Real-time Work Environment Optimization using Multimodal Media and Body Sensor Network

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Abstract

The ambient environment has a significant influence on our cognition and behavior. We envision an adaptive space that improves our productivity and wellbeing at work and related settings by forming a closed control loop around our responses to the environment's properties. To explore this vision, we created a responsive office named Mediated Atmospheres (MA) that can transform it's ambiance as driven by a network of physiological sensors. We conducted a user study investigating near-natural use of the system with a panel of non-experts and experts in the field of the built environment (N=9). Two control modes were implemented: (1) Learning Mode, where the system learns from the user's response and (2) Preset Mode, where the office responds to the user's physiological state based on predefined rules. Our result showed that using the Learning Mode, participants were able to increase the amount of time in which they were focused when the system optimized for both focus and stress restoration rather than focus alone. Participants were able to double the time in which they achieved high-stress restoration when their environment optimized for restoration rather than focus. Both application modes achieved high System Usability Scores (SUS $>$ 82), which is evidence that our method for compressing the multivariate control problem into a multidimensional model of the user's physiological state is a viable approach for closed-loop control of a multimodal environment. We offer a discussion on the preferred level of control for an office application.

Keywords: Ubiquitous Computing, Ambient Intelligence, Body Sensor Network, Preventative Care, Affective Computing, Well-being, Cognitive Performance, Mediated Atmospheres

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1. Introduction

A smart living space equipped with sensors and advanced building control technologies offers new possibilities for personalized health support. Traditionally, building control systems don't regulate to parameters directly derived from the users - rather, all feedback variables are canonically derived from sensors fixed in the user's environment (e.g., temperature, light, air quality, etc.). As it has become recently possible to unobtrusively measure variables that correspond to how users physically and/or affectively respond to their surroundings by leveraging simple wearables or sensors like cameras or thermal monitors trained on the users, these user-based variables can now be inferred and applied in environmental control methodologies. In this paper, we introduce a vision and prototype for real-time optimization of the user's physiological state using multimodal media and a body sensor network.

The research introduced in this paper particularly addresses a growing need in the knowledge economy to improve work environments. In our modern society, an average person spends 90% of their time indoors, and a third of that time in a workspace [1], which makes the interior a determining factor for people's health. The composition of light, sound, view, and thermal stimuli in buildings has an important impact on well-being and productivity. Personalized control of the building environment can significantly improve stress levels and productivity and thus reduce absenteeism and

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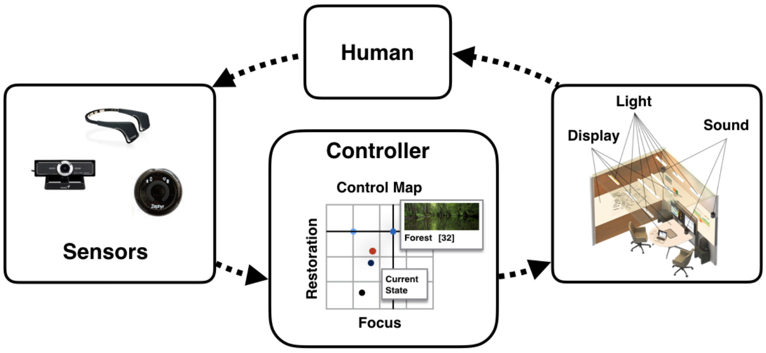


Figure 1: Closed-loop Mediated Atmospheres system.

complaints in the workplace [2, 3]. In this paper, we discuss the opportunity to enhance productivity and well-being through advanced control of the ambient environment in the office and related settings.

Building on the overwhelming evidence that the properties of the ambient environment can alter stress response and cognitive processing [4, 3], we envision a space that can dynamically transform its qualities to support the user by servoing against data that reflect the user's response to the intervention. We call this vision *Mediated Atmospheres* (MA) [3] — sensing and computation that mediate between occupants' actions and a responsive environment in a closed-loop fashion. We aspire to make an environment that acts as an intrinsic extension of their occupants' sense of well-being, rather than rooms that regulate partially-related parameters like temperature measured on the wall.

To advance our vision, we created a prototype system for sensor-driven multimodal control of lighting, video projection, and sound in an office. The prototype office continuously supports the user's goal by learning and adapting according to the user's physiological response. It is equipped with real-time physiological sensing and data processing capabilities for sensor-features such as heart rate variability, head orientation, brain activation pattern, and facial expression.

We created an application called *Learning Mode*, in which the user can specify the desired physiological state as described by a combination of the aforementioned sensor features. The system learns and re-weights the atmospheric setting in a user model according to the user's real-time physiological response and controls ambient changes in a continuous fashion to help the user achieve the desired physiological state. We conducted a preliminary near-natural-use study with a panel (N=9) of experts and non-experts in the field of the built environment to examine Mediated Atmospheres in three aspects:

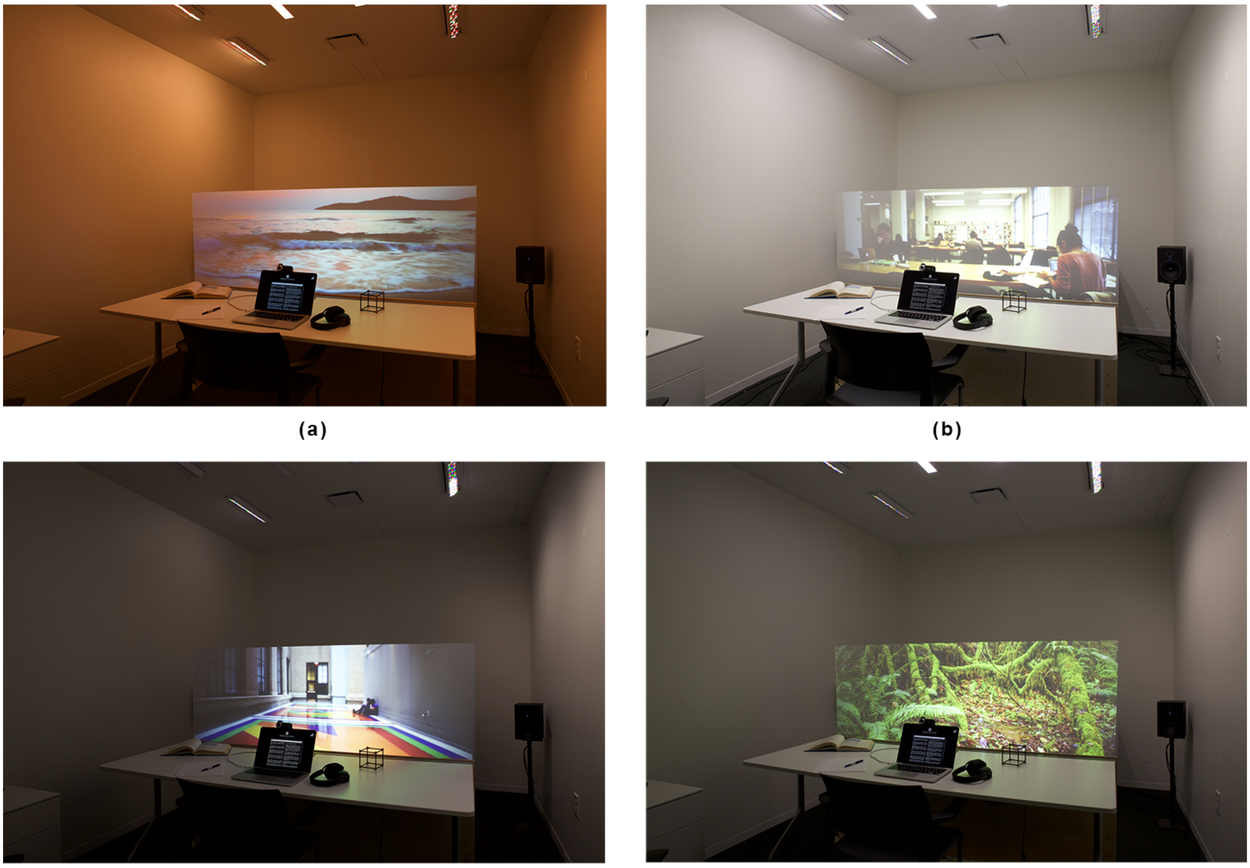
1. the effect of the system on the user's ability to achieve the desired physiological state and on their work experience,

