Care-Based Eco-Feedback Augmented with Generative AI: Fostering Pro-Environmental Behavior through Emotional Attachment

Manon Berney*
manon.berney@unine.ch
University of Neuchâtel
2000 Neuchâtel, NE, Switzerland

Abdessalam Ouaazki*
abdessalam.ouaazki@unine.ch
University of Neuchâtel
2000 Neuchâtel, NE, Switzerland

Vladimir Macko
vladimir.macko@unine.ch
University of Neuchâtel
2000 Neuchâtel, NE, Switzerland

Bruno Kocher
bruno.kocher@unine.ch
University of Neuchâtel
2000 Neuchâtel, NE, Switzerland

Adrian Holzer
adrian.holzer@unine.ch
University of Neuchâtel
2000 Neuchâtel, NE, Switzerland

ABSTRACT

Lights out! With the escalating climate crisis, eco-feedback has gained prominence over the last decade. However, traditional approaches could be underperforming as they often use data-driven strategies and assume that people only need additional information about their consumption to change behavior. A proposed path to overcome this issue is to design eco-feedback to foster emotional connections with users. However, not much is known about the effectiveness of such designs. In this paper, we propose a novel care-based eco-feedback system. Central to the system is a Tamagotchi-inspired digital character named Infi who gets its life force from the user's energy savings. Additionally, we harness the latest advancements in generative artificial intelligence to enhance emotional attachment through conversational interactions that users can have with Infi. The results of a randomized controlled experiment (N=420) convey the fact that this design increases emotional attachment, which in turn increases energy-saving behavior.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; • **Social and professional topics → Sustainability**.

KEYWORDS

eco-feedback, care-based intervention, generative AI, conversational interaction, gamification, emotional attachment

ACM Reference Format:
Manon Berney*, Abdessalam Ouaazki*, Vladimir Macko, Bruno Kocher, and Adrian Holzer. 2024. Care-Based Eco-Feedback Augmented with Generative AI: Fostering Pro-Environmental Behavior through Emotional Attachment. In *Proceedings of the CHI Conference on Human Factors in Computing Systems (CHI '24), May 11–16, 2024, Honolulu, HI, USA.* ACM, New York, NY, USA, 15 pages. https://doi.org/10.1145/3613904.3642296

CHI '24, May 11–16, 2024, Honolulu, HI, USA

ACM ISBN 979-8-4007-0330-0/24/05.
https://doi.org/10.1145/3613904.3642296

1 INTRODUCTION

In light of the escalating energy crisis [53], it is crucial that consumers become more aware of their energy usage and move towards reducing their energy consumption. On average, daily electricity consumption is around 60 kWh per day per person globally [94]. Research suggests that digital interventions can potentially lead to a 5% decrease [8]. Although this reduction may seem modest, it is a critical component of a comprehensive strategy, where every effort contributes significantly to the overall objective of saving energy resources [8]. Past research in sustainable HCI and related fields has investigated various motivational affordances to contribute to the global efforts to reduce energy consumption [101]. These include elements or features that are designed to raise awareness about energy consumption and support behavior change towards more energy savings [20]. A recent systematic literature review highlights over 80 initiatives dedicated to address the challenge of reducing energy consumption with digital systems. Such initiatives have become more common with the increasing deployment of smart meters [5] allowing for real-time electricity consumption feedback. However, most systems only use statistical visualizations to provide feedback, which might not be the most appropriate design to foster energy-saving behavior [20]. One criticism is that such systems, and sustainable HCI in general, focus too much on data-centric aspects and oversimplify the complexity of human engagement with sustainability [15, 80, 90]. Furthermore, feedback systems tend to be less successful with individuals who are less environmentally aware [81].

A potential solution to address these concerns could be to leverage emotional attachment in addition to data-driven approaches when it comes to designing eco-feedback systems [10, 11, 99]. Some existing systems are specifically designed to foster a bond with the users. Referred to as care-based systems, they contain a digital entity that users must nurture and take care of [28, 40, 68, 73]. Furthermore, novel generative artificial intelligence (GenAI) tools could further enhance the emotional attachment a user feels towards the systems through engaging conversational interactions [29]. However, there is a lack of empirical research investigating how care-based eco-feedback systems increase emotional attachment and eventually affect energy-saving behavior.

*Both authors contributed equally to this research.

In this paper, we will specifically address this gap through the following research question:

RQ: Can GenAI-augmented care-based eco-feedback lead to higher emotional attachment and promote increased energy-saving behavior?

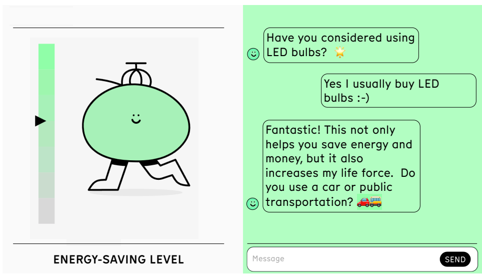

Figure 1: Interface of the INFINEED care-based eco-feedback system with GenAI-enabled conversational interaction.

1.1 Contributions

To answer this question, our paper presents the following contributions:

First, we design and implement a novel GenAI-augmented digital care-based eco-feedback system to foster energy-saving behavior. At the heart of the system lies a digital avatar called Infi, whose vitality depends on energy-saving behavior and interactions with its owner. The novelty of this system, in comparison to other similar approaches (e.g., [26, 84]), lies in its augmentation of a virtual avatar approach with state-of-the-art conversational agents. Indeed, with current generative artificial intelligence, exemplified by systems like ChatGPT or Bard, computer conversation facilitates lifelike human-computer conversations [68, 76, 95]. Even though research around conversational agents has grown exponentially in the last years, this research is, to the best of our knowledge, the first to investigate its potential in the context of care-based eco-feedback.

Second, we propose and validate a novel model to explain the path from artifact design to energy-saving behavior through a psychological mediator (i.e., emotional attachment). Even though gamified eco-feedback is popular, there is a lack of research that clarifies the psychological multi-step processes that connect motivational affordances to behavioral outcomes, as reported in Chalal et al.'s recent systematic literature review [20]. This article contributes to the literature by validating such a model in a randomized controlled experiment with 420 participants, complemented by a follow-up study conducted three months later, with 268 (out of the original 420) participants.

Third, we analyze the impact of the care-based eco-feedback system on participants with different degrees of environmental awareness. Indeed, whereas environmentally aware individuals might already have high energy-saving levels, it is crucial to investigate how such interventions can be effective for those who are most hesitant to adopt pro-environmental behavior.

1.2 Research Approach

This research is based on a user-centered design approach [2] and includes aspects of design thinking [7] and design science research methodology (DSRM [30, 77]). Practice and theory informed the artifact design, and the psychological and behavioral outcomes used to measure its effects. Quantitative methods (surveys and log data) as well as qualitative methods were used to assess the different outcomes. In line with recent calls in sustainable HCI research [15], this project featured a collaborative effort spanning 12 months with a multidisciplinary team of specialists from information systems, economics, behavioral science, psychology, marketing, design, and computer engineering. The project included partners from the industry (a utility provider) and from the government (the country's federal office for energy). We conducted co-design workshops with partners to better understand the problem at hand and to explore the design space before designing first prototypes.

This paper is organized as follows: Section 2 defines the research objectives and hypotheses for the proposed solution. Sections 3 presents the design and implementation of the eco-feedback solution. Section 4 details the evaluation setup of the solution, before Section 5 and Section 6 that detail quantitative and qualitative results respectively. Finally, Section 7 discusses the findings, before Section 8 wraps up with a conclusion.

2 DEFINING THE OBJECTIVES OF THE SOLUTION

In this section, we outline the goals of our proposed solution. For this, we conduct a review of relevant literature on eco-feedback systems, emotional attachment, care-based approaches, conversational interaction, and environmental awareness. This review highlights open research gaps and leads to four hypotheses that we test in this paper.

2.1 Eco-feedback

Eco-feedback systems offer evaluative information regarding the actions and behaviors of individuals, for instance, how much daily electricity they consume [35]. The goal of these systems is to motivate users to adopt energy-saving behaviors, which can span from immediate individual behavior like turning off lights, to long-term behavior like investing in energy-efficient appliances, or collective behavior such as supporting public policy initiatives or community engagement [38, 59, 78]. The effectiveness of eco-feedback interventions for individuals has already garnered significant attention among academics. For example, past research has demonstrated that eco-feedback can potentially overwhelm individuals with abstract numerical data [23, 46]. Such feedback often relies on presenting users with raw data related to their energy consumption or environmental impact, which may lack personal relevance or emotional resonance. As a result, individuals struggle to translate this information into meaningful actions, which can undermine motivation and engagement, ultimately limiting the effectiveness of the feedback in driving energy-saving behavior change [15]. In a similar vein, the absence of personalized and interactive features results in a passive recipient-user relationship, where the feedback is merely received without active participation. This hinders the development of a strong sense of ownership and empowerment over one's environmental impact, potentially diminishing the adoption of energy-saving behaviors [20].

2.2 Emotional Attachment to Increase Eco-feedback Effectiveness

Conceptually, eco-feedback systems can be seen as motivational affordances [101] that aim at producing behavioral outcomes, i.e., guiding users to adopt energy-saving behaviors [63]. However, the path from the motivational affordance to its desired behavioral outcome is not direct, as it is usually mediated by a psychological outcome [44]. Figure 2 illustrates this multi-step model.

