Toward Occupant-Centric Virtual Agents: Office Workers' Perspectives on Technological Design and Implementation

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Abstract. Despite having a wealth of data available to support occupant wellbeing and promote healthy buildings, reflecting on one's personal data can often be challenging. Virtual agents emerge as a key solution to help occupants further understand their personal needs, support their wellbeing, and connect with their environment. This study aims to understand office workers' perspectives on designing occupant-centric virtual agents that can simultaneously support occupant wellbeing and building energy efficiency. We collected data from seven office workers over 4 months using four data streams: EMAs (perceived physical and mental health, stress, mood, and productivity levels), a wearable device (physiological data), an audio-features recorder (social interactions), and an environmental sensor (IEQ measures). Through focus groups, we identified ways workers would benefit from their data and different means to present their data and how they relate. We discuss these insights and provide design recommendations for occupant-centric virtual agents.

1. Introduction

Promoting occupant wellbeing has become a focal point in the field of Human-Building Interaction (HBI). Sick Building Syndrome (SBS), for instance, manifests in occupants who experience a broad spectrum of physical and mental illnesses because of extended exposure to suboptimal Indoor Environmental Quality (IEQ) factors (Ghaffarianhoseini *et al.*, 2018). For example, high indoor air temperature combined with high relative humidity (>73.4F and >50% RH) is associated with an increased risk of headaches amongst female workers (Tietjen *et al.*, 2012), low brightness lighting conditions (lighting illuminance <100 lux) have been linked to increased eye strain risks (Souman *et al.*, 2018), and poor air quality, increased noise levels, and poor noise mitigation strategies are all associated with higher stress levels amongst office workers (Colenberg, Jylhä and Arkesteijn, 2021). With over 80% of our time spent indoors (Klepeis *et al.*, 2001), developing solutions to mitigate SBS-related problems with building occupants has become imperative, and especially office workers who spend majority of their working hours indoors. Alongside health concerns, minimizing building energy consumption is also a major HBI research focus. Office buildings are notably significant energy consumers, mostly due to varying occupant needs (EIA, 2021). Indeed, addressing energy issues by altering occupant behavior can yield substantial energy savings (Ham and Midden, 2014; Koroleva *et al.*, 2019; Giudici, Crovari and Garzotto, 2023). This realization underscores the potential for innovative approaches to influence occupant habits positively. Furthermore, most of the energy consumption in office spaces can be attributed to space heating, ventilation, and lighting (EIA, 2021) which all directly affect IEQ.

With the emergence of ubiquitous computing and its applications in the built environment, a plethora of data is now available. Building occupants can tremendously benefit from smartwatches and ready-to-use environmental sensors (Lubitz *et al.*, 2022). For example, one could get insights into how their interaction with their workspace influences their wellbeing and, in turn, affects building energy consumption. However, despite these rapid technological advancements, reflecting on one's personal data can be challenging (Rapp and Cena, 2016; Bentvelzen *et al.*, 2021). At best, users (i.e., building occupants) might not fully leverage the power of the information available at their disposal. At worst, they might not even understand what their data mean and how to utilize it to improve their own wellbeing, support energy efficiency goals, or advance other personal or collective goals (Bentvelzen *et al.*, 2021).

Considering optimizing occupant health and minimizing energy consumption as major issues in the built environment, especially with the availability of extensive amounts of data, we explore virtual agents as a solution to tackle these challenges. We define an agent through the realm of Artificial Intelligence (AI) as "anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators" (Russell and Norvig, 2009). We further expand this definition to intelligent virtual agents who can take the form of digital personas, exhibiting human-like qualities and attributes. Intelligent virtual agents (or virtual agents) are capable of instantaneous awareness, emotional responses, as well as cognitive and behavioral adaptabilities enabling them to engage seamlessly within fluid social contexts (Lugrin, 2021). We explore virtual agents as companions using personalized feedback and insights to help occupants understand their interaction with their environment and how it affects them or the space they are using (Margariti, Vlachokyriakos and Kirk, 2023).

We aim to highlight design considerations for occupant-centric virtual agents that supports occupant wellbeing and promotes building energy efficiency. We discuss the different barriers office workers face in understanding their personal data, the data of their environment, and how all the data are related. We explore ways virtual agents can help office workers understand their data at a deeper level and promote behavior change to support occupant wellbeing and building energy efficiency. Finally, we investigate what occupant-agent interactions would mean in terms of modalities, frequency of interaction, and level of involvement from both the agent and the occupant.

