RESEARCH-ARTICLE

Reimagining Emotion AI at Home: Exploring the Potential of Emotion-adaptive Eco-feedback in Personal Assistant Using Matchmaking for AI

LU JIN

APOSTOLOS VAVOURIS

NICO CASTELLI

DOMINIK PINS

ALEXANDER BODEN

LINA STANKOVIC

View all

Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, Volume 10, Issue 1 (March 2026)
https://doi.org/10.1145/3789680
EISSN: 2474-9567

Reimagining Emotion AI at Home: Exploring the Potential of Emotion-adaptive Eco-feedback in Personal Assistant Using Matchmaking for AI

LU JIN*, University of Siegen and Fraunhofer-Institute for Applied Information Technology FIT, Germany
APOSTOLOS VAVOURIS, University of Strathclyde, United Kingdom
NICO CASTELLI, Fraunhofer-Institute for Applied Information Technology FIT, Germany
DOMINIK PINS, Fraunhofer-Institute for Applied Information Technology FIT, Germany
ALEXANDER BODEN, Bonn-Rhein-Sieg University of Applied Science and Fraunhofer FIT, Germany
LINA STANKOVIC, University of Strathclyde, United Kingdom
VLADIMIR STANKOVIC, University of Strathclyde, United Kingdom

Emotion Artificial Intelligence (AI) is transforming the capabilities of personal assistant by enabling real-time adaptation to user emotions, behaviours, and contextual needs. This paper explores the potential of emotion-adaptive eco-feedback in personal assistant, particularly within home environments, to foster well-being, energy efficiency, and personalised user experiences. Currently, there is limited research on how users perceive emotion-adaptive eco-feedback and how emotion AI can be adopted in the eco-feedback within personal assistant in real-world settings. To address this, we employed a co-design method — Matchmaking for AI — to facilitate collaboration between real users and researchers. We built a living lab with 11 participants in Germany for half a year and conducted two experimental sessions: a pre-interview to understand user behaviours, requirements, and expectations on eco-feedback, and a co-design session using matchmaking for AI after half a year based on their appliance energy consumption data collected by our smart plugs using our open.DASH platform. The co-design sessions collaboratively brainstorm ideas for potential emotion AI adoptions and identify what their needs should be addressed by emotion AI technology. Through a co-design session, we generated eight design ideas that integrate emotion AI into eco-feedback. These concepts include emotion-adaptive eco-feedback framing, emotion-timed interaction and delivery and emotion-aware environment and social adaption. Our work explores the potential of using Emotion AI in eco-feedback within personal assistant and also provides new insights into AI co-design methodologies.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**.

Additional Key Words and Phrases: Eco-feedback, Emotion-adaptive design, Participatory design, Personal Assistant

ACM Reference Format:
Lu Jin, Apostolos Vavouris, Nico Castelli, Dominik Pins, Alexander Boden, Lina Stankovic, and Vladimir Stankovic. 2026. Reimagining Emotion AI at Home: Exploring the Potential of Emotion-adaptive Eco-feedback in Personal Assistant Using

*Corresponding author.

Authors' Contact Information: Lu Jin (corresponding author), University of Siegen and Fraunhofer-Institute for Applied Information Technology FIT, Siegen, Germany, lu.jin@student.uni-siegen.de; Apostolos Vavouris, University of Strathclyde, Glasgow, United Kingdom, apostolos.vavouris@strath.ac.uk; Nico Castelli, Fraunhofer-Institute for Applied Information Technology FIT, Bonn, Germany, nico.castelli@fit.fraunhofer.de; Dominik Pins, Fraunhofer-Institute for Applied Information Technology FIT, Bonn, Germany, dominik.pins@fit.fraunhofer.de; Alexander Boden, Bonn-Rhein-Sieg University of Applied Science and Fraunhofer FIT, Sankt Augustin, Germany, alexander.boden@fit.fraunhofer.de; Lina Stankovic, University of Strathclyde, Glasgow, United Kingdom, lina.stankovic@strath.ac.uk; Vladimir Stankovic, University of Strathclyde, Glasgow, United Kingdom, vladimir.stankovic@strath.ac.uk.

ACM 2474-9567/2026/3-ART5
https://doi.org/10.1145/3789680

Matchmaking for AI. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 10, 1, Article 5 (March 2026), 24 pages. https://doi.org/10.1145/3789680

1 INTRODUCTION

The global energy crisis [18, 23, 49] has emerged as one of the most pressing challenges of the 21st century, driven by escalating energy demands, depleting natural resources, and the urgent need to mitigate climate change. As the world aims to reduce energy consumption, the role of individual and collective behaviours in energy consumption has become important [80]. In this context, eco-feedback has gained attention as an innovative way to inform and empower users about their energy usage, fostering more sustainable habits [20, 28, 33, 53, 60, 70, 71]. Eco-feedback involves providing users with real-time or retrospective information about their energy consumption. By making energy use more visible and understandable, eco-feedback aims to bridge the gap between abstract environmental concerns and everyday action. The development of eco-feedback starts from simple energy meters [19, 20] and digital data platforms [34, 80] to personalised intelligent assistants [30, 59]. In sustainable human-computer interaction (HCI), many approaches have been developed towards eco-feedback. These approaches have focused on various aspects such as visualisation, gamification, and user-centered design [21, 52]. Besides these approaches, emotion Artificial Intelligence (AI), also called affective computing, or artificial emotional intelligence, as a new technology, has been successfully integrated into other domains, including education [57] and gaming [78]. For example, in education [57], emotional AI can enhance learning experiences and engagement by enhancing learners' emotional engagement and motivation, fostering more effective and fulfilling learning experiences. In gaming [78], emotion AI can improve performance and user satisfaction by tailoring game experiences to players' emotional states, creating more immersive and enjoyable gaming sessions.

Emotion AI has the potential to enhance user experiences, improve performance, and create more personalised and responsive systems. However, its application in eco-feedback remains largely unexplored. In this paper, we investigate the design opportunities to integrate emotion AI technology into eco-feedback by building a living lab with 11 participants in Germany. We explore the expectations and concerns of eco-feedback and how emotion AI can be integrated with eco-feedback to fulfill user needs. Specifically, our research focuses on answering the following research questions (RQ):

- **RQ1:** What are the expectations and concerns that users have regarding current eco-feedback systems?
- **RQ2:** How can emotion AI be integrated with eco-feedback systems to fulfill user needs and expectations within a personal assistant?

To address the research questions, we recruited 11 participants from diverse households. Over a six-month period, we conducted two interview sessions: a pre-interview and a co-design session. Alongside these sessions, we collected energy consumption data from participants' appliances using smart plugs over the period of six months. These data served as a foundational material for the co-design session, enabling participants to be more engaged in brainstorming and collaborative design activities using their own data. Our analysis of results showed the opportunities of three themes and eight design ideas to involve the emotion AI into eco-feedback. The contribution of this work can be summarised as follows:

(1) This work identifies the values and needs of home users in eco-feedback;
(2) demonstrates several design opportunities of involving emotion AI into eco-feedback; and
(3) reflects an example of using co-design methods — Matchmaking for AI in the AI/HCI research area.

2 RELATED WORK

2.1 Eco-feedback

Eco-feedback technologies have been explored as a way to narrow the gap in environmental literacy by providing individuals with information on how their daily behaviours can affect the environment [7, 39, 41, 74].

Recent advances in technologies, such as real-time sensing, ambient displays, ubiquitous computing platforms, have enabled a growing number of feedback systems that aim to increase awareness and promote sustainable behaviour [47, 50]. However, the effectiveness of these systems depends not only on the data they provide, but also on how and when the information is communicated.

How and when the feedback is presented plays a crucial role in user engagement and behavioural outcomes. Froehlich et al. [21] emphasised that the need for eco-feedback design must go beyond technical visualisation to behavioural models from environmental psychology. Their findings underscored that static information alone is insufficient, as it must align with users' motivations, habits and social contexts. Bartram [5] confirmed this finding by arguing that dashboards and analytic reports can provide rich analysis but lack in supporting in-the-moment decision making due to the high cognitive overload and lack of ecological fit in the home, and called for affective, ambient, and aesthetically meaningful visualisation that blends into everyday domestic routines. Based on these argument and the technology development, research started to investigate how the eco-feedback should be presented to and when the eco-feedback should be delivered. Studies demonstrated that feedback timed close to energy-related actions, e.g., when leaving a room or using an appliance, is more actionable and impactful [5, 21]. In this direction, emotion has entered into the eco-feedback discussion, though primarily in terms of how users respond emotionally to different message framing. For example, Wilson et al. [76] found that affective message framing—positive or negative—evokes stronger emotional intensity when aligned with users' pro-environmental attitudes. This suggests that tailoring the emotional tone of eco-feedback to individual profiles enhances its motivational impact. Similarly, Bao et al. [4] showed that preferences for eco-feedback design vary by user background: technical users prefer quantitative clarity, while non-technical users respond more to emotionally evocative and metaphorical designs.

Despite these advances, real-time emotional adaptation remains largely unexplored in eco-feedback. Emotion AI — technology that detects and responds to affective cues — has proven effective in other domains [57, 78], but its application to eco-feedback is still in its infancy. In addition, significant challenges remain in applying Emotion AI to eco-feedback systems. Technical limitations in emotion detection—particularly in dynamic or real-world domestic environments — can reduce detection accuracy, as models often struggle with variable conditions such as background noise, fluctuating lighting, and diverse social contexts[12, 35, 56, 79]. Beyond these technical constraints, there are important ethical concerns related to privacy, informed consent, and potential data misuse[37, 62]. Furthermore, public discourse has become increasingly critical of emotion-sensing technologies, with growing debates around their societal implications, risks of emotional surveillance, and potential misuse in everyday contexts[68].

Our work focuses on the integration of Emotion AI into user-facing eco-feedback. To explore this, we conducted a co-design session using the Matchmaking for AI method with participants in a living lab. The main goal is to explore the opportunities of involving emotion AI in the eco-feedback field. Specifically, our research aims to explore more design ideas into personalised, responsive, and engaging eco-feedback that aligns with users' emotional and behavioural contexts.

2.2 Co-design for AI: Matchmaking for AI

Co-design has been developed and refined for many years as a participatory design approach that involves stakeholders in the design process [9, 46, 58]. The development of AI system often involves complex algorithms, large datasets and technical expertise that can distance the design process from the people who are using these system. Co-design offers a participatory way to involve users, domain experts and other stakeholders that shapes the design of AI system. Many researchers have applied the co-design method in their AI-related work. For example, Panigutti et al. [51] employed an iterative co-design process involving healthcare professionals to develop a human-centered, explainable AI system for clinical decision support. Payne et al. [3] explored the integration of an AI visualisation tool, *Vizcom*, within a co-design workshop aimed at product design.

