Reef: Exploring the Design Opportunity of Comfort-Aware Eco-Coaching Thermostats

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ABSTRACT
Smart thermostats have been proposed as a way to reduce energy consumption in the home. While occupancy-based thermostat control and scheduling has been shown to provide energy savings, more recent work in comfort-aware thermostats promises to provide even greater savings. Comfort awareness and adaptive thermal comfort models, combined with the mixed-initiative *eco-coaching* approach to thermostat control, offer a promising approach to optimizing savings by offering both schedule and setpoint recommendations and actionable plans. In this paper, we investigate the design space of *comfort-aware eco-coaching thermostats*. Through a user enactment study wherein 11 participants encountered fifteen design probes covering various design attributes and interaction scenarios, we uncover insights on how to design such thermostats in a way that respect people's values relating to comfort, sustainability, control, convenience, and allocation of agency while also encouraging more energy efficient behaviors.

Author Keywords
Sustainability; Thermostat; Energy Savings; Smart Home

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
In the U.S., the domestic sector consumes more than 20% of the total energy produced, and half of this is consumed by heating and cooling usage [35]. The high level of usage can be reduced. Researchers have pointed out that consumption is highly dependent on occupants' behaviors [29], as well as the inefficient use of existing manual and programmable thermostats [20,33].

Over the past decade, numerous intelligent thermostats have thus been proposed to mediate temperature control, helping people to save energy while maintaining comfort (e.g., [12,18,21,28]). Such thermostats may have occupancy-responsive control (e.g., [17]), learning capability (e.g., [1,36]), and/or eco-coaching features (e.g., [25]). However, there are still two problems with these thermostats that limit the energy savings that can be achieved.

First, the majority of intelligent thermostats assume occupants have a fixed temperature preference at home while in reality this can be quite dynamic, changing depending on occupants' activities and other contextual factors [22]. While researchers have recently explored comfort-aware thermostats—thermostats that can react to people's changing preferences by predicting their comfort based on sensed conditions (e.g., [9])—such thermostats have been principally studied in office settings, and are not suitable for the home due to the sensors used and low accuracy [15].

Second, a fundamental assumption underpinning most smart thermostat development is the view that occupants are primarily receivers of comfort (i.e., comfort is given by the heating and cooling system), rather than active agents that can utilize other means, such as changing clothes, to maintain their comfort. Researchers like Clear et al. [5] have therefore proposed to investigate approaches based on *adaptive thermal comfort* [16], an approach that emphasizes occupants' agency in performing adaptive behaviors to achieve comfort, and challenges the notion that comfort and controlled indoor temperatures exist in a fixed relationship.

Our work in this paper proceeds from the observation that a comfort-aware approach can be combined with *eco-coaching* [25,34] to provide additional opportunities for reducing heating- and cooling-related energy waste. In the eco-coaching approach, an intelligent system models user behavior and produces recommendations for energy-saving actions that can be taken by users. Recent work has shown that eco-coaching can save 5-12% of energy expended for cooling when recommending thermostat control schedules [25], and that users find eco-coaching to ease the selection and execution of more energy-efficient actions [34]. Previous work, however, only examined recommendations based on occupancy schedules—the opportunity for gaining efficiency by optimizing temperature setpoints was not explored. By including knowledge of users' comfort preferences and recommendations derived from the adaptive thermal comfort model, additional savings can be realized.

Thus in this paper, we report our initial steps in exploring the design space of *comfort-aware eco-coaching thermostats*,

DIS 2017, June 10-14, 2017, Edinburgh, United Kingdom.

ACM 978-1-4503-4922-2/17/06…$15.00.
DOI: http://dx.doi.org/10.1145/3064663.3064685

i.e. thermostats that seek to synthesize comfort-awareness, adaptive thermal comfort, and the eco-coaching approach.

Our work makes two contributions: 1) We illustrate the design space of comfort-aware eco-coaching thermostats by systematically mapping the design space and producing fifteen diverse prototypes representing key points in the space; 2) By further carrying out User Enactments [6,23,24] wherein we engaged 11 thermostat users in scenarios involving the prototypes we had developed, we were able to uncover underlying values and tensions that are likely to drive user reactions to different design directions if and when they are encountered in the wild. Our work provides a critical first step towards the realization of comfort-aware eco-coaching thermostats, and provides valuable insights for future system development and field deployments.

RELATED WORK

Many researchers have developed smart thermostats to help reduce energy consumption and increase comfort [2,9,12,17,18,21,25,28]. These smart systems have achieved their goals in various ways, including the ability to: react to residents' occupancy status (e.g., [28]), adapt to building characteristics or user preference (e.g., [36]); and respond to people's thermal comfort (e.g., [9]).

Occupancy-based thermostats [12,17,18,28] focus on reducing the heating or cooling time when people are away from home. Most of these systems make a simplistic assumption that people are satisfied with a fixed temperature when they are at home. While occupancy-based thermostats have been shown to be successful in reducing energy usage, this simplistic assumption misses a chance for both further energy savings and increased comfort, as in reality people's temperature preference at home is dynamic according to their activities and other context [13].

Preference-based thermostats may be able to cope with people's dynamic preferences, for example, by learning the desired setpoints at different times of day (e.g., [36]) or at different pricing conditions (e.g., [1]). However, users still struggle to understand the smart features of such thermostats, leading to suboptimal use or abandonment [33]. In addition, current preference-based thermostats only scratch the surface of how smart thermostats can interact with their users. While this work largely focuses on thermostats that learn people's preferences passively, more recent work on *eco-coaching* [25,34] finds that thermostats that provide actionable recommendations based on their learning capability are more promising in reducing energy consumption.