2. the usability of the user interface, *the control map*, which establishes a multidimensional model of the user's physiological state, and

3. the level of control that is needed for Mediated Atmospheres in the workspace.

1.1. Multidimensional Model of the User's Physiological State

To realize our vision of continuous optimization of the ambient environment, we developed a multidimensional model to represent the user's physiological state along with the system's control state. Existing implementations of building automation, e.g. Smart Home, both in the commercial and research space, repeatedly demonstrated that controllability for the end-user is core to the success of the system [5, 6, 7]. Failure often happens because of poor understanding of technical limitations and reasoning behind system decisions [8]. For this reason, it is crucial to provide transparency. The design of a clear architecture and a well-founded, explicit relationship between environment and adaptation is considered the key to unlock context-aware computing at a global scale [9].



(a) (b) (c) (d)

Figure 2: Mediated Atmospheres prototype office in four different atmospheric scenes, side by side.

Learning Mode	Preset Mode
• The user specifies a desired physiological state • The system continuously learns and re-weights the atmospheric setting in the user model and updates the Control Map according to the user's real-time physiological response during use • The system automatically controls the atmospheric setting according to the user model to help the user achieve the desired physiological state • The user can skip a setting or change their goal state anytime using the GUI	• The system continuously detects the user's real-time physiological state • The system automatically controls the atmospheric setting according to a user-defined Control Map to match the detected physiological state • The user cannot manually skip a setting or set their goal state

Table 1: Key Feature Highlights of Learning vs. Preset Control Mode.

A transparent interface is "one that makes explicit the knowledge and processes for which the man and computer share a common understanding" [10]. Accordingly, we seek an embedded model of the control space (with low-dimensionality) to adequately represent and reduce the complexity of the multimodal system (lighting network, sound, and visuals) and frame the user's understanding of the control algorithms. In the implementation introduced in this article, we chose a two-dimensional model also called the *Control Map*. Our approach was to identify the problem-solving language that a user would use to configure the space based on prior research that investigated typical work activities and when they require changing of work settings [11, 12]. The selected dimensions are *Focus* — individual work involving concentration and attention devoted to a particular task — and *Restoration* — recharge of diminished mental resources.

We evaluate the usability of the control map interface through a survey in our preliminary user study with a panel of experts and non-experts in the field of the built environment. The survey is describe in Section 4.4.

1.2. Level of Control for Human-in-the-Loop Operation

An important aspect of user interaction for building automation is the user's remaining degree of control, also called the human-in-the-loop design. Not having control could cause distress and negative feelings, especially when control over adverse stimuli is not available [13, 14]. Other benefits are, for example, that having a degree of individual control over lighting can improve work motivation throughout the day [15]. Yet, having to make choices could be overwhelming and cause concerns of self-presentation [16, 17], especially if the user thinks that an expert could make better choices, or there is a risk of embarrassment by making the wrong choice.

Given that MA is a dynamic immersive experience, the system could easily cause distraction or discomfort when undesired behavior occurs, for example, due to sensing and inference limitations or due to a poor model in the initial learning phase. We seek to understand the appropriate level of user control that maximizes system usability for continuous multimodal workspace optimization. To examine the impact of the degree of control on system usability, we implemented an additional control algorithm called *Preset Mode* in which the user has a reduced degree of personalization in comparison to the *Learning Mode*.

For the Learning Mode, participants can specify the desired focus and restoration goals at any time. The system adapts the atmospheric setting according to the user's physiological data and their specified goal. In the Preset Mode, the system is driven entirely by the user's physiological data. In this application, the system's goal is to match the ambient conditions to the detected physiological state based on preset rules. Study participants experienced both modes in the preliminary user study. Through the comparison of the results, we derive recommendations for the level of control for Human-in-the-Loop operation in the office application.

1.3. Paper overview

This paper is organized in the following way. We first provide an overview of the background. We then introduce the closed-loop Mediated Atmospheres system and the implementation of the two application modes in detail. Afterward, we present the human subject study followed by results and discussion. Finally, we conclude with our main findings.

2. Background

2.1. The Influence of the Ambient Atmosphere on Focus and Restoration

The same ambient environment can promote different or even reversed effects [4], depending on the desired activity to be performed in the space. For example, ambient stimuli, such as ceiling height, colors, textures, ambient noise, and music, even if they do not directly relate to a task, can attract people's attention and enhance their ability to focus [4]. For stress restoration, on the other hand, much research has shown the therapeutic effect of nature, e.g., exposure to sounds and images of nature can accelerate the physical and mental recovery from a stressful situation [18, 19, 20, 21, 22]. Besides qualities related to nature, the sense of being away and a feeling of fascination are central characteristics of restorative environments [23, 24]. Certain lighting conditions are suitable for activities that require a vigilant state of mind but should be avoided if the reverse effect is desired. High intensity and cool color temperature lighting have an acute effect on alertness, e.g. elevated heart rate, change of brain activation patterns to a more alert state [25, 26, 27], and can improve learning performance [28, 29].

In prior work, we introduced a multimodal media prototype office, which uses video projection, sound, and controllable lighting, to create atmospheric scenes [3]. The scenes vary in their themes (such as nature, urban, indoor and outdoor) as well as their properties (e.g. color, brightness, motion, and repetitiveness). They borrow from existing environments - for example, a walk through a crowded city, a forest in autumn, an ocean sunset, and a living room with a glowing fireplace. Through a series of experiments with users, Zhao et al.[3] evaluated the impact and benefit of the atmospheric scenes and showed significant effects on focus and restoration. In this paper we introduce a sensor-driven, closed-loop controlled MA system that continuously adapts the atmospheric scenes based on the user's physiological data and a study on its effect on users.