Among the various co-design methods, Matchmaking for AI [10] is one of the promising approaches that narrow the gap between technical capabilities and practical applications. This method enables participants to collaboratively envisage future systems by mapping human needs to the potential functionalities of AI technologies. For example, Liu et al. [40] used Matchmaking for AI to bridge the gap between natural language processing (NLP) technologies and the practical needs of fact-checkers. The study yielded 11 novel design ideas aimed at enhancing information search, processing, and writing tasks for efficient and personalised fact-checking. Anirban et al. [45] conducted a co-design study by adapting the Matchmaking for AI method with three phases. By co-designing with six students, the study explored how generative AI could address the key challenges in the Open source Intelligence (OS-INT) Investigations for cybersecurity.

Our work is another example of applying the Matchmaking for AI method, conducted in collaboration between users and researchers. The study focuses on exploring how to involve emotion AI into eco-feedback within the personal assistant. We conducted co-design session that brought participants from diverse backgrounds to brainstorm and prototype design ideas for emotion-adaptive eco-feedback. By situating our work within the broader landscape of human-AI co-design, we contribute by effectively translating user needs into tangible AI functionalities.

2.3 Personal Assistant and Emotion AI

Personal assistants [11, 15, 69], like Siri, Alexa, Google Assistant are AI-driven tools or applications designed to help users manage tasks, retrieve information, and perform actions through natural language interactions. They provide personalized support through voice recognition based on technology like natural language processing (NLP) and machine learning (ML). Emotion AI [44, 55] represents a significant advancement in AI, enabling machines to recognise and respond to human emotions. This technology integrates various methodologies, including sentiment analysis, facial expression recognition, and physiological signal processing, to enhance human-computer interaction more natural, empathetic, and effective. Rather than focusing only on efficiency, emotion AI brings interaction modes from efficiency to emotionally engagement and personalisation [36].

As a result, there is a growing trend to integrate emotional AI into personal assistant in many domains. For example, in the education field [54], the personal assistant can be adapted to the emotional state of the learner in order to improve engagement and retention. In gaming [78], personal assistant have been used in adaptive game environments that respond to player emotions. In the workplace [55], personal assistant can provide tools to monitor employee well-being and engagement.

Our work is built on these research by expanding on how emotion-adaptive personal assistant can support sustainable behaviour change. Specifically, we conduct this study in the context of eco-feedback. By integrating emotion AI into personal assistant, we aim to explore the design ideas of personalised, emotion-adaptive eco-feedback.

3 THE LIVING LAB

3.1 The Purpose of Living Lab

The living lab was established as part of a broader research initiative exploring how Emotion AI can support energy-saving behaviours in the real-world home environments. It has two purposes: 1) as a **data collection platform** to capture real-world appliance-level energy consumption patterns for six months. 2) as a **situated design space** for engaging participants in reflective design activities.

Fig. 1. Appliances with smart plugs.

We conducted a two-phase study. **Phase 1** examined participants' initial perceptions, expectations, and concerns about eco-feedback, providing a foundation for Phase 2. Based on these findings, **Phase 2** used a smart watch-sized web-based prototype and the Matchmaking for AI co-design method to collaboratively envision Emotion AI-enabled eco-feedback solutions grounded in the participants' own actual energy use data. By combining longitudinal energy monitoring with participatory design, our paper seeks to bridge the gap between technical feasibility and user-centred innovation in Emotion AI applications.

3.2 The Participants

Participants (see Table 1) for the living lab were recruited in Germany through the external website and internal networks, ensuring a mix of diverse backgrounds and living situations. The participant demographics included variations: household composition (single-person households, couples, and families with children); gender (a balance of male and female participants was represented); technology usage (some participants were experienced with technology, while others were new to it). This diversity ensured that the study captured a wide range of perceptions to the emotion-adaptive eco-feedback under different lifestyle contexts. We used the Local Bytes smart plug to monitor energy consumption in participants' households (see Figure 1). Each participant was provided with 3-5 smart plugs. The smart plugs were installed on appliances that participants assumed most energy was consumed such as refrigerators, washing machines, dishwashers, entertainment systems, and heating devices (see Table 2).

The smart plugs were equipped with Wi-Fi connectivity and data were transmitted via MQTT to our custom-built web platform (open.DASH)[16]. This platform allowed the smart plugs to transmit real-time energy consumption data directly to a central database.

Overall, we recruited 11 living lab users (see Table 1). All 11 participates (7 males and 4 females) took part in the first phase of the study — first-round formative study between March and April 2024. 10 participants (6 male and 4 female) successfully collected energy data for six months. For the second phase of the study — the co-design session in December 2024 — 6 participants (3 males and 3 females) took part.

This study was conducted in accordance with the first author' institutional guidelines - Fraunhofer Institute, which do not require formal ethics board approval. In line with these guidelines, all participants signed an informed consent agreement prior to the interviews. Participants were informed about the purpose of the research, the voluntary nature of their involvement, and their right to withdraw at any time without penalty. All collected data, including interview transcripts, energy usage records, and co-design artifacts, were anonymised to remove personally identifiable information.

Table 1. Participants (P) Information

No.	Data	Phase 1	Phase 2	Age	Gender	Occupation	Living Condition
P1	Y	Y	N	40	M	Assistant Director of Finance	House/Living with partner
P2	Y	Y	Y	43	F	Translator	Apartment/Living with family
P3	Y	Y	Y	35	M	Research Associate	Apartment/Living alone
P4	N	Y	N	54	M	Undisclosed	House/Living with partner
P5	Y	Y	N	41	F	Supply Chain	House/Living with family
P6	Y	Y	Y	40	F	Freelance	Apartment/Undisclosed
P7	Y	Y	Y	64	F	Retired	House/Living with partner
P8	Y	Y	Y	66	M	Lecturer	House/Living with wife, 2 children
P9	Y	Y	Y	64	M	Retired Electrical Engineer	House/Living with partner
P10	Y	Y	N	36	M	Researcher & Software Developer	Apartment/Living with partner
P11	Y	Y	N	45	M	Safety Engineer	Apartment/Living with partner

Table 2. Energy Consumption Appliances for Each Participant

Participant No.	Energy Monitored Appliances
P1	Heat Pump, Water Heater, Refrigerator
P2	Tea Kettle, Microwave, TV
P3	Fridge, TV, Coffee Machine
P4	Refrigerator, TV, Coffee Machine
P5	Home Office Setup, Coffee Machine, TV
P6	Computer, Washing Machine, Induction Stove
P7	Microwave, Oven, TV
P8	Dishwasher, Washing Machine, Kettle
P9	Washing Machine, Freezer, Coffee Machine
P10	TV, Dishwasher, Refrigerator
P11	TV, Computer, Washing Machine

4 PHASE 1 — FORMATIVE STUDY

4.1 Interview Process

Eleven 1-on-1 in-depth semi-structured interviews were conducted. Each lasted from 30 minutes to 1 hour. The interviews were video-recorded with participants' written oral consent obtained prior to the sessions. In the interview, we explored participants' experience, preferences and expectations regarding eco-feedback for energy consumption. Our interviews focused on the following areas:

- **Part 1**: Demographic questions
- **Part 2**: The daily usage of the most energy-consuming appliances that the participants choose
- **Part 3**: User Stories: Participants were asked to share experiences with eco-feedback or smartwatch technology and identify pain points and expectations
- **Part 4**: Eco-Feedback Preferences: Discuss what kinds of eco-feedback they preferred in different emotional states

4.2 Results

Based on a thematic analysis of the eleven interviews, the results revealed three themes in eco-feedback: **1) the dominant role of context-triggered eco-feedback**, **2) the supporting role of emotion-triggered eco-feedback**, and **3) the skepticism towards emotion-adaptive eco-feedback**. Below is a detailed analysis.

4.2.1 The dominant role of context-triggered eco-feedback. Across all participants, the most significant requirement for eco-feedback was practical and contextual information. Users expect feedback to be delivered at the right time, in the right context, and with a clear purpose rather than generalised insights about their energy use. **1) Users prioritised information that fits into their routines.** *"I don't want to check an app every day; I want to know when I'm doing something that wastes energy at the moment it happens." (P04)* **2) Users prefer feedback that support their practical decision-making.** User desire actionable, context-aware feedback that can provide concrete decision-making opportunities. *"If I start my dishwasher at night, I'd like a suggestion about whether this is the best time based on electricity costs." (P01)* We can see from here that context-based feedback should be the primary mechanism for eco-feedback delivery. Users engage best when feedback directly links to their actions at the right time.

4.2.2 The supporting role of emotion-triggered eco-feedback. While context-based feedback remains the primary mechanism for the users preference of eco-feedback, several participants mentioned that emotion-based eco-feedback could serve as a valuable enhancement when used appropriately. **1) Emotion-based adaptation is helpful for framing eco-feedback.** Participants emphasised that emotion-adaptive eco-feedback should only affect how feedback is presented, and not when it is delivered. It could guide the tone of style of feedback, but not determine when it is delivered. Participants viewed emotion-adaptive functions as potentially helpful for enhancing empathy, but not as the core of the system. **2) Emotion-based feedback should act as a motivational nudge, not a directive.** Participants prefer clear and direct guidance. Emotion-based feedback was perceived as a gentle nudge, suitable for motivation rather than instruction. As P09 noted,when faced with high energy costs, *"I don't care if the system 'encourages' me — I just want to know what I should do."*

4.2.3 The skepticism towards emotion-adaptive eco-feedback. Despite some openness to the emotion-based adaptation, many users expressed some doubt towards its value. For these users, the value of feedback is its practicality, clarity, and timing. **1) Preference for simplicity and straightforwardness.** Some participants think that emotion-adaptive eco-feedback is too complex. Many users prefer simple, actionable recommendations over AI *"understanding"* their emotions. They think the basic functionality and clarity is far more important. As P04 put it, *"I don't want my appliances to make me feel bad. Just give me the numbers, and I'll decide."* **2) Practicality and efficiency take precedence over emotion-adaptation.** For some participants with well-established routines or life priorities, emotionally adaptive function seems irrelevant. As P05 put it, *"I'm currently valuing comfort over energy saving... I don't turn off the TV entirely because it's connected to Apple TV and I can control it remotely."* And also when technical issues happen, participants think that emotion-adaptive feature might make users more frustrated.