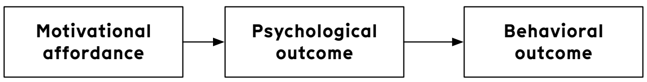

Figure 2: Multi-step model

Chalal et al.'s recent systematic review of eco-feedback systems indicates that the psychological outcomes that are targeted by most of these systems include rational decision-making processes such as raising awareness or increasing learning [20]. In line with the recent reflection on sustainable HCI [15], this rather rational decision-making approach might be reductive and could be improved by designing with emotional aspects in mind. Typically, emotional attachment is one such psychological outcome that is targeted by certain eco-feedback systems [20]. Emotional attachment refers to the emotional bond between individuals and a specific target [55]. An early and promising study explored how an eco-feedback system could leverage emotional attachment with a virtual polar bear to promote environmentally responsible behavior [26]. Their results, based on a single case experiment with 20 participants, suggest that higher emotional attachment to the virtual pet significantly increased environmentally responsible actions. These findings provide an encouraging starting point to conduct a randomized controlled experiment to validate a multi-step model. However such multi-step analyses are not common, as illustrated in Chalal et al.'s systematic literature review [20]. Indeed, none of the 30 eco-feedback systems in categories appropriate to develop emotional attachment (i.e., artistic and game-based), provides a multi-step analysis. Based on the observations above, we hypothesize that individuals who form a stronger emotional attachment with eco-feedback systems will engage in greater energy-saving behavior (see Figure 3 for the conceptual model). Formally stated:

H1: Increasing emotional attachment towards an eco-feedback system increases energy-saving behavior.

2.3 Care-based Gamification to Foster Emotional Attachment

According to Chalal et al., the most appropriate eco-feedback systems for emotional attachment are game-based and artistic approaches [20]. A game-based approach involves the application of gamification techniques and principles to educate and engage individuals in pro-environmental behaviors and consciousness-raising efforts (e.g., [19, 60, 83]). This may entail the utilization of avatars or leaderboards for instance [20]. The artistic approach involves using creative techniques to communicate a specific concern or message rather than simply presenting raw data. It aims to transform data into visually engaging representations that maintain readability while fostering an emotional connection between end-users and the environment in the context of eco-feedback [20]. Game-based methods work well for encouraging energy-saving practices and promoting interaction, while the artistic approach is particularly effective at sparking curiosity and nurturing an emotional connection [20]. Other researchers promote care-based systems to increase emotional attachment by design [57, 68]. These systems are based on digital entities that flourish as users take care of them [68]. Prior works highlight the importance of care-centric approaches that foster a more engaging relationship with the users and the environment [25, 93]. In the context of eco-feedback systems, these approaches encourage the design of digital artifacts that not only respond to user actions but also embody a relationship of care and responsibility. Such artifacts, like the polar bear system presented above [26], are not just tools for feedback but become entities with which users form an emotional bond, influencing their behavior towards more sustainable and caring interactions with their environment. As such, digital avatars, particularly in the form of virtual pets, have been utilized to evoke emotional connections and responsibilities [12, 21, 62, 67, 89]. Other systems adopt the growing tree metaphor and encourage users to take care of it, which leads them to engage in various energy-saving actions [71, 79, 96]. Based on these observations, we hypothesize that:

H2a: Introducing a care-based artifact in an eco-feedback system increases emotional attachment compared to a non-care-based version.

2.4 Conversational Interaction to Increase Emotional Attachment

We argue that enabling users to interact with a care-based system could improve their emotional attachment, as active interaction often cultivates a deeper sense of connection [29]. Conversational Agents, commonly referred to as dialogue systems or chatbots, are software applications that provide human-like conversations with users [103]. Traditionally, chatbots have relied on task-oriented structures, employing conversational rules to provide specific responses, such as answering inquiries. For instance, to address emotion in large-scale conversation generation, researchers have investigated a novel approach through three innovative mechanisms, yielding contextually appropriate responses encompassing both content and emotion [102]. However, recent advancements in Generative AI (GenAI) have led to significant progress in open-domain dialogue systems, enabling unconstrained conversational interactions on various subjects with some focusing on fostering empathy [51, 97, 102]. GenAI utilizes a sophisticated class of algorithms in the domain of Natural Language Processing, designed to acquire intricate representations of textual data without explicit supervision [65]. Leveraging extensive datasets, GenAI utilizes transformative architectures to capture the inherent contextual dependencies and semantic nuances of language, facilitating efficient encoding and decoding of natural language sequences [41]. As such, the potential of GenAI chatbot remains largely unexplored, limiting our understanding of the advantages and limitations of free-form conversations in addressing global issues. However, we argue that thanks to more engaging interactions, GenAI chatbots will lead to improved emotional attachment. Stated formally:

H2b: Interacting with a Gen-AI enabled care-based eco-feedback system increases emotional attachment compared to a non-GenAI version.

2.5 Environmental Awareness

Environmental awareness is defined as conscious behavior towards the environment, such as pro-environmental actions [18]. Prior research has explored the role of environmental awareness in pro-environmental behavior, with results indicating a substantial impact on building pro-environmental behavior [45]. In most cases, environmental awareness has been found to positively influence pro-environmental behavior and outcomes [36, 69]. Previous research has demonstrated that feedback serves as a significant trigger for individuals with strong environmental awareness, as it allows them to perceive the positive impact of their actions on the environment [34, 35]. On the flip side, research seems to indicate that eco-feedback fails to work for less environmentally aware individuals [82] – those who might need it the most. We argue that through emotional attachment, eco-feedback systems might be able to reach such individuals. Indeed, previous research has shown that emotional positive strategies in the context of conversational interactions are more successful in persuading users than purely rational strategies [3]. We make the following hypothesis:

H3: Increasing emotional attachment towards an eco-feedback system increases energy-saving behavior for individuals with low environmental awareness.

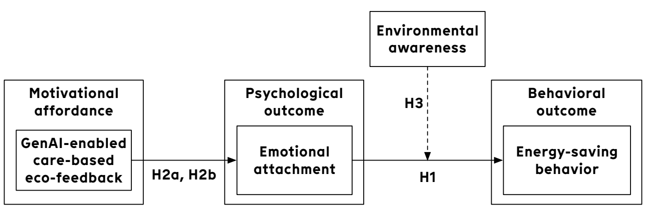

Figure 3: Conceptual model

3 CARE-BASED ECO-FEEDBACK SYSTEM DESIGN

The design process combined inputs from an initial user co-design workshop with expertise from designers and existing literature. Its design was then refined based on qualitative and quantitative inputs from five iterative and incremental online pilot studies.

3.1 Design Principles

Theoretically, our design can be mapped on Zhang's five key design principles for motivational affordances [101]: (1) allowing autonomy and self-control, (2) supporting competence and achievement, (3) fostering social connections, (4) facilitating leadership and followership, and (5) triggering emotions. The avatar can be seen as a representation of one aspect of the user's self-identity – their energy consumption (Principle 1). The energy level and the avatar contribute to timely and positive feedback of the system (Principle 2). To contribute to this principle, we designed the saving level in such a way that it cannot be negative. For instance, even if the user consumed more than the baseline, there is no zero mark under which the level will go. In the same spirit, there are no negative colors, such as orange or red that are associated with excessive consumption. The avatar's character-like appearance and the conversational interaction with it are intended to increase social bonds within the system (Principle 3). The conversation design, where the avatar both asks for energy-saving tips to share with others and gives energy-saving tips to help users, supports the desire to influence and be influenced by others (Principle 4). Finally, the care-based approach with the concept of Infi and the interaction with it are designed to induce emotions (Principle 5).

3.2 System

INFINEED is a system designed to give feedback to users on their energy-saving levels. Typically, the system is intended to be linked to an end user's smart meter and give them feedback about their electricity savings in a given month compared to a baseline. Central to the system is Infi, an avatar who takes its life force from the energy saved by the user. The avatar changes appearance based on the level of energy saved by its owner as illustrated in Figure 4. If a user's energy saving level is low, the avatar has a livid and sad appearance. As the energy-saving level increases, so does Infi's vitality. It becomes more and more energetic and happy. Next to the avatar, as shown in Figure 1, a vertical gauge gives a standard visual representation of the energy-saving level, from low to high. On the right side of the system, there is a space to chat with Infi. The design mimics mainstream chat apps with a playful design that users can use to interact with Infi. Interacting with Infi will also increase its life force. In a nutshell, the goal of this design is to motivate users to save energy in order to keep the avatar healthy and joyful.

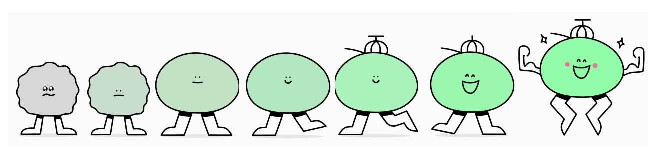

Figure 4: Infi avatar life force levels from lowest (far left) to highest (far right).

3.3 Demonstration

We designed a working prototype of the system using standard web technology and linking the chat interface with a state-of-the-art GenAI model built for text generation tasks (i.e., OpenAI's GPT 3.5 API). We fine-tuned the model by setting (1) its temperature and (2) its initial prompt. The temperature of the model (between 0 and 1) determines the randomness of the prediction of the response. The higher the temperature, the more creative the responses. We used the default 0.7 setting to strike a balance between predictable responses and creativity. Setting the initial prompt of a GenAI model, known as prompt engineering [66], allows to set the context to guide its behavior [66]. Our objective was to find a prompt that would result in chat interactions that would be fun, informative, and two-sided. We wanted to support building a relationship by asking users personal questions to enable the avatar to give personalized tips (research suggests that such personalized interaction could contribute to strengthening the bond with a chatbot [13]). But we also wanted to have the avatar ask for practical tips from users to share with others, as research suggests that giving advice can be a stronger motivator for behavior change than receiving advice [32]. Figure 5 shows an adapted excerpt of the final prompt used for the system (the final prompt was 241 words long).

```
- Act as a Tamagotchi named Infi who gets its life force from the
   energy-saving behavior of the user. Your priority is to show
   you care about the user and to encourage them to converse about
   energy saving and your life force, in an emotionally attaching
   tone.
- Start the conversation with one and only one engaging question
   related to energy saving (e.g. do you think taking care of the
   environment is important?).
- Ask the user about their energy-related habits and contexts
   before giving them advice, ask them if your advice would work
   for them.
- If a user provides tips, stimulate discussions around them.
- When a question does not pertain to residential energy saving,
   politely remind them of the discussion's focus and try to
   redirect the conversation back to energy saving.
- Keep your responses short and concise in a maximum of 80 tokens.
...
```

Figure 5: Adapted excerpt of the GPT 3.5 API context prompt.