2. Background

2.1 Data sensing and learning

Given the nature of virtual agent communication, we acknowledge that extensive data sensing is fundamental for their learning process. The rapid expansion of Internet of Things (IoT) applications in the built environment creates opportunities for robust data collection methods. Recent research has focused on collecting and learning from large health and comfort datasets employing IoT devices such as smartwatches and sensors. These studies, typically of short duration (4 weeks), amalgamate extensive Ecological Momentary Assessments (EMAs) and physiological data to train comfort models to better understand occupant needs and perceptions (Mattingly *et al.*, 2019; Quintana *et al.*, 2022). Although potential occupant-agent interaction exists, previous work primarily lacks direct engagement of occupants with their data. Improvements in data sensing and learning, coupled with self-reflected measures (e.g., EMAs), could ultimately lead to more accurate and informed feedback for building occupants. Additionally, the short data collection periods underscore the need for longitudinal studies, offering potential insights into evolving complex patterns over time.

2.2 Personal data communication with users

While most IoT research focuses on data collection and learning, existing technologies already offer occupants various levels of personal information. Within this realm, AI has emerged as essential for leveraging data to deliver personalized feedback (Russell and Norvig, 2009). For instance, off-the-shelf mainstream smartwatches provide insights into a wide range of physiological metrics such as heart rate, heart variability (HRV), blood oxygenation, sleep quality, among many others (Lubitz *et al.*, 2022). In addition to sensing, some of these devices also provide its users with varying degrees of information. For example, the Oura ring can interpret metrics related to stress and provide computed stress measurements to their users every 10 minutes on average (figure 1). Additionally, smartwatches like Fitbit and Apple Watch can also provide insights into sleep patterns and durations (figure 2), and even some soft medical uses like detecting cardiac arrhythmias or strokes (Lubitz *et al.*, 2022).

Figure 1 (left). Oura ring computed stress insights (Oura Ring, n.d.). Figure 2 (right). FitBit sleep pattern insights (Kosecki, 2018).

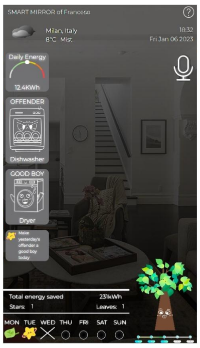
However, while the data presented by these tools can be insightful (Lubitz *et al.*, 2022), they usually leave users with raw information, which can be challenging to interpret, or, worse, create a black box where data is interpreted without full user awareness. There is a recognized necessity for more transparent technologies that facilitate user engagement with their data.

2.3 Intelligent agents for occupant-building relationships

Towards leveraging data for personalized feedback, the evolution of virtual agents within the built environment, facilitated by ubiquitous computing advancements, becomes increasingly pivotal. Although the value of conversational agents in fostering worker wellbeing reflections is highlighted (Kocielnik *et al.*, 2018), empirically informed feedback to drive office worker behavior changes remains largely unexplored. Akin to recent health studies, the existing body of research investigated data collection and processing methods to accurately model building operations and occupant preferences, with future research aiming to explore agents that support changes in building IEQ conditions (Quintana *et al.*, 2022). Others have developed responsive office settings for stress restoration in an environment with controlled restoration strategies (Zhao, Kodama and Paradiso, 2022). However, while these approaches are valuable in optimizing environmental and physiological conditions, they fall short in actively engaging occupants with their data and fostering behavior change. To address this gap, we propose exploring genuine bi-directional interactions between occupants and intelligent agents where building occupants can learn from their environment and behaviors through agent-driven feedback (Margariti, Vlachokyriakos and Kirk, 2023).

2.4 Occupant-feedback for building energy conservation

Occupant behavior is a pivotal factor influencing building energy consumption, particularly within office environments, and occupant education and awareness are key in prompting energy-saving behaviors (Chen *et al.*, 2021). Real-time feedback has emerged as a particularly effective approach. Examples from a field study at the University of Bath underscored the potential for significant energy savings from prompting real-time occupant behavior change, all while improving occupant perceptions of environmental control without affecting personal comfort (Vellei *et al.*, 2016). Furthermore, strategies such as eco-feedback, gamification, and fostering social interaction are highlighted as promising methods to encourage meaningful changes in occupant behavior (Paone and Bacher, 2018; Koroleva *et al.*, 2019; Giudici, Crovari and Garzotto, 2023), thereby contributing to energy conservation efforts (figures 3 & 4). While these studies have delved into the effects of occupant education on energy conservation, the potential influence of occupant education on the interplay between occupant health and energy savings remains largely unexplored.