5 PHASE 2 — CO-DESIGN STUDY

5.1 Matchmaking for AI

"Matchmaking" as a co-design concept refers to the process of "integrating user domain knowledge into the early stages of design when a technology prototype is already available. [10]"

This approach, as defined by Bly and Churchill [10], transitions from a technology-centred design perspective to user-centred design perspective. The difference between Matchmaking for AI and traditional design methods is that, while traditional approaches start by identifying user requirements and then move through iterative prototype development, Matchmaking for AI begins by exploring the capabilities of emerging technologies. It aims to identify possible use cases and proposes initial designs during the user-centred co-design process. Usually, Matchmaking for AI contains the following four steps: 1) describing technology capabilities; 2) mapping those capabilities into associated work activities; 3) identifying work domains and specific tasks; and 4) verifying whether these tasks match technology capabilities (see Figure 2).

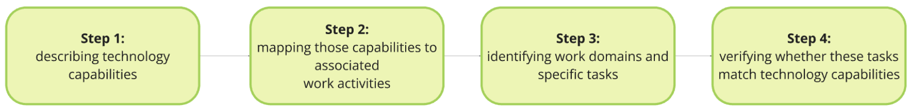

Fig. 2. Matchmaking for AI.

5.2 Study Protocol

Based on the matchmaking for AI process, we built an AI co-design canvas with detailed tasks. The details are shown in Figure 3.

5.2.1 Step 1: Describing technology capabilities. In Step 1, we firstly introduced our goals to the participants; Secondly, we clearly introduced the technology capabilities of emotion AI to the participants, which are illustrated in Table 3. Thirdly, we showcased a demo of a smartwatch-sized personal assistant (see Figure 4) to exemplify how these features can be implemented. This step ensured that stakeholders gain a clear understanding of how emotion AI can be embedded into the personal assistant and its potential to address specific challenges and enhance personalised eco-feedback.

5.2.2 Step 2: Mapping those capabilities to associated activities. After introducing the technological capability of emotion AI, we conducted a brainstorming session in Step 2 to explore and expand various home activities where emotion AI can add value. This process involves participants to generate ideas about specific activities that can align with the functions of emotion AI. During the session, the interviewer probed into the reasoning behind each idea and discussion and assessed the feasibility of technology implementation. By mapping AI capabilities to concrete activities, stakeholders were able to identify practical use cases and understand how the technology could be integrated into everyday home activities.

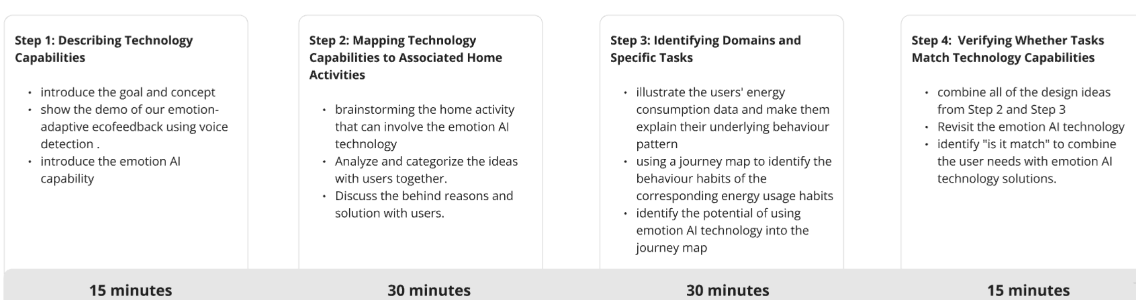

Fig. 3. Co-design procedure.

Table 3. Emotion-AI functions and Example Use Cases.

Emotion AI Can Help To...	**Example Use Case**
1. Personalise feedback based on emotional states	"You just made a big difference by turning off those lights! Feel proud!"
2. Reduce resistance to eco-feedback	If the user is frustrated, feedback is postponed to a calmer moment.
3. Improve communication for vulnerable emotional states	Instead of "You wasted energy today," use "It's okay, let's try better tomorrow."
4. Reinforce sustainable habits with emotional rewards	User receives praise for eco-friendly behaviour, reinforcing habits.
5. Nudge behavioural change through emotional framing	"Every little bit helps, and you're doing a great job so far!"
6. Detect emotional triggers for eco-behaviours	"We noticed busy days make recycling feel like a chore. How about a reminder?"
7. Engage users with gamification and emotional metrics	Gamified challenges appear when users are excited; fun facts if disinterested.
8. Real-time adaptive feedback in IoT ecosystems	"We've dimmed the lights to help you relax and conserve energy."

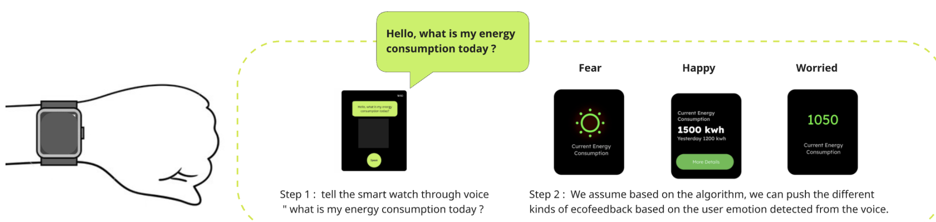

Fig. 4. Prototype: The prototype was designed as a smartwatch interface that integrates real-time emotion detection with personalised eco-feedback. The interface enables users to interact seamlessly with their energy consumption data by using a voice command feature. For example, users can query, "What is my energy consumption today?" The system responds by analysing the user's emotional state, such as "Happy" or "Worried", displayed alongside visual indicators of energy consumption. Key interactive elements include a "Speak" button to initiate the query, a "Stop" button to end it, and a visual status for emotion analysis in progress. The code can be accessed here: https://github.com/higreetings/usability.

5.2.3 Step 3: Identifying work domains and specific tasks. In Step 3, our goal was to search for the specific contexts and tasks where Emotion AI can be applied. To build a personalised co-design experience, we collected user energy consumption data over a six-month period based on the appliances participants selected and those assumed to be the highest energy consumption appliances. Using these data, we generated 24-hour energy consumption pattern heatmaps for each appliance (See Figure 5). These heatmaps served as the basis for creating journey map, which

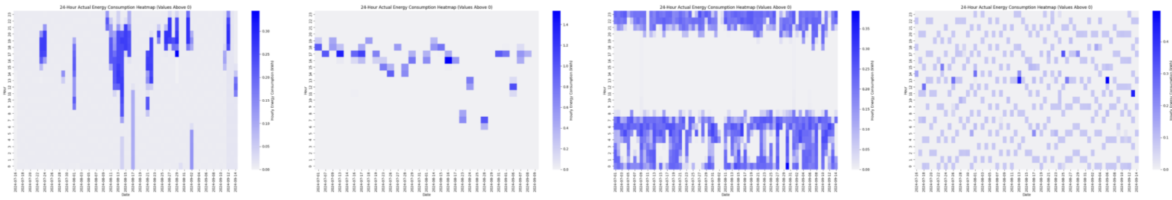

Fig. 5. Example of one participant's appliances energy consumption heat map.

guided participants in identifying opportunities for integrating Emotion AI into their daily routines. This step ensures that the application of emotion AI is grounded in real-world needs.

5.2.4 Step 4: Verifying whether these tasks match technology capabilities. In Step 4, the focus was on verifying whether the previously identified design ideas aligned with the technology capabilities of Emotion AI. This step involved synthesising insights gathered from Step 2 and Step 3, conducting a matchmaking process between design ideas and AI functions, and evaluating the feasibility of each idea.

This step ensured that the Emotion AI was not only theoretically compatible with the identified tasks but also practically viable, delivering meaningful and effective outcomes in real-world home environments. By rigorously verifying the alignment between design ideas and technology capabilities, stakeholders can confidently move forward when implementing AI solutions that meet user needs.

5.3 Prototype

We chose to use the smartwatch-sized web-based prototype (See Figure 4) for two key reasons. First, it served as a design probe and conceptual anchor during the co-design session. Rather than representing a fully realised or deployable system, the web-based prototype simulated how Emotion AI-enabled eco-feedback could look and feel in a smartwatch-like interface, helping participants reflect on when, how and where emotionally adaptive eco-feedback might fit into their daily routines. Second, the smartwatch metaphor was not intended to represent the sole form of a personal assistant but to illustrate one example within a broader ecosystem of PA devices. Using this familiar, compact form factor as a web-based simulation provided an accessible entry point for participants to envision Emotion AI–driven interactions in context.

Our prototype used a speech-based modality to detect emotions, analysing vocal prosody (tone, pitch, rhythm) from short audio recordings via a web-based interface. Participants provided short audio recordings through a web-based interface, which were processed using **the Hume Expression Measurement API**[32]. The pipeline followed a sequential flow: audio input was first captured and transmitted for API-based inference, where Hume's pretrained models performed features extraction and classification to map prosodic patterns to discrete emotional states. The system produced the top-scoring emotion across all speech segments as an output, along with a transcription of the recorded text. We then applied a predefined rule-based mapping to link the detected emotional states to corresponding eco-feedback types.

We conducted a small-scale usability test with diverse background (four from our living lab, one from a living lab partner, and one from external). The participants completed four assigned tasks during the usability testing including exploring demo and engaging in scenario-based tasks. The system achieved an average score of 81.25 (M = 81.25, SD = 7.87) from the SUS evaluation framework[14], indicating good overall usability. Qualitative feedback shows that: for effectiveness, participants successfully understood and completed all test scenarios, demonstrating that the emotion-based feedback concept could effectively support energy awareness. For completeness, users acknowledged that while the prototype covered core functionalities (emotion detection and visualisation adaptation). For satisfactory, most participants expressed positive engagement with the system's design, appreciating its simplicity, adaptability, and potential for daily use. However, participants also identified shortcomings and future improvements regarding transparency and control. For transparency, it means combining emotion and contextual sensing (e.g., time, location) to make feedback more situationally appropriate. For control, it means allowing users to manually override or customise the system's adaptive responses.

5.4 Co-design Process

Following a six-month data collection period during which participants' energy consumption patterns were monitored, we conducted a co-design session aimed at collaboratively developing emotion-adaptive eco-feedback in personal assistant. To facilitate this process, we used the AI co-design Canvas, structured with the four steps described in Section 5.2, and implemented the session in Miro Board (a collaborative whiteboarding tool) to cooperatively interact with our participants. Our main goal was to generate design ideas that can integrate emotion AI to support and encourage energy-saving behaviour. Each co-design session lasted approximately 90 minutes and followed the four-step process (See Figure 3).