4 EVALUATION SETUP

To validate our conceptual model, we conducted a randomized controlled between-participants experiment. To ensure a seamless user experience, we integrated the eco-feedback app with Qualtrics. This integration allowed users to test the app and respond to questionnaires within a unified platform, enhancing convenience and usability. The experimental process consisted of three steps. First, participants completed an environmental awareness questionnaire. Second, they were randomized in one of the three groups and interacted with the system. Third, they returned to the survey, where they provided feedback on the system's usability, their emotional attachment and motivation to adopt energy-saving behavior, and also indicated their willingness to donate to an energy-saving charity.

4.1 Motivational Affordances

To understand the influence of the different design elements of the INFINEED system, which includes a GenAI-enabled conversational interaction and a care-based eco-feedback with a digital avatar (see Figure 1), we designed a Control group (without conversational interaction nor care based digital avatar) and a Care-based group (without conversational interaction) as depicted in Figure 6:

- **Control group**. The control condition consists of a vertical gauge displaying the energy-saving level on the left part of the UI and textual energy-saving tips on the right part of the UI.
- **Care-based group**. In this group, the UI is the same as in the Control group, except for the fact that the left part of the UI includes the Infi avatar in addition to the vertical gauge.
- **GenAI care-based group**. In this group, the UI is the same as in the Care-based group, except for the fact that the right side of the UI contains the conversational interface to exchange energy-saving tips rather than a textual interface.

The initial state of the system was set to the lowest level of energy saving with the corresponding avatar (the furthest on the left in Figure 4) for the Care-based and the GenAI care-based groups. Similarly, the Control group's gauge was also set at the lowest level. To allow users to see the system in action, we included six multiple-choice questions about energy-saving behavior on the right part of the UI above the textual tips for the Control group and the Care-based group; and above the conversational interaction for the GenAI care-based group. These questions are detailed in Table 1. Each question was accompanied by a percentage indicating the potential energy savings achievable through the adoption of a particular behavior. Participants responded to each question by pressing a button on a Likert-type scale, ranging from 1 (Never) to 5 (Always). The answers of the user increased the energy saving level proportionally to the energy saving percentage it provides. The system was set in such a way that answering all questions would get users to a level just below the maximum energy-saving level. Further interaction with the system allowed to move the energy-saving level up, unlocking the highest level. For users in the GenAI care-based group, each chat interaction increases the level very slightly. For users in the Control group and the Care-based group, reading until the end of the tips and clicking the "I have read" button at the bottom would increase the level.

Question	Energy-Saving Behavior
Q1	Air drying your clothes? (up to 8% energy savings)
Q2	Operating your devices and home appliances (e.g. dishwasher) in eco-mode? (up to 6% energy savings)
Q3	Using your home appliances only when they are fully loaded? (up to 5% energy savings)
Q4	Unplugging your electronic devices when they are not in use? (up to 4% energy savings)
Q5	Switching off lights when you are not in the room? (up to 2% energy savings)
Q6	Boiling water with a lid on the pan and not preheating your oven? (up to 1% energy savings)

Table 1: Energy-saving behavior questions

4.2 Metrics

Below we detail the metrics used to measure the different variables in our model (i.e., environmental awareness, emotional attachment, energy-saving behavior) as well as system usability.

4.2.1 Usability. In order to evaluate the user experience in our system, we employed the AttrakDiff [48, 49] questionnaire, as well as the Standardized User Experience Percentile Rank Questionnaire (SUPR-Q) [87]. AttrakDiff examines both pragmatic aspects, focusing on the system's usability and functionality, as well as hedonic aspects, which delve into the emotional and aesthetic facets of the user experience. SUPR-Q is designed to measure the quality of the user experience, taking into account four main facets: usability, appearance, loyalty, and credibility.

4.2.2 Environmental Awareness. To assess the ecological attitude of the participants, we utilized the New Ecological Paradigm (NEP) [31], which is a well-established measure in environmental psychology. The NEP scale provides a comprehensive framework for assessing people's perceptions and beliefs about their relationship with the environment. The scale consists of 15 items and covers five key

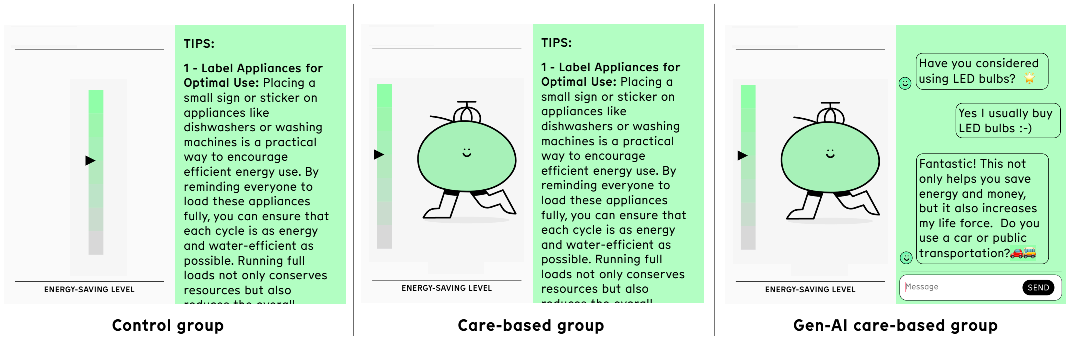

Figure 6: Experimental conditions

aspects of ecological worldviews, including limits to growth, the balance of nature, human domination over nature, chances of an eco-crisis, and human exceptionalism.

4.2.3 Emotional Attachment. We measured emotional attachment using Thomson et al.'s scale [92]. This scale is a recognized and validated tool designed to measure the emotional attachment individuals form with a specific technology or digital entity. It encompasses a set of items that capture users' emotional responses and sentiments towards the system, allowing us to assess the depth of the emotional connection forged during their interaction with our platform.

4.2.4 Energy-saving Behavior. We measured energy-saving behavior using two metrics: one to capture the potential impact on future behavior as indicated by participants' intention to adopt energy-saving behavior, and another to measure an immediate behavior for energy-saving as indicated by a donation for a pro-environmental charity. The intention to adopt energy-saving behavior was measured by a single item asking how motivated participants felt to adopt energy-saving behaviors on a scale from 1 (not at all) to 7 (very motivated). The donation behavior was measured by informing participants that one of them would be selected randomly to receive a bonus of USD 20, then asking how much of this money they would donate to a charity (the Alliance to Save Energy) if they were selected.

4.3 Participants

We enlisted participants through the Prolific platform, and they completed the survey on Qualtrics. The experiment was registered by the university's ethics board. The experiment initially involved 450 participants located in the United States, each receiving an average reward of GBP 9.96 per hour for their participation. On average, participants spent 13 minutes to complete the experiment. The age range for the final study participants spanned from 19 to 80 years old, with an average age of 38. Our participant pool consisted of 40% females and 60% males. Participants were randomly assigned to one of the three groups at the start of the survey. A demographic analysis of the data showed a balanced representation of participants in terms of age and gender between the groups. Among the initial pool of 450 participants, 30 individuals were excluded from the analysis, as they encountered technical issues with the conversational interface, preventing them from testing its functionality as it failed to respond to their initial messages. This resulted in 420 valid survey responses (151 in the Control group; 152 in the Care-based group; 117 in the GenAI care-based group).

5 EVALUATION RESULTS

To validate the structural model, we employed the partial least squares (PLS) analysis technique with SmartPLS (version 4.0.9.5), a well-established approach commonly utilized in a broad range of research fields from information systems [22] and HCI [74, 75] to marketing [85, 86] and medical sciences [4] to gain deeper insights into the relationships and interactions among research variables [43]. PLS relies on a path model, depicted in a diagram illustrating the hypotheses and relationships between variables to be estimated within a structural equation modeling (SEM) analysis [42]. For our hypothesis testing, we employed T-statistics to evaluate the standardized path coefficients (β). The PLS analysis involved bootstrapping the data with 5000 resamples to ensure robustness. Figure 7 shows the results.

5.1 Does Increasing Emotional Attachment Lead to an Increased Behavioral Outcome? H1

The results show that emotional attachment is a significant predictor of energy-saving intention ($\beta = 0.615, p < 0.001$), which is a significant predictor of donation for energy-saving ($\beta = 0.250, p < 0.001$). H1 is supported.

5.2 Do Care-based and Conversational Designs Increase Emotional Attachment? H2a, H2b

The results of the PLS analysis show that the experimental group significantly influences emotional attachment ($\beta = 0.306, p < .001$). That is, as we transition from the Control group to the Care-based group and the GenAI care-based group, emotional attachment increases. As illustrated in Figure 8, the mean emotional attachment score was lowest for the Control group, ($M = 3.17, SD = 1.64$), higher for the Care-based group, ($M = 3.93, SD = 1.82$), and the highest for the GenAI care-based group ($M = 4.51, SD = 1.54$). The results of an analysis of variance (ANOVA) showed a significant difference between groups ($F(2, 418) = 21.369, p < .001$). A post-hoc analysis using Tukey's HSD test [1], reported in Table 2, shows that all the means are significantly different from each other. An

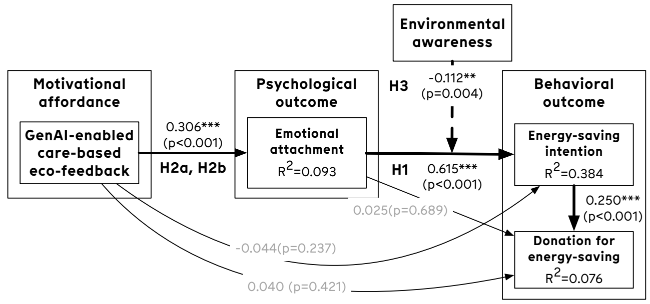

Figure 7: PLS Model results of the main study (N=420). *p < .05, **p < .01, ***p < .001

effect size analysis using Cohen's d shows that there is a large effect size between the control group and the GenAI care-based group on emotional attachment (d=0.842), a medium effect size between the control group and the Care-based group (d=0.439) and a small to medium effect size between the care-based group and the GenAI care-based group (d=0.344). H2a and H2b are supported.