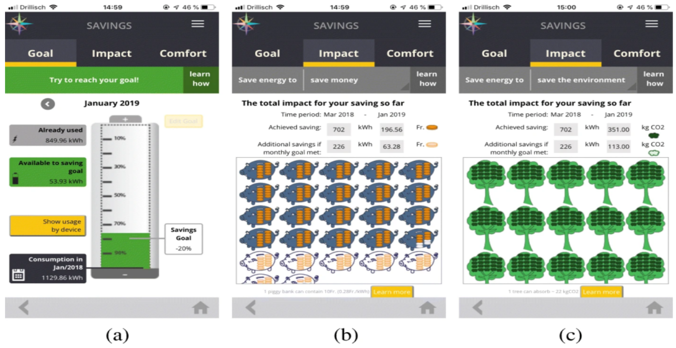


Figure 3 (left). A conversational smart mirror interface to minimize building energy consumption (Giudici, Crovari and Garzotto, 2023). Figure 4 (right). Metaphorical feedback visualizations to help occupant reduce their energy consumption (Koroleva *et al.*, 2019).

3. Methods

3.1 Study Design and Participants

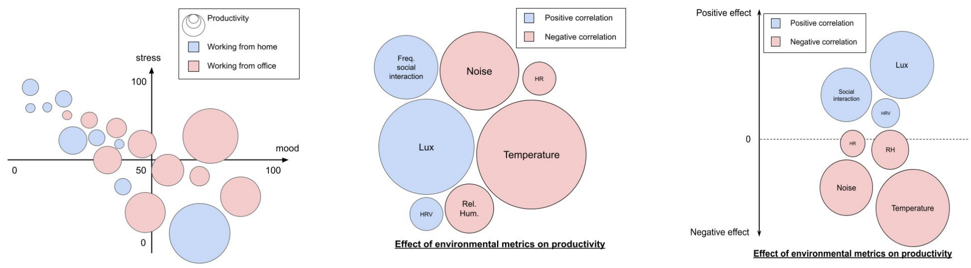
This preliminary study was conducted with 7 office workers affiliated with the University of Southern California with offices across four different campuses: Information Sciences Institute (N=2), Institute for Creative Technologies (N=2), Health Sciences Campus (N=2), and University Park Campus (N=1). Participants were 4 female and 3 male office workers, averaging 42.6 years of age (min=27, median=46, max=51), and worked in various hybrid arrangements with an average of 77.9% of their work time spent at their university-provided office (min=25%, median=90%, max=100%). We collected data when participants worked at their university and home offices.

3.2 Measures

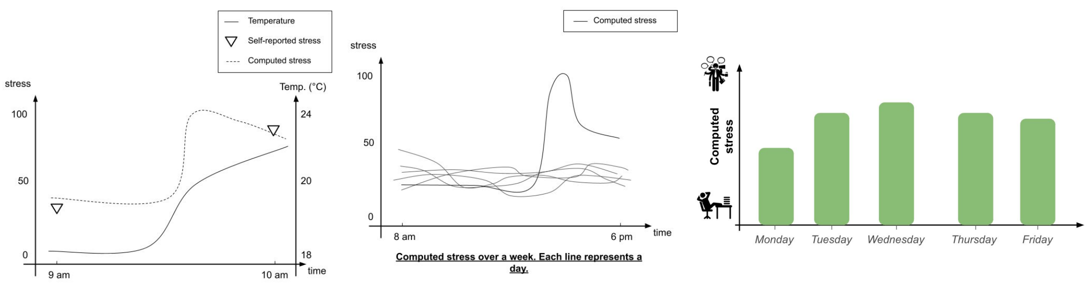
We collected data from 7 participants through four different types of data across 4 months, including (1) the participants' perceived physical and mental health symptoms, stress, mood, and productivity levels, (2) physiological data, (3) levels of social interaction, and (4) continuous IEQ measurements of their office spaces. First, we collected EMAs through four questionnaires sent at semi-random times: one EMA at the beginning, two randomly throughout, and one at the end of the workday. For every questionnaire, participants described their current activity (e.g., job- or non-job-related activity) and rated their productivity, mood, and stress levels (100-point scale), their activity as a source of opportunity or pressure (6-point Likert scale), and their level of comfort with respect to specific IEQ factors (e.g., lighting, temperature, air quality, noise) in their current workspace (6-point Likert scale). For the first EMA of the day, participants were asked to report their sleep quality from the previous night (10-point Likert scale), and at the end of their workday, participants reported SBS symptoms they experienced throughout their day. Second, a Fitbit smartwatch captured the participants' physiological data continuously. We measured the participants' heart rate, HRV, skin temperature, oxygen saturation, step count, and sleep cycles. Participants wore the device during work hours as well as during the night to gain insights into their sleep patterns and quality. Third, an audio-features recorder measured each participant's social interaction level. When the device picked up signals in the speech frequency ranges, we collected audio data for a maximum of ten minutes. We only measured changes in the spectral field to ensure that the data was anonymized (i.e., intensity changes at specific frequencies prevent any data from being synthesized). Fourth, we collected environmental data through an Awair sensor. IEQ measurements included office temperature, relative humidity, air quality (PM2.5, PM10, and TVOCs), and light and noise intensity. Environmental data were logged every 5 minutes.