Seven participants initially agreed to take part in this study; however, one dropped out during the process, resulting in six participants completing the session. We chose an online format due to the constraints of participants coming from different cities in Germany. Online participation allowed a greater flexibility for our study, also enabling participants from diverse household contexts to join conveniently. We opted for one-on-one co-design sessions for several reasons. Firstly, scheduling group sessions was challenging due to time constraints, and individual sessions offered greater flexibility and allowed for more focused, in-depth discussions. Secondly, personalisation of co-design materials was essential. Each participant was presented with their own energy usage data visualisations, derived from specific appliances such as refrigerators, televisions, or washing machines, ensuring that the eco-feedback designs were tailored to their unique behaviours and preferences. Thirdly, individual sessions enabled a deeper contextual integration of participants' home environments, helping them more vividly imagine how the eco-feedback system could be embedded into their daily routines.

5.5 Data Analysis

We conducted all co-design sessions with recruited participants using Miro Board (a collaborative whiteboarding tool) and Google Meet (a video conferencing tool). Co-design sessions were recorded with consent from the participants and then transcribed. Our main goal was to extract and synthesise design ideas that emerged through discussion and co-creation with participants. The majority of these ideas were generated during **Step 2** and **Step 3** of the co-design process, where participants actively explored how emotion-adaptive eco-feedback can be applied in daily home activities. In Step 4, the focus is shifting from idea exploration to evaluating the feasibility of these design ideas by comparing them to the actual capability of emotion AI technology.

Our results focus on the emotion-adaptive eco-feedback concepts co-designed with participants. In Step 2, participants collaboratively ideated a wide range of household scenarios where emotion-adaptive eco-feedback could be meaningful. Ideas spanned across tasks such as cooking, gaming, or reading, and considered the role of mood, timing, and user context in eco-feedback delivery. In Step 3, participants examined heatmaps of energy consumption patterns of home appliances (e.g. TV, PC, kitchen devices). They annotated a timeline of a typical day — morning, noon, afternoon and night with their own emotional and situational contexts. This session aimed to identify how, when and in what form participants preferred to receive eco-feedback through their daily routines.

Based on the 18 design ideas (See Appendix Table 5) generated through the co-design sessions, we conducted a qualitative evaluation (See Appendix Table 5) to determine which ideas use the emotion as the primary input. We reduced the overlapped ideas by removing the redundant ideas. As a result, 8 design ideas were selected.

6 PHASE 2 — RESULTS

We deployed the co-design method — Matchmaking for AI to facilitate participatory design session aimed at envisioning the opportunities of involving emotion AI into eco-feedback. Building on our insights from Study 1 – formative study, we focused on how the eco-feedback can be framed based on emotion. Unlike the formative study, where participants directly responded to the questions and had pre-defined concepts, Study 2 – co-design process, was more interactive with more material. These rich contexts allowed participants to project themselves into real-world environments and generate a range of novel ideas where emotion AI could take a more proactive role in shaping sustainable behaviour, not only in how eco-feedback is framed, but also in when it is delivered (See Table 4).

Table 4. Final 8 selected design ideas from Matchmaking for AI co-design session. Our process leads to 8 design ideas that can involve emotional AI technology in eco-feedback within personal assistant to foster energy-saving behaviour.

No.	Design Idea
1	Show minimal, digestible info (e.g., one number or colour) to avoid overload during the stress time.
3	Postpone feedback when users are emotionally overwhelmed.
4	Use supportive rather than judgmental language when stress or guilt is detected.
5	Trigger challenges, goals, or comparisons during playful or upbeat moods.
6	Reinforce eco-actions with praise when users show pride or satisfaction.
10	Use visual feedback when users are calm; audio or minimal cues when tired or distracted.
11	Adjust lighting and heating automatically based on emotional state (e.g., dim lights for relaxation).
17	Only present peer comparisons when users are emotionally ready; avoid during negative moods.

6.1 Emotion-adaptive Eco-feedback Framing

6.1.1 Show minimal, digestible info (e.g., one number or colour) to avoid overload during the stress time. Through the co-design session, a recurring narrative emerged: users wanted to have a simplified eco-feedback during the moments when they are stressed or cognitively overloaded. These participants indicated that while they valued energy-related insights, their capacity to process complex feedback diminished during emotionally depressed moments. This suggests a crucial gap in current eco-feedback systems, which often treat all users' states equally, neglecting the complexity of format or timing of eco-feedback based on the user's emotional condition.

Participants frequently associated stress with a reduced ability to process data or make behavioural changes. For example, P6 mentioned that *"When I'm unhappy or in a depressed mood, I just want to know the result or maybe I just want to know numbers"*. Similairly, P8 echoed this idea saying, *"When I'm very stressful or angry, I prefer feedback that's very simple. Maybe just numbers. No long explanations."* P3 reinforced this idea on specific scenarios, suggesting that stressful time period like post-work evenings or time-pressured mornings demand eco-feedback that does not "overwhelm" the user: *"If you had a stressful day and you're washing the dishes, maybe then it's better to say: use the dishwasher. It's easier."* The feedback should support, not burden the decision-making process during the emotional down period.

This user need points to the principle in HCI that cognitive bandwidth is not constant [43]. Eco-feedback that is too detail-oriented, visually complex, or poorly timed during the stress time might be ignored, misinterpreted, or even resistance to future engagement. P7 stated that: *"If the system gives me too much information when I'm already stressed, I won't even look at it."* Ignoring this variability in user receptivity risks might make eco-feedback technically informative but emotionally dissonant.

Despite many studies[16, 17, 22] on eco-feedback formats such as visualisation, gamification, few eco-feedback systems dynamically tailor their content based on affective states. Current eco-feedback systems focus mainly on the static display level and rarely account for emotional readiness of users to absorb or act upon the feedback. This suggests a mismatch between eco-feedback delivery mechanism and variable human emotion states and emotion AI can be involved to bridge this gap.

6.1.2 Use supportive rather than judgmental language when stress or guilt is detected. Participants also care towards the empathetic language, especially during the emotionally sensitive states. During these moments, users preferred the eco-feedback with more understanding and encouragement tone rather than using judgemental or rational phrasing. Multiple participants (P03,P06,P08) reported that the emotional framing of eco-feedback influence their willingness to engage with it. P06 explained that *"When I'm already stressed or tired, I don't want a message that tells me I'm wasting energy. That just feels like criticism."* and *"If it said something like 'you've had a busy day, maybe we try again tomorrow'—that would feel more supportive."* P03 also confirmed this, he suggested that the eco-feedback should *"encourage without blaming"*. P08 emphasised the psychological impact for the emotional insensitive eco-feedback, *" If it feels like the system is blaming me for using too much energy, I just shut it off. But if it says something more like 'we understand—it happens,' then I stay open to listening."*

Within the personal assistant, language tones shows the same importance as content. When users already feel overwhelmed, as explained by P02, *"Sometimes I know I'm not doing everything right. I just don't want the app to make me feel worse about it."*, a good empathic language can maintain users' engagement.

Research on eco-feedback[4, 6] often emphasises the accuracy, visualisation or nudging strategies, and limited research focuses on adapting their language tone to match users' emotional state. Previous eco-feedback on messages tend to be like generic messages — "You used 4.4 kWh more than average. "or instructional messages — "Turn off the devices." With the technology development, voice can be used as a detection of emotion, and the adaptation of message tone follows users' emotions has emergent as a way to increase the users' engagement and improve user experience.

6.1.3 Reinforce eco-actions with praise when users show pride or satisfaction. Participants also emphasised the importance of positive reinforcement, especially when they had taken some energy-saving action. Many participants mentioned that when they felt proud, satisfied, or accomplished, they were more open to receiving feedback and treated it in a more valuable manner when their efforts were acknowledged. This suggests another key emotional entry point for sustainable engagement to reinforce the pro-environmental habits by emotion-adaptive eco-feedback. P07 expressed her idea, *"If I just did something good, like switching everything off, it would be nice if the system noticed and said something like 'great job!'"* P11 also expressed a similar thought, *"You turn something off and then maybe it says, 'well done, you saved this much today.' It's motivating to know it mattered."* These moments can be treated as critical emotional reinforcements that can make energy-saving behaviour feel more meaningful and noticeable. Users want their eco-action to be seen and appreciated. It can help them to establish a positive emotional loop. P09 confirmed this, *"I don't need rewards. But if the system tells me I did something right, it helps me keep doing it."*

Previous research in eco-feedback were more focused towards problem detection[17, 20, 66], while fewer systems were designed to recognise and celebrate the success, especially when users felt proud. Eco-feedback with emotion AI can detect the moments of pride or positive emotion peaks and deliver encouragement to reinforce such sustainable behaviour.

6.2 Emotion-timed Interaction and Delivery

6.2.1 Postpone feedback when users are emotionally overwhelmed. A recurring concern among participants was their lack of emotional readiness to receive eco-feedback when they were upset, frustrated, or emotionally disengaged. Many interviewees articulated that when experiencing negative emotional states, they were less likely to process or act upon eco-feedback—no matter how well-designed the message or visualisation was. In these moments, even minimal feedback could be perceived as intrusive or irritating, further undermining the effectiveness of the intervention.

Participants emphasised the importance of emotional timing. P07 explained, *"If the system gives me feedback right when I'm annoyed or exhausted, I'll just ignore it—or worse, I'll be annoyed at the system itself"*. P06 echoes this argument, said *"When I'm in a bad mood, I don't want to deal with numbers or messages. It's better to leave me alone and try later."* P03 described this in his everyday evening routines: *"After a long day, I just want to chill. If a notification pops up telling me I used too much energy, I'll just swipe it a way."* It shows that the users' emotional state not only affect their willingness to engage with eco-feedback and how they respond to it.

6.2.2 Trigger challenges, goals during playful or upbeat moods. Beyond just adapting the delivery time or change the tone message, several participants were interested in playful and motivational eco-feedback when they were in a good mood. Mood-triggered eco-challenges can be seen as another effective way to increase engagement.

P06, P07, and P11 described the joy, calm time as an ideal opportunity for deeper engagement. P06 said,*"If I'm in a good mood, I'd actually enjoy a little challenge—like comparing with my neighbours or getting a fun fact about how much I saved."* P11 also argued that when in a good mood, he was excited to see how much energy he consumed and embraced the challenge. By introducing challenges or rewards when the user is emotionally open—such as feeling accomplished, calm, or curious—systems can foster a stronger relationship with the user, increasing engagement, and enjoyment to sustainable behaviour.