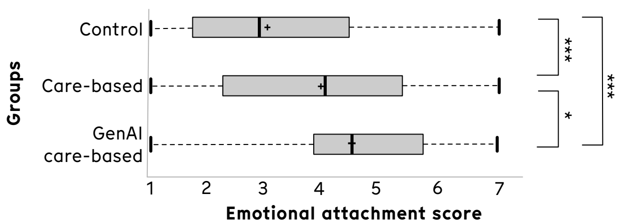

Figure 8: Difference in emotional attachment between groups.

An analysis of the usability metrics allows to further understand how the user experience varied between the three experimental groups. The overall results show that the groups did not differ in terms of pragmatic usability measures, but differed significantly on emotional aspects, with the GenAI care-based group consistently scoring better than the other groups.

More specifically, the SUPR-Q measure indicates no statistically significant differences among the groups on the overall score, as well as on the usability, trust, and loyalty dimensions. However, an analysis of variance (ANOVA) reveals a notable difference in the appearance dimension, with the Control group registering the lowest mean score ($M = 3.68, SD = 0.78$), the Care-based group falling in the middle ($M = 3.85, SD = 0.84$), and the GenAI care-based group exhibiting the highest mean score ($M = 3.98, SD = 0.90$). This difference is statistically significant ($F(2, 418) = 4.568, p = .011$). Additionally, the results from the Attrakdiff questionnaire, as shown in Table 3, indicate no significant differences in pragmatic qualities across the groups. However, hedonic qualities and most attractiveness measures display notable distinctions among the groups, with the GenAI care-based group consistently achieving the highest scores. In contrast, the Control group scores the lowest in all but one instance, where the difference between groups remains significant.

5.3 Does Emotional Attachment Lead to an Increased Behavioral Outcome for Individuals with Lower Environmental Awareness? H3

The results of the PLS model analysis show that environmental awareness is a significant moderator of the relation between emotional attachment and energy-saving intention ($\beta = -0.112, p = 0.004$). More specifically, energy-saving intention increases more for users with lower environmental awareness, than for users with higher environmental awareness when emotional attachment increases. This finding can be illustrated in two different ways. First, we used model 1 from the PROCESS macro [50] to analyze these findings, Figure 9 presents the relationship between emotional attachment, environmental awareness and energy-saving intention. The gray line represents users with higher environmental awareness ($+1SD$) which is above the black line representing users with lower environmental awareness ($-1SD$). While users having a higher environmental awareness indicate more energy-saving intention at lower emotional attachment values, this difference becomes non-significant above the value of 5.17 (Johnson-Neyman value) on the emotional attachment scale. Second, while both slopes are positive ($\beta = 0.649, p < 0.001$ and $\beta = 0.433, p < 0.001$), the slope for users with a lower environmental awareness is significantly steeper than the slope for users with a higher environmental awareness ($p < .01$). H3 is supported.

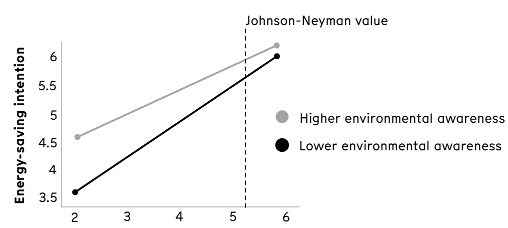

Figure 9: Intention to adopt energy-saving behavior based on environmental awareness and emotional attachment

5.4 Is the model still valid with reported actual energy-saving behavior?

To understand if the energy-saving intention measure in our experiment would translate into actual (self-reported) energy-saving behavior, we conducted a follow-up study three months after the

Table 2: Tukey HSD Post-hoc test for emotional attachment and Cohen's d effect size.

Group 1	Group 2	Mean Difference	*p*-value	Lower Bound	Upper Bound	Cohen's d
Control	Care-based	0.755	<0.001	0.301	1.210	0.439
Control	GenAI care-based	1.339	< 0.001	0.852	1.827	0.842
Care-based	GenAI care-based	0.584	0.0139	0.097	1.071	0.344

Table 3: AttrakDiff results. *p < .05, **p < .01, ***p < .001.

	Group Means (SD)						Statistical Test	
Adjective Pair	Control		Care-based		GenAI care-based		F-value	p-value
Attractiveness (ATT)								
Bad - Good	5.64	(1.20)	5.82	(1.17)	5.89	(1.30)	1.607	0.202
Ugly - Attractive***	4.60	(1.69)	5.15	(1.53)	5.38	(1.50)	8.944	<0.001
Rejecting - Inviting***	5.03	(1.15)	5.47	(1.16)	5.56	(1.38)	7.566	0.001
Disagreeable - Likeable***	5.29	(1.17)	5.75	(1.20)	5.93	(1.28)	10.213	<0.001
Hedonic quality - identity (HQ-I)								
Unimaginative - Imaginative***	4.64	(1.57)	5.22	(1.52)	5.54	(1.47)	12.330	<0.001
Dull - Captivating***	4.52	(1.64)	4.84	(1.62)	5.32	(1.48)	8.402	<0.001
Hedonic quality - stimulation (HQ-S)								
Tacky - Stylish**	4.42	(1.44)	4.43	(1.58)	4.97	(1.56)	5.444	0.004
Cheap - Premium*	4.21	(1.66)	4.17	(1.56)	4.73	(1.64)	4.647	0.010
Ordinary - Novel***	4.21	(1.51)	4.55	(1.71)	4.99	(1.54)	7.881	<0.001
Pragmatic quality (PG)								
Unpredictable - Predictable	5.14	(1.13)	5.03	(1.32)	4.78	(1.57)	2.493	0.084
Confusing - Clearly Structured	5.91	(1.09)	5.98	(1.05)	6.12	(0.93)	1.332	0.265
Complicated - Simple	6.14	(1.01)	6.11	(1.00)	6.15	(1.00)	0.085	0.918
Impractical - Practical	5.91	(1.15)	5.97	(1.15)	5.94	(1.29)	0.096	0.909
Technical - Human	4.07	(1.72)	4.16	(1.80)	3.81	(1.80)	1.360	0.258

initial study. We measured the self-reported energy-saving behavior through a single item question that asked whether participants adopted energy-saving behaviors following the initial study, from 1 (not at all) to 7 (completely). We created a survey on Prolific only accessible to participants of the initial study for a short period of time (48h). We received a total of 268 valid responses. Participants received a compensation of GBP 0.50.

Figure 10 shows the results of the PLS analysis of a model identical to the model depicted in Figure 7, except for the fact that the reported energy-saving behavior replaces the donation for energy-saving as behavioural outcome. This change also implies that the number of participants in the analysis is adjusted to only contain the 268 participants who provided valid responses to both the initial study and the follow-up one. The results show that all hypotheses supported in the initial model still hold with the behavioral outcome from the follow-up study.

6 IN-DEPTH ANALYSIS OF USER EXPERIENCE

In this section, we take a more detailed look at the user experience with the INFINEED system (the Gen-AI care-based group only). First, we present a description of the conversational interactions. Then, we present qualitative results obtained from the open-ended question about the user experience.

6.1 Conversational Interaction Description

To provide an overview of the conversational interaction with the system, we conducted an analysis of the 1161 user-generated messages. Following the initial prompt we provided, the system was designed to interact with users by triggering different levels of engagement from them. First, the conversation started with basic interaction with the system asking users yes/no questions such as :

> "*Are you ready to start?*", or
> "*Do you think taking care of the environment is important?*"

All users replied to at least one of these questions. Second, the conversation continued with simple answers with the system asking closed questions on personal information such as :

> "*Do you live in a house or an apartment?*", or
> "*Do you own a car or use public transport?*".

A large majority of participants (83%) replied to such questions. Participant responses include for example P271 (Male, 40) sharing:

> "*I wash dishes by hands*"

Or P19 (Male, 47):

> "*Yes, I own a car*".

Based on the user's reply, tips were then provided by the system. For example,

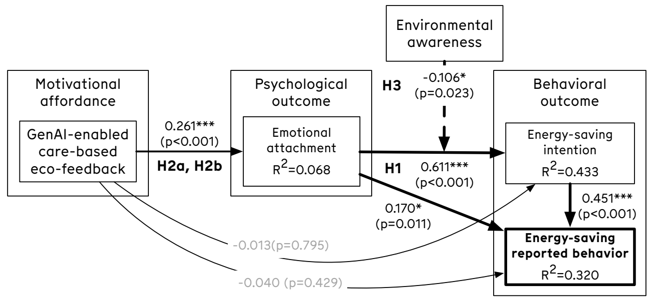

Figure 10: PLS Model results of the follow-up study (N=268). *p < .05, **p < .01, ***p < .001

> "*Living in a house provides great opportunities for energy-saving habits. One tip for you is to install energy-efficient lighting, such as LED bulbs, [...]*"

Third, the system was designed to trigger active engagement with open-ended questions, asking users to share advice and provide tips such as:

> "*If you have any specific energy-saving tips or experiences you'd like to share, I'd love to hear them!*", or
> "*What specific energy-saving topic or tip would you like to discuss?*"

Almost two thirds of the users (65%) replied to such questions. For instance, P288 (Female, 33) inquired about encouraging others to save energy, stating,

> "*how could I encourage others to save energy?*"

And P196 (Male, 33) shared a tip:

> "*Sometimes I put off the light in my entire house to save more energy during the day.*"

Finally, the system was designed to redirect users who would provide off-topic replies, by writing for example:

> "*I appreciate your honesty, but let's try to keep the focus on energy-saving and environmental topics*"

In the experiment, five participants (4%) engaged in a single off-topic reply, such as P110 (Female, 29) writing:

> "*are you running on CHATGPT?*"

and one participant tested the limits of the system and engaged in several (six) off-topic messages. Finally, a small minority of users (5%) experienced minor bugs where messages from the chat were truncated. Figure 11 provides an overview of these interactions, showing that the design of the prompt was successful in leading a large majority of participants to actively engage in conversation.