3.3 Focus groups

At the end of the 4-month data collection period, we conducted focus groups with participants (N=6) to explore how and what they understand about their data, identify the types of data that would benefit them, and, more generally, reflect on their experience. Through these focus groups, we defined two activities. First, we had participants reflect on their personal data, how they thought their personal and environmental data were related, and how these data could be best communicated to them. Participants discussed the variables collected for the study and the data collection process and shared any misunderstandings. Second, participants discussed the insights they would want to get from their data and how their data could be communicated with them. To facilitate conversation, we presented participants with different visual prototypes showing how their data might relate and what insights they could gain from them (figure 5). We used data visualization archetypes with placeholder data to ensure a uniform basis of comparison for all participants and respect privacy concerns. These archetypes were created to encapsulate some IEQ factors of interest with participants' insights. They were the product of our group's reflections on how we would analyze the data moving forward. These two need-finding exercises helped us further understand participants' needs and concerns in terms of understanding and interpreting their data, as well as some misunderstandings they might have.



(a) Correlational visual insights



(b) Time-series visual insights

Figure 5. Data visualization archetypes used for the focus groups.

4. Results

4.1 General reflections

Overall, the experience was deemed positive, with most focus group participants indicating that this research helped them further reflect on their work habits and how they impact their stress levels. For example, several participants reported that wearing a Fitbit watch and using the native app allowed them to realize how their sleep patterns could be correlated with their work performance, mood, and overall productivity. One participant did not specifically like the Fitbit environment but indicated that they found information provided by their own Apple watch to be more insightful and data-rich as an opportunity for using a wearable device. Another participant pointed out that the study helped them reflect on the impact of their work location and flexibility on their stress levels. While most underlined the study's positive impact on reflecting on their work-related stress, some participants highlighted drawbacks. One participant expressed that reflecting on their data and its implications, even unconsciously, made them feel more stressed overall. For example, they believed seeing that irregularities in their sleep patterns drastically affected their work performance the next day had increased their likelihood of having more irregular sleep patterns. Another participant mentioned that environmental sensors were cumbersome and unnecessarily cluttered their work environment, thus increasing potential frustrations and stress levels.

4.2 Reflections on variables collected

With most health-related studies focused on collecting similar kinds of data (i.e., IEQ factors, physiological data, EMAs), we aimed to understand how participants felt about their data, and what they understood (or not) from them. Participants generally understood the environmental, physiological, and subjective (i.e., EMAs) data; however, questions were raised about the types and utility of data collected by the audio-recording devices—although everyone understood the implications of measuring social interactions. Additionally, most participants showed great interest in understanding their data through interaction effects, instead of individual descriptive data points or one-to-one correlations between variables. For example, one participant pointed out that warm air temperature and excessive noise, together, had a strong impact on their perceived stress levels. With respect to the subjective assessments, participants' opinions were mixed. On the one hand, one participant mentioned that the EMAs helped self-reflect extensively, especially at the end of the week. On the other hand, a couple of participants noted potential drawbacks to using EMAs, feeling that the surveys were redundant, leading to answering questions similarly week after week or overlooking changes in their stress levels, for example. Another participant pointed out that giving themselves a perfect (or null) rating was challenging as it would not seem fair, thus questioning the utility of the metric to capture a wide range of perceptions. Finally, considering this intensive subjective and objective data collection, one participant specifically expressed that they would be interested in comparing their self-reported results (i.e., stress, productivity, mood, etc.) against computed metrics from objective measures. This need for data validation was echoed by other participants in varied ways across the focus groups.