6.2.3 Use visual feedback when users are calm; audio or minimal cues when tired or distracted. Another emergent need from the participants was the ability of emotion AI to trigger eco-feedback on how information is presented based on users' emotional states. Based on the various modalities of personal assistant, the selection can be different feedback modalities, like visual, auditory, haptic or textual. Many participants said that their emotion state shaped how they preferred to receive feedback. *"If I am in a rush or annoyed, I do not want to read anything. A simple tone or light would be better than a screen full of numbers.(P09)"* P03 offered a classic use case: *"In the morning, I might prefer a quick light cue—like green if energy use is okay. But at night, maybe I'd check the app or graph if I'm in a better mood."* These non-uniform needs across time and emotion exposes the opportunities of modality flexibility through emotion AI.

The multi-modal eco-feedback has already been explored in the smart home research. Existing research [2] [26] [67] emphasised the effectiveness of combining these modalities to address the problem in real-world setting. Limited research explores the emotion-triggered method with real-time affective signals. The potential of emotion-adaptive modality eco-feedback is underexplored.

6.3 Emotion-aware Environment and Social Adaptation

6.3.1 Adjust lighting and heating automatically based on emotional state. From the interviews, participants expressed a strong interest in automated environmental adaptation based on mood, especially in lighting and temperature. When intelligently adapted, lighting and temperature adjustments can promote energy efficiency while supporting users' emotional and physiological needs.

From the participants' view, home environments and home appliances can be treated as an extension of their emotional state. For example, P11 said that, *"When watching a movie and I'm in a special mood, the room could adapt to this. Dim the lights, adjust the temperature—it just makes everything feel better."* These adjustments help users feel more at ease, focused, or calm, depending on their needs. P07 also mentioned that she treated lighting as an emotional regulator, she said,*"If I do sports or something active, I want bright lights. But if I am just trying to relax or cook in the evening, I want something softer."* Our results show that these emotion preferences for lightning also open the opportunities for energy savings. Emotion AI can be triggered as a bridge not only to support the mood but also to conserve energy.

Traditional smart home research always focus on optimising the lighting and temperature based on occupancy and scheduling for energy saving [1, 29, 42]. These research neglected the potential context of emotion, and missed the opportunities for emotion-sensitive energy saving. Also, there is limited research exploring into how lighting and heating can be served as non-verbal eco-feedback and adjusted to users' mood to encourage sustainable settings, for example, dim lights when calm, lower heat when active.

6.3.2 Only present peer comparisons when users are emotionally ready; avoid during negative moods. From the literature review in eco-feedback [63], social comparison is a powerful motivator for behaviour change in energy consumption. Previous research neglected the involvement of emotion AI into social comparison in eco-feedback. Our results from the co-design approach with the participants showed that the effectiveness of social comparison depended on when it is delivered. When users are emotionally receptive, they welcomed comparison as motivation; whereas when they are stressed or disengaged, it is seen as unhelpful or even demoralising. These insights underscore the need for emotion-aware social comparison, where comparisons are only acceptable when users are in a state of receptivity.

These results come from our co-design session, participants expressed mixed feelings about being compared to others. When in a positive mood, they found it helpful or motivating. For example, P06 said, *"If I'm in a good mood, I'd actually like to see how I'm doing compared to others. It makes it more interesting."* P11 also commented on that, *"If I am relaxed and open to it, I would enjoy seeing if I saved more than my neighbours this week - it is like a friendly competition."* In contrast, during the stress or low confidence moments, participants believed that social comparison felt judgemental. P03 explained that, *"If I'm having a bad day, I don't want to be told I'm doing worse than others. That just makes me shut off."* P07 has a similar feeling, saying that *"Sometimes I'm already trying hard. Being told I'm behind just makes me feel worse."*

Social comparison is one of the common persuasive strategies in eco-feedback. Our results show that the social comparisons method of eco-feedback should be more effective when it combines with emotion AI. Under some situations where social comparison were presenting at the wrong time, it can create resistance rather than motivation. Current eco-feedback systems only offer static comparison and current research focus largely on the design of comparison metrics [21], but not on when and how to deliver them based on the user's mood. The one-size-fits-all messaging that fails to create the personalised user experience. Emotion AI can enable receptive-aware social comparison delivery by detecting the emotional states and adjusting the timing, tone accordingly.

7 DISCUSSION

7.1 The Summary of Design Ideas

In our formative study, the results from users' perception strongly emphasised the dominance of context-based eco-feedback; participants believed that feedback should be timely, actionable, and situationally relevant and be grounded in the environmental context. This preference aligns with the foundational HCI and sustainability research which emphasises the situated, real-time eco-feedback is more effective at influencing behaviour than energy reports or abstract summaries [5, 21]. Participants preferred eco-feedback that supports their decision-making in their daily routines without requiring their time and effort. Emotion-based eco-feedback was initially treated as a supportive role during the formative study and participants expressed that it should only modify how feedback is framed, not when it is delivered. As one participant put it, emotional adaption of eco-feedback is welcome only if it does not interfere with the actual information they need. This argument shows that users have a scepticism attitude towards emotion-adaption eco-feedback. However, during our co-design session where participants engaged with a conceptual overview of emotion AI and an interactive prototype — participants began to explore more design possibilities. Through a richer design context, emotion AI was not only accepted but reimagined as a central mechanism for delivering eco-feedback.

Through collaborative ideation, participants proposed three primary directions for emotion-adaptive eco-feedback: **1) emotion-adaptive content framing** Eco-feedback can be emotionally framed to match the users' mood (idea 1, 4, and 6). **2) emotion-timed interaction and delivery** Participants imagine that the eco-feedback can dynamically deliver based on the users' real-time emotional state (idea 3, 5, and 10). **3) emotion-aware environment and social adaption** Beyond individual interaction, participants also envisioned emotion AI can be extended to the environmental and social context — such as adapting lighting and temperature settings (idea 11) and triggering social comparison based on emotional receptivity (idea 17). These design ideas demonstrate emotion-based adaptation has potential design opportunities in content framing, delivery time, modality, and ambient context.

The combination of Study 1 and Study 2 offer complementary insights into how users perceive and envision emotionally adaptive eco-feedback in domestic settings. Table 6 illustrates how participants' concerns, routines, and emotional responses in Study 1 evolved into concrete design ideas in Study 2. Specifically, it presents the progression from experience to ideation across six co-design participants. The transition from Study 1 to Study 2 shows an evolution from retrospective understanding to prospective ideation. In Study 1, the participants' feedback are grounded in their real-world behaviours, whereas in Study 2, the same group of participants were empowered to envision the adoption of technologies through a co-design method with data and emotion AI conception. The participants' real energy data and visualised prototypes triggered their reimagination of the emotion AI in the home context. The progressions show the power of co-design as a transformative bridge by shifting reflection to ideation, combining empirical evidence with generative exploration.

We also found that professionals with structured routines (P1-assistant director of Finance, P10-Software Developer) preferred actionable and context-based eco-feedback with their daily routine. For example, P1 expressed the desire for energy tips during routines tasks like using the dishwasher at night. Freelancer and retirees (P6-Freelance, P7-retired, P9-retired) often had more flexibility in routines and expressed more openness to the emotionally adaptive feedback. Participants who are living alone or with one partner (P3, P10) often emphasise the simplicity in eco-feedback, showing less interest in emotion-based framing and more in clarity and usefulness. Female participants were more likely to discuss the tone and empathy of eco-feedback, expressing stronger preference for supportive language, while male participants were generally more focused on the content accuracy and clarity. Participants who are living in the house often had more energy-consumption appliances, leading to more detailed discussion about specific energy behaviour in some appliances.

Overall, our findings contribute and extend prior work in several ways. Previous work from Wilson et al. [76] examined the emotional message framing based on user attitudes, our study expands how emotion can also drive the timing and modality of eco-feedback itself with Emotion AI technology. This extends the design space from static emotion framing towards real-time affective adaption. Our two-phase study also reveals a new picture, while users initially expressed scepticism toward emotion-triggered eco-feedback, their engagement in the co-design session led to open design ideas that embrace Emotion AI. This highlights the value of participatory design methods in reshaping users' perceptions towards emerging AI technologies (See Section 7.2). Our results also show the potential of future eco-feedback - where the system may benefit from combining contextual intelligence with emotional intelligence - enables the adaptive systems that are both informative and empathetic. This hybrid approach might enhance user engagement and long-term behavioural change.

7.2 The Benefits of Using the Co-design Method — Matchmaking for AI

It has been a challenge to bridge the gap between AI research and its real-world application. Through our co-design method — matchmaking for AI, we translated abstract emotion AI capabilities into user-centred design ideas for emotion-based eco-feedback within the personal assistant. This approach reduced the misalignment between what AI can do and what users need, a gap frequently mentioned in HCI/AI literature [31].

By situating the participants within the real environment we enabled participants to make meaningful engagement with the Emotion AI technology — despite most of them having limited technical understanding. We can see that in study 1 — formative study, participants has limited imagination and scepticism towards the use cases of emotion-adaptive eco-feedback. However, during the study 2 — co-design session, after they were introduced to 1) the overview of emotion AI capabilities, 2) a visualised prototype, and 3) their own visualised energy data, they were able to reimagine new opportunities for emotion-based eco-feedback. The two-steps sessions helped participants shift from vague understanding to concrete design ideas and considered AI as a design material [77].

This transformation reinforces that the value of co-design can facilitate a collaborative imagination of technical possibility. It became a generative space. It can allow participants to make a reflection on their own daily routines and find the design space of new technology with co-creation collaboration. These findings support the prior literature on the role of co-design in uncovering specific needs [64] [51] [25]. Furthermore, Matchmaking for AI allowed stakeholders to embed AI capabilities into contextual real-world environments, rather than designing solely from top-to-bottom technical perspectives.

Our work demonstrated the power of participatory AI. Rather than treating emotion AI as a technology, we use the co-design method to explore its role as a material. This method not only revealed what the user wants from AI, but also how they want it to behave, when and why. It showed that including the end-users in the early-stage of AI development is valuable and making the system more human-centred. In addition, the benefits of our co-design process also become more apparent when participants comes from diverse demographic backgrounds and have different electricity consumption patterns. The adoption of demographic diversity and real energy data in the co-design phase enabled a more grounded and personalised exploration of the Emotion AI application. For example, participants living in larger households tended to generate more systemic and automation-oriented ideas. In contrast, single-person and apartment dwellers tended to generate lightweight, minimalistic eco-feedback mechanisms that emphasised simplicity and clarity. Occupational and lifestyle differences also shaped the ideation process. Participants with structured professional routines valued timely, actionable, and context-based eco-feedback that could fit into their daily schedules. On the contrary, retirees and freelancers, who had more flexible routines, showed greater openness toward emotion-driven eco-feedback. Female participants more frequently discussed emotion tone, while male participants prioritised functional precision and system transparency. These variations shows that co-design can not only function as a participatory design method but also as an analytical lens for revealing how demographic and behavioural diversity influences perceptions of emerging AI technologies. By integrating participants' electricity consumption data with their lived experiences, our co-design sessions enhanced user engagement and triggered a more grounded, personal, and meaningful ideation process.

