations per Kano model factor and participant

Categorization	Study 1 (n = 188)						Study 2 (n = 178)					
	Min ^a	Med ^a	Mean ^a	Max ^a	None ^b	≥9 ^b	Min ^a	Med ^a	Mean ^a	Max ^a	None ^b	≥9 ^b
Attractive	0	6	6.3	20	11%	30%	0	7	7.3	23	8%	40%
One-dimensional	0	2	3.0	25	24%	9%	0	2	2.4	13	29%	5%
Must-be	0	3	3.1	17	15%	3%	0	3	3.2	11	13%	3%
Indifferent	0	10	10.2	24	1%	65%	0	9	9.5	23	2%	57%
Reverse	0	1	2.1	15	45%	6%	0	0	2.3	22	52%	10%
Questionable	0	0	0.2	2	84%	0%	0	0	0.2	4	83%	0%

^aNumber of features with the respective categorization per participant; ^bShare of participants who categorized either none or at least nine (i.e., more than one-third) of the features as a specific Kano model category

evaluation, as its sample size consists of 188 participants, whereas study 2, excluding the repeat participants, has a smaller sample size of 138 participants. For *visualization over time (B1)*, there is a change in the sequence of categories in the mixed category in favor of the must-be quality, which comes first in the overall evaluation. This change is reasonable, as in study 2, the feature was categorized as a must-be, with the category strength being significant at the ten-percent level according to the Fong test, and therefore giving it the potential to affect the overall evaluation.

Our findings are also underlined when examining the categorization of features on the participant level. Table 3 presents the minimum, median, mean, and maximum count of Kano model factor categorizations per participant for both studies. The shares of participants categorizing none or at least nine (i.e., more than one-third) features as one of the six Kano model factors are indicated. To illustrate how this table can be interpreted, we explain the results for the attractive categorization in study 1. The value 0 in the “min” (minimum) column indicates that at least one participant did not find any features attractive. Conversely, the value 20 in the “max” (maximum) column shows that at least one participant identified 20 features as attractive, with no participant selecting more than 20 features. The value 6 in the “med” (median) column represents the middle number of attractive features among the 25. This means, half of the participants found 6 or fewer features attractive while the other half found 6 or more attractive. The value 6.3 in the “mean” column indicates that participants, on average, rated 6.3 features as attractive. The 11% in the “none” column signifies that 11% of the 188 participants found none of the features attractive. Lastly, the value of 30% for “greater than or equal to 9” means that 30% of the participants found 9 or more features attractive, which represents more than one-third of the 25 features. The numbers show the similarity of study 1 to study 2 – the changes in means and medians as well as in percentage shares of none and at least nine categorizations per Kano model factor are not tremendous.

In view of the slight changes in the categorization between study 1 and study 2, we observe different mean

values per Kano model factor. The mean of categorization as attractive increased from 6.3 to 7.3, and the mean of categorization as indifferent decreased from 10.2 to 9.5, indicating that features manage to delight customers slightly more often in study 2 than in study 1. There is also a shift in categorizing at least nine features per Kano model factor. The percentage of at least nine categorizations per participant as indifferent decreased from 65 to 57%, indicating the features are more relevant to participants in study 2.

Furthermore, the percentage share of zero categorizations as reverse increased from 45 to 52%. Only 8% of the participants of study 2 categorized none of the features as attractive. With 84% and 83% of participants having no questionable results and those having a maximum of four questionable results, we can assume that the participants understood the task in both studies and participated diligently.

Since both users and non-users of smart home apps participated in the surveys, we also analyzed these subgroups.⁴ The socio-demographic data for the subgroups shows that the users are on average older than the non-users, the proportion of men is higher and the proportion of students is lower for users (Table 8 in the supplementary material).

There are also some differences in the Kano categorization; a summary of the categorization can be found in Table 9 in the supplementary material. For 18 features, there is no difference between non-users and users in either study, we summarize the differences as follows:

- (1) For *visualization over time (B1)*, *visualizing previous year's energy consumption (B2)* and *display unit in Euro (B5)*, the analysis of users and non-users results in (more) mixed categories.⁵

⁴ The subgroup of users consists of those participants who use a smart home app at least from time to time.

⁵ It is important to note that the design of the method makes it more likely that a subgroup analysis with smaller sample will result in a mixed category. See also footnote 3.