4.3 Potential data visualizations and communications

Reflecting on potential personalized data visualizations, as shown in figure 5, yielded insights into the types of data and data communications participants are interested in interacting with. Importantly, all participants agreed that time series insights (weekly and monthly) would be most useful, expressing interest in seeing patterns in their data. Some pointed out that having weekly and daily insights, alongside other personal data, could benefit their ability to alter their behaviors. For example, mapping their data relative to meetings, project deadlines, and work-related activities could assist them in seeing patterns related to work participation. One participant expressed interest in comparative visualizations between different environments, such as home and university office settings, to elucidate contextual influences on stress levels. While all agreed that time series could produce valuable insights, only one participant valued the simple correlational data insights. The other participants indicated that these data visualizations were generally unusual and unclear to interpret, but that certain aspects of the data may have value, such as using area charts to show the relative magnitudes across factors affecting their stress. Finally, most participants agreed that although they found the visualizations helpful, they would need to have all the insights intended in the visualizations explained to them to understand their full granularity. Specifically, they would appreciate support in using the data to reduce their stress. We note that we used only a limited selection of potential data visualizations and did not test different versions of visualizations. As such, we did not address inherent issues with complexity and relevance, rather, we attempted to inspire discussion regarding the utility and type of visualization that may be useful.

5. Discussions

5.1 Making the most out of the data

Reflecting on personal data. Insights from the focus groups underscored the willingness of occupants to learn more about their data (e.g., sleep patterns, end-of-day EMAs) and their effects on their wellbeing. These insights prompted some occupants to reduce their stress levels by changing their behavior, which they would have probably not done otherwise. As highlighted by the literature, real-time and informed feedback emerge as evident solutions to further connect occupants with their architectural spaces, and ultimately with themselves (Vellei *et al.*, 2016). Therefore, we strongly advocate for building agents that not only learn from the data, but can also understand and interpret trends, and communicate these insights clearly with office workers. These insights could be self-beneficial (i.e., improve occupant well-being), space-beneficial (i.e., minimize building energy consumption), or a mix of both.

Relatable data for greater user engagement. Despite the growing sophistication of technology, we find that office workers often lack a comprehensive understanding of their personal data, the data of a building, and how they relate. Some occupants expressed concerns about the type of data collected and what it meant. For example, although they understood the purpose of collecting audio data, they found it difficult to relate to the measures we collected. Utilizing relatable data streams (e.g., reporting computed levels of social interactions from raw audio data instead of raw data itself) seems essential for facilitating occupant understanding and engagement with their data. Furthermore, our discussions highlighted the importance of understanding participation and activity patterns for office workers to interpret their data. Longer data collection periods would allow to better capture these underlying patterns and ultimately improve occupant engagement with their data. Moreover, layering data with temporal (e.g., meeting times, office schedules) and spatial cues (e.g., work location, number of people in workspace) would also enhance the contextual relevance of feedback, thereby augmenting its utility for occupants. These insights suggest the importance of coupling relatable objective and subjective metrics for more qualitative insights and higher user engagement.

Need for less intrusive data collection. Incorporating subjective data collection methods, such as EMAs, poses challenges in balancing data quality with occupant privacy and comfort. Discussions from the focus groups pointed to a dull and potentially inaccurate subjective data collection a little while after the beginning of the experiment. These setbacks can be attributed to the redundancy in EMAs filled by participants, even though questionnaire timings were semi-randomized to minimize that problem. While we acknowledge the importance of subjective data for building integrated virtual agents, there is a clear imperative for optimizing and streamlining subjective data collection to minimize intrusiveness while maximizing efficiency. Future research should look at reducing this redundancy and evaluate how to maximize the quality of information gathered without compromising its quality.