7.3 The Limitation of Using Co-design Method — Matchmaking for AI

While the co-design method — Matching making for AI is valuable in translating the complex emotion AI capabilities into user-driven design ideas, our work revealed several limitations.

First, the quality and depth of co-design results were influence by the participants' technical background. We observe a difference in engagement between users with and without prior AI or technical experience. Participants with some AI literacy not only spent more time in Step 2 for brainstorming but also do more dual-layered thinking: they not only ideated creatively but also assessed the feasibility of those ideas simultaneously. Their process reflected a design thinking pattern of divergence (exploration) following by convergence (refinement and evaluation). In contrast, non-technical participants tended to do the session from a pure exploratory perspective, focusing more on scenario imagination. While their ideas were often grounded in real-world environments and real needs, they lacked the attention to the constraints or possibilities of the technology. This shows a tension between imaginative ideation and technical viability, which echos the known challenge in the participatory AI noted by Birhane et al. [8] and Zytko et al. [81]. Zytko et al. [81] observed that the participants may misjudge what AI can really do, and Birhane et al. [8] emphasized the need to balance imagination with accessible technical understanding. Bratteregi et al. [13] also warned that insufficient support can limit the effectiveness of participation. Therefore, future co-design for Matchmaking for AI should involve roles with expertise.

Second, our 90-minutes co-design session encourage rapid reflection but may have constrained deeper iteration. Due to our one-on-one session format, while allowing for individual focus, participants had not got opportunities to refine or build on others' ideas — a key component of traditional co-design. While this limitation does not undermine the value of co-design in AI development, it does suggest the opportunities for enhancement. For example, we could consider mixed-expertise pairing and offer more time for iterative design cycles, where can facilitate co-evolution.

7.4 Privacy Implications and Data Governance

The integration of Emotion AI into domestic environments raises the concerns towards ethical questions, including privacy, transparency, and data governance. As emotion-triggered eco-feedback systems rely on personal and affective data to adapt their interaction, questions arise about how such data is collected, interpreted and shared. In our studies, privacy concerns emerged repeatedly, particularly when eco-feedback was displayed in shared or social settings. The home has traditionally been perceived as a personal retreat and an embodiment of privacy, where people can develop freely and undisturbed by the public and the "external world" [72]. Yet, data-driven technologies such as IoT and AI are permeating these private spaces, they blur the boundaries between private and public spheres and raise the challenges for protecting privacy within the domestic environments [24]. The home is therefore regarded as a place of peace and openness, where people can act freely and express their emotions without restraint. However, ubiquitous devices and sensors are constantly collecting data, creating a comprehensive data profile of the user and their household, which can be shared with device manufacturers, third parties, or even used by actors with criminal intentions [65]. This data can include information about usage, but may also reveal sensitive content, especially when data is processed in rooms such as bedrooms or bathrooms [38]. The use of emotional AI carries the risk that sensitive information about a person's emotional state will also be recorded and processed. This information could then be shared with manufacturers and providers, allowing conclusions to be drawn about the person's general mood, character, or even mental health [65].

In addition, participants expressed awareness of the regulatory sensitivity surrounding Emotion AI technology, particularly within the European context. One participant questioned how such a system could comply with strict AI and data protection regulations in the EU. She worried about how Emotion AI can be compatible with European data protection norms. Also, participants demonstrate the implicit expectations for local data governance — preferring systems that keep emotional and behavioural data localised or user-controlled rather than automatically shared across systems. These concerns highlight the need for the transparency of user-controllable data flow and design strategies that align with the regional data government policy.

Furthermore, our studies showed that, particularly in stressful or annoyed moments, users do not want to be challenged or reprimanded by interacting with emotional AI, but rather want to be supported or emotionally uplifted. In such situations, unobtrusive notifications were especially desired, ones that primarily provide status updates on efficient energy usage rather than information or instructions that could be perceived as critical and thus as a threat to the feeling of comfort in one's own home [73]. However, the provision of eco-feedback using both emotional and contextual intelligence offers the potential to promote the home as a place of relaxation and balance, by appropriately generating and communicating context-based content. Finally, the negotiation of privacy and the disclosure of data is a very individual and personal matter, which also depends heavily on the context and can change over time [48]. Therefore, one-size-fits-all solutions are not suitable for a positive user experience; instead, they must be adapted to users' moods and data protection preferences [75]. Furthermore, privacy concerns emerged in situations when feedback was presented during shared or social time, as our studies have shown. Therefore, when designing emotional AI solutions, it should also be taken into account that users can determine when and with whom eco-feedback data is shared, as sharing within a community can, on the one hand, motivate for energy saving through social comparison, but on the other hand, also carries the risk of exposure and thus has an undesirable effect by intruding on privacy [27, 61].

8 LIMITATION

We acknowledge three limitations of our study. First, our findings are not intended to be broadly generalizable, as our work is an empirical, exploratory study designed to investigate the potential of emotion-adaptive eco-feedback rather than to evaluate its efficacy at scale. Our study relied on a small and context-specific sample, which enabled us to capture rich, qualitative insights into participants' everyday eco-feedback attitudes and experiences, which was essential for our exploratory goals. Second, while our co-design sessions and interviews generated promising ideas, they remain conceptual. Implementing and testing these ideas in real-world deployments, across diverse contexts and populations, will be better to fully understand the effectiveness of emotion-adaptive eco-feedback. Third, our online co-design format reduces the opportunities for participants to engage in physical prototyping and also limits our observation of non-verbal cues - such as gestures, body language - which can provide more valuable insights during the sessions.

9 CONCLUSION AND FUTURE WORK

Our study explored potential applications for emotion-adaptive eco-feedback within the context of the personal assistant. We built a living lab with 11 participants in Germany and conducted two experimental sessions. Our findings reveal that initially, participants perceived the emotion-based adaptive eco-feedback as unnecessary; they expect eco-feedback to be practical, timely, minimal descriptive, with a strong preference for context-based eco-feedback in daily routine **(RQ1)**. However, through co-design sessions and exposure to the Emotion AI capabilities, users reimagined its potential to enhance the eco-feedback by adjusting not only how eco-feedback is framed, but also when and how it is delivered. Users saw a new value in emotion-adaptive systems — not only to frame eco-feedback in more supportive and motivational ways, but also to adjust the timing, modality of eco-feedback based on emotional states **(RQ2)**. We identified eight emotion-adaptive design ideas that expand this vision, including emotionally sensitive framing, real-time delivery adjustments, adaptive modality selection, and social-aware comparison. These findings suggest that Emotion AI, when applied thoughtfully, can augment traditional context-based systems by aligning eco-feedback with users' emotional states. It bridges the gap between what AI can do and what users need. Future work should explore real-world deployment, emotional sensing accuracy, and ethical considerations to refine emotion intelligence eco-feedback systems further.

Acknowledgment

This work has been funded by the EU Horizon 2020 Marie Skłodowska-Curie International Training Network GECKO, Grant number 955422 (https://gecko-project.eu/).

References

[1] Fahad R Albogamy, Mohammad Yousaf Ishaq Paracha, Ghulam Hafeez, Imran Khan, Sadia Murawwat, Gul Rukh, Sheraz Khan, and Mohammad Usman Ali Khan. 2022. Real-time scheduling for optimal energy optimization in smart grid integrated with renewable energy sources. *IEEE Access* 10 (2022), 35498–35520.

[2] Nuno Almeida, Samuel Silva, António Teixeira, Maksym Ketsmur, Diogo Guimarães, and Emanuel Fonseca. 2018. Multimodal interaction for accessible smart homes. In *Proceedings of the 8th International Conference on Software Development and Technologies for Enhancing Accessibility and Fighting Info-exclusion*. 63–70.

[3] Anders-Petter Andersson, Cecilie Eide, Eleftherios Papachristou, Anne-Britt Torkildsby, Yavuz Inal, et al. 2024. Co-design with persons with disabilities as an innovative resource set free by ai. In *DS 131: Proceedings of the International Conference on Engineering and Product Design Education (E&PDE 2024)*. 563–568.

[4] Qifang Bao, Mian Mobeen Shaukat, Asmaa Elantary, and Maria C Yang. 2016. Eco-feedback designs: A balance between the quantitative and the emotional. In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Vol. 50190. American Society of Mechanical Engineers, V007T06A022.

[5] Lyn Bartram. 2015. Design challenges and opportunities for eco-feedback in the home. *IEEE Computer Graphics and Applications* 35, 4 (2015), 52–62.

[6] Lyn Bartram. 2015. Design Challenges and Opportunities for Eco-Feedback in the Home. *IEEE Computer Graphics Applications* 35, 4 (2015), 52–62.

[7] Tracy Bhamra, Debra Lilley, and Tang Tang. 2011. Design for sustainable behaviour: Using products to change consumer behaviour. *The Design Journal* 14, 4 (2011), 427–445.

[8] Abeba Birhane, William Isaac, Vinodkumar Prabhakaran, Mark Diaz, Madeleine Clare Elish, Iason Gabriel, and Shakir Mohamed. 2022. Power to the people? Opportunities and challenges for participatory AI. In *Proceedings of the 2nd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization*. 1–8.

[9] Erling Bjögvinsson, Pelle Ehn, and Per-Anders Hillgren. 2012. Design things and design thinking: Contemporary participatory design challenges. *Design issues* 28, 3 (2012), 101–116.

[10] Sara Bly and Elizabeth F Churchill. 1999. Design through matchmaking: technology in search of users. *Interactions* 6, 2 (1999), 23–31.

[11] Muktanandh Bombothu, Yaseen Abdul, Umasri Katragadda, and Ds Bhupal Naik. 2023. INTELLINEO–An Intelligent Personal Assistant. In *2023 International Conference on Quantum Technologies, Communications, Computing, Hardware and Embedded Systems Security (iQ-CCHESS)*. IEEE, 1–7.