- (2) For *appliance specific granularity (C2)* and *social comparison to the average of a similar housing situation (F2)*, there is a difference in the categorization of smart home app users in study 2. Compared to the other three groups that rated these features (C2 and F2) as attractive, the users in study 2 rated them (C2 and F2) as indifferent.
- (3) For *saving opportunities as environmental contribution (E3)*, there is a difference in the categorization of smart home app users in both studies. Compared to the non-users that rated this feature (E3) as attractive, the users rated it (E3) as indifferent.
- (4) For *push notifications for high energy consumption (D1)*, the classification of indifferent and attractive is exactly the opposite: In study 1, non-users rate this feature (D1) as indifferent, and in study 2, users do.

Interpretation

This study was motivated by the question of *how* potential and actual smart home app users evaluate a broad set of eco-feedback nudge features (short: features) designed to nudge towards energy conservation behavior (RQ1), and *if* the evaluation of these features is *robust over time* (RQ2), and, thus, whether medium-term product strategies for app development can be derived from this approach. To address both research questions, we analyzed the categorization of features in two studies and for subgroups (i.e., users and non-users). We compared the similarities and differences between the two studies that took place in similar settings and with similar samples at two distinct points in time.

There are notable differences between users and non-users regarding RQ1. Recognizing that the design of the method makes it more likely that smaller samples result in mixed category, we refrain from interpreting the different categorizations of *visualization over time (B1)*, *visualizing previous year's energy consumption (B2)*, and *display unit in Euro (B5)* in the analysis of users and non-users as these are samples consisting of 50 to maximal 129 participants. The composition of our user- and non-user-subsamples shows slight differences. The user groups had more male participants and were older than the average in the overall samples. Furthermore, less students than in the overall sample were represented in the user group. This may be due to the fact that the usage of smart home apps requires smart home ecosystems, which are more likely to be installed in owner-occupied houses and apartments than in rented apartments, as smart home ecosystems usually represent important investments. Nevertheless, for *appliance specific granularity (C2)*, *social comparison to the average of a similar housing situation (F2)*, and *saving opportunities as environmental contribution (E3)*, we found differences in the categorization

of smart home app users in both studies. As non-users rate the listed features as attractive, and users rate them as indifferent, we see the importance of possible personalization of app features. For non-users, hence potential adopters, it is crucial that the smart home app includes innovative features (e.g., the mentioned ones C2, F2, E3) and that these features are exciting and impressive ("attractive"). These innovative aspects can be the deciding factor that convinces them to adopt the technology. The novelty and advanced capabilities attract non-users and create enthusiasm for the new system.

In contrast, for existing users, the presence of innovative features is often taken for granted ("indifferent"). Once users have adopted the app, they expect it to function reliably and efficiently. Their focus shifts to how well the app meets their everyday needs and integrates into their routines. The innovative features that once excited them become a standard part of their user experience. This distinction highlights the importance of continually addressing different aspects of user expectations and experiences in both the adoption and post-adoption phases.

Comparing the results of the two studies in RQ2, we see slight differences in the categorization between the studies. We had an identical categorization for 23 out of 25 features, i.e., a different categorization for two features. Among the two features only the feature *near real-time update frequency (A1)* showed a significant and therefore important measurable change. We searched for possible effects of users' changing interaction with digital technologies by measuring Affinity for Technology Interaction (ATI) (Franke et al., 2019) and adapted pro-ecological behavior by measuring the revised New Ecological Paradigm (NEP) (Dunlap et al., 2000). As displayed in Table 1, the means and standard deviations of both constructs only vary slightly and negligibly. Thus, changes in users' affinity for technology and their pro-ecological behavior do not seem to cause the changes in categorizations of the features.

Although only the change in the feature *near real-time update frequency (A1)* is significant, both changes in Kano categorization are in line with Kano lifecycle theory (Kano, 2001) and, thus, theoretically plausible. Overall, the results suggest that the features became more important, as they were less often categorized as indifferent and more often seen as attractive in study 2 – for instance, the statistically significant feature *near real-time update frequency (A1)*. Participants are delighted by the feature in study 2, which indicates a growing interest in transparency regarding their current energy consumption. Furthermore, the feature *visualization over time (B1)*, assigned to a mixed category in study 1, is seen as a must-be by most participants in study 2. As this change is not significant, it remains open for interpretation. One possible interpretation could be that users need to understand and analyze their own energy conservation behavior to adjust it. As mentioned above, both cases