2.2. Building Automation and Healthcare

Early examples of domestic systems that can respond to the user's context range from the iconic IR badges at the dawn of Ubiquitous Computing [30] that, for instance, allowed desk phones to ring in any office a user was visiting [31] to cars that would automatically adapt the seats and mirrors to conform to a particular driver as determined by their key fob [32]. This extended to leveraging RFID and/or facial recognition for smart displays that would customize content depending on who is nearby, starting with installations like the famous 'Bill Gates House' in the 1990's [33] to present developments in Pervasive Displays [34].

Ubiquitous Computing is seen as an integral part of future health care concepts [9]. A living space equipped with sensors and interactive technologies creates enormous opportunities for smart healthcare, including detecting medical emergencies, monitoring personal health conditions, and enhancing the user's well-being. For example, researchers developed pressure-sensitive floor tiles [35] and distributed sensor networks [36] to detect when a patient falls to timely notify healthcare personnel. Related research investigated methods for understanding and predicting health trends [37] and classifying various activities at home [38] from domestic sensor data to aid in providing preventive measures. A variety of smart health services have been developed for managing chronic diseases, for example, diabetes [39] and memory loss [40].

Interactive technology such as smart lighting and smart appliances can learn favorite ambient settings to support daily activities [41]. A classic example in this space is Michael Mozer's smart house from the early 1990s, where he used light switch flips and thermostat settings as reinforcement to train a neural net that autonomously controlled the lighting and heating in his house [42]. Other research leveraged both wearable and infrastructure sensing to build personalized mobile comfort models that can customize building HVAC response, working to lower energy costs while maximizing user satisfaction as inhabitants move across entire buildings [43].

Different than prior work, our system forms a closed control loop between the user's physiological response and the controllable environment using a body sensor network. Low-cost physiological sensors enabled new control

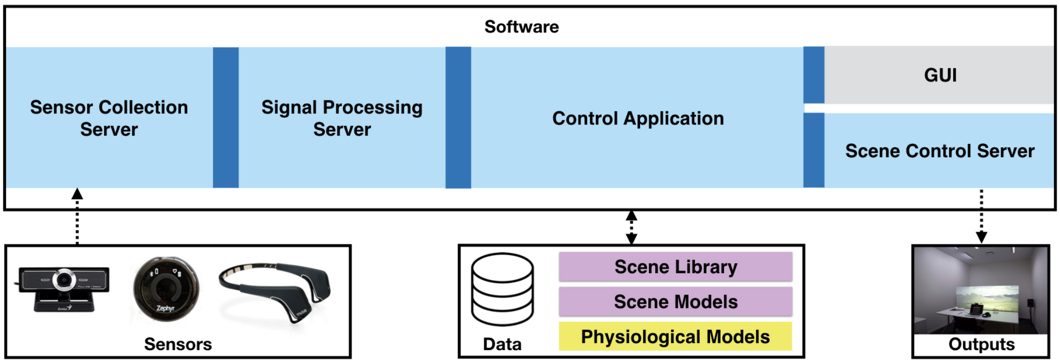


Figure 3: System overview.

applications with an emphasis on health and wellbeing. Early work such as the Meditation Chamber [44] and the more recent example of ExoBuilding [45] use real-time physiological monitoring to manipulate the user's environment and to teach the user to control involuntary physiological events. This technique is broadly known as Biofeedback and usually uses visual or acoustic feedback signals to instigate or compensate physiological states. Biofeedback is used for treatment of anxiety disorders [46] and treatment for substance abuse disorders [47]. In this work, we go beyond visualizing the user's physiological state by delivering multimodal ambient stimuli that have a measurable effect on the user's physiological response [3] to support focus and stress recovery. The system is a calm technology [48] which interacts with the user at the periphery of their attention and thus allows the user to primarily focus on their work task at hand.

3. Prototype System

3.1. Hardware, sensors, and software

The prototype is in a rectangular windowless office, 4.2 m by 2.8 m with a ceiling height of 2.6 m, shown in Figure 2. Its outputs consist of a lighting network with five-channel color LED fixtures, rear projection on a large surface, and sound output through a set of wireless noise canceling headphones (*Bose, Quite Comfort*). The closed-loop system builds on the open-loop Mediated Atmospheres prototype office introduced in [3, 49, 50].

Sensors in the closed-loop system include a low-cost commercial EEG headband (*InteraXon, Muse Headband*), a physiological monitor chest strap (*Zephyr, Bioharness 3*), and a wide angle USB camera (*Genius, WideCam F100*) in combination with a facial feature tracking library (*CMU Human Sensing Laboratory and University of Pittsburgh Affect Analysis Group, Intraface*).

The software consists of four independent modules implemented in Python. The Sensor Collection Server manages incoming data streams, data parsing, and logging to storage. The Signal Processing Server receives real-time raw sensor data from the Sensor Collection Server and computes the focus and restoration indicators as shown in Figure 5. Figure 4 shows the web-based graphical user interface, the Control Map, which visualized the user's active state and the available scenes along the control dimensions. The interface also allows the user to configure the initial position of the scenes in the Control Map through drag and drop. In the Learning Mode, an addition marker is added to allow the user to set a goal.

3.2. User Data and Models

For each available scene, we calculate user-specific lightweight statistical models, called Scene Models, using the P-squared algorithm [51]. These models describe the suitability of each scene for focus and restoration. We use a "hot-start" approach, where users initiate their Scene Models with manual preference inputs. Users position the scenes

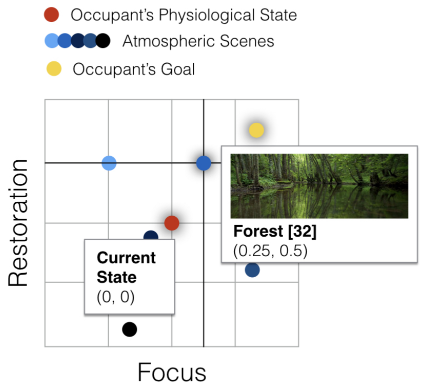


Figure 4: Control Map. The user's current physiological state is visualized as a red marker. When the user selects or hovers over the marker, a visualization with the coordinates, for example (0,0) in this case, pops up. The user's current goal is visualized as a yellow marker. The user can change the goal by selecting and dragging the goal marker inside the Control Map. Lastly, the available scenes are visualized as markers in shades of blue. When the user clicks or hovers over a scene maker it shows a window with a representative image and more details about the scene (e.g. scene name, id, and coordinates). During the on-boarding of a new user, the user initializes the Control Map by selecting and dragging scenes from the scene library onto the Control Map at the desired position.

through drag and drop on the Control Map according to their perceived suitability for focus and restoration. When physiological observations are added, the model slowly shifts towards the actual physiological response. The speed of adaptation is heuristically determined to reduce the influence of the user's initial selection by half after 15 minutes.

All incoming sensor data are added to user-specific Physiological Models (see Figure 5) using the P-squared algorithm [51]. We use multimodal sensing of Heart Rate Variability, Respiration Rate, Electroencephalogram, and Facial Features for the inference of focus and restoration levels.