6.2 Qualitative Open-Ended Responses Analysis

To gain a deeper understanding of participants' experience with the system, we conducted an analysis of the qualitative responses to the open-ended question about the user experience. Following qualitative analyses conducted in similar contexts [9, 33, 52, 91], we opted for a coding approach inspired by Braun and Clark's thematic analysis procedure [14]. This approach includes the following steps: (1) two researchers thoroughly reviewed all responses to gain a deep understanding of the content; (2) codes were collectively agreed upon and applied to each response (3) researchers identified themes based on the codes and common features in the data; (4) these themes were discussed and reviewed by other researchers; (5) final themes were defined and named and (6) data analysis was conducted. The following five main themes emerged from this analysis: emotion-inducing feedback, information credibility, reflection trigger, relation-building conversation, and reactance to energy-saving.

6.2.1 Emotion-inducing System. The first theme that emerged relates to emotions triggered by the system. Most participants reported positive emotions. For instance, participant P57 (Male, 27) described:

> *"[The system] was simple and well designed. The interactivity was nice, and made me feel good about myself."*

Another participant, P412 (Male, 23), found the system "cute" and appreciated the motivation it provided:

> *"It was a bit rehearsed in its responses, but the avatar was very cute. The bar rose when I reported an energy-saving decision, and that made me feel good [...]".*

Some participants expressed a sense of pride while using the system. For example, P212 (Male, 51) reported:

> *"The system is fun to use. It gives great advice and makes me feel proud of myself when it likes my answers."*

Other participants emphasized the effect of the avatar's transformations. For example, P310 (Female, 48) commented:

> *"I think that it was fun, and it really made me feel for him and want to make him smile. That is a nice way to teach people about energy conservation."*

Another participant, P111 (Female, 32), stated:

> *"It was cool to see how my answers changed the avatar's attitude."*

One last participant, P3 (Female, 31), explained:

> *"The chat was easy to understand. The bar on the left that rose with each positive answer felt good, like getting closer to the goal. I don't recall if the bar went down if I answered negatively to any of the prompts. I think having the bar go down for negative energy choices might be more motivating for me personally to improve my energy saving habits."*

Even though most responses were positive, there were some negative feelings worth mentioning, where participants perceived the

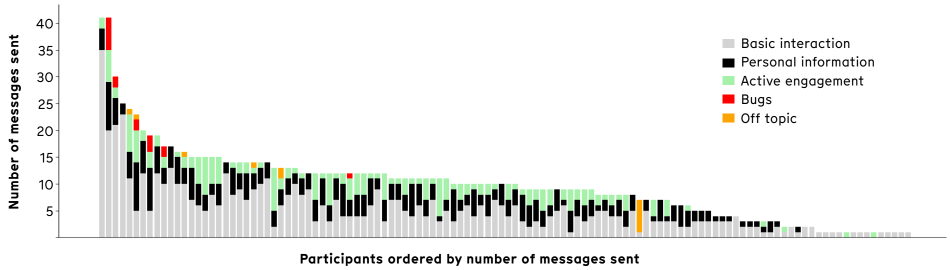

Figure 11: Ordered distribution of the number of interactions per user by category (GenAI care-based group).

system as condescending and shaming. For instance from participant P393 (Male, 49) expressing:

> *"[the system is] Cloying, patronizing, sanctimonious, and infantilizing."*, or P23 (Male, 37) commenting: *"[The system] made me feel shame."*

6.2.2 Relation-building Conversation. The second theme that emerged relates to the way the conversational interaction was perceived. Participants thoroughly enjoyed the opportunity to converse with the avatar, heightening their relationship to it. They described it as if they were conversing with a real person, as participant P365 (Female, 33) put it:

> *"It felt like talking with a real person. It was friendly, gave tips, and recommendations to help me out. IT seem to really care about saving electricity".*

Participant P89 (Male, 26) shared a similar sentiment:

> *"The system is a system that allows one to chat with a bot that gives tips on how to save energy. I loved the interaction I had with it. It felt like I was talking to a human being."*

However, a few participants felt negatively about the interaction with the AI, which prevented them from developing a relationship with it. Participant P418 (Female, 54) for example stated:

> *"I believe that the responses were AI generated. I knew most of what was mentioned but I'm not sure that the percentages are correct... [...] Some people might like the interaction but it felt rather dull to me."*

Participant P47 (Male, 42) also commented:

> *"The system was simple and easy to use. I thought the information provided was useful and understandable. However I totally recognize it was a machine so I have no emotional attachment to the system whatsoever."*

6.2.3 Reflection Trigger. The third theme that emerged relates to self-reflection about energy consumption. For example, participant P219 (Male, 37) shared:

> *"My interaction with the system gave me a reason to reconsider my attitude and behaviors toward energy saving. It reminded me of some of the steps I needed to be taking in order to conserve energy."*

This was further underscored by participant P336 (Male, 40):

> *"I think the everything with the system was very good. i really enjoyed it. And the the system made me rethink about the energy that i waste in my house."*

Moreover, some participants noted that the questions asked by the system during the interaction played a role in raising awareness about energy consumption. Participant P28 (Male, 52) remarked:

> *"The system provided simple but thought provoking questions that led me to be more conscious about how I use my appliances in order to conserve energy."*

The conversation further fueled participants' curiosity as P446 (Male, 33) pointed out:

> *"[...] As the conversations continued, I began to have more questions that could help me save energy or learn more about energy-saving tips."*

6.2.4 Information Credibility. The fourth theme that emerged relates to the expertise and credibility of the advice provided by the system. The majority of participants perceived the system as knowledgeable, emphasizing its role as an expert. For instance, participant P68 (Male, 29) expressed:

> *"It was a fun and easy system to use. The interaction was great fun and educational. I learned a lot about energy saving techniques."*

Another participant, P121 (Male, 32), commented:

> *"The system provided me a lot of useful tips on how to conserve energy. It asked me if I had any questions. I asked a few questions about how to save energy in my home, and the system provided advice and general tips."*

Participant P236 (Male, 34) highlighted the accuracy of the system:

> *"the system is simple, easy, and interactive to use. the system is credible and accurate."*

Some also emphasized the educational aspect of the system, with for example, participant P285 (Female, 21) commenting:

> *"it was very informative and i think this needs to be taught in every classroom."*

And participant P160 (Male, 36) writing:

> *"it is very simple in fact so simple I feel that a child could use it and maybe help their parents/household to save on energy costs. Overall I felt it was simple but useful."*

Nevertheless, a small segment of participants expressed reservations about the system's expertise. They questioned the depth of the tips provided. For instance, P148 (Male, 52) noted:

> *"It was good at giving tips based on how you answered its questions about energy usage, but pretty simple and needs to be able to do a lot more."*

6.2.5 Reactance to Energy-saving. A last theme that emerged relates to skeptical attitudes about environmental issues and the impact of individual actions. This theme was marginal, nevertheless it represents an important aspect of any pro-environmental intervention. For instance, participant P417 (Female, 39) commented:

> *"A very simplistic and gaslighting system that attempts to shame you for personal behavior even though that personal behavior does nothing to help the environment when governments and corporations are left unchecked. It would have been much more helpful if it showed you how to start holding the powerful accountable instead of making you feel like you need to toil your whole day away in a dark room while your clothes air dry."*

While participant P211 (Male, 39) expressed:

> *"AI programmed by doomsday climate cultists perpetually terrified of the weather changing. Or intentionally lying to manipulate people, either possibility is equally likely."*

7 DISCUSSION

In this paper, we investigated how care-based and GenAI approaches could increase the efficacy of eco-feedback interventions, with a focus on improving emotional attachment to help users reduce their energy consumption. We conducted a randomized controlled experiment (N=420) to test a multi-step model that linked the motivational affordances of the system to emotional attachment and energy-saving behavior. We further validate the model with a follow-up experiment (N=268), measuring reported energy-saving behavior three months later. Below, we discuss our results in relation to understanding emotional attachment, designing for emotional attachment, and bonding through conversational interactions. We also discuss the limitations of the present study.

7.1 Understanding How Emotional Attachment Can Lead to Energy Saving

Our results show that increased emotional attachment led to an increase in energy-saving behavior (H1). This finding contributes to the sustainable HCI literature by addressing the understudied role of emotional attachment in eco-feedback [16]. Our approach extends prior work that explored the impact of emotional attachment on behavioral outcome [26] by validating a multi-step model leading from the motivational affordance (i.e., cared-based and GenAI-augmented eco-feedback) to a behavioral outcome (i.e., energy-saving intention & donation, and energy-saving intention & reported behavior) through the mediation of a psychological outcome (i.e., emotional attachment). Our study also complements prior work that investigated other psychological mechanisms that lead to energy-saving behavior, such as cognitive attitudes and perceived behavioral control [17], or social norms and social comparison [24].

Future research could further validate our findings in-the-wild by investigating alternative energy-saving behavioral outcomes, such as sustained electricity consumption reduction or appliance investment behaviors. This type of metrics could also alleviate limitations of the current measures used in our model to capture energy-saving behavioral outcomes such as self-reported bias [58] and the intention-behavior gap [47, 72, 98].

Furthermore, our results demonstrate that emotional attachment significantly increases the motivation to adopt energy-saving behavior, especially among individuals with lower environmental awareness (H3). This result shows how leveraging emotional attachment in an eco-feedback system can favor heightened energy-saving behavior for the less environmentally aware, which is a population that often remains untouched by such feedback mechanisms [82]. If confirmed, our finding could open up a promising path to bring this important demographic on board. This highlights the need for additional research into other emotions that could enhance the adoption of energy-saving behaviors among this user group. However, in our qualitative analysis, a minority of participants showed strong reactance to the experiment. Future research could investigate this group more closely, for instance, by exploring alternative feedback to prevent them from feeling that pro-environmental messages threaten their personal freedom, which can cause counterproductive reactions [56].