[12] Patrícia J. Bota, Chen Wang, Ana L. N. Fred, and Hugo Plácido Da Silva. 2019. A Review, Current Challenges, and Future Possibilities on Emotion Recognition Using Machine Learning and Physiological Signals. *IEEE Access* 7 (2019), 140990–141020. doi:10.1109/ACCESS.2019.2944001

[13] Tone Bratteteig and Guri Verne. 2018. Does AI make PD obsolete? exploring challenges from artificial intelligence to participatory design. In *Proceedings of the 15th Participatory Design Conference: Short Papers, Situated Actions, Workshops and Tutorial-Volume 2*. 1–5.

[14] John Brooke. 1996. SUS-A quick and dirty usability scale. In *Usability evaluation in industry*. CRC Press, 189–194.

[15] Nil Goksel Canbek and Mehmet Emin Mutlu. 2016. On the track of artificial intelligence: Learning with intelligent personal assistants. *Journal of Human Sciences* 13, 1 (2016), 592–601.

[16] Nico Castelli, Corinna Ogonowski, Timo Jakobi, Martin Stein, Gunnar Stevens, and Volker Wulf. 2017. What Happened in my Home?: An End-User Development Approach for Smart Home Data Visualization. *ACM* (2017).

[17] Nico Castelli, Gunnar Stevens, Timo Jakobi, and Niko Schönau. 2016. Beyond Eco-feedback: Using Room as a Context to Design New Eco-support Features at Home. *Springer International Publishing* (2016).

[18] Jean-Marie Chevalier. 2009. The new energy crisis. In *The New Energy Crisis: Climate, Economics and Geopolitics*. Springer, 6–59.

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

[20] Corinna Fischer. 2008. Feedback on household electricity consumption: a tool for saving energy? *Energy efficiency* 1, 1 (2008), 79–104.

[21] 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*. 1999–2008.

[22] 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* (Atlanta, Georgia, USA) *(CHI '10)*. Association for Computing Machinery, New York, NY, USA, 1999–2008. doi:10.1145/1753326.1753629

[23] Bożena Gajdzik, Radosław Wolniak, Rafał Nagaj, Brigita Žuromskaitė-Nagaj, and Wieslaw Wes Grebski. 2024. The influence of the global energy crisis on energy efficiency: A comprehensive analysis. *Energies* 17, 4 (2024), 947.

[24] Simson Garfinkel and Heather Richter Lipford. 2014. *Usable security: History, themes, and challenges*. Springer Cham.

[25] Florian Geissler, Karsten Roscher, and Mario Trapp. 2024. Concept-guided llm agents for human-ai safety codesign. In *Proceedings of the AAAI Symposium Series*, Vol. 3. 100–104.

[26] Serena Graziosi, Francesco Ferrise, Alessandro Achille Maria Costanzi, Monica Bordegoni, et al. 2015. The Use Of Multisensory Feedback To Make Users Behave In A Sustainable Way. In *DS 80-11 Proceedings of the 20th International Conference on Engineering Design (ICED 15) Vol 11: Human Behaviour in Design, Design Education; Milan, Italy, 27-30.07. 15*. 011–020.

[27] Catherine Grevet, Jennifer Mankoff, and Scott D Anderson. 2010. Design and evaluation of a social visualization aimed at encouraging sustainable behavior. In *2010 43rd Hawaii international conference on system sciences*. IEEE, 1–8. doi:10.1109/HICSS.2010.135

[28] Fernanda Guasselli, Apostolos Vavouris, Lina Stankovic, Vladimir Stankovic, Sébastien Didierjean, and Kirsten Gram-Hanssen. 2024. Smart energy technologies for the collective: Time-shifting, demand reduction and household practices in a Positive Energy Neighbourhood in Norway. *Energy Research & Social Science* 110 (2024), 103436.

[29] Punit Gupta and Jasmeet Chhabra. 2016. IoT based Smart Home design using power and security management. In *2016 International Conference on Innovation and Challenges in Cyber Security (ICICCS-INBUSH)*. IEEE, 6–10.

[30] Tianzhi He, Farrokh Jazizadeh, and Laura Arpan. 2022. AI-powered virtual assistants nudging occupants for energy saving: proactive smart speakers for HVAC control. *Building Research & Information* 50, 4 (2022), 394–409.
[31] Chen Huang, Xinwei Yang, Yang Deng, Wenqiang Lei, JianCheng Lv, and Tat-Seng Chua. 2024. Co-Matching: Towards Human-Machine Collaborative Legal Case Matching. *arXiv preprint arXiv:2405.10248* (2024).
[32] Hume AI. 2025. Hume AI Developer Introduction. https://dev.hume.ai/intro. Accessed: 2025-10-17.
[33] Beth Karlin, Joanne F Zinger, and Rebecca Ford. 2015. The effects of feedback on energy conservation: A meta-analysis. *Psychological bulletin* 141, 6 (2015), 1205–1227.
[34] Jack Kelly and William Knottenbelt. 2015. Neural nilm: Deep neural networks applied to energy disaggregation. In *Proceedings of the 2nd ACM international conference on embedded systems for energy-efficient built environments*. 55–64.
[35] Smith K. Khare, Victoria Blanes-Vidal, Esmaeil S. Nadimi, and U. Rajendra Acharya. 2024. Emotion recognition and artificial intelligence: A systematic review (2014–2023) and research recommendations. *Information Fusion* 102 (2024), 102019. doi:10.1016/j.inffus.2023.102019
[36] Nitendra Kumar, Surya Kant Pal, Priyanka Agarwal, Joanna Rosak-Szyrocka, and Vishal Jain. 2024. *Harnessing artificial emotional intelligence for improved human-computer interactions*. IGI Global.
[37] S. Latif, R. Rana, and J. Qadir. 2022. AI-Based Emotion Recognition: Promise, Peril, and Prescriptions for a Prosocial Path. *arXiv preprint arXiv:2211.07290* (2022).
[38] Josephine Lau, Benjamin Zimmerman, and Florian Schaub. 2018. Alexa, are you listening? Privacy perceptions, concerns and privacy-seeking behaviors with smart speakers. *Proceedings of the ACM on human-computer interaction* 2, CSCW (2018), 1–31.
[39] Debra Lilley and Vicky Lofthouse. 2009. Sustainable design education–considering design for behavioural change. *Engineering education* 4, 1 (2009), 29–41.
[40] Houjiang Liu, Anubrata Das, Alexander Boltz, Didi Zhou, Daisy Pinaroc, Matthew Lease, and Min Kyung Lee. 2024. Human-centered NLP Fact-checking: Co-Designing with Fact-checkers using Matchmaking for AI. *Proceedings of the ACM on Human-Computer Interaction* 8, CSCW2 (2024), 1–44.
[41] Daniel Lockton. 2013. *Design with intent: a design pattern toolkit for environmental and social behaviour change*. Ph. D. Dissertation. Brunel University School of Engineering and Design PhD Theses.
[42] JF Martins, JA Oliveira-Lima, V Delgado-Gomes, Rui Lopes, D Silva, S Vieira, and C Lima. 2012. Smart homes and smart buildings. In *2012 13th Biennial Baltic electronics conference*. IEEE, 27–38.
[43] Earl K Miller and Timothy J Buschman. 2015. Working memory capacity: Limits on the bandwidth of cognition. *Daedalus* 144, 1 (2015), 112–122.
[44] Scott Monteith, Tasha Glenn, John Geddes, Peter C Whybrow, and Michael Bauer. 2022. Commercial use of emotion artificial intelligence (AI): implications for psychiatry. *Current Psychiatry Reports* 24, 3 (2022), 203–211.
[45] Anirban Mukhopadhyay and Kurt Luther. 2025. OSINT Clinic: Co-designing AI-Augmented Collaborative OSINT Investigations for Vulnerability Assessment. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI '25)*. Association for Computing Machinery, New York, NY, USA, Article 868, 22 pages. doi:10.1145/3706598.3713283
[46] Michael J. Muller. 2002. *Participatory design: the third space in HCI*. L. Erlbaum Associates Inc., USA, 1051–1068.
[47] Muhammad Nabeel, Basel Ali, and Allam Hamdan. 2019. Real-Time Feedback on Consumer's Behavior: Literature Review. *International Journal of Energy Economics and Policy* 9, 5 (2019), 489–493.
[48] Patricia A Norberg, Daniel R Horne, and David A Horne. 2007. The privacy paradox: Personal information disclosure intentions versus behaviors. *Journal of consumer affairs* 41, 1 (2007), 100–126. doi:10.1111/j.1745-6606.2006.00070.x
[49] Peterson K. Ozili and Ercan Ozen. 2023. *Global Energy Crisis*. John Wiley & Sons, Ltd, Chapter 29, 439–454. doi:10.1002/9781394167944.ch29
[50] Jeni Paay, Jesper Kjeldskov, Mikael B Skov, Dennis Lund, Tue Madsen, and Michael Nielsen. 2014. Design of an appliance level eco-feedback display for domestic electricity consumption. In *Proceedings of the 26th Australian Computer-Human Interaction Conference on Designing Futures: The Future of Design*. 332–341.
[51] Cecilia Panigutti, Andrea Beretta, Daniele Fadda, Fosca Giannotti, Dino Pedreschi, Alan Perotti, and Salvatore Rinzivillo. 2023. Co-design of human-centered, explainable AI for clinical decision support. *ACM Transactions on Interactive Intelligent Systems* 13, 4 (2023), 1–35.
[52] John E Petersen, Vladislav Shunturov, Kathryn Janda, Gavin Platt, and Kate Weinberger. 2007. Dormitory residents reduce electricity consumption when exposed to real-time visual feedback and incentives. *International Journal of Sustainability in Higher Education* 8, 1 (2007), 16–33.
[53] Petromil Petkov, Felix Köbler, Marcus Foth, and Helmut Krcmar. 2011. Motivating domestic energy conservation through comparative, community-based feedback in mobile and social media. In *Proceedings of the 5th International Conference on Communities and Technologies*. 21–30.
[54] Stefan Reindl. 2021. Emotion AI in education: a literature review. *International Journal of Learning Technology* 16, 4 (2021), 288–302.
[55] Kat Roemmich, Florian Schaub, and Nazanin Andalibi. 2023. Emotion AI at work: Implications for workplace surveillance, emotional labor, and emotional privacy. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–20.

[56] Stanisław Saganowski. 2022. Bringing Emotion Recognition Out of the Lab into Real Life: Recent Advances in Sensors and Machine Learning. *Electronics* 11, 3 (2022). doi:10.3390/electronics11030496
[57] Peter Salovey and John D Mayer. 1990. Emotional intelligence. *Imagination, cognition and personality* 9, 3 (1990), 185–211.
[58] Elizabeth B-N Sanders and Pieter Jan Stappers. 2008. Co-creation and the new landscapes of design. *Co-design* 4, 1 (2008), 5–18.
[59] Manuela Sanguinetti and Maurizio Atzori. 2024. Conversational agents for energy awareness and efficiency: A survey. *Electronics* 13, 2 (2024), 401.
[60] P Wesley Schultz, Mica Estrada, Joseph Schmitt, Rebecca Sokoloski, and Nilmini Silva-Send. 2015. Using in-home displays to provide smart meter feedback about household electricity consumption: A randomized control trial comparing kilowatts, cost, and social norms. *Energy* 90 (2015), 351–358.
[61] Tobias Schwartz, Gunnar Stevens, Leonardo Ramirez, and Volker Wulf. 2013. Uncovering practices of making energy consumption accountable: A phenomenological inquiry. *ACM Transactions on Computer-Human Interaction (TOCHI)* 20, 2 (2013), 1–30. doi:10.1145/2463579.2463583
[62] Elaine Sedenberg and John Chuang. 2017. Smile for the Camera: Privacy and Policy Implications of Emotion AI. *CoRR* abs/1709.00396 (2017). arXiv:1709.00396 http://arxiv.org/abs/1709.00396
[63] Frans W Siero, Arnold B Bakker, Gerda B Dekker, and Marcel TC Van Den Burg. 1996. Changing organizational energy consumption behaviour through comparative feedback. *Journal of environmental psychology* 16, 3 (1996), 235–246.
[64] Marc Steen, Menno Manschot, and Nicole De Koning. 2011. Benefits of co-design in service design projects. *International journal of design* 5, 2 (2011).
[65] Gunnar Stevens and Paul Bossauer. 2017. Dealing with personal data in the age of big data economies. *Zeitschrift für Geistiges Eigentum= Intellectual Property Journal* 9, 3 (2017), 266–278.
[66] Yolande A. A Strengers. 2011. Designing eco-feedback systems for everyday life. In *ACM*. 2135–2144.
[67] Yuka Tanaka, Takuto Nakamura, and Hideki Koike. 2022. Posture-based golf swing instruction using multi-modal feedback. *Journal of Information Processing* 30 (2022), 107–117.
[68] The Guardian. 2024. Are you 80% angry and 2% sad? Why 'emotional AI' is fraught with problems. Available at: https://www.theguardian.com/technology/article/2024/jun/23/emotional-artificial-intelligence-chatgpt-4o-hume-algorithmic-bias.
[69] Onuralp Ulusoy and Pinar Yolum. 2021. Panola: A personal assistant for supporting users in preserving privacy. *ACM Transactions on Internet Technology (TOIT)* 22, 1 (2021), 1–32.
[70] Iana Vassileva, Monica Odlare, Fredrik Wallin, and Erik Dahlquist. 2012. The impact of consumers' feedback preferences on domestic electricity consumption. *Applied Energy* 93 (2012), 575–582.
[71] Apostolos Vavouris, Fernanda Guasselli, Lina Stankovic, Vladimir Stankovic, Kirsten Gram-Hanssen, and Sébastien Didierjean. 2024. A complex mixed-methods data-driven energy-centric evaluation of net-positive households. *Applied Energy* 367 (2024), 123404. doi:10.1016/j.apenergy.2024.123404
[72] Samuel D Warren and Louis D Brandeis. 1890. The right to privacy. *Harv. L. Rev.* 4, 5 (1890), 193–220.
[73] Alan F Westin. 1968. *Privacy and freedom*. Vol. 25. Washington and Lee Law Review. 166 pages.
[74] Renee Wever, Jasper Van Kuijk, and Casper Boks. 2008. User-centred design for sustainable behaviour. *International Journal of Sustainable Engineering* 1, 1 (2008), 9–20. Available at: http://www.tandfonline.com/doi/abs/10.1080/19397030802166205.
[75] Daricia Wilkinson, Moses Namara, Karla Badillo-Urquiola, Pamela J Wisniewski, Bart P Knijnenburg, Xinru Page, Eran Toch, and Jen Romano-Bergstrom. 2018. Moving beyond a "one-size fits all" exploring individual differences in privacy. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*. Association for Computing Machinery, New York, NY, USA, 1–8. doi:10.1145/3170427.3170617
[76] Sara L Wilson, Zainab J Khan, Bianca Lee, Supreetha Krishnan, John E Fernández, and Maria C Yang. 2024. Investigating Pro-Environmental Attitude for Designing Affective Eco-Feedback. In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Vol. 88407. American Society of Mechanical Engineers, V006T06A007.
[77] Qian Yang. 2020. *Profiling artificial intelligence as a material for user experience design*. Ph. D. Dissertation. Carnegie Mellon University.
[78] Georgios N Yannakakis and Julian Togelius. 2018. *Artificial intelligence and games*. Vol. 2. Springer.
[79] Eman M. G. Younis, Someya Mohsen, Essam H. Houssein, and Osman Ali Sadek Ibrahim. 2024. Machine learning for human emotion recognition: a comprehensive review. *Neural Computing and Applications* 36, 16 (01 Jun 2024), 8901–8947. doi:10.1007/s00521-024-09426-2
[80] Kaile Zhou, Chao Fu, and Shanlin Yang. 2016. Big data driven smart energy management: From big data to big insights. *Renewable and sustainable energy reviews* 56 (2016), 215–225.
[81] Douglas Zytko, Pamela J. Wisniewski, Shion Guha, Eric PS Baumer, and Min Kyung Lee. 2022. Participatory design of AI systems: opportunities and challenges across diverse users, relationships, and application domains. In *CHI Conference on Human Factors in Computing Systems Extended Abstracts*. 1–4.

A Design Ideas

Based on the original 18 design ideas, our evaluation approach only selected emotion as the primary input and reduced the overlap between several ideas. In the end, we shortlisted 8 design ideas. Table 5 expands on the reasoning behind this selection.

No.	Design Ideas	Evaluation	Decision
1	Show minimal, digestible info (e.g., one number or color) to avoid overload during the stress time.	Emotion is the primary input; directly adapts feedback complexity in real time to reduce overload. Slight conceptual overlap with Idea 14.	Selected
2	Provide detailed feedback (graphs, trends) when users are relaxed or curious.	Emotion is secondary to curiosity or engagement level; not a strong emotion-driven trigger.	No
3	Postpone feedback when users are emotionally overwhelmed.	Emotion (e.g., frustration) is the trigger; supports feedback suppression based on stress. Slight overlap with Idea 9.	Selected
4	Use supportive rather than judgmental language when stress or guilt is detected.	Clearly adapts feedback tone based on detected mood (e.g., guilt, stress).	Selected
5	Trigger challenges, goals, or comparisons during playful or upbeat moods.	Emotion (e.g., happiness) triggers gamified engagement. Overlaps conceptually with Idea 7 but is broader.	Selected
6	Reinforce eco-actions with praise when users show pride or satisfaction.	Emotion (pride/satisfaction) is the direct input; strengthens positive reinforcement.	Selected
7	Use fun facts or gentle nudges to re-engage bored or disinterested users.	Overlaps with Idea 5; Idea 5 offers a more comprehensive framing.	No
8	Send feedback during idle tasks or low-stress periods, like cooking or watching TV.	Trigger is typically context- or task-based (e.g., idle time), not emotion-first.	No
9	Suppress or delay notifications during cognitively demanding or emotional tasks.	Emotion or cognitive stress suppresses poorly timed feedback. Overlaps with Idea 3.	No
10	Use visual feedback when users are calm; audio or minimal cues when users are tired or distracted.	Emotion state (e.g., tiredness, calm) guides modality choice (audio, visual, minimal).	Selected
11	Adjust lighting and heating automatically based on emotional state (e.g., dim lights for relaxation).	Emotion (e.g., stress or calm) triggers environmental changes (e.g., light dimming).	Selected
12	Suggest energy-efficient meals based on mood (e.g., fast meals when tired, batch cooking when energized).	Emotion plays a minor role; context/task is the main driver.	No
13	Lower heating or lighting during VR/gaming sessions when emotional signals indicate immersion or movement.	Driven by activity detection; emotion inferred, not directly detected.	No
14	Learn from past emotional reactions to tailor future feedback tone, timing, and format.	Overlaps with Idea 1, but focuses on historical trends, not real-time adaptation.	No
15	Enable manual override for feedback depth or frequency when users want more or less information.	Control mechanism, not an emotion-triggered adaptive behaviour.	No
16	Provide transparency and opt-in controls for emotional data collection and use.	Important for ethics, but not an adaptive design idea.	No
17	Only present peer comparisons when users are emotionally ready; avoid during negative moods.	Emotion is the trigger (e.g., only show comparisons when user is emotionally open).	Selected
18	Trigger shared energy-saving goals when group emotion is positive (e.g., playful, cooperative).	Group mood is collective and indirect; lacks strong emotion-as-primary-input framing.	No

Table 5. Overall design ideas from co-design session

B Combined Insight from Both Study 1 and Study 2

Table 6. Combined Insights from Study 1 and Study 2

Participant	Emotion-Adaptive Content Framing	Emotion-Timed Interaction & Delivery	Emotion-Aware Environment & Social Adaptation
P02	Avoids emotionally eco-feedback, prefers data with neutral tone → Suggested light framing with basic advice.	Eco-feedback timing should align with moments of decision-making → Proposed delay when overloaded.	Lives with family and emphasises non-intrusive cues → Favoured ambient signals over explicit prompts.
P03	Sceptical of emotional tone in data → Designed calm visual feedback for low-stress moments.	Prefers eco-feedback only in morning → Suggested postponing messages when stressed.	Lives alone, avoids emotional overload → Proposed mood-based lighting for solo evenings.
P06	Valued empathy over raw numbers → Co-designed friendly tone, e.g., gentle encouragement.	Avoids complex eco-feedback when tired → Proposed minimal cues when overwhelmed.	Works from home → Imagined ambient cues for home office energy mood alignment.
P07	Prefers calm tone; dislikes overwhelming emotional messages → Suggested soft, positive messages with polite wording.	Avoids eco-feedback during quiet time → Recommended postponing feedback until daytime hours.	Values privacy during shared time → Proposed silent mode of eco-feedback when guests are present.
P08	Wants actionable suggestions, less emotional → But accepted pride-based encouragement in eco-feedback.	Morning preferred for reflection → Proposed motivational eco-feedback only during morning routine.	Shared space; avoids conflict → Supported individual mood-based eco-feedback in shared rooms.
P09	Critical of vague emotional eco-feedback → Tolerated it if it supported decision-making.	Prefers delay when stressed → Recommended system to wait and only active when calm.	Technically skilled; wants control → Resist automatic adjustments, prefer explainability