3.3. Signal Processing

3.3.1. Heart Rate Variability

Heart Rate Variability (HRV) is an established psycho-physiological measure for stress development and restoration e.g. in [52, 53, 3]. High HRV is generally believed to indicate parasympathetic regulation [53]. Using the Zephyr Bioharness 3 [54], we recorded RR intervals — the times interval between consecutive heartbeats, which are generated on the device with the ECG waveform sampled at 1000 Hz. We converted data to an equidistantly sampled series (18 Hz) by cubic spline interpolation. Overlapping (92%) data arrays of 1024 consecutive RR interval values were buffered with an update rate of 0.1 Hz, containing approximately 1-minute data. We then applied the standard deviation of RR intervals (SDNN) method to the buffer to compute HRV.

3.3.2. Head Orientation

Head Orientation indicates where participants directed their visual attention. Previous experiment [3] established that participants' head pitch angles correlated with focus and restorative states. As suggested by previous results, We split Head Orientation into two features. The Viewing Scene feature is close to one when the user's head orientation points toward the projection screen and decreases as the user turns away. The Viewing Desk feature is close to one when the head orientation points towards the desk. Head orientation was measured using a camera with a facial feature tracking software library (see section 3.1).

3.3.3. Neutral Facial Expression

Neutral Facial Expression is the raw confidence level for a detected neutral facial expression. It lies between 0 and 1, with a value of 1 indicating a confident detection. In a prior experiment, the neutral facial expression was significantly more often observed in focus environments [3]. Facial expression was measured using a camera and a facial feature tracking software library (see section 3.1).

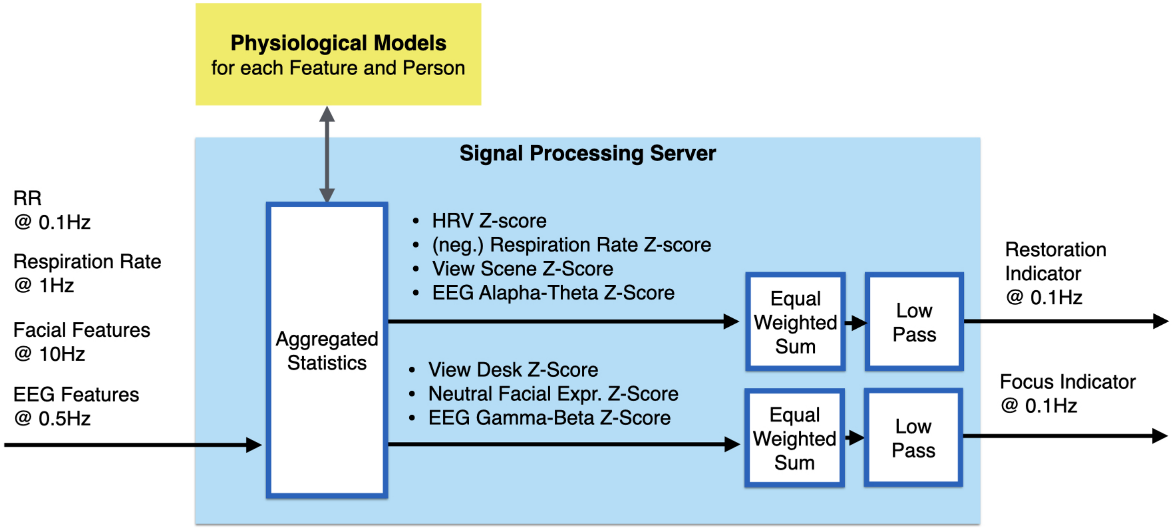


Figure 5: Diagram of the Signal Processing Server.

3.3.4. Respiration Rate

Respiration Rate was included in this configuration because of its important role for self-regulation. Breathing techniques have been widely used for treatment of many psychiatric disorders, such as anxiety and depression, as well as for relaxation training and mood regulation for healthy individuals [55]. It is also traditionally part of exercises like meditation and Qigong. Breathing rate varies in response to a person's activity and emotional state. Low respiration rates are generally considered as more relaxed and restorative [55]. In this configuration, we included the respiration rate measured using the Zephyr Bioharness 3 [54] as an component of the Restoration indicator.

3.3.5. EEG

The electroencephalogram (EEG) is a noninvasive method to monitor the state of the brain. Traditionally, EEG is used in neuroscience and cognitive science for applications such as sleep and memory research, epilepsy monitoring, or attention deficit hyperactivity disorder (ADHD) [56]. In our application, we use EEG monitoring to infer the occupant's cognitive state. EEG spectral analysis commonly divides the signal into five frequency bands that are associated with different mental states [57]. Alpha waves can be observed in healthy individuals when they are awake but are in a relaxed, resting mental state or when their eyes are closed [57, 56]. An increase of Theta activity, on the other hand, has been associated with a state of drowsiness in adults [58]. Beta and Gamma waves are of higher frequency and occur during focused mental activity [59, 60]. In our implementation, we used the Muse Headband and an entropy-based approach to compute focus and relaxation scores from relative spectral band powers. This method was introduced and evaluated in [61]. For the relaxation score — EEG Alpha-Theta — Tsallis entropy was computed using the relative spectral power of the Alpha and Theta bands. For the Focus score — EEG Gamma-Beta — Gamma and Beta bands were used respectively. The samples for each channel were interpreted as random variables $x_i, i \in \{\theta, \alpha, \beta, \gamma\}$ with the conditions $p_i \geq 0$ and $\sum_i p_i = 1$. We used order $\alpha = 3$ [62] Tsallis entropy H_{Ts} [63] defined as:

$$H_{Ts} = \frac{1}{\alpha - 1} \cdot \sum_i (p_i - p_i^\alpha) \,. \tag{1}$$

3.3.6. Focus and Restoration Indicators

We computed Z-scores for each sensor feature using:

$$x_{p,f} = (x - \mu_{p,f})/\sigma_{p,f} \tag{2}$$

where x is the sensor data point, p is the occupant's ID, and f is the sensor feature. $\mu_{p,f}$ and $\sigma_{p,f}$ denote the mean and standard deviation of occupant p and sensor feature f. Z-scores are then low pass filtered (rolling mean with a 10 s window) and combined into a weighted sum with equal weights as shown in Figure 5 to compute the focus and restoration indicators. If a feature is temporarily not available, then its weight is distributed to the other features.

3.4. Control Mode Algorithms

We introduce a dissimilarity (unfitness) metric, which is the Euclidean distance between the focus (f'_s) and restoration (r'_s) scores of a scene (s) and the reference focus (f) and restoration (r) coordinate in the Control Map as defined by:

$$d_s = \|(f,r) - (f'_s, r'_s)\| \,. \tag{3}$$

In the Learning Mode, the user selects a focus and restoration goal by dragging a goal marker on the Control Map. The marker's position can be readjusted at any time. For each update cycle the application calculates the dissimilarity metric for each available scene and the current goal coordinate. The system then displays the optimal scene with the lowest dissimilarity score.

If the optimal scene is the same as the last active scene, then the system continues to display the active scene. If a scene change is required, the system then triggers a transition routine. In order to avoid startling the users, our system smoothly dissolves between different lighting states and images dissolve through a neutral state with no image displayed, with transitions taking a few seconds to complete.

Using the Skip option, the user can skip the automatically selected scene and change to a the next scene, sorted by the dissimilarity measure. The Scene Model, which determines the scenes' coordinates on the Control Map, is updated with the incoming focus/restoration indicator values (see Section 3.2).

In the Preset Mode, for each update cycle the application calculates the dissimilarity metric for each available scene and the current focus/restoration indicator coordinate. The system displays the optimal scene with the lowest dissimilarity score. A heuristically-determined threshold was added to prevent frequent scene changes. The difference between the dissimilarity scores of the optimal scene and the active scene must be grater than the threshold in order to trigger a scene change. A scene change leads to a transition routine as described above.

4. User Study

4.1. Participants

The population of interest are knowledge workers, who mainly work in office-type settings. Therefore, the panel (N=9) consisted of graduate students and local knowledge workers who work in offices. To improve the diversity of responses for this preliminary experiment, we controlled for the level of expertise of the participants. The panel comprised of 30% technical experts with special interest in Internet of Things (IoT) and/or Affective Computing, 30% interior and furniture design experts, and 30% non-experts. To be considered an expert, the participant must have several years of experience and be actively working in their field.

4.2. Procedure

At any time during the experiment, the participant was allowed to open the office door, leave the office, and notify the study personnel about any concerns or needs. Each experimental session began with an introduction of the system. The study personnel demonstrated several atmospheric scenes and explained what physiological signals were collected. For each mode, the participant received a tutorial from the study personnel. Every participant experienced both control modes, but their order was selected randomly.

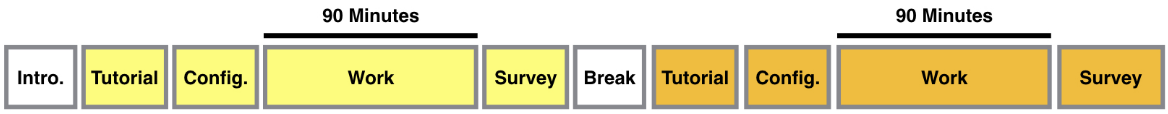


Figure 6: Experiment procedure.

After the tutorial, the participant configured the application by themselves. Participants were instructed to place scenes into the control Map (Figure 4) through drag and drop, hence the position of the scenes should reflect their focus and restoration preferences. For the Preset Mode, they were instructed to only choose four scenes that personally corresponded to the different axis combinations, and place one into the center of each quadrant. We constrained the number of scenes to four so it would be easier for participants to remember which scene was associated to which state. In the Learning Mode, participants were allowed to place as many scenes as they wanted into the control map.

When the participant was finished with the configuration, they worked for 90 minutes on their normal desk-based work tasks. The system measured the user's physiological state and controlled the ambient environment during this work period. After 90 minutes, the participant completed the survey and was asked to take a break. After the break, the same procedure repeated for the second control mode.

4.3. Goal Achievement Metric

For the Learning Mode we analysed the user's ability to achieve their self-reported goal by computing the amount of time relative to the duration of the experiment session in which the user was in the desired state. The desired states are "focus" (focus indicator (FI) above average), "high focus" (focus indicator (FI) above average by 0.5 standard deviation), "restoration" (restoration indicator (RI) above average), and "high restoration" (restoration indicator (RI) above average by 0.5 standard deviation). For this analysis, participants' goals are categorized as "focus" (focus goal $FG > 0$ and restoration goal $RG < 0$), "restoration" (focus goal $FG < 0$ and restoration goal $RG > 0$) and "focus and restoration" (focus goal $FG > 0$ and restoration goal $RG > 0$).

4.4. Survey

We used the System Usability Score (SUS) [64] with additional survey questions. Participants answered six additional questions on a 5-point Likert scale supplemented by essay questions, where they were able to write short paragraphs about their experience. We split each essay into smaller statements and summarized the statements into overarching themes. Each statement contained either one sub-sentence, one sentence, or multiple sentences that described a single phenomenon.

5. Results

5.1. Goal Achievement

Table 2 summarizes the result of the goal achievement analysis for the Learning Mode. Participants achieved the most amount of restoration when the selected goal was restoration (only). When participants selected the focus (only) goal, their focus time increased and restoration time decreased in comparison to the restoration (only) setting. When the focus and restoration goal was selected, focus time was even higher than in the focus (only) setting. At the same time, the amount of restoration time reduced. Despite less time spend on restoration, participants were in fact more often in the high restoration state when the selected goal was focus and restoration in comparison to focus (only).

Figure 5.1 shows several examples of the learned user model. It visualizes the user's scene models as 2D histograms of focus (x-axis) and restoration (y-axis) indicators for five most used atmospheric scenes and three examples for each scene. The area of high numbers of observations (labeled as Very Often in the diagram) corresponds to the area on the Control Map where the associated scene would be located. The distribution of physiological states are often unique for each participant and atmospheric setting. For example, for one participant the Sunset scene was more likely to introduce a restorative state; for another participant it was more likely to reduce restoration and increase focus.

	Goal Achievement			
Goal Setting	Focus (FI >0)	High Focus (FI >0.5)	Rest. (RI >0)	High Rest. (RI >0.5)
Restoration (FG <0, RG >0)	44.6%	6.5 %	65.1%	18.2 %
Focus (FG >0, RG <0)	64.2 %	26.1 %	51.8%	6.8 %
Focus and Rest. (FG >0, RG >0)	74.9%	27.8 %	45.0%	7.8 %

Table 2: Result of the goal achievement analysis. Focus and restoration goal achievement are measured as the amount of time in which a physiological state was achieved relative to the duration of the experiment session. We classify measurements of the participant's physiological state into Focus, High Focus, Restoration, and High Restoration based the Focus Indicator (FI) and Restoration Indicator (RI). We consider three goal settings, Focus (only), Restoration (only), and Focus and restoration, which have the specified ranges of Focus Goal (FG) and Restoration Goal (RG) settings.