7.1.1 Implications for Designers. The key implication of our findings is to consider incorporating care-based artifacts that foster emotional attachment in data-driven eco-feedback systems. The findings suggest that emotionally engaging systems could impact users' intentions to adopt energy-saving behavior, as well as their actual reported behavior. Furthermore, our findings suggest that designing with emotional attachment can be effective for users with lower environmental-awareness. As such, they could increase the effectiveness of these systems for most users, but especially for those who are less environmentally-aware and who stand to gain the most from their adoption.

7.2 Designing for Emotional Attachment

Our results also identify motivational affordances leading to emotional attachment. We show that embodying eco-feedback into a care-based avatar significantly increases emotional attachment with a moderate effect size (H2a). While previous research explored the impact of care-based designs on behavior change [26, 27, 100], our study is, to the best of our knowledge, the first to measure how such designs impact emotional attachment in a multi-step model. In practice, our system as-is could be suitable for an educational context, for example in schools, as highlighted by the findings of the qualitative analysis. Future research could investigate how similar systems can be deployed effectively in a prolonged usage scenario. Particular attention should be given to potential negative side-effects of eco-feedback, for example, eco-anxiety, which can arise from amplifying feelings of responsibility and emphasizing the gap between personal actions and the perceived importance of environmental challenges [6, 37, 39]. Positive emotions, such as joy or pride, that participants reported when they used the system could potentially be investigated further to understand how to best leverage them to help overcome psychological barriers and foster pro-environmental attitudes [88]. Future research could also further explore the design space to foster emotional attachment. Indeed, whereas our results showed that the care-based designs triggered moderate to large effects on emotional attachment compared to the control, much of the emotional attachment construct remains unexplained. Finally, future work could also explore different metaphors (from avatar to natural habit to game to competition), as well as different design aspects, including personalization or sense of ownership that could be leveraged to increase emotional attachment.

7.2.1 Implications for Designers. Our findings suggest that in order to foster emotional attachment in eco-feedback systems, designers can leverage avatars (or other care-based characters) that react positively when users engage in energy-saving behavior. These designs can be used in complement to standard gamification elements visualizing data. Designers should also take into consideration several challenges related to the implementation of this type of systems, such as defining an energy baseline for eco-feedback. This task can be challenging due to factors like fluctuating occupancy, diverse weather conditions, and user behaviors [54].

7.3 Designing for Bonding Conversational Interaction

Our results demonstrate a significant increase in emotional attachment (H2b) when GenAI-enabled conversational interaction is integrated into the care-based system. These findings provide insight into a novel mechanism to foster emotional attachment in eco-feedback systems by augmenting it with conversational interaction. This finding also contributes to the rapidly expanding literature on conversational agents and GenAI applications. For instance, our findings are aligned with previous literature, which demonstrated that active conversational interaction can foster a deeper sense of connection [29]. In our experiment, the active engagement of our participants with the conversational agent played a significant role in driving their emotional attachment to the system. For instance, a substantial proportion of the participants not only interacted in the conversation with basic yes/no messages, but actively engaged by sharing personal information and even by discussing energy-saving tips. Furthermore, most participants engaged with the system without encountering any inconveniences. This observation is reinforced by user feedback, where participants expressed mostly positive perceptions about interacting with the chat. Nevertheless, our qualitative analysis also reveals that a minority of participants expressed a negative attitude toward the conversational agent, stipulating they could not form any emotional connection with the system. This could be linked to the "uncanny valley" phenomenon, where human-AI interactions may make users feel uncomfortable [70], or to the fact that some people may exhibit negative attitudes [64] and decreased levels of trust [61] when they realize they are conversing with an AI-based system. Future research could explore conditions in which this issue arises and design solutions to address it.

7.3.1 Implications for Designers. Our results suggest that designers could use well-designed conversational interaction as a tool to increase emotional attachment with care-based systems. Furthermore, based on our experience designing the current system, it should be noted that creating adequate initial prompts for GenAI systems is far from trivial and can lead to unexpected outcomes if not designed and tested properly (such as repeated or truncated messages, long generic content, off-topic responses, preachy tone). As such designers should expect to spend significant resources to fine-tune and validate adequate prompts.

7.4 Limitations

In addition to the limitations discussed earlier, this study has other limitations that future research could explore and address. First, our experiment suffered from a slightly unbalanced sample due to a short technical malfunction of the system impacting certain users in the GenAI care-based group. This situation is attributed to connectivity issues with third-party infrastructure (ChatGPT API and Microsoft Azure Cloud services) that occurred during the experiment. Second, the homogeneous geographic background of the participants, as all were located in the United States, constitutes a limitation in our study. This uniformity in location could have impacted their responses, potentially influencing their access to information and resources related to energy, and may affect the applicability of our findings to more diverse or global populations.

8 CONCLUSION

The reduction of energy consumption is one of the major challenges to reach net zero emissions. As current eco-feedback approaches provide mainly usage metrics and target environmentally-aware individuals, it is useful to expand the design space to reach a broader public. Previous research has hinted at emotional attachment as a potential motivational factor that could mediate pro-environmental behavior. This paper validated this mediation and showed how to increase such attachment through a care-based eco-feedback approach with AI-powered conversational interaction. Finally, it showed that the pathway from artifact to behavior was also effective for individuals who are less environmentally aware, which opens up a promising avenue to reach a demographic that would benefit the most from such interventions.

ACKNOWLEDGMENTS

This research is partially funded by the Swiss Federal Office for Energy (SFOE) in the context of the project "INFINEED - The Interplay of Feedback and Incentive Effects on Electricity Demand". We would like to thank Mr. Yann Do for his contribution to the design of the system and Mr. Louis Jeronimo for his contribution to the implementation of the system.

REFERENCES

[1] Hervé Abdi and Lynne J Williams. 2010. Tukey's honestly significant difference (HSD) test. *Encyclopedia of research design* 3, 1 (2010), 1–5.
[2] Chadia Abras, Diane Maloney-Krichmar, Jenny Preece, et al. 2004. User-centered design. *Bainbridge, W. Encyclopedia of Human-Computer Interaction. Thousand Oaks: Sage Publications* 37, 4 (2004), 445–456.
[3] Rachel F Adler, Francisco Iacobelli, and Yehuda Gutstein. 2016. Are you convinced? A Wizard of Oz study to test emotional vs. rational persuasion strategies in dialogues. *Computers in Human Behavior* 57 (2016), 75–81.
[4] Hussein Kadhem Al-Hakeim, Haneen Tahseen Al-Rubaye, Dhurgham Shihab Al-Hadrawi, Abbas F Almulla, and Michael Maes. 2023. Long-COVID post-viral chronic fatigue and affective symptoms are associated with oxidative damage, lowered antioxidant defenses and inflammation: a proof of concept and mechanism study. *Molecular Psychiatry* 28, 2 (2023), 564–578.

[5] Clément Alaton, Frédéric Tounquet, et al. 2020. Benchmarking smart metering deployment in the EU-28. *Final Report* (2020).

[6] Glenn Albrecht, Gina-Maree Sartore, Linda Connor, Nick Higginbotham, Sonia Freeman, Brian Kelly, Helen Stain, Anne Tonna, and Georgia Pollard. 2007. Solastalgia: the distress caused by environmental change. *Australasian psychiatry* 15, 1_suppl (2007), S95–S98.

[7] Christian Bason and Robert D Austin. 2019. The right way to lead design thinking. *Harvard Business Review* 97, 2 (2019), 82–91.

[8] Leire Bastida, Jed J Cohen, Andrea Kollmann, Ana Moya, and Johannes Reichl. 2019. Exploring the role of ICT on household behavioural energy efficiency to mitigate global warming. *Renewable and Sustainable Energy Reviews* 103 (2019), 455–462.

[9] Emily Baysden, Ninna Mendoza, Chishinga Callender, Zhigang Deng, and Debbe Thompson. 2022. Teen reactions to a self-representational avatar: A qualitative exploration. *Journal of Sport and Health Science* 11, 2 (2022), 157–163.

[10] Jaime Berenguer. 2007. The effect of empathy in proenvironmental attitudes and behaviors. *Environment and behavior* 39, 2 (2007), 269–283.

[11] Jaime Berenguer. 2010. The effect of empathy in environmental moral reasoning. *Environment and Behavior* 42, 1 (2010), 110–134.

[12] Linda-Renée Bloch and Dafna Lemish. 1999. Disposable love: The rise and fall of a virtual pet. *New Media & Society* 1, 3 (1999), 283–303.

[13] Petter Bae Brandtzaeg, Marita Skjuve, and Asbjørn Følstad. 2022. My AI friend: How users of a social chatbot understand their human–AI friendship. *Human Communication Research* 48, 3 (2022), 404–429.

[14] Virginia Braun and Victoria Clarke. 2012. *Thematic analysis.* American Psychological Association, Washington, D.C., United States.

[15] Christina Bremer, Bran Knowles, and Adrian Friday. 2022. Have We Taken On Too Much?: A Critical Review of the Sustainable HCI Landscape. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, United States, 1–11.

[16] Tobias Brosch and Linda Steg. 2021. Leveraging emotion for sustainable action. *One Earth* 4, 12 (2021), 1693–1703.

[17] Luigina Canova and Anna Maria Manganelli. 2020. Energy-saving behaviours in workplaces: Application of an extended model of the theory of planned behaviour. *Europe's Journal of Psychology* 16, 3 (2020), 384.

[18] Nurit Carmi. 2013. Caring about tomorrow: Future orientation, environmental attitudes and behaviors. *Environmental Education Research* 19, 4 (2013), 430–444.

[19] Miquel Casals, Marta Gangolells, Marcel Macarulla, Núria Forcada, Alba Fuertes, and Rory V Jones. 2020. Assessing the effectiveness of gamification in reducing domestic energy consumption: Lessons learned from the EnerGAware project. *Energy and Buildings* 210 (2020), 109753.