are consistent with Kano lifecycle theory (Kano, 2001) as they show how people initially did not recognize the value of seeing their energy consumption displayed in different ways, which changed in study 2. Furthermore, it leads to the conclusion that with time, as users get more experienced, they expect an increasing number of features. When must-be features are not implemented, they lead to users' dissatisfaction, which may result in the discontinuation of smart home app use. In this context, it should be noted that user expectations are likely to be driven not only using smart home apps, but that such a change can also be transferred from other domains to the requirements of a smart home app. For example, it can be generally observed that real-time feedback has become more relevant in recent years, not only in the smart home app domain (e.g., Hribernik et al., 2022; Lechermeier et al., 2020), partly because of the increasing availability of real-time data (e.g., Tiefenbeck et al., 2019). Therefore, potential users may already have expectations similar to those of actual users. For instance, a person using a weather app which provides real-time weather forecasts of high quality might not be easily delighted by a feature only updating energy consumption on a weekly basis (periodically) and may rather see this as a must-be, while others with less comparable experience might categorize periodically updated information as attractive. However, as only for one of 25 features a change in categorization is substantial and significant, we refrain from claiming empirical support for Kano lifecycle theory. Instead, we restrict the interpretation to saying that the categorizations of the features remain mostly the same from study 1 to study 2.

In addition, for many features, the category strengths increased from study 1 to study 2. We explain this phenomenon with the help of the SERVQUAL approach by Parasuraman et al. (1994), as personal needs, word of mouth, and past experiences may moderate these changes. For example, the category strength of *periodically update frequency* (A2) categorized as must-be increased from 8 to 35% (Table 2). This means that more participants expect the feature and take it for granted, suggesting that, for example, more people are looking for better information to better control their energy consumption as for example especially young app users tend to have higher expectations in the features of new apps based on their pool of experiences in digital environments (Tam et al., 2020). For *display of environmental impact* (B6), also categorized as must-be, the category strength also increases from 14 to 21% (Table 2). Hence, for (potential) smart home app users, energy consumption and knowing about the environmental impact go hand in hand. This strengthens the argument that sustainable behavior can be promoted through digitalization. The *display of financial savings* (E2) is categorized as attractive at both times and gains in category strength. Even though the feature is not explicitly

demand, it shows that more (potential) users are interested in potential savings.

Discussion

The categorization of features according to Kano factors for both potential and actual smart home app users answers RQ1, see Table 2 in section Results and Table 9 in the supplementary material. The fact that the categorizations of the features remain mostly the same from study 1 to study 2 with only one feature showing a significant change in categorization confirms the usefulness of the applied method by showing the robustness of the results, answering RQ2.

For those features with identical Kano categorizations in both studies, it is possible to deduce overarching recommendations. Beginning with features classified as must-be quality, these are considered essential for smart home apps, as their absence leads to user dissatisfaction, making them critical to fulfilling user expectations. Overall, three features were assigned as must-be qualities: *periodically update frequency* (A2), *display in kWh* (B4), and *display of the environmental impact* (B6). Additionally, *visualization over time* (B1) is assigned to both categories, must-be and one-dimensional quality in the overall evaluation. Both categories lead to user dissatisfaction if not implemented and should therefore be in focus. Therefore, all four features (A2, B4, B6, and B1) should be implemented to prevent user dissatisfaction, which can adversely affect continued app usage (Bhattacharjee, 2001). Users see these features as basic, which is why most of the features are commonly regarded as standard features in research (Chatzigeorgiou & Andreou, 2021) and in state-of-the-art smart home apps (see Table 5 in the supplementary material).

Then, there are features categorized as attractive quality. Users may not expect these features, but their inclusion can pleasantly surprise them, offering an opportunity to enhance user satisfaction. Attractive quality features constitute the largest group (11 out of 25), emphasizing the importance of allowing users to personalize the app based on their individual preferences and what they find appealing (e.g., implementing a *comparison with similar housing situation* (B3) or *push notification on high energy consumption* (D1)). Our findings, therefore, underscore the significance of individualization and personalization, aligning with insights from prior research (Hubert et al., 2020). The app could either enable users to customize features themselves or automatically adjust based on user data, such as their prior experience with smart home apps. Differentiating between actual and potential users may be advantageous in this context.

Finally, the ten features classified as indifferent quality do not impact user satisfaction, meaning users show no interest

in including them in a personalized feature set for a smart home app. However, our findings offer valuable insights into which features should be prioritized if they positively influence energy conservation behavior and are easy to implement. Out of the ten indifferent features, eight belong to the dimension *social comparison* (*F*). Even though these features are well-established in research (e.g., Brülisauer et al., 2020; Nemati & Penn, 2020), Table 5 in the supplementary material shows that these are barely implemented in state-of-the-art smart home apps, potentially due to the data privacy and IS security issues addressed by Nehme and George (2022) and Gerlach et al. (2022), which would result from sharing information on smart home app users' energy consumption.