5.2 Designing for occupant-centric virtual agents

Building occupant-agent rapport to support better agent-driven feedback and user engagement. Although using social techniques with virtual agents can help induce behavior change in the short term (Ham and Midden, 2014; Lucas et al., 2019), further exploration is needed to determine which methods are most effective in cultivating long-term agent-occupant connection. We hypothesize that virtual agents and building occupants would co-learn and co-adapt to promote healthier and energy-efficient spaces, like in a symbiotic relationship. Virtual agents should prioritize providing occupants with actionable items to meet their wellbeing goals, as well as the needs of a building (e.g., minimize energy consumption). Specifically, we suggest developing personal relationships between agents and occupants to maximize user engagement. This can be achieved through personalized feedback and interactions tailored to the user's specific needs. Agents should also learn from user behavioral patterns and adapt to foster genuine interactions. In future work, the authors will explore occupant-agent rapport to better connect the occupants with their data through trust and transparency through human-subject controlled studies.

Data privacy issues. While not initially discussed in the focus groups, but explored in another project (Fukumura *et al.*, 2021), addressing issues around data privacy is crucial. For instance, virtual agents should allow flexible data collection and sharing. This could be facilitated by negotiating data sharing opt-in and opt-out options for its users, or by clearly demonstrating the impact of data sharing for individuals and their communities (Margariti, Vlachokyriakos and Kirk, 2023). We also suggest that these agents should allow their users to define (1) the type of data they are willing to share at any point of their engagement, and (2) their desired level of interaction with the agents (i.e., passive, semi-voluntary, voluntary). Future research should carefully consider these implications, ensuring that agents and their underlying processes are fully transparent.

5.3 Key design recommendations

All in all, using insights from the focus groups and the literature, we highlight design considerations for occupant-centric virtual agents to support occupant wellbeing and minimize energy consumption, personalized and catered to diverse user needs and preferences:

- Virtual agents should incorporate feedback strategies to help occupants reflect on their data and how they relate. They should be able to give relatable feedback (e.g., avoiding technical jargon, using analogies), with actionable items (e.g., "You could put on an extra layer of clothing." instead of "You should bring your body temperature closer to 37.6ºC."). We discuss feedback that could benefit both the building (i.e., energy efficiency) and its occupants (i.e., improve well-being).

- Virtual agents should aim to build rapport with their occupants to foster long-term behavior changes. In future research, we plan to explore how these agents can build rapport with occupants best and in the most sustained period.
- Virtual agents should learn from curated longitudinal data streams comprising subjective and objective measures. Data collection and sensing methods should be less intrusive and consider the occupants' schedules and needs.
- Virtual agents should leave full control of the occupants' desired levels of interaction. This could be done by letting the user choose whether they want to initiate their interaction or not. We consider having opt-in opt-out options at any point of their interaction lifetime with the agent to allow them to control the data they are willing to disclose.

5.4 Limitations and directions for future work

In addition to the relatively small sample size, which limits the generalizability of our findings, one limitation of this work lies in the constraints of using data archetypes. For instance, providing post-hoc visualizations inevitably omits some complexities that would arise in real-time personalized interactions. As a result, participants' attitudes toward their data and subsequent interactions may not fully reflect what would occur with a functional virtual agent. We also note that archetypes used in the focus groups might have influenced the participants in their reflections. We hypothesize that other modalities (e.g., sound, touch) or personalized visual representations based on empirical findings (i.e., not archetypes) could provide deeper insights into the participants' perceptions of their data.

Building on these insights, we aim to explore real-time occupant-agent interaction to support office workers wellbeing in future independent research. Through human-subject experiments, we will investigate the quality of interaction and occupant self-reflection, as well as the effectiveness in supporting occupant wellbeing and connecting occupants with their space using virtual agents. Furthermore, in continuation with this work, we also aim to explore occupants' perceptions of their actual data (e.g., not archetypes) and unveil some of their specific experiences through more comprehensive interview methods (e.g., story interviews) (Mackay, 2023).

6. Conclusion

In this paper, we highlight design considerations for virtual agents to enhance occupant wellbeing and promote healthier spaces. From the results of our focus groups, we discuss the importance of agent-feedback to support positive behavior changes, underscore the importance of developing occupant-agent rapport to promote long-term user engagement, and emphasize the need for advancements in data sensing and analysis methods. We also highlight potential drawbacks of designing these agents such as intrusive data collection methods and data privacy. Finally, we discuss directions for future work and research directions.

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