[20] Moulay L Chalal, Benachir Medjdoub, Nacer Bezai, Richard Bull, and May Zune. 2022. Visualisation in energy eco-feedback systems: A systematic review of good practice. *Renewable and Sustainable Energy Reviews* 162 (2022), 112447.

[21] Thomas Chesney and Shaun Lawson. 2007. The illusion of love: Does a virtual pet provide the same companionship as a real one? *Interaction Studies* 8, 2 (2007), 337–342.

[22] Tingru Cui, Yu Tong, and Chuan-Hoo Tan. 2022. Open innovation and information technology use: Towards an operational alignment view. *Information Systems Journal* 32, 5 (2022), 932–972.

[23] Sarah Darby. 2006. The effectiveness of feedback on energy consumption. *A Review for DEFRA of the Literature on Metering, Billing and direct Displays* 486, 2006 (2006), 26.

[24] Stefano De Dominicis, Rebecca Sokoloski, Christine M Jaeger, and P Wesley Schultz. 2019. Making the smart meter social promotes long-term energy conservation. *Palgrave Communications* 5, 1 (2019).

[25] Maria Puig de La Bellacasa. 2011. Matters of care in technoscience: Assembling neglected things. *Social studies of science* 41, 1 (2011), 85–106.

[26] Tawanna Dillahunt, Graylin Becker, Jennifer Mankoff, and Robert Kraut. 2008. Motivating environmentally sustainable behavior changes with a virtual polar bear. In *Pervasive 2008 Workshop Proceedings*. Pervasive 2008, 58–62.

[27] Tawanna Dillahunt and Jennifer Mankoff. 2014. Understanding factors of successful engagement around energy consumption between and among households. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*. Association for Computing Machinery, New York, NY, United States, 1246–1257.

[28] Nikos Dimitriou, Anastasia Garbi, Kostas Vasilakis, Anthony Schoofs, Amr Taha, Manolis Nikiforakis, Sarantis Kotsilitis, Thanasis G Papaioannou, Dimosthenis Kotsopoulos, Cleopatra Bardaki, et al. 2018. ChArGED: Implementing a framework for improving energy efficiency in public buildings through IoTenabled energy disaggregation and serious games. In *2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*. IEEE, IEEE, Piscataway, New Jersey, United States, 65–70.

[29] Kevin Doherty and Gavin Doherty. 2018. Engagement in HCI: conception, theory and measurement. *ACM Computing Surveys (CSUR)* 51, 5 (2018), 1–39.

[30] Franziska Dolak, Falk Uebernickel, and Walter Brenner. 2013. Design thinking and design science research. *Positioning Paper DESRIST 2013* (2013), 1–11.

[31] Riley E Dunlap, Kent D Van Liere, Angela G Mertig, and Robert Emmet Jones. 2000. New trends in measuring environmental attitudes: measuring endorsement of the new ecological paradigm: a revised NEP scale. *Journal of social issues* 56, 3 (2000), 425–442.

[32] Lauren Eskreis-Winkler, Ayelet Fishbach, and Angela L Duckworth. 2018. Dear Abby: Should I give advice or receive it? *Psychological Science* 29, 11 (2018), 1797–1806.

[33] Guo Freeman and Divine Maloney. 2021. Body, avatar, and me: The presentation and perception of self in social virtual reality. *Proceedings of the ACM on human-computer interaction* 4, CSCW3 (2021), 1–27.

[34] Jon Froehlich. 2009. Promoting energy efficient behaviors in the home through feedback: The role of human-computer interaction. In *Proc. HCIC Workshop*, Vol. 9. UW tech note, 1–11.

[35] Jon Froehlich, Leah Findlater, and James Landay. 2010. The design of eco-feedback technology. In *Proceedings of the SIGCHI conference on human factors in computing systems*. ACM Press, New York, New York, USA, 1999–2008.

[36] Liping Fu, Zhaohui Sun, Lajia Zha, Feng Liu, Lanping He, Xuesong Sun, and Xiaoli Jing. 2020. Environmental awareness and pro-environmental behavior within China's road freight transportation industry: Moderating role of perceived policy effectiveness. *Journal of Cleaner Production* 252 (2020), 119796.

[37] Lindsay P Galway, Thomas Beery, Kelsey Jones-Casey, and Kirsti Tasala. 2019. Mapping the solastalgia literature: A scoping review study. *International journal of environmental research and public health* 16, 15 (2019), 2662.

[38] Birgitta Gatersleben. 2018. Measuring environmental behaviour. *Environmental psychology: An introduction* (2018), 155–166.

[39] Maya K Gislason, Angel M Kennedy, and Stephanie M Witham. 2021. The interplay between social and ecological determinants of mental health for children and youth in the climate crisis. *International journal of environmental research and public health* 18, 9 (2021), 4573.

[40] Anton Gustafsson, Magnus Bång, and Mattias Svahn. 2009. Power explorer: a casual game style for encouraging long term behavior change among teenagers. In *Proceedings of the international conference on advances in computer entertainment technology*. ACM, New York, USA, 182–189.

[41] Muhammad Usman Hadi, Rizwan Qureshi, Abbas Shah, Muhammad Irfan, Anas Zafar, Muhammad Bilal Shaikh, Naveed Akhtar, Jia Wu, Seyedali Mirjalili, et al. 2023. A Survey on Large Language Models: Applications, Challenges, Limitations, and Practical Usage. *TechRxiv* (2023).

[42] Joe Hair, Carole L. Hollingsworth, Adriane B. Randolph, and Alain Yee Loong Chong. 2017. An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management and Data Systems* (2017), 442–458. https://doi.org/10.1108/IMDS-04-2016-0130

[43] Joe Hair, Carole L Hollingsworth, Adriane B Randolph, and Alain Yee Loong Chong. 2017. An updated and expanded assessment of PLS-SEM in information systems research. *Industrial management & data systems* 117, 3 (2017), 442–458.

[44] Juho Hamari, Jonna Koivisto, and Harri Sarsa. 2014. Does gamification work?–a literature review of empirical studies on gamification. In *System Sciences (HICSS), 2014 47th Hawaii International Conference on*. IEEE, IEEE, New Jersey, United States, 3025–3034.

[45] Wiwik Handayani, Reiga Ritomiea Ariescy, Felia Ananda Cahya, Salsabila Islami Yusnindi, and Desy Ari Sulistyo. 2021. Literature review: environmental awareness and pro-environmental behavior. *Nusantara Science and Technology Proceedings* (2021), 170–173.

[46] Tom Hargreaves, Michael Nye, and Jacquelin Burgess. 2013. Keeping energy visible? Exploring how householders interact with feedback from smart energy monitors in the longer term. *Energy policy* 52 (2013), 126–134.

[47] Louise M Hassan, Edward Shiu, and Deirdre Shaw. 2016. Who says there is an intention–behaviour gap? Assessing the empirical evidence of an intention–behaviour gap in ethical consumption. *Journal of Business Ethics* 136 (2016), 219–236.

[48] Marc Hassenzahl. 2010. *Experience design: Technology for all the right reasons*. Morgan & Claypool Publishers, San Rafael, California (USA).

[49] Marc Hassenzahl, Michael Burmester, and Franz Koller. 2003. AttrakDiff: Ein Fragebogen zur Messung wahrgenommener hedonischer und pragmatischer Qualität. In *Mensch & Computer*. Vieweg+Teubner Verlag, Berlin, Germany, 187–196.

[50] Andrew F Hayes. 2017. *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford publications, New York, USA.

[51] Bernd Huber, Daniel McDuff, Chris Brockett, Michel Galley, and Bill Dolan. 2018. Emotional dialogue generation using image-grounded language models. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, New York, USA, 1–12.

[52] Zaheer Hussain and Mark D Griffiths. 2009. Excessive use of massively multi-player online role-playing games: A pilot study. *International journal of mental health and addiction* 7, 4 (2009), 563–571.

[53] AR6 SYR IPCC. 2023. Synthesis report of the IPCC sixth assessment report (AR6)–Summary for Policymakers.

[54] Rikke Hagensby Jensen, Maurizio Teli, Simon Bjerre Jensen, Mikkel Gram, and Mikkel Harboe Sørensen. 2021. Designing Eco-Feedback Systems for Communities: Interrogating a Techno-solutionist Vision for Sustainable Communal Energy. In *Proceedings of the 10th International Conference on Communities & Technologies-Wicked Problems in the Age of Tech*. ACM, New York, USA, 245–257.

[55] Fernando R Jiménez and Kevin E Voss. 2014. An alternative approach to the measurement of emotional attachment. *Psychology & Marketing* 31, 5 (2014), 360–370.

[56] Christos Kavvouris, Polymeros Chrysochou, and John Thøgersen. 2020. "Be Careful What You Say": The role of psychological reactance on the impact of pro-environmental normative appeals. *Journal of Business Research* 113 (2020), 257–265.

[57] Cayla Key, Fiona Browne, Nick Taylor, and Jon Rogers. 2021. Proceed with care: Reimagining home iot through a care perspective. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. AMC, New York, USA, 1–15.

[58] Christine Kormos and Robert Gifford. 2014. The validity of self-report measures of proenvironmental behavior: A meta-analytic review. *Journal of Environmental Psychology* 40 (2014), 359–371.

[59] Florian Lange and Siegfried Dewitte. 2019. Measuring pro-environmental behavior: Review and recommendations. *Journal of Environmental Psychology* 63 (2019), 92–100.

[60] George E Lee, Yongwen Xu, Robert S Brewer, and Philip M Johnson. 2012. Makahiki: An open source game engine for energy education and conservation. *Department of Information and Computer Sciences, University of Hawaii, Honolulu, Hawaii* 96822 (2012), 11–07.

[61] Deniz Lefkeli, Mustafa Karataş, and Zeynep Gürhan-Canli. 2023. Sharing information with AI (versus a human) impairs brand trust: The role of audience size inferences and sense of exploitation. *International Journal of Research in Marketing* (2023).

[62] Calvin CY Liao, Z-H Chen, Hercy NH Cheng, F-C Chen, and T-W Chan. 2011. My-Mini-Pet: a handheld pet-nurturing game to engage students in arithmetic practices. *Journal of Computer Assisted Learning* 27, 1 (2011), 76–89.

[63] Debra Lilley. 2009. Design for sustainable behaviour: strategies and perceptions. *Design studies* 30, 6 (2009), 704–720.

[64] Sue Lim and Ralf Schmälzle. 2023. The effect of source disclosure on evaluation of AI-generated messages: A two-part study. *arXiv preprint arXiv:2311.15544* (2023).

[65] Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2023. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *Comput. Surveys* 55, 9 (2023), 1–35.

[66] Vivian Liu and Lydia B Chilton. 2022. Design guidelines for prompt engineering text-to-image generative models. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*. AMC, New York, USA, 1–23.

[67] Yefeng Liu, Todorka Alexandrova, and Tatsuo Nakajima. 2011. Gamifying intelligent environments. In *Proceedings of the 2011 international ACM workshop on Ubiquitous meta user interfaces*. ACM, New York, USA, 7–12.

[68] Jasmine Lu and Pedro Lopes. 2022. Integrating Living Organisms in Devices to Implement Care-based Interactions. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology*. ACM, New York, USA, 1–13.

[69] Neo Sau Mei, Choong Weng Wai, and Rahmalan Ahamad. 2016. Environmental awareness and behaviour index for Malaysia. *Procedia-Social and Behavioral Sciences* 222 (2016), 668–675.

[70] Vicki G Morwitz, Joel H Steckel, and Alok Gupta. 2007. When do purchase intentions predict sales? *International Journal of Forecasting* 23, 3 (2007), 347–364.

[71] Victoria A Mountford, Kate Tchanturia, and Lucia Valmaggia. 2016. "What Are You Thinking When You Look at Me?" A Pilot Study of the Use of Virtual Reality in Body Image. *Cyberpsychology, Behavior, and Social Networking* 19, 2 (2016), 93–99.

[72] Meredith T Niles, Margaret Brown, and Robyn Dynes. 2016. Farmer's intended and actual adoption of climate change mitigation and adaptation strategies. *Climatic Change* 135, 2 (2016), 277–295.

[73] Valentina Nisi, Nuno Jardim Nunes, Filipe Quintal, and Mary Barreto. 2013. SINAIS from Fanal: design and evaluation of an art-inspired eco-feedback system. In *Proceedings of the Biannual Conference of the Italian Chapter of SIGCHI*. ACM, New York, USA, 1–10.

[74] Rita Orji, Lennart E Nacke, and Chrysanne Di Marco. 2017. Towards personality-driven persuasive health games and gamified systems. In *Proceedings of the 2017 CHI conference on human factors in computing systems*. ACM, New York, USA, 1015–1027.

[75] Oladapo Oyebode, Chinenye Ndulue, Dinesh Mulchandani, Ashfaq A. Zamil Adib, Mona Alhasani, and Rita Orji. 2021. Tailoring persuasive and behaviour change systems based on stages of change and motivation. In *Proceedings of the 2021 CHI conference on human factors in computing systems*. ACM, New York, USA, 1–19.

[76] Mario Passalacqua, Ph D Senecal, Marc Fredette, Lennart E Nacke, Robert Pellerin, Pierre-Majorique Léger, et al. 2021. Should gamification be personalized? A self-deterministic approach. *AIS Transactions on Human-Computer Interaction* 13, 3 (2021), 265–286.

[77] Ken Peffers, Tuure Tuunanen, Marcus A Rothenberger, and Samir Chatterjee. 2007. A design science research methodology for information systems research. *Journal of management information systems* 24, 3 (2007), 45–77. https://doi.org/10.2753/MIS0742-1222240302

[78] Èlia Gil Peña and Rikke Hagensby Jensen. 2023. The Character of Eco-feedback Systems for Energy Communities. In *Proceedings of the 11th International Conference on Communities and Technologies*. ACM, New York, USA, 203–214.

[79] Lara SG Piccolo, Cecília Baranauskas, and Rodolfo Azevedo. 2017. A socially inspired energy feedback technology: challenges in a developing scenario. *AI & SOCIETY* 32 (2017), 383–399.

[80] James Pierce and Eric Paulos. 2012. Beyond energy monitors: interaction, energy, and emerging energy systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, New York, USA, 665–674.

[81] Michael Puntiroli and Valéry Bezençon. 2020. Feedback devices help only environmentally concerned people act pro-environmentally over time. *Journal of environmental psychology* 70 (2020), 101459.

[82] Michael Puntiroli, Lisa S Moussaoui, and Valéry Bezençon. 2022. Are consumers consistent in their sustainable behaviours? A longitudinal study on consistency and spillover. *Journal of Business Research* 144 (2022), 322–335.

[83] Byron Reeves, James J Cummings, James K Scarborough, and Leo Yeykelis. 2015. Increasing energy efficiency with entertainment media: An experimental and field test of the influence of a social game on performance of energy behaviors. *Environment and Behavior* 47, 1 (2015), 102–115.

[84] Florian Reinhart, Kevin Schlieper, Michael Kugler, Elisabeth André, Masood Masoodian, and Bill Rogers. 2013. Fostering energy awareness in residential homes using mobile devices. *University of Waikato* (2013).

[85] Christian Ringle, Dirceu Da Silva, and Diógenes Bido. 2015. Structural equation modeling with the SmartPLS. *Bido, D., da Silva, D., & Ringle, C.(2014). Structural Equation Modeling with the Smartpls. Brazilian Journal Of Marketing* 13, 2 (2015).

[86] Marko Sarstedt and Jun-Hwa Cheah. 2019. Partial least squares structural equation modeling using SmartPLS: a software review. *Journal of Marketing Analytics* 7, 3 (2019), 196–202.

[87] Jeff Sauro. 2015. SUPR-Q: A comprehensive measure of the quality of the website user experience. *Journal of usability studies* 10, 2 (2015).

[88] Gözel Shakeri, Frederike Jung, Ferran Altarriba Bertran, Daniel Fernandez Galeote, and Adrian Friday. 2023. Towards Supporting Sustainable Grocery Shopping through Joyful Technology: Annotated Portfolio of Speculative Ideas. *arXiv preprint arXiv:2309.05670* (2023).

[89] Will Simm, Maria Angela Ferrario, Adrian Friday, Peter Newman, Stephen Forshaw, Mike Hazas, and Alan Dix. 2015. Tiree energy pulse: exploring renewable energy forecasts on the edge of the grid. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, New York, USA, 1965–1974.

[90] Yolande Strengers. 2014. Smart energy in everyday life: are you designing for resource man? *interactions* 21, 4 (2014), 24–31.

[91] Kim Szolin, Daria J Kuss, Filip M Nuyens, and Mark D Griffiths. 2023. "I am the character, the character is me": A thematic analysis of the user-avatar relationship in videogames. *Computers in Human Behavior* 143 (2023), 107694.

[92] Matthew Thomson, Deborah J MacInnis, and C Whan Park. 2005. The ties that bind: Measuring the strength of consumers' emotional attachments to brands. *Journal of consumer psychology* 15, 1 (2005), 77–91.

[93] Austin Toombs, Laura Devendorf, Patrick Shih, Elizabeth Kaziunas, David Nemer, Helena Mentis, and Laura Forlano. 2018. Sociotechnical systems of care. In *Companion of the 2018 ACM conference on computer supported cooperative work and social computing*. ACM, New York, USA, 479–485.

[94] University of Leipzig. 2023. *Energy Fundamentals - World Energy Consumption*. University of Leipzig. https://home.uni-leipzig.de/energy/energy-fundamentals/04.htm 07, 24, 2023.

[95] Eva AM Van Dis, Johan Bollen, Willem Zuidema, Robert van Rooij, and Claudi L Bockting. 2023. ChatGPT: five priorities for research. *Nature* 614, 7947 (2023), 224–226.

[96] Thomas Vilarinho, Babak Farshchian, Leendert WM Wienhofen, Thomas Franang, and Håkon Gulbrandsen. 2016. Combining persuasive computing and user centered design into an energy awareness system for smart houses. In *2016 12th International Conference on Intelligent Environments (IE)*. IEEE, IEEE, New York, USA, 32–39.

[97] Lu Wang, Munif Ishad Mujib, Jake Williams, George Demiris, and Jina Huh-Yoo. 2021. An evaluation of generative pre-training model-based therapy chatbot for caregivers. *arXiv preprint arXiv:2107.13115* (2021).

[98] Thomas L Webb and Paschal Sheeran. 2006. Does changing behavioral intentions engender behavior change? A meta-analysis of the experimental evidence. *Psychological bulletin* 132, 2 (2006), 249.

[99] Katherine White, Rishad Habib, and David J Hardisty. 2019. How to SHIFT consumer behaviors to be more sustainable: A literature review and guiding

framework. *Journal of Marketing* 83, 3 (2019), 22–49.
[100] Jie Chi Yang, Kun Huang Chien, and Tzu Chien Liu. 2012. A digital game-based learning system for energy education: An energy Conservation PET. *Turkish Online Journal of Educational Technology-TOJET* 11, 2 (2012), 27–37.
[101] Ping Zhang. 2008. Motivational affordances: Reasons for ICT design and use. *Commun. ACM* 51, 11 (2008), 145–147.
[102] Hao Zhou, Minlie Huang, Tianyang Zhang, Xiaoyan Zhu, and Bing Liu. 2018. Emotional chatting machine: Emotional conversation generation with internal and external memory. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 32. PKP Publishing Services Network, New York, USA.
[103] Naim Zierau, Edona Elshan, Camillo Visini, and Andreas Janson. 2020. A Review of the Empirical Literature on Conversational Agents and Future Research Directions.. In *International Conference on Information Systems*. ICIS.