Fortunately, none of the features was categorized as being of reverse quality. If implemented, these features would have had a negative effect on user satisfaction, while the absence of these features would have a positive effect on user satisfaction. This would have been the case when smart home app users experience fear and see their data privacy threatened and thus would have avoided the app's use (Nehme & George, 2022).

Theoretical contributions

With this research endeavor, we contribute to scientific literature on smart home apps. While Berger et al. (2022b) focus on framing nudges and default settings to promote energy conservation behavior in smart home apps, we add a perspective on feedback nudging. To provide a valuable contribution, we used research on feedback nudging in the smart home context such as Tiefenbeck et al. (2019) and Kim et al. (2020) as input for our features. Tying in with Hubert et al. (2020) and Hagejård et al. (2023), we also underline the importance of personalization of features in the configuration of smart home ecosystems and apps, as (potential) users of smart home apps in our studies presented different needs.

Compared to prior research, we approached digital nudging elements to promote energy conservation behavior from a different angle. Previous endeavors aimed at researching the effectiveness of single digital nudging elements (e.g., Asmare et al., 2021; Callery et al., 2021) or of combinations of multiple digital nudging elements (e.g., Berger et al., 2022b; Brandsma & Blasch, 2019; Cellina et al., 2024) in various experimental contexts such as university residential buildings (e.g., Jorgensen et al., 2021), private households (e.g., Marangoni & Tavoni, 2021), or tertiary buildings (e.g., Casado-Mansilla et al., 2020; Tiefenbeck et al., 2019). Measuring the effectiveness of using digital nudging elements to promote energy conservation behavior is an established approach (Kürschner et al., 2024), which is why we were able to build upon insightful and seminal meta-analyses such as Karlin et al. (2015) and Khanna et al.

(2021). We focused on feedback as one specific digital nudging element which has already proven to be effective and can be employed with a variety of configurations (e.g., Nemati & Penn, 2020). Feedback is expressed in different smart home app features as shown in the literature review and the analysis of contemporary smart home apps. As we assumed that these differences in configuration may manifest in different degrees of user satisfaction, we applied the Kano method on the features. Hence, we extend the existing body of research by enabling user-centric development of smart home apps combining effectiveness in promoting energy conservation behavior (e.g., Brandsma & Blasch, 2019; Schultz et al., 2015) and promoting adoption and continuous smart home app use by supporting user satisfaction.

By applying the Kano method to evaluate user satisfaction with features at two distinct points in time, we could confirm the significance of our results of both studies on the one hand and the usefulness of the Kano method in the given context on the other hand. Since most of the categorizations were confirmed by the second user survey, we can demonstrate that the results of the user surveys are reliable and, thus, suitable for practical implications. Our results supported Kano lifecycle theory for the two features with changing categorizations between surveys (Kano, 2001). Hence, it is important to keep an eye on such transitions over time. Nevertheless, we show that these transitions are not overly fast or intense. We thus contribute to the growing body of measuring user satisfaction in digital environments (e.g., Gimpel et al., 2021; Malinka et al., 2022; P. Li et al., 2024).

The fact that the societal discourse about energy consumption is on the rise (e.g., due to increasing and variable energy prices in between our surveys in early 2022 and 2023), the two points of measurement allowed us to observe changes on users' preferences for eco-feedback nudging. Our results show that user preferences are somewhat resistant throughout the period of approximately one year including the given external factors. However, the slight changes regarding the category strength that cannot be directly attributed to Kano lifecycle theory (Kano, 2001) support the findings of Parasuraman et al. (1988), who described the impact of personal needs, word of mouth, and past experiences on users' expectations of service quality.

Practical implications

With the growing prevalence of smart home devices, there is a need to analyze and enhance the configuration of smart home apps that control these technologies to influence energy conservation behavior.

Firstly, the findings of this paper show that no feature is categorized as contributing to dissatisfaction (reverse categorization). This is consistent with the fact that smart homes and the use of smart home apps are on the rise as they

promote convenience, such as turning off the heat when you have already left the house or turning on the heat when you are on your way home so that the rooms are comfortable and warm whenever you need it. In this case, digitalization can help improve the user experience and encourage sustainable behavior. In many other cases, this is counterintuitive, as promoting sustainable behavior may mean sacrificing convenience, e.g., in instances where taking public transport takes more time than driving a private car.