Comfort-aware thermostats, although a less explored alternative, provide the potential of reacting to people's changing temperature preferences. Such thermostats infer occupants' thermal sensation in real-time using wearable and indoor sensors and predictive models to map environmental conditions and user activity onto inferred thermal sensation [9]. While this approach seems promising [15], the imperfection of comfort inference means that full automation is infeasible. Researchers have proposed employing mixed-initiative design in creating smart thermostats [25,33], emphasizing the collaboration between machines and humans to reach a shared goal. *Eco-coaching* [25,34], employs a mixed-initiative approach wherein the system offers suggestions for actions to take and users are held responsible for finalizing the decisions. Although this approach is helpful for dealing with misprediction, it has not yet been applied to design *comfort-aware thermostats*, as previous implementations were constrained to suggesting timing for setbacks (energy-efficient *away* and *sleep* temperatures) rather than alternative temperature settings for times when the home is occupied.

While researchers have demonstrated that occupancy-based and comfort-aware thermostats can reduce energy consumption by 7-57% (e.g., [9,28]), the fundamental design philosophy that underpins such thermostats has been criticized on the basis that it limits the potential to reach more sustainable ways of living [4,5,16]. Past work on smart thermostats assume *comfort as a product*, something that is delivered to us by the indoor environment. However, recent research on adaptive thermal comfort has proposed to reconsider *comfort as a goal*, a view that emphasizes the role of human agency: occupants can leverage different adaptive behaviors such as adjusting their clothing level to reach comfort in addition to cranking their thermostats up or down. In alignment with this view, Clear et al. [5] have proposed to create systems that facilitate adaptive behaviors and temperature variations, yet limited work has been done in exploring this design opportunity.

In this work, we therefore explore comfort-aware thermostats' potential in reacting to occupants' dynamic temperature preferences while accommodating mispredictions by leveraging eco-coaching. We also broaden the concept of eco-coaching to include the view of *comfort as a goal* rather than just *a product.* Therefore, rather than only suggesting to users how to control their temperature setpoints, we explore thermostats that might also encourage adaptive behaviors such as changing clothing or drinking warm beverages. We call such thermostats *comfort-aware eco-coaching thermostats*.

METHOD & DESIGN

The aim of our study was to advance understanding of how to design comfort-aware eco-coaching thermostats. While others have explored technologies that seek to challenge or overturn people's expectation or values around thermal comfort (e.g., [4]), we sought to explore more subtle approaches that work within the existing constraints of people's cultural expectations of mechanically-mediated thermal comfort. We thus pursued designs that encourage more efficient behaviors through being adaptive while respecting people's expectation on thermal comfort.

To illuminate the design space and understand how people would react to possible design approaches, we chose user enactments as our method [6,24]. User enactments allow researchers to rapidly explore how potential users' values, expectations, and social identities inform their reactions to different design possibilities. Through simulating real world scenarios involving potential technological futures, researchers gain insights into how users might react to technology designed with different attributes, as well as the values users bring to bear when assessing design alternatives. While prior thermostat work has employed field deployments to validate the effectiveness of various designs (e.g., [1,25]), our designs require significantly more complex technology (e.g., personalized comfort prediction and room-level localization) which makes deployment a less reasonable action to take as a first step. Applying user enactments in understanding users' values is essential to ensure that costly system development and field deployment efforts are well-grounded and more likely to succeed.

Our study involved three main steps. First, through synthesizing prior literature and conducting multiple rounds of brainstorming, affinity diagramming, and expert review, we delineated the design space of comfort-aware eco-coaching thermostats. We distilled three key design dimensions (Table 1) that guided our later designs and summarized the technology constraints of state-of-the-art smart thermostats and comfort prediction approaches. Second, we operationalized our concept through iterative prototyping. We generated numerous ideas and low fidelity prototypes before creating fifteen design probes (D) in the form of high fidelity interactive prototypes (Figure 1). Third, we conducted user enactments to qualitatively probe our target users' opinions: how they perceive the different design concepts and how these designs might encourage or impede users from reaching higher energy savings.

Reef: Thermostat Designs

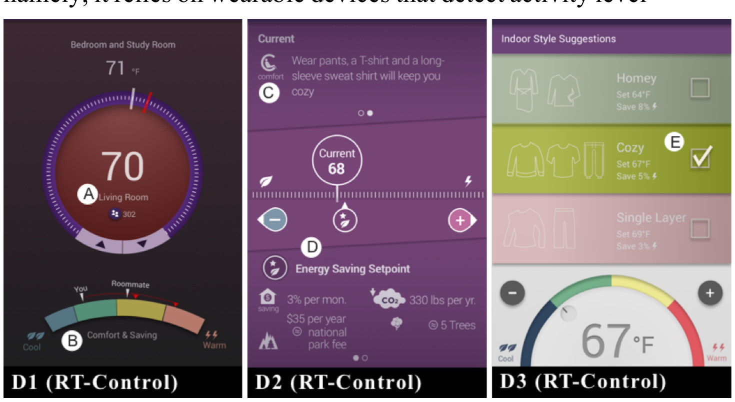
We first identified the key technology constraints of state-of-the-art smart thermostats and comfort prediction, focusing on constraints that are likely to persist for the foreseeable future. We used such constraints to guide the design of Reef, a hypothetical thermostat that can predict people's comfort, react, and encourage energy savings. First, we assumed Reef employs a sensing approach similar to Huang et al. [15], namely, it relies on wearable devices that detect activity level

Eco-Coaching Style	Persuasive Strategy	Timing of Interaction				
		Real-time Control	Short Engagement	Plan.	Mis-pred.	Refl.
Informative	NA	D1				
	RT			D7		D13
Advisory	NA		D4	D8	D10	
	RT	D2				D15
Proactive	NA					
	RT		D5	D9	D11	
Adaptive	NA					D14
	RT	D3	D6		D12	

Table 1: The key design dimensions and the corresponding prototypes. NA: Norm-Activation, RT: Rational Thinking.

and near body temperature (e.g., [37]), as well as in-home sensors that capture humidity and temperature (e.g., [38]). Second, we assumed that Reef is able to detect and predict people's house occupancy status, room-level location and sleep status, which have been demonstrated feasible in prior research [19,25]. Therefore, Reef can use its users' status to determine whether to trigger an Away, Asleep or Awake mode (i.e., users are at home but not sleeping). Third, Reef can learn personalized comfort preferences by soliciting feedback from users, ultimately generating comfort predictions on a five-level scale ranging from uncomfortably cold to uncomfortably warm [15]. Fourth, due to limited sensing and inference capabilities, Reef will sometimes make mispredictions (e.g., predicting occupants are comfortable while they are slightly cold) [15]. Finally, as the smartphone-based control has emerged as a common approach for interacting with smart thermostats (e.g., [36]), we expected users to interact with Reef through a smartphone application. Our interfaces were therefore all designed for mobile screens.