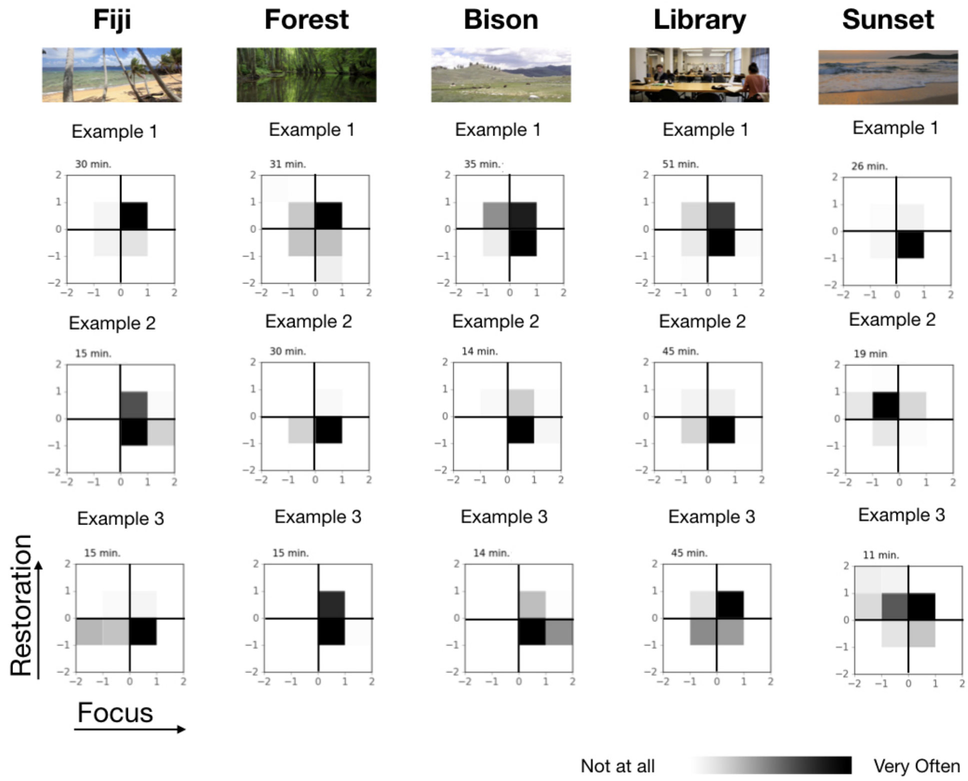


Figure 7: Diagram of participants' physiological states as 2D histograms in the Focus (x-axis) and Restoration (y-axis) map. It shows five of the most used scenes and three examples for each scene. The duration of time spent in the scene by the example participant is shown in the left upper corner of each histogram diagram.

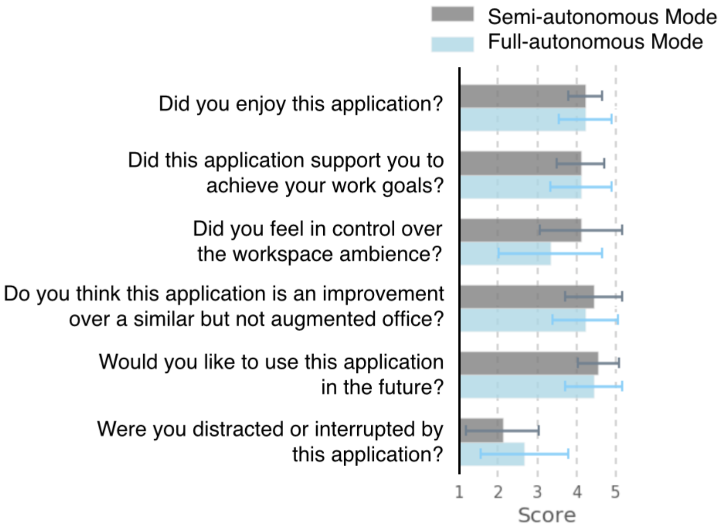


Figure 8: Results of the Experience Survey. The x-axis represents the user's ratings from 1 (Not at all) to 5 (Very much).

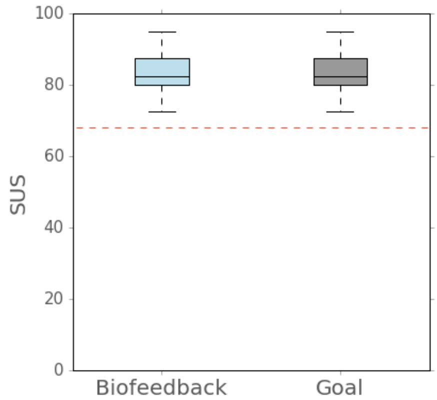


Figure 9: Results using the System Usability Scale (SUS). The x-axis shows the two application modes and the y-axis shows the SUS score. SUS above the red line (> 68) is considered above average.

5.2. Survey Results

SUS was above General Average Performance (> 68) for both application modes (see Figure 9). Mean SUS was slightly higher for the Learning Mode ($M = 85.0, SD = 8.6$) than the Preset Mode ($M = 82.2, SD = 8.8$). Ratings from the additional six questions are visualized in Figure 8. Participants reported that both applications were enjoyable, supporting their work activities, and an improvement to the neutral office. Except for two questions, the survey results are very similar for both application modes. The difference is that participants felt more in control and less distracted when they used the Learning Mode in comparison to the Preset Mode.

Participant's written answers can be summarized into six central topics: Scenes, Self-observation, Adaptive Control, Outcome, Future Features, and Novelty.

Scenes The first topic, Scenes, discusses the effects and attributes of the atmospheric scenes. Participants choose scenes from the same scene library in both application modes. The difference between the two modes is that in the Preset Mode participants were limited to use only four scenes, while in the semi-automatic mode they could use the entire scene library or as many scenes as they wanted.

For both application modes, participants wrote that being able to switch between different virtual locations improved their focus level and work experience. After using the Learning Mode, participants wrote for example: "I really enjoy to work in different locations."(S7), "I also like discovering the scenes" (S1), "I liked the possibility of switching between different scenes to stay focused." (S5), and "the scenes help me to feel good or focused on my work" (S8). After using the Preset Mode, they wrote for example: "The immersing experience of relaxing in a forest while working was incredible." (S9) and "the four [scenes] allowed me to focus perfectly on my work but in different ways"(S8).

Sometimes participants discovered something new about themselves through the new experience. After using the Preset Mode, they wrote for example: "At first, I wasn't sure I was going to like the lighting changes, but it really enhanced my work experience!" (S4) and "I realized that I focused easily when the lights go[es] down. I feel more concentrated when people are walking and talking in Shibuya, contrary to what I could think. It put myself in more safe position to work." (S8).

Participants' comments also showed that on the one hand, the video projection gave them the necessary context to provide a sense of escape or change of location, but on the other hand lighting and sound had a more lasting effect when they were visually focused on their work. For example participants commented after using the Learning Mode: "[I enjoyed the application] very much because it's realistic" (S8) and "I think the effect of the screen was even more powerful during short breaks in which I was not looking at the laptop or the papers" (S7) Other participants wrote after using the Preset Mode: "I think the combination of lighting and sound were what made the most impact, as opposed to the visual and dynamic scenes on the screen." (S6) and "For example when I started sketching the scene changed from the forest to the library, which was nice. The light was the main improvement, because it became brighter." (S2)

Participants commented negatively about peripheral movements and undesired movements in the video projection. After using the Learning Mode one participants wrote: "Some movement in "calm" environments (library, reading room) distracted me. That student fiddling with his pen drove me nuts." (S5). Another participant commented that "I had to stop each scene with train (chicago or rollercoaster) because [of] the speed sensation on the train" (S9).

Participants also reacted negatively to interrupting lighting changes and lighting that was not suitable for their task. One participant wrote after using the Learning Mode "Some times I got an scene with lighting that was not appropriate for my reading so I changed the setting." (S7) Another participant wrote after using the Preset Mode: "light changes broke my concentration at times." (S9)

Self-observation The topic Self-observation discusses statements related to the experience of seeing one's own physiological state. Participant were able to use the graphical interface to track their inferred physiological state in the Focus-Restoration Control Map. They were also able to observe the adaptive settings in the office, which directly reacts to physiological changes.

Participants positively commented on their learning experience. For example, one participant wrote after using the Learning Mode: "I felt like I had a much better understanding of what environments actually do lend themselves to different work states" (S6). Another wrote after using the Preset Mode: "[the application] allowed me to realize lots of things about my concentration" (S8). In the Preset Mode, ambient changes notified participant's about changes in their physiological state, for example one participant wrote: "I appreciated the cues, especially when I was on the distracted side of the spectrum and adjust back to a focused place" (S4) and "I also enjoyed the change, it kept me more mindful and aware. When the environment changed, I could understand very quickly that I was moving outside of the zone I wanted to be in and used that feedback to either understand I needed a break or make other adjustments to get back to the preferred zone" (S4)

Beside scene changes, repetitive sounds and looping of the video also functioned as a trigger of self-reflection. One participant wrote after using the Learning Mode: "[I] would react mostly where something would happen in the sound (e.g. a voice or some other interruption). In those circumstances I felt prompted back to my task if I had been procrastinating and otherwise did not feel affected." (S1) and "Those bottom up distractions are distinct from the top-down interest in checking the application, and tended to semi-passively alert me to my current activity (i.e. am I reading the news or am I working?)." (S1)

Participants responded more often negatively to self-observations in the Preset Mode than the Learning Mode. They felt distracted by the ambient changes, especially, when they were not able to achieve the desired physiological state. Participants wrote for example: "I want the focused and relaxed scene[,] but the more I think about it, the less focused and relaxed [I] am" (S5), "If I didn't like the fact that I was in the energizing/distracting zone, it wasn't because I disagreed with the program putting me there - it was because I didn't like that I wasn't relaxed or focused" (S4), "I must admit that becoming conscious of the changes in the scene and what I had conditioned it to mean to my concentration was a bit distracting" (S9), and "Distractions were mostly caused by a transition I didn't expect (usually during a focused moment)" (S1). For the Learning Mode one participant wrote: "I am a procrastinator, so naturally I was interested to check regularly on what the application was doing or measuring, or to pick a new goal" (S1).

Adaptive Control Comments about sensing, context recognition, and control algorithms were summarized to the topic Adaptive Control. This group of comments discusses the perceived intelligent, transparency and usefulness of the applications, as well as accuracy and timeliness of sensing and actuation.

For the Learning Mode, participant responded positively about having control, They wrote for example: ”Getting to articulate what my goal is certainly helped the feeling of control” (S4), ”I felt in control because the controller offered fine grained control over both the target and the scene choice, leaving me free to adjust as necessary” (S1), ”It was very easy to jump from one scene to another” (S7), ”The App is easy to use and as I see it, it leads you to set a mood / background to the work you are doing, so the level of control was sufficient to direct the mood” (S2), ”Totally in control of it, and it was a very conscious decision when I would change scenes because I realized the scene I had been on did not lend itself well to what I was working on, and a different scene would” (S6), and ”I could just skip scenes that did not work for me”(S5).

Participants also commented positively on the system’s ability to learn and adapt to their responses. For example one participant wrote: ”I might have misjudged what [scenes] worked for me, but overtime as the program learns individual preferences from the feedback - I imagine that would self-correct” (S4).

Negative comments were directed towards the need of selecting scenes during the setup, for example: ”I enjoyed this application, but I did not like having to consciously think about which environment I should select to help aid in my work flow” (S6) ”I might have misjudged what worked for me” (S4), and ”When I didn’t feel the environment hit the goal as well as I wanted, then I felt less in control” (S4).

For the Preset Mode participants commented positively about the system’s timely response to activity changes and how atmospheric changes would trigger a break or different work activity, for example participants wrote: ”Most of the time I deliberately took a break, the system did exactly the right thing (matched my break state with a nice scene). Other times, I took a break because the system had transitioned to a break scene unexpectedly. That’s nice too though, I suppose, to be prompted into taking breaks”, ”sometimes I start an activity and the scene would follow. [...] Sometimes the scene changes first and then I changed my activity” (S2), ”When the environment did change, I felt the shift was very accurate based on what I was thinking about at the time” (S4), and ”I really liked how the scene changed depending on what I was working on because I felt like it allowed me to not focus on where I was but rather what I was doing” (S6). Participants also mentioned that it was enjoyable to not be in control for example ”[It] feels like [I was] 50% in control... but it was still fairly interesting ... I think it is positive to not be in control” (S2).

Sometimes the system did not respond as the participant expected. Participants commented negatively about frequent and unexpected changes: ”[...] it sometimes changes between focused relaxed and focused energizing (while I feel I am the same). I don’t know why” (S3), ”And sometimes it felt like it was doing the right thing and other times I wasn’t sure what prompted the system to transition to another scene” (S1), and ”I did not like the frequent changes” (S5).

Outcome In some comments, participants described the outcome as a measure of their experience. For example participants wrote after using the Learning Mode ”[I] worked pretty well!” (S3), ”I think I had (in my view) 2 productive hours of work” (S2), and ”I think I was very focused and relaxed while working” (S7). Similarly, participants wrote after using the Preset Mode: ”Towards the end, as it became a little more familiar, I found it to actually help me get farther into that mindset, such as focused/relaxed” (S4) and ”I felt like my work was greatly enhanced” (S6).

Future Features Comments that describe missing features and expansion of existing features are summarized as Future Features. After using the Learning Mode, one participant suggested including additional environmental control: ”I would have wished to further feel the wind and smell from different locations” (S7) and another participant mentioned additional control over lighting ”The only thing I would have changed is, again, the brightness” (S5).

For the Preset Mode, in which participants only used four atmospheric scenes, feature requests are related to adding more scenes: ”I enjoyed the experience but as I only selected four scenes, it end[ed] up being a bit repetitive.” (S7) and ”would have been nice to add more scenes per zone. Since there are only 4 scenes, they sometime feel too much in contrast.” (S2).

Novelty In a few comments, participants described how the novelty of this application distracted them from focusing on their work, for example: ”Toward the beginning I think the distraction was mostly due to the novelty” (S2) and ”That impulse [of checking one’s data] is also a function of novelty. I am certain that in more regular usage that would diminish” (T1). In another comment a participant suggested a longer usage period ”I think the idea of ambient biofeedback is quite interesting but I guess longer experiments need to be done to experience complex states such as focus level” (T3).

6. Discussion

6.1. Goal Achievement

The results for goal achievement indicate that in our experiment the user was able to achieve more focus time with less restoration time when the selected goal was both focus and restoration. This result is in line with the attention restoration theory, which describes that certain environmental properties, such as sound and images of nature, can recharge depleted mental resources more quickly than other kinds of environments, e.g. city landscape. Despite spending less time in the restorative state, participants were able to achieve high restorative states more often.

The differences in participants’ physiological responses, as shown in Figure 5.1, indicate that personalization can achieve a better outcome than a generalized approach. Additionally, differences in how participants interacted with the system and their comments indicate that the user’s preference is likely to change over time in a long-term user study. Some users might need more choices of scenes to keep the experience appealing, while others might settle on favorite scenes. In the experiment detailed in this paper, some users frequently changed the atmospheric setting, while others only configure their goal once at the beginning of the session. Some people noted in the comments that the limited number of scenes will become less interesting after a long time of use, while other participants preferred to use a few settings. Therefore we believe that personalization and continuous learning are crucial for the Mediated Atmospheres application. The user could potentially design or record their own scenes by specifying the lighting, visuals, and sounds.

Our observations also indicate that the adaptive environment can help the user to overcome unwanted behavioral patterns through repetitions and just-in-time transitions of the scene. Participants reported that a change of atmospheric scenes prompted them to adapt their activities. Besides scene changes, participants’ also said that repetitions in the video or sound helped to break procrastination behavior. In some scenes, the video and sound repeated after 10 - 20 minutes by looping back and transitioning with a cross-fade to a random previous position in the video. One participant commented that the repetition provided a sense of time and a reminder to reflect on one’s active task. These environmental cues could be used intentionally to *calmly* — as defined in the foreground/background classification of Human-Computer Interaction [48] — notify users.

6.2. Multidimensional Model of the User’s Physiological State

Both modes achieve above-average usability compared to the benchmark score. This result suggests that participants overall understood the user interface. The control map effectively communicated the system’s control capabilities as well as the intended use of the system. Some participants even used the control map to monitor their physiological state. Participants noted that they enjoyed seeing the marker that represented their physiological state ”move around” in the control map and in particularly when it took ”big steps”.

The two-dimensional orthogonal representation of focus and restoration is a gross approximation of complex phenomena of the human body, which, in reality, are not independent of each other. As our preliminary result indicates, improved restoration, in fact, leads to higher focus. However, the control map was easy for the user to understand and is, therefore, a viable approach for future research. Our findings suggest that we could use the control map with only two instead of four quadrants (Restoration (only) and focus and restoration) for maximizing focus and restoration in the workspace.

In future research, we plan to include additional control dimensions in the control map. For example, creativity and sociability are both relevant control dimensions in the workspace. Much research has shown the impact of the ambient environment on creative cognition and social behavior. Yet we need to develop sensor features that can evaluate these dimensions.

The MA prototype introduced in this paper uses multimodal media and sensing. We can easily extend the system with additional sensors and output modalities. In future research, we plan to include new media outputs, such as olfactory experiences or a responsive display for increased immersion. While existing research strongly suggests that scent will have a significant impact on the user's response, there many remaining questions about how to introduce the olfactory experience in the multimodal context and how the outcome compares to the existing setup. We will also explore alternative sensors for non-intrusive, contact-free physiological sensing. Wrist-worn sensors are less intrusive than sensors in the chest region. However, wrist-worn sensors are prone to motion artifacts, which could be challenging in the work context, where the user's hands and arms are moving. Alternative contact-free solutions for heart rate and respiration rate tracking are Ballistocardiography, radar-based, and vision-based sensors.

6.3. Level of Control for Human-in-the-Loop Operation

The results indicate that the Learning Mode has the preferred level of control. However certain features of the Preset Mode could be used to enhance the Learning application. Despite a lower level of perceived control and an increased distraction, the Preset Mode provided an attractive alternative to the goal-driven system through context-awareness and achieved a similar SUS value. Participants described that they enjoyed losing control in the Preset Mode. They felt especially supported when the Autonomous system responded as they changed their work task and transformed automatically according to their activities. This learning suggests that the timing of scene changes in the Learning Mode should follow the user's activity change rather than using a fixed or random timing.

The Preset Mode was, on average, more distracting for the participants, because they were notified about every physiological state change. This made them aware of their physiological state, and sometimes even prompted them to check the visualization of their physiological signals to learn more. In the Learning Mode, this effect was reduced, although driven by curiosity, some participants nevertheless checked the graphical interface regularly. We expect that this kind of behavior and ensuing distractions will decrease over time, as the user becomes more familiar with the system. However, the preliminary study result suggests that we should limit the means of self-observation in future implementations to reduce distraction.

From the participants' answers, we learned that positive self-observation - an indication of the desired state - was perceived as a reward or a source of motivation, while negative self-observation - when the observation indicated an undesired state - caused further distress. This finding could be related to the theory of introspective awareness. It was found that people with heightened ability to perceive their bodily states, e.g. heart rate, also experienced emotions more intensely [65]. It was also found that the visualization of the desired state or physiological signal could be used to guide the user to achieve their desired state.

6.4. Ethical Considerations

Thinking forward, preferences and affective response could be aggregated across networked users everywhere, resulting in a large generated library of scenes calibrated over a multitude of different users. Although this work points towards improving indoor work environments, it also raises a multitude of ethical questions that inspire rich debate. Is it proper to degrade a physical workspace if it is virtually compensated or augmented in some way? Could our interdependence with deeply augmented environments eventually make us incapable of living without them (a theme explored in speculative fiction for over a century now [66]). In the not too distant future, machine models of our reactions to controlled stimuli may make us very gullible to persuasion and suggestion. This is a tactic long-exploited in advertising and recently honed for divergent purposes in today's online world, often with a negative consequence. As our digital extension gets to know us at this level of intimacy under the expansion of IoT, it becomes important to be confident that it is working mainly on our behalf and that the user is, in principle, ultimately in control. This will undoubtedly be the topic of many important future studies.

7. Conclusions

We introduced Mediated Atmospheres — a closed-loop control system for an office equipped with a sensor network and multimodal media (controllable lighting, projection, and sound). This system adapts the ambient properties of the workspace continuously according to the user's physiological states to improve the user's productivity and stress restoration in the workspace. The results of a preliminary near-natural use study showed that the closed-loop system can create an improvement over the unaugmented office. We found that participants were able to increase the amount of time in which they achieved deep focus when the system optimized for both focus and stress restoration rather than focus alone. Participants were able to double the time in which they achieved high restoration when then environment optimized for restoration rather than focus. We measured focus and stress restoration through a combination of sensor features including heart rate variability, electroencephalogram (EEG), and facial expression. We achieved a System Usability Score above average, which is evidence that our method for perceptual embedding using the control map created a useful and transparent interface for closed-loop control of a multimodal environment. The control map establishes a multidimensional model of the user's physiological state in relation to system control space. To gain insight on perceived control, we compared two application modes: Autonomous and Learning Mode. Surprisingly, both modes achieved similar usability ratings, and ratings on perceived support, despite differences in perceived control and distraction. This outcome reveals opportunities to combine the advantages of both application modes. Thinking forward, MA could aggregated preferences and affective response across a network of users, to generate a large library of scenes calibrated over a multitude of different users. We have concentrated on applications in an office scenario, but these ideas could apply in many other situations where a user's stimulation is restricted - e.g., in quarantine (as much of this paper is being edited under the COVID-19 lockdown, such applications are poignant), on extended manned space missions, etc.

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