Secondly, conducting user surveys at two distinct points in time enhances the paper's value for practitioners, such as app developers. The stable categorization of features indicates reliable user satisfaction results, and any changes in categorization signify increasing importance following the Kano lifecycle (refer to the [Changes in user behavior and attitudes over time](#) section). Therefore, the findings are usable in the long-term. Since features can entail significant implementation challenges, particularly concerning temporal resolution and data privacy issues (such as comparing individuals' values with neighbors), conducting a temporal investigation is essential for making informed configuration decisions.

Thirdly, our research emphasizes the importance of avoiding excessive implementation of features in smart home apps. Our findings recommend a curated selection of features best offered as optional features within a personalized area, empowering users to activate them based on their preferences (features with attractive categorization). In this context, our results need to be analyzed in conjunction with the existing literature on effectiveness. We see this as an important step, considering that smart home apps that are currently available in app stores and that are in usage in smart homes already employ different feedback configurations as digital nudging element and a reflection on employed features may lead to a more effective and attractive promotion of energy conservation behavior.

Limitations and future research

Researchers and practitioners should be mindful of the following limitations. Due to the online nature of our user survey approach, it may lack real-world consequences and context. During the survey, participants had to envision the features, which might lead to different interpretations of the provided feature descriptions. In our setup, participants evaluated each feature only once. In real-life situations, where users are nudged by the feature every time they open the app, the results might vary compared to our setup. To compare the results of study 1 and study 2, having a similar sample of people was important. Therefore, we recruited participants again via e-mail and social media. However, our sample differs from the German population, e.g., in terms of age structure (mean age is 33.2 and 31.5 years in studies 1 and 2, compared to 44.6 years for the population (Destatis,

2023)). This means that the results do not reflect those of the entire population. Although people without internet access may not be the most crucial target group for smart home apps, we did not include them in our study. Furthermore, we discussed that using the Kano model also has disadvantages.

In future research, we highlight four key areas of focus. Firstly, while we opted for the use of the Kano model, we also see potential in combining the Kano model with other methods like cluster analysis to compensate for its weaknesses. Secondly, we measured the aggregated user satisfaction of 25 features. Therefore, our analysis did not account for differences based on participants' characteristics. Given our findings indicating diverse individual perceptions, future research can delve deeper by examining various subgroups within the participant pool. Thirdly, for now, the two studies show that features remain essential, and in some cases are becoming more critical, for user satisfaction. For future research, it would be interesting to evaluate whether there is a period or certain experience of external events that trigger users' categorization changes. Fourthly, when extracting features from the literature, we focused on features with theoretical and empirical support for a positive effect on energy conservation behavior. However, we did not further study the features' effectiveness but focused on user satisfaction. A combined analysis of effectiveness and user satisfaction would be an essential next step to achieve the goal of promoting energy conservation behavior in addition to continuous use.

Conclusion

There is a growing urgency to promote energy conservation behavior through behavior change. The increasing use of smart home devices provides an excellent opportunity to use digital nudging elements in a smart home app. Previous research has explored eco-feedback to reduce energy consumption and tested different features. Although there is knowledge about the effectiveness of certain features, there is a lack of information about user expectations and preferences for these features. Understanding these preferences is critical to ensuring IS adoption and user satisfaction for continuous app usage. To address this gap, we conducted two surveys with actual and potential smart home app users, approximately one year apart, to categorize 25 features identified from a structured literature review and verified by an analysis of contemporary smart home apps. With these user surveys, we examine the impact of different features on user satisfaction and consider whether possible changes in Kano categorization are discernible. Our study adds a perspective of user satisfaction over time to account for potential changes, in addition to the traditional

focus on the effectiveness of these nudges. The findings suggest which features are essential as their categorization leads to dissatisfaction if not implemented and which features are optional regarding continuous use and should be evaluated for effectiveness.

Furthermore, since both studies produce almost identical results or follow the Kano lifecycle theory – where features become prerequisites over time – this research confirms previous findings. It illustrates the usefulness of categorization to practitioners. The categorization is reliable and, therefore, beneficial for app development. Accordingly, our results enhance the understanding of using behavioral interventions in this study as feedback nudges in smart home app configuration to promote energy conservation behavior in the context of digitization trends. By focusing on user satisfaction for continuous app usage, we aim to contribute to the long-term goal of promoting energy conservation behavior.

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Data Availability The raw data required to reproduce the above findings are available to download from <https://doi.org/10.17605/OSF.IO/FJ4AU>. Please note that raw data has been collected in German.

Declarations

Declaration of generative AI and AI-assisted technologies in the writing process During the preparation of this work the authors used Grammarly, ChatGPT and DeepL Write to improve readability and language as well as Consensus for advanced scientific literature search. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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