Through prior literature, we identified three key design dimensions for smart thermostats (see Table 1). These dimensions facilitated the systematic generation of fifteen distinct interface prototypes. The three design dimensions we chose include *eco-coaching style*, *persuasive strategy*, and *timing of interaction*. Here we will describe these three design dimensions in detail as well as their relationship with the various prototypes we created.



Ⓐ Show the number of Reef users using this setpoint to provoke reaction about norms.

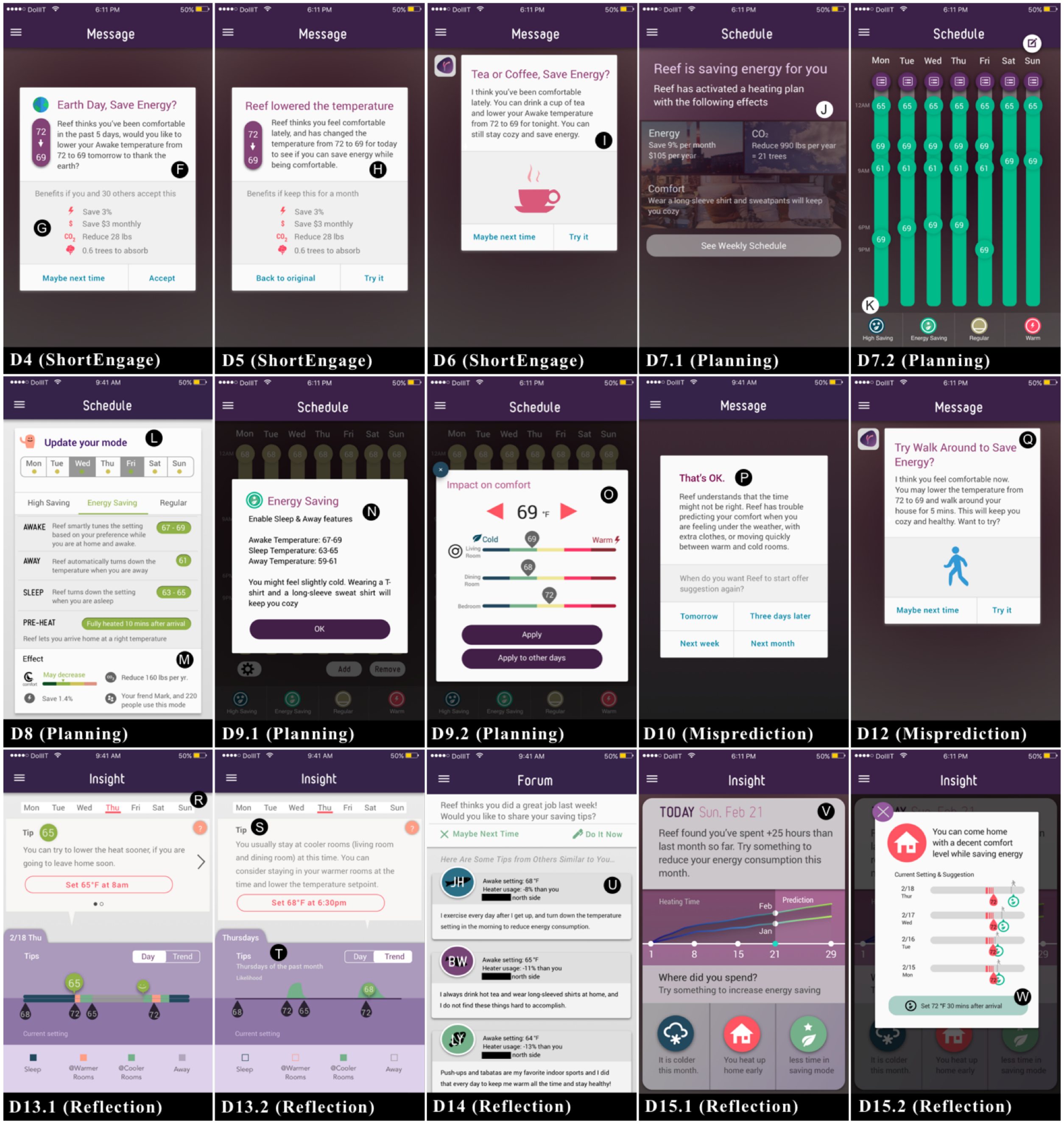
Ⓑ Show the predicted current and future comfort levels for both residents in white and red.

Ⓒ Suggest the clothing needed if the temperature is set at 68°F.

Ⓓ Suggest a personalized energy saving setpoint, 70°F, with benefits as well as recommended clothing in the next card.

Ⓔ Provide three options of clothing with the corresponding setpoints and benefits. Users can click on one option to change the setpoint.

Figure 1: Selected interfaces for our 15 prototypes. We skip D11 as it looks the same as D5 but was tested in a different scenario.



- (F) Track comfort history and only recommend short-term adjustments when users have been feeling comfortable for five days.
- (G) Show the benefits if the user and 30 others accept this recommendation.
- (H) Automatically adjust the setpoint for its users if they've been comfortable lately.
- (I) Suggest users to drink a cup of tea and lower the setpoint briefly.
- (J) Automatically activate a personalized energy saving plan without asking users' permission. It shows the benefits and the clothing needed for this plan.
- (K) Users can easily switch the thermostat schedule by choosing different plans.
- (L) Users can assign different days to different energy saving plans.
- (M) Show the benefits as well as friends of the users who use this setting.
- (N) Explain how to be rated as "energy saving". Users need to manually adjust the setpoints themselves.
- (O) Users need to manually create their own schedule. They can view the effect of different setpoints on comfort and the temperature differences in different rooms.
- (P) Reef first sends a notification to recommend users to lower their setpoints. If they don't accept, Reef reveals it's sensing limitations.
- (Q) Recommend an immediate activity (walk around) to warm themselves up and lower the setpoint.
- (R) Show data-driven suggestions. For example, Reef recommends that users could lower their setpoint in the morning since they usually leave home soon after they wake up.
- (S) Offer other adaptive thermal comfort tips (e.g., change to stay in a warmer room.)
- (T) Show data to support the tips, including people's sleep pattern and when they are usually at a warmer or cooler room.
- (U) Show adaptive behavior suggestions shared by people living in the similar area.
- (V) Show current usage before the month ends, to give opportuntiies for changes.
- (W) Provide reasons for increased heating usage and actionable items (e.g., encouraging users to only fully heat up their home 30 minutes after arrival).

Eco-coaching style refers to the approach Reef takes to communicate with users. At one end of the spectrum, Reef seeks to be *informative* by showing useful eco-feedback to help decision-making, letting users remain in control [11,14,26]. This information might include comfort level prediction, estimated financial savings, and environmental impact. While respecting users' agency was one reason that we explored such a hands-off approach, this approach also handles inaccuracy. Due to the inevitability of imperfect prediction, it may not be most favorable for Reef to automatically change the temperature according to its comfort prediction [8]. One prototype that implements such an approach is D1, which shows the predicted comfort of different household members at home in four colors. Similarly, D9 shows users the predicted comfort level in different rooms at different settings while requiring them to manually create their temperature schedules. At the other end of the spectrum, Reef can be *proactive* [6,27], making decisions for users and only informing them about the benefits. In some situations users might feel that the benefits of automation outweigh the cost of minor mispredictions. D5 and D7 are two prototypes that implement the proactive approach. In D5, Reef identifies that the user has been comfortable for a few days and therefore automatically lowers the setpoint for an evening. It only informs the user about the decision and the benefits without first asking permission. Similarly, in D7, Reef automatically generates and activates an energy-saving schedule after observing occupants' behaviors and comfort level for a month.

A third approach lies in the middle of these extremes, offering suggestions to users and letting them make the final decision [25,34]. Here we probed two possible design directions: one is to offer suggestions directly related to temperature settings (*Advisory*), the other is to encourage adaptive behaviors [5] *(Adaptive)*. For the former type, two different saving suggestions were implemented in Reef's prototypes, namely, personalized saving modes and short-term variation. D2, D4 and D8 are examples that implement such strategies. Inspired by ThermoCoach's [25] saving suggestion design, Reef offers four similar modes: high energy saving, energy saving, regular and warm. Each mode has a corresponding temperature when people are at home and awake (i.e., the Awake setpoint). This temperature is determined by Reef's learning of occupants' comfort. In winter, for example, when running in regular mode Reef will pick a temperature that the user mostly feels comfortable with, and in energy saving mode Reef will find an Awake setpoint that is likely to feel slightly cold. The second strategy is short-term variation, meaning that Reef might suggest users to lower their setpoints for only a short period of time (e.g., a night or a day). The rationale is that while people care about their own comfort, they might be willing to lower their expectation shortly for saving energy. Whereas in some prototypes Reef suggests users to directly change thermostat settings, in others Reef encourages *adaptive* behaviors. One of the adaptive behavior Reef encourages is to change indoor clothing style. The suggestions are made in different ways. For example, in D2 Reef shows the appropriate clothing to wear at different setpoints; In D3 Reef makes the suggestion more salient—users can pick a clothing option and Reef will adjust the setpoint to a corresponding temperature. Besides clothing level, we also explored other adaptive behaviors suggestions such as drinking a hot beverage (D6), walking at home for a few minutes (D12), lowering the setpoint in the morning when users are leaving soon for work (D13), and delaying the time to heat up one's home after arrival (D15).

Persuasive Strategy refers to the approaches used to promote energy-saving behaviors [7,10,11,14,26]. Froehlich et al. [11] highlighted two major strategies: *Rational Thinking (RT)* and *Norm-Activation (NA)*: While some people might respond better to analytical insights, others might be more easily persuaded by emphasizing cultural norms and leveraging social influence.

In our study, we probed different persuasive strategies to encourage saving. Besides information about financial savings, we explored the use of environmental impact framed under a 2015 U.S. government's policy to reduce CO_2 emission by 17% [31] (e.g., D2 and D4). In other prototypes, we showed users about friends that use a similar saving mode (e.g., "Mark and 33 others also use this mode" in D8), as well as adaptive behavior tips shared by households similar to the user (D14). These are also two examples demonstrating how we combined the eco-coaching style dimension with persuasive strategy to create the final prototypes.

Timing of Interaction refers to the various situations in which users might interact with thermostats. We chose to explore five situations and created one user enactment scenario for each (as shown in Figure 2), including *real-time control*, *short engagement*, *planning*, *misprediction* and *reflection*. Although timing of interaction is slightly different from other design dimensions—in the sense that the options in this dimension are not mutually exclusive and can be supported by one thermostat—this dimension helps us understand if a particular approach that works well in one situation also works well in another. Here we briefly explain the first three situations while discussing *misprediction* and *reflection* in more depth. Note that all of our scenarios were created for winter settings.

Real-time control (UE-RT) refers to the situation when one feels uncomfortable and wants to change the setpoint. In our scenario, a participant encounters this situation when watching TV in the living room. He feels cold and opens up Reef to see if he can make any adjustment. *Short engagement* (UE-ShortEngage) refers to the situation that a notification is sent from the thermostat to the user to encourage energy saving. In our scenario, a participant faces this situation when reading books in their study room. Reef recalls that she has been comfortable for a few days thus sends a message to encourage saving. *Planning* (UE-Planning) refers to the situation when one is thinking about next week's plan and checking the thermostat schedule. In our scenario, a participant does this on Saturday night before going to bed or another self-selected time that the participant usually plans his next week's schedule.

Misprediction (UE-Mispred) refers to the situation that the thermostat inaccurately predicts an occupant's comfort and makes an inappropriate decision or suggestion. In our scenario, while the participant feels cold and sick, Reef inaccurately predicts she is comfortable, thus suggesting her to lower the setpoint. From previous literature [15] we already knew that comfort prediction is not perfect, especially when people are sick, wear extra clothes, or are affected by other local factors that are challenging to track by sensors [15]. We were curious to explore how to work around technology constraints regarding comfort prediction. For example, a thermostat might apologize [30] and inform its users about its limitations when it makes mistakes (i.e., a form of incidental intelligibility suggested by Yang et al. [32]). We therefore created a prototype, D10, to present an implementation of incidental intelligibility and compared it with other designs (D11, D12) that do nothing when mispredictions happen.

Reflection (UE-Reflect) refers to the situation when users are thinking about their long-term usage of the thermostats, reflecting on their practices, and reassessing actions they took. We designed a scenario where the participant has just finished checking their energy bill and becomes curious about the heater usage. We explored different ways to support reflection. This includes strategies to support data-driven reassessment proposed by Yang et al. [34]. For example, in D13, Reef allows reassessment by tracking people's in-home behaviors and their schedules. It shows a visualization depicting when the user is likely to go to bed based on behavior tracking. In some prototypes, Reef supports reassessment by considering other real-world factors. For example, in D15 Reef explains how colder temperatures cause additional heater usage, potentially helping users understand why their actions may not lead to the expected outcomes. In addition to supporting reflection by data-driven reassessment, we also explored the inclusion of a discussion board, D14, which helps users share and learn from peers about different ways to maintain their comfort while not turning their thermostat up.

User Enactments Study

Our interactions with study participants involved three steps: an initial interview, a diary study, and the user enactment sessions. The purpose of the initial interview was to understand how participants currently used their thermostats. This interview also shed light on how participants chose their default setpoints, their attitudes toward climate change and sustainability, and how they viewed the relationship between comfort and energy-saving. We then conducted a diary study lasting three to seven days. The purpose of this study was to raise participants' awareness of their own temperature preferences, facilitating better feedback during the user enactments. We installed an experience sampling app, PACO [39], onto participants' phones and gave them two thermometers to place in their homes. Participants were asked to report their comfort and the corresponding indoor temperature three times a day. On average each participant created 13 reports (min: 7, max: 24).

After the diary study we then conducted the user enactments in our two-story smart home testbed (a.k.a. the first author's home). Inspired by Rodden et al.'s [27] approach to ground participants, we presented a series of storyboards to 1) illustrate the current energy problem, 2) envision the future and introduce Reef, and 3) offer the context of enactment.

We first introduced the problem—the high energy usage of heating systems at home and the variation in consumption caused by different usage practices [29]. We showed each participant an estimate of their potential financial savings using the average household size in our region of study. By factoring in the energy sources, we also illustrated the potential environmental impact a participant could make in terms of CO_2 reduction. Finally, to offer a frame of reference for a possible environmental impact goal, we introduced the policy announced by the U.S. government in 2015 [31], which is to reduce 17% of CO_2 emissions by 2020. We made a simplistic assumption that the domestic sector should contribute equally by reducing 17% of energy use.

Afterward, we asked participants to envision the year 2020, four years in the future from the time of the study, and a new thermostat product, "Reef," has been released. We described the key characteristics of Reef, namely its use of wearable and in-home sensors for predicting people's comfort; the ways it learns from its users; its capability to predict whether residents are sleeping or away from home; and its support for user-defined Away, Awake and Asleep temperatures.

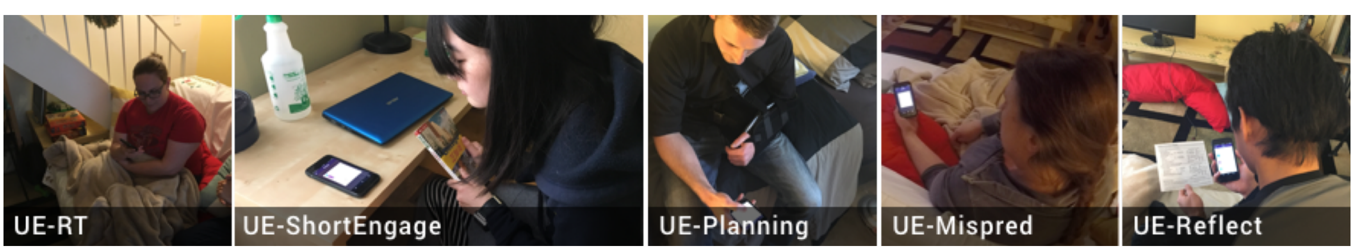


Figure 2: Participants reacted to our prototypes in five different scenarios. From left to right: real-time control; short engagement; planning; misprediction and reflection. Note that each UE took place in a different part of the home.

We asked participants to imagine living in a smart home in February 2020, and gave them a simulated calendar showing what their daily schedules might look like at the time. They were also provided with a simulated weather app interface showing the "current" week's weather ranging from 21 °F to 55 °F. We also asked them to imagine living with another person in the house, either a partner or a roommate. After showing them this information, we asked them to walk through the scenarios we designed.

As described earlier, we developed five scenarios and created three prototypes for each scenario. To ensure the session time was bounded in two hours, we let each participant experience a subset of 3-4 scenarios (thus each design was experienced by 7-8 participants and each participant experienced 9-12 designs). We showed one prototype at a time in a scenario, and we repeated the subset of scenarios three times to show all the design variations. In each scenario we first briefly explained the interface of the prototype and asked participants to interact with it. To increase realism, we tried to match the indoor temperature of our smarthome testbed with what was depicted on our prototype thermostat displays (within 1°F difference). At the end of the session, we then displayed all the 9-12 selected prototypes together for participants to compare. All of the user enactment sessions were video recorded for later analysis by the study team.

Participants & Data Analysis

We conducted our study with 11 participants. We recruited participants through emails, online forums, and social networking sites. Participants were compensated with $50 for completing the interview, diary and UE study. Six males and five females participated in the study, representing a range of occupations including teacher, midwife, finance manager, school administrator, software engineer, among others. Most of them were between ages of 26-35 except for U6 (36-45), U7 (>55) and U11 (46-55). Only U8 owned a smart thermostat with the rest using either manual or programmable thermostats. The study was conducted from the end of April to the beginning of May 2016 where the average temperature in the region of the study was 52 °F (max: 79 °F, min: 28 °F). Thus people were still using their heaters at the time, though the outdoor temperature was somewhat warmer than the simulated temperatures depicted in the study.

To analyze the data we conducted a debriefing session for each enactment within 48 hours. During the debriefing, three of the authors reviewed the whole video and discussed emerging patterns and questions to probe during later sessions. After all the UE sessions, we transcribed all the videos and conducted a thematic analysis [3] to identify common patterns in participants' reactions and understand the underlying expectations and values.

FINDINGS

In the following section, we present three major themes that emerged in our thematic analysis: the desire for comfort and its relationship with sustainability; the desire for control and its tension with the desire for convenience (e.g., the desire to have the system make decisions); and the importance of careful allocation of agency while being pertinent.

Comfort & Sustainability

In this section we present findings related to short-term variation, adaptive suggestions, comfort visualization, and personalized saving modes which helped us uncover participants' values regarding comfort and sustainability.

Our design probe (D4) that encouraged short-term variation based on prior comfort history received polarized responses. Before user enactments, we expected participants to be fairly open to this suggestion because the suggestion was only triggered when they had been "comfortable" for five days. However, some participants felt that being comfortable now didn't imply they should compromise their comfort in the future. According to U1, *"That does not make any sense. If I feel comfortable in the past five days, then what I should do is just keep the same temperature, so that I can keep feeling comfortable."* Others were fine with compromising their comfort for a limited time. U2 said, *"That's fine [for me to live less comfortably for a day]. That's reasonable and just for tomorrow. I think it's like, five days I use temperature I like, and one day I lower it. It sounds OK. … Because I am not constantly sacrificing my comfort level, so it's just temporary."* We suspect this discrepancy is due to differences around how our participants valued comfort. Although they all desired to be comfortable, some perhaps viewed comfort more as a necessity while some others viewed it as something more like a luxury. Participants who viewed comfort as more of a luxury might be more willing to compromise their comfort, as long as it's temporary and as long as their comfort needs had been reasonably satisfied.

In addition to short-term variation, some of our adaptive suggestions also shed light on the dynamic nature of comfort. Participants had different expectations of comfort at certain times of the day, such as in the morning when they are leaving home soon (e.g., it would be OK to lower the setpoint in the morning slightly earlier) or when they come back home (e.g., delaying the time to fully heat up home upon arrival.). U3: *"I don't mind waking up a little chilly"* (D13); U9: *"Well as long as it's warmer than outside. [In February] it's going to feel better than what we just came from. I think that would be a great solution that I heat up halfway and heat up rest of the way [after] I get home."*(D15) This suggests that although they valued comfort, their perception of comfort varied within a day. Thermostats designed to fit this dynamic expectation may increase the chance for savings.

Most participants had a strongly positive reaction to the design (D1) that allowed them to view the comfort level of their roommate or partner. Three participants who currently lived with their partners specifically said they were willing to sacrifice their own comfort to keep their partner comfortable. U9: *"I would probably just grab a blanket and leave how it is … I think a lot of changes in the thermostat is* *the regulation between my wife and myself and the baby honestly. But if I could see that me trying to get more comfortable would [de]crease hers that much ... then I wouldn't do it."* These participants valued some household members' comfort more than their own.

In UE-Planning, participants were shown a design (D8) that suggests three different energy-saving modes (e.g., "energy saving" and "regular") that were personalized according to inferred comfort preferences. While we expected that such saving modes would encourage participants to explore a slightly more energy efficient setting, three of our participants raised a similar concern with this design. U6 explained: *"There [is] something interesting to me about describing the level as high saving, energy saving, very comfortable, ... Because being very comfortable, is like a qualitative statement about my own personal experience of the temperature, these two levels describing high saving and energy saving feels distant from me. It shifts the priority from my comfort to external energy savings and so even though I'm motivated by it ... it seems like to put [me] in a conflict: saving energy or being comfortable."* Whereas these participants valued both comfort and energy saving, and thought they could achieve both—*"I can be quite comfortable in the colder [mode, i.e.] in the energy saving to high saving [mode] with proper [clothing], like having a blanket, that to me is comfortable, I'm more comfortable in cooler environment anyway"* (U6). It seems that rendering energy saving and comfort in a mutually exclusive relationship created a conflict where none need exist.

Control & Convenience

A major question explored in our study is what types of eco-coaching styles better fit participants' values regarding control and convenience. We were especially interested in the intersection of eco-coaching style and the timing of the interaction.

As we expected based on prior research, participants valued user control and favored a more advisory and informative (as opposed to proactive) approach when presented with short-term saving opportunities in UE-ShortEngage. However, in the UE-Planning scenario, the majority of them preferred a more proactive Reef, even though in this prototype (D7) Reef activates an energy-saving schedule without asking participants' permission. U6: *"I don't mind [Reef acting on my behalf] ...I think it's why people engage with smart devices in general. I think that's part of the payoff. [That] is, you have this intelligent device using the data to make data-driven decisions, but does not maximize unless it's making the decision. So I want it to go ahead and use the data that is collected and I would have the real world experience of feeling it. And so if I don't agree ... [like] 'oh gosh that was way too far to being cold' then I know I can adjust it."* This indicates that participants' values regarding comfort and convenience may shift based on interaction context. This openness to Reef's proactivity was also contingent on their trust in the system's capability to capture behavioral information, the value placed on convenience, and the ease of control.

Prototypes (e.g., D8) featuring short-term variation also helped us uncover insights relating to the differing weighting of control and convenience among our participants. Our participants' reactions toward short-term variation were polarized. Some favored consistency rather than variation. U7: *"I guess that is [like] my eating philosophy, I have two days when I eat less and the other day I get [what] I want so. I can see that. But it seems like for the temperature I would rather find the lowest temperature during [a] day that are still comfortable. Try maximize that [aspect] as opposed to being uncomfortable on days."* This could be related to valuing convenience—they didn't want to fiddle with the thermostat—, or could be related to the challenges of planning ahead. U6: *"I don't think I would pick two days a week [to be more energy-saving] ... because I wasn't sure what will make these two days [more] special than the rest of the days."*

However, some participants thought it was possible to set some days to be more energy-saving than usual. U5: *"I would consider [lowering the setpoint for a day every 6 days]."* Interestingly, this willingness to compromise comfort and convenience is also fluid and negotiable depending on different conditions. U5: *"I think it also depends on, again, like, the temperature outside. If it's going to be significantly colder, and then it asks me to lower the temperature tomorrow, I [would] probably say no. ... If I perceive it's going to be colder, even though the inside temperature theoretically should stay the same... I don't want be colder"*.

Whereas the prototypes mentioned above were probed under the situations where Reef made accurate predictions, we also explored participants' attitudes and values when mispredictions happened. We expected our "incidental intelligibility" [32] design (D10, UE-Mispred) to receive positive feedback from participants. In this enactment, we told participants to imagine that Reef had misjudged their comfort, and suggested lowering their setpoints while they were sick and cold. If they chose not to, Reef then showed a sample interface attempting to explain why it may have made that mistake. However, almost all the participants expressed that they didn't even want to look at Reef's explanation when they were sick and when Reef made a misprediction. U1, for example completely dismissed the explanation, saying that, *"I don't' want to debug it."* Participants' first reactions were to just increase the temperature to a comfortable point—they didn't necessarily want to fix Reef. This finding suggests that for some people, understanding the system models and capabilities is not as highly valued as we expected based on prior work (e.g., [32]). To them, convenience and error recovery are more important.

However, some participants found that Reef's transparency made it more considerate. U5: "*I like this one better [D10] because it's more honest…, it makes me feel like it does* *understand like you are a human, you are doing different things, different things might affect you, and we are an app, and we might not be able to get that all the time... It feels kinder, doesn't feel quite as harsh"* (U5). This transparency could also help users trust the thermostat more by mitigating the negative perception that might result from mispredictions. U4: *"If I never knew that Reef knew that [i.e., its limitations], and I came to my own [conclusion] and said like 'oh, Reef is terrible at figuring out when I am sick' then that makes me lose faith in the device."*

Impertinence, Irrelevance & Allocation of Agency

By engaging participants through different scenarios and prototypes, we were able to gain insight into participants' attitudes about the appropriate allocation of responsibility between a thermostat and its users. Finding the boundary between what is and isn't appropriate for a smart thermostat to ask of its users is critical for mixed-initiative design, and more generally for designing technology that will be perceived as appropriate.

Participants' responses toward designs that suggest alternative indoor clothing were polarized (e.g., D3 and D7). Some expressed negative feedback on these designs because they thought they knew how to dress already. For some, such suggestions were seen as impertinent as they felt indoor clothing was a personal domain that the thermostat should not be involved with. U11: *"It's OK [for Reef to change] the temperature but I'm not very excited about it picking what clothes I want to wear. I find that's more personal… part of yourself. Temperature, you know, in your house, that's not part of you. What you wear, it's part of you. If I want to feel comfortable today, I'll wear this, if I don't, if I want to wear shorts around, I will wear what I want to" (D7)."* For others, clothing suggestions were acceptable but they were not enthusiastic about it as they had been wearing more layers of clothes at home already and viewed it mainly as reminders. Clothing selection, including what to wear at home, emerged as an area of personal choice incorporating lifestyle choice and personal expression, in addition to comfort preferences. The difference in reaction may be partly attributed to participants' views of the role of the thermostat, e.g., as a passive instrument versus a cooperative agent.

Besides clothing, the majority of participants reacted negatively to adaptive suggestions that required them to change their routines and living styles (e.g., D13, D14). Suggesting a move to a different room or exercising at certain time of the day to reduce heater usage are examples of such suggestions. Most of the user-generated tips we prototyped fell into this category. Participants hoped to see tips and suggestions that fit their current lifestyle. For example, U10 mentioned a tip he would like to share on the Reef forum (D14). After describing how warm he had to keep the house in order to keep his baby comfortable since safety guidelines prevent the use of blankets on infants, he added: "*It's like impossible. And we are on Amazon, and we found a wearable blanket that they can like clip on and zip into it, it's like a sleeping bag, that's attached to them, which then let us…keep us house colder,... If I was on this [forum], that would be a tip I would have."* This tip reflects a useful adaptive behavior tip that similar users would be more likely to accept. However, participants felt that tips that were irrelevant to them failed to resonate with their identity (e.g., as "parents") and damaged their trust in the system.

DISCUSSION

Our findings allowed us to gain a deeper understanding of how various designs of comfort-aware eco-coaching thermostats might align with or oppose people's values with respect to comfort, sustainability, convenience, control and agency. Here we discuss how our study extended or challenged insights produced from prior research, specifically in terms of coordinating comfort and sustainability, balancing control and convenience, and allocating of agency while avoiding impertinence.

Coordinating Comfort & Sustainability

While prior systems have incorporated comfort sensing for temperature automation in offices [9], there has been limited work investigating how people value comfort-aware systems in the home. Although we knew that people desire to be comfortable and hope to be environmentally responsible [33], it was unclear if people are open to smart thermostats that actively encourage sustainability while considering their comfort. Our study explored this question by surfacing comfort in different ways, including showing sensed comfort in visualizations (D1), suggesting short-term variation only when people have been comfortable for a few days (D4), suggesting adaptive behaviors when people may have a lower expectation on comfort (e.g., D15), and offering personalized saving modes (D8).

First, our findings point out that for some people, the comfort of certain others is more important than individual comfort. Interestingly, while prior research [9] resolves multi-user conflict around comfort through automatically identifying a middle ground, our findings point to the possibility that in small households, visualizing comfort or using an important person as a reference might also be a solution, even a better outcome in some cases. In addition, our findings suggest that some people might value their comfort more as a necessity while others view it more as luxury. People who view comfort more as a luxury are more likely to compromise their comfort, and respond more favorably to recommendations of short-term variation. Furthermore, we found that while people desire comfort, their expectation and perception of comfort change throughout the day. This finding challenges previous measurements of comfort for smart thermostats: For example, PreHeat [28] aimed to optimize comfort by minimizing "MissTime", which the authors define as the amount of time where the users are at home but the temperature does not reach the target temperature. Our findings point out that this measurement of thermostat efficiency is not in line with people's changing expectations of their comfort. Finally, our design of saving modes raised some concerns. Inspired by the success of prior research [25,34], we chose to use a similar framing of saving mode suggestions (i.e., “energy saving”, “comfortable”). However, our findings point out that this framing renders energy saving and comfort in a mutually exclusive relationship. This implicitly highlighted conflict may steer people to weight their comfort as more important their adaptive potentials.

Balancing Comfort & Convenience

We knew from prior work that leaving users in control is essential, yet in a situation like thermostat scheduling, people appreciate some degree of automation [1,32]. However, these prior insights were produced from reactions to smart thermostats that take a passive stance on energy savings (e.g., Nest). We were unclear whether these insights would still hold for eco-coaching thermostats that actively probe comfort boundaries by lowering the setpoint. It was also unclear whether implementing incidental intelligibility would help strike a balance between convenience and control, making them more tolerant to a proactive design even in the face of mistakes.

Our findings related to eco-coaching styles suggest that due to people’s value of convenience, many people are accepting of a proactive design when doing temperature scheduling. This is of course contingent on people’s trust in the system’s capability to make data-driven decisions, and the perceived ease of control if adjustments need to be made. Although people might still adjust the temperature back if they feel uncomfortable, this brings up an opportunity to view eco-coaching as a negotiation process. Prior work has only explored eco-coaching in a more passive way [1,25,34], but our findings point to the potential for smart thermostats to negotiate a more energy-saving configuration by setting a first reference point.

Our findings also point out that incidental intelligibility [32] was helpful for some participants, although error recovery was even more important when mispredictions happened. For these people incidental intelligibility helped them sustain their trust in the system. However, some other participants didn’t value intelligibility as highly as we expected. We suspect there are multiple factors that contribute to the observed reactions. These factors include context (i.e., participants were asked to imagine being sick), the nature of interaction (i.e., system-initiated push notification), and the presentation (i.e., verbal explanation). More research is still needed to see whether implementing incidental intelligibility in user-initiated actions, and with other forms of presentation, might yield better results.

Being Pertinent & Respecting Allocation of Agency

Researchers [4,5] have already proposed to incorporate adaptive thermal comfort into the design of energy-saving systems. However, it was still unclear to us how to operationalize this concept in an appropriate way that can result in a useful system. Our findings suggest the importance of making adaptive suggestions that are pertinent and relevant to people’s identity and situations.

Our findings point out that supporting appropriate user agency in making personal decisions at home is critical. Indoor clothing suggestions, even for passive designs like D3 and D7, might step into some people’s private domain and be perceived as impertinent. Our findings also point out that many people already engage in adaptive behaviors. Suggesting these already-familiar adaptive behaviors without bringing in new insights comes across as ignorant and does not represent an effective approach to impacting behavior. Further, it is important to offer adaptive suggestions that fit people’s lifestyles and routines. People are usually quite resistant to changing their lifestyle or routines. Many of the common adaptive behaviors mentioned in prior adaptive thermal comfort work (e.g., drinking hot beverages) elicited negative responses from our participants due to their highly user-dependent nature.

LIMITATIONS

The insights from our study were obtained through User Enactments, which involve short-duration engagements with possible future designs. We expect that users’ reactions to the designs proposed in our study would evolve during a longer engagement. Our prototypes were also all probed in a single-participant setting. While we did ask participants to envision co-habitation, and we designed our interfaces with multiple users in mind, our study did not capture the complex social dynamics that may emerge in a longer field deployment. Given the early stage of design for both comfort-aware and eco-coaching thermostats, however, we felt that an important first step would be to survey a broader set of potential design directions using an approach that gives us insight into the underlying expectations and values that would drive responses to different approaches, as such values would influence both immediate and longer-term reactions. We look forward to future research that addresses the evolution of usage and complex social dynamics at home in a long-term deployment.

CONCLUSION

This work represents the first attempt to explore the design opportunity of *comfort-aware eco-coaching thermostats*: smart thermostats that can understand occupants’ thermal comfort while persuading them to save energy. To research this opportunity, we created fifteen prototypes covering a diverse set of design attributes and conducted a user enactment-based study with 11 participants. Our study provides insights into how different designs of comfort-aware eco-coaching thermostats might align with or against people’s values related to comfort, sustainability, control, convenience and allocation of agency.

ACKNOWLEDGMENTS

This work was funded in part by NSF grant 0905460. We thank our participants and also Tawanna Dillahunt and members of the Interaction Ecologies group for their thoughtful comments on this work.

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