Mediated Atmospheres
Context-aware Adaptive Lighting and Multimodal Media Environments

by

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Dipl.-Ing., RWTH Aachen University (2011)

Submitted to the School of Architecture and Planning
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Abstract

This dissertation introduces a controller for a context-aware office space that seamlessly and continuously transforms itself to support the activities of its occupants. Properties of the workspace, such as light, sound, textures and objects, have a remarkable influence on the human body, with measurable effects on physiology, cognition, and emotion. New control capabilities, e.g. wireless-controlled lighting and digital media displays, offer an opportunity to dynamically enhance the workspace for recreation, creativity, and productivity, in unison with the occupant's activities. Besides benefits for work engagement, personalized control could optimize for energy efficiency and foster Loose Fit planning to maximize flexible use of limited space.

Accordingly, this controller incorporates sensing and computation to mediate between occupants' actions and the adaptive environment in a closed-loop fashion, producing what I call Mediated Atmospheres — seamless transitions of harmonious compositions of (1) light and (2) multimodal media. Through a series of studies, I evaluated this controller and demonstrated its potential to improve the workspace. Improvements were observed in energy savings (52% estimated energy savings compared to static illumination), significant ($p < 0.05$) increases of perceived fitness for focus and stress restoration, and significant ($p < 0.05$) physiological changes towards preferred conditions, e.g. in heart rate variability and facial expression. Furthermore, this work discusses the effects of adaptation as a form of behavioral feedback and raises broadly applicable questions about how to best balance automatic control and manual preference setting.

The controller, in its core, builds on two contextual control dimensions, Focus and Restoration, which were experimentally discovered. They establish a lower dimensional representation (control map) that facilitates continuous mapping of the sensing and adaptive capabilities. Each unique space produces a new control map, which I computed using either subjective ratings, image analysis or physiological monitoring of the occupant. I performed an in-depth comparison of the image and rating approach for lighting and found that image analysis of either photographs or 3D renderings can accelerate the mapping process by reducing the amount of required human input. This finding allows us to generalize the subjective rating approach, and for the first time enables practicing designers to quickly link the positioning of lighting instruments to perceptual models of space.

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This doctoral thesis has been examined by a Committee as follows:

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

This dissertation introduces an intelligent workspace that can dynamically transform its ambient appearance or atmosphere according to the user's activities in a closed-loop fashion. I call this concept *Mediated Atmospheres*, where sensing and computation mediate between occupants' actions and the responsive environment. As an example, the responsive office might provide a bright, energizing lighting design for demanding work activities and an elegant, cozy atmosphere for casual meetings. To not overwhelm the user with additional control and maintenance duties, the office senses the occupants' context and seamlessly and continuously adapts to the situation. The system can offer a personalized experience as it is aware of the user's unique response to the ambient changes. Accordingly, the office might turn into an artifact-strewn artist's living room when it is time to spark creativity and into a flowering mountain meadow when it is the moment to recharge. Because the room is aware of the occupant's physiological state, it can provide feedback and guidance to promote wellbeing and a healthy work routine. This research aims to discover and discuss the advantages of this adaptive concept over static conditions, in particular how it might improve the workplace.

This introductory chapter examines why such system could be useful, feasible and relevant to today's needs in the workplace. The introduction begins with a brief survey of environment-induced effects on physiology, cognition, and wellbeing to motivate the potential advantages of Mediated Atmospheres and the justifiability of this research effort. Building on this survey I define *Atmospheric Composition* for digital control. A subsequent depiction of the emerging challenges in workplace design gives context for potential future deployment of this technology. Lastly, I explain the control system and discuss why the *Control Map* — a lower-dimensional representation of the control capabilities is a viable solution to the existing technical challenges and constraints.

1.1 Effects of the Ambient Environment on Physiology, Cognition, and Wellbeing

Light has an acute effect on alertness. In particular, certain types of lighting have been shown to elevate heart rate, increase core body temperature, enhance psychomotor performance, and change brain activation patterns to a more alert state [45, 127, 22]. Exposure to this kind of lighting condition during learning exercises can improve performance in the long term [105, 7]. These discoveries suggest that a brightly illuminated space is suitable for activities, which require a vigilant state of mind but should be avoided if the reverse effect is desired.

In a complex interplay, ambient light, sound, and visual images produce cues to retrieve memory and can enhance or limit cognitive performance. Exposure to irrelevant auditory or visual stimuli - noise - can take mental resources away from the tasks at hand and make it difficult to recall memories and sustain motivation to continue the task [28, 50, 121, 32]. However, a low level of ambient noise — for example, the sound of a coffee shop — has been shown to enhance creative cognition [99]. A possible explanation for this phenomenon is that certain kinds of stimuli, even if they do not directly relate to the task, can attract people's attention and enhance their interests, thus help them to invest more mental effort [28]. Likewise, the space geometry, color, and materials of the work environment also have an influence on cognitive load and performance [101, 95, 98]. Depending on the type of task, e.g., creative problem solving vs. a memory span task, the same environment might promote different or even reversed effects. Hence, an updated Cognitive Load Model recognizes the surrounding environment as one of its primary causal factors [28]. People possess an intuition to seek the environment that is suitable for their activities. For example, a student might attend a library to study for an exam but is more attracted to a bench underneath a tree when she wants to write a creative essay.

While some environmental qualities enhance productivity, others are more suitable for restoration, the renewal of diminished mental resources. Much research has considered the

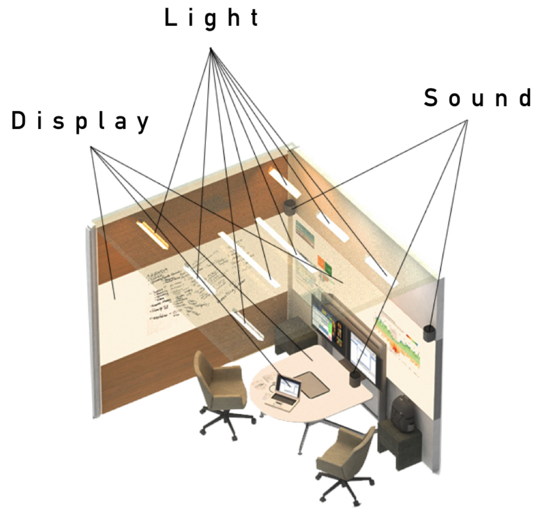


Figure 1-1: Example office with controllable lighting, image displays and sound.

therapeutic effect of natural environments [57]. The evidence suggests that images and sounds of nature promote positive shifts in mood, a decline in arousal, and improved ability to focus attention [112, 43, 56, 130]. The Attention Restoration Theory (ART) in particular highlights the benefits of such experience to accelerate recovery from mental fatigue [77, 76]. Prolonged periods of concentration exhaust the ability to endure challenging tasks and require a subsequent recharge. Besides qualities related to nature, the ART also describes the sense of being away and a feeling of fascination as central characteristics of restorative environments.

1.2 Atmospheric Compositions

Building on the overwhelming evidence that the ambient environment can enhance wellbeing and productivity, my research explores how new digital control capabilities could be used to improve the workspace. The *Atmospheric Composition* encompasses the combination of factors that determine occupants' experiences of the space. In theater and art, artificial lighting is a primary tool to create experiences for the viewer. Numerous works, in particular by the artists James Turrell, have demonstrated the power of light to decompose architecture and to redefine the viewer's perception. In a series of installations titled Ganzfeld, Turrell used diffused colored lighting to create rooms that have no feeling of depth [141]. Saturated colors erased all corners and surfaces in the room from the viewer's experience. The lack of orientation, Turrell explains, gives people no point of focus and induces an effect similar to sensory deprivation, which relaxes the mind and allows the person to become fully present [97].

An example of atmospheric composition in current practice is the office design of the technology company Google, which stands out with the playful use of non-work related visuals and artifacts. In the Budapest branch, one meeting room appears to be a swimming pool showing a game of water polo, which is a popular sport in Hungary [66]. The floor displays a painted image of swimming pool water. On top of it, the chairs are in a matching color of blue. A wall-to-wall image shows a cheering audience at a water polo game. While the furniture and equipment in the office support work activities the atmosphere reflects an environment of recreation and play, competition, and national pride. The interior designer created a visual story to engage the occupant's interest and imagination.

With advances in Ubiquitous Computing and the advent of Internet of Things (IoT), products such as wirelessly controllable light fixtures and sound speakers with ultra-short-throw projectors or large flat displays are unlocking new possibilities to augment the interior of everyday living- and workspaces. In this work, I use these technologies to create atmospheric compositions or *Scenes*. The composition of these outputs can form a singular experience, similar to theatrical stage design. For many practical reasons, these devices rarely work collectively. For example lighting and displays, despite their fundamental similarity as light emitters, are commonly controlled independently and often through different means of interaction. However, the combination of different media outputs can form a multimodal sensory experience that is much more powerful in transforming one's experience in the room. In this work, I therefore, consider them as a collective. The design of atmospheric scenes takes into account the environmental impact of light, imagery, and sound on performance and wellbeing.

This work especially focuses on Solid State Lighting technology. Compared to fluorescent or incandescent lighting, Light Emitting Diodes (LED) offer an increased resolution for temporal and spectral control. The spectral specification has been shown to have a significant impact on human physiology in the short- and long-term.

1.3 Towards a Dynamic Workplace

In the knowledge economy, worker satisfaction is paramount to retention and productivity. In the last decade, there has been a decline in workplace satisfaction in the United States related to recent developments and trends in workspace design [48, 131]. Emerging digital work tools has unleashed new flexibility to work from nearly anywhere at any time, which has clear advantages but is also a challenge for existing structures [52, 9]. Recent trends for workplace organization are in line with this advancement towards more flexibility, for example, on-demand offices that can be leased for short periods of time and unassigned desks, where the employee chooses a new workstation on a daily basis. Related concepts such as open-plan offices and Loose Fit, programmable spaces enable more efficient use of the available space and bring justifiable benefits for sustainability. Because workstation density has been steadily growing and will further increase in the future, the limited space becomes increasingly valuable [51]. However, the temporary and open-ended nature of these approaches tend to reduce the level of individual control over the work experience, which is one reason for the decline of workplace satisfaction. Current data also show that office workers who have more control or choice in their workspace are more engaged and more productive [48, 131, 52]. Employees are companies valuable asset [132]. The annual cost of work-related stress in the U.S. is estimated to be 300 billion dollars and the cost of disengagement at work is 550 billion dollars [52]. Accordingly, companies' investment in wellness related initiatives is increasing and the benefit of healthy workspaces has been highlighted in this context [52].

Emerging digital control capabilities could potentially realize a personalized yet flexible work environment. By giving the control to the occupant, the work experience can be adjusted according to their contexts and personal needs. This research, therefore, envisions an office that can dynamically optimize itself in a closed-loop fashion (see Figure 1-2). With the appropriate interface and algorithms, the occupant could train a customized profile containing their preferred configurations. This dynamic approach offers the opportunity to personalize the workspace even when it is only used temporarily. The office might transform from a organized meeting room into a creative idea hub or from a tense library into a rejuvenating nature experience according to the situation.

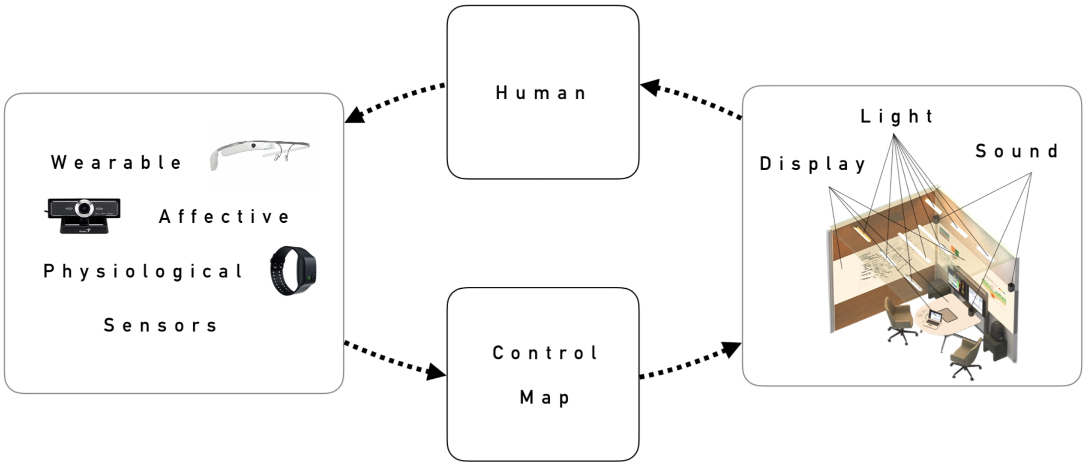


Figure 1-2: Conceptual overview of the closed-loop controller for Mediated Atmospheres.

1.4 Research Overview

One might imagine an office space with twenty ceiling luminaires, each with ten brightness levels. In this setup, there are more than a billion billion possible configurations. Every additional control parameter, e.g. color, expands the number of solutions. Given the near-infinite variation of possible lighting combinations, how might one design a control system for everyday use? The complexity of control must be at an acceptable level to not overwhelm the user with additional maintenance and operational responsibility in an already demanding work context.

A natural user interface is one that is easy to understand and quick to learn despite little prior knowledge about the system. Such an interface must assume some shared understanding or mutual intelligibility between human and machine [133]. It has been argued that because the computer at present only has access to a very limited model of the world, a natural interface is "one that makes explicit the knowledge and processes for which the man and computer share a common understanding" [46]. This form of system transparency is especially crucial for context-aware, automated systems, for instance, the integration of sensing and actuation in smart homes. The lack of transparency in black-box-type control, which conceals the underlying mechanisms from the user, makes it difficult for them to understand the reasoning behind system decisions [161]. Research has shown an understanding gap and intention gap in commercial home automation products and demonstrated the need to address this problem in the future [100]. A possible approach to create a transparent system is to study the user's thought process around the desired application and design a solution using the same problem-solving vocabulary [46].

I introduce an approach that connects expert knowledge with the user interpretation to create a *human-centered* rather than *device-centered* representation or interface of the control capabilities. As an example, the human-centered variation would describe a lighting network according to the activities that the lighting conditions afford, such as their implications for focus or restoration, whereas a device-centered representation would reflect the abilities of the lights, the brightness or color values. A person's experience of the lit environment does not directly translate into device settings. Light hits and reflects from objects and surfaces before it reaches the eye. Hence, the perceptual mapping depends on the lighting setup in the space in addition to the subjective response of the user. Two types of mapping are examined in this research, a *sensor-based* and *rating-based* approach. The later relies on the verbal response of the user to extract meaning from the settings. A sensor-based approach aims to simplify the mapping process for the user. It uses sensor measurements of the environment and the user's physiological response to ambient attributes to reduce the amount of human input required for mapping.

A continuous *Control Map* visualizes the human-centered interpretation of the control capabilities (see Figure 1-3). Similarly to how a two-dimensional city map describes a three-dimensional world through the projection of relevant points in the landscape onto a lower dimensional representation, the map metaphor for Mediated Atmospheres describes a process of finding a compact representation of the output solution space. The solution space for atmospheric composition contains nearly infinite configurations. However, most of them are irrelevant. Since it is impossible to sample all points in the solution space, we rely on *landmarks* for mapping. Landmarks are example compositions or scenes. They can be designed by a practitioner, the user, or computer generated based on domain knowledge. The similarities or differences of the landmarks, either derived from subjective user ratings or objective sensor measurements, establish their coordinates on the map. A dimensionality reduction technique is applied to find a lower dimensional representation which preserves distances between landmarks as much as possible. To achieve a continuous map, it is then necessary to estimate intermediate points between the landmarks.

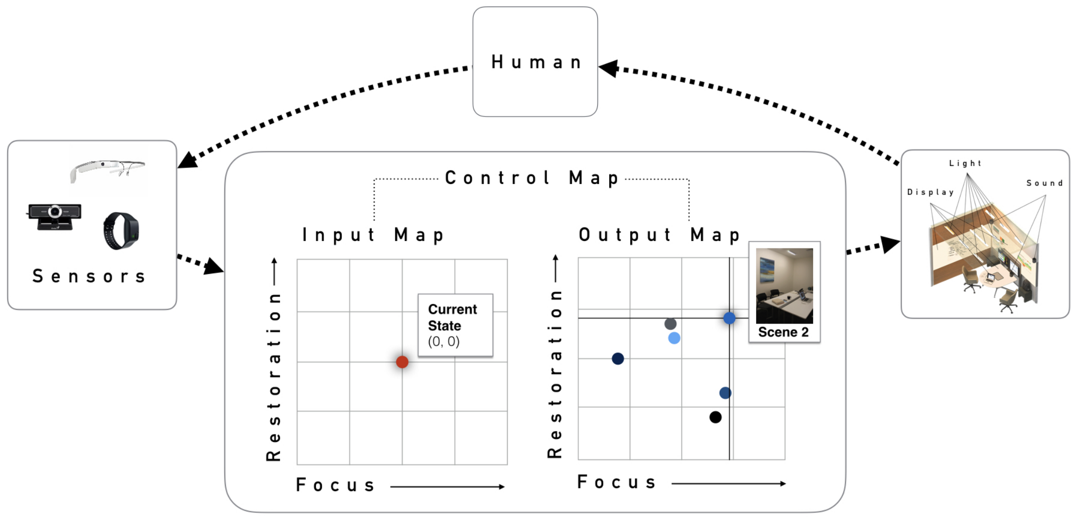


Figure 1-3: Conceptual overview of the *Control Map* in the closed-loop controller for Mediated Atmospheres. It contains and *Input* and *Output Map*.

Using a *compass*, which describes global directions in the map, we can determine the path towards or away from a landmark. In other words, the compass establishes the *control dimensions*. The control dimensions should reflect the user's intention and needs — the problem-solving vocabulary that a person would use to configure the space. Therefore the control map is a template of the mental states that the occupant desires. Using this template, I construct an *output map* that describes how the output modalities or scenes correspond to the control dimensions and an *input map* for context-inference that converts sensor stream to an interpretation of the user's activity state along these dimensions. Using these two maps, the application software defines the behavior of Mediated Atmospheres.

Two variations of Mediated Atmospheres are examined, first an implementation of context-aware lighting and second a multimodal media environment. Context-aware lighting uses 20 digitally controllable multi-color ceiling luminaires and lighting scenes, which vary in color, intensity, and degree of contrast and uniformity. The scenes are produced in collaboration with a lighting designer. The multimodal media environment uses video projection and sound in addition to illumination. In this setup, the atmospheric scenes 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. These scenes vary in their themes such as nature, urban, indoor and outdoor as well as their properties e.g. color, brightness, motion, and repetitiveness. Through a series of experiments with users in life-like work scenarios I evaluate the impact and benefit of these systems.

In summary, this research advances state of the art in two aspects. First, it explores the benefits of adaptive environments for work experience through prototyping and experimentation with users. Building on existing work for energy conservation, comfort, and information delivery, my experiments aim to demonstrate additional possibilities for adaptive environments to influence productivity and physical wellbeing. Second, this work considers multimodal and multivariate control — the control of multiple outputs and media sources simultaneously using atmospheric compositions. I introduce the control map method to simplify and visualize the underlying mechanisms of the context-aware controller and to improve system transparency. A series of experiments establishes the control map and evaluates the generalizability of this approach for context-aware lighting in different kinds of workspaces.

1.5 Thesis Outline

Chapter 2 offers an overview of related research on Adaptive Environments — spaces with sensor-driven digital actuation. Building on this foundation, I then explain the unique contributions of this work in juxtaposition to prior research and the advances it brings to this field. The following three chapters outline three primary research investigations, the methods, results, and discussions. Chapter 3 introduces the work on context-aware lighting. Chapter 4 studies the generalizability of the lighting approach using a sensor-based mapping method rather than one relying on user ratings. Chapter 5 describes the context-aware multimodal controller and its impact on work experience. Finally, in the concluding chapter, I provide a summary of the research results and outlook for Mediated Atmospheres.

Chapter 2

Related Work

An *Adaptive Environment* is a flexible, responsive, and intelligent space that is capable of learning and adapting. Variations of this idea are known as Smart Home, Ambient Intelligence, or the Electric Home, a vision formulated as early as in 1939 [17]. The Adaptive Environment relies on an infrastructure of connected sensors and actuators, and computational intelligence, which processes data in the background. In the last three decades, efforts in Ubiquitous Computing have made significant advances in establishing such infrastructure. State of the art hardware and software solutions have enabled the "Internet of Things", connected devices ranging from hobby projects to luxurious consumer products. These are for example pet feeders that can be activated over the internet and wine containers that can maintain the perfect temperature and recommend wines for the user. However, security and scalability are remaining technical challenges in this field [100].

In this chapter, I introduce related research on Adaptive Environments in three sections. The first section describes context-aware systems that can automate the home or office based on information such as the user's location and preference. I conclude this survey with a discussion of lessons for future development. In the second section, I present related work on multimodal media environments. These environments are not necessarily context-aware, but they can transform their properties to subtly influence the occupant. The last section describes research related to experiential control — systems or interfaces based on models of perception.

2.1 Context-aware Adaptive Environments

The objective to control a building based on routine and preference models is to lower energy consumption and to automate building operations for convenience. Given that illumination accounts for 15% of the total energy consumption in the residential and commercial sectors in the U.S. [41], there is much potential to reduce energy usage through intelligent control, e.g. by deactivating indoor illumination when it is not needed. Researchers developed various methods to learn user preference and predict user needs to achieve this energy goal.

In the Adaptive House project, Mozer et al. retrofitted a home residence with environmental sensors and actuators [106]. The interactions of the residents with the house trained a neural network through reinforcement learning. The authors implemented event-based instead of clock-based segmentation and assumed independent lighting zones with five dimming levels to reduce the complexity of lighting control. Machado and Mendes also applied neural networks to predict light on/off states [89]. In contrast, Callaghan et al. chose fuzzy logic for the control of a dormitory room [24]. The authors preferred fuzzy logic over neural networks because the knowledge acquired by the agent would be in human linguistic terms. In addition, they compared the online agent to an end-user programming approach - programming-by-example. Vainio et al. applied a different fuzzy control technique for control of light intensity and the window blind and demonstrated robustness against temporary user behavior change [143].

In the office context, Aldrich et al. used a portable light sensor to optimize lighting for the detected area of interest and dim lighting in the unoccupied areas [3]. Linear optimization was used to calculate the most efficient setting. Closed-loop feedback adjusted settings to compensate for ambient conditions. In a different study, using a network of motion sensors, Aldrich et al. were able to derive the physical and social boundaries in an open-plan office space [2]. Alongside learned occupancy patterns, the authors were able to determine correct lighting zones and improve turn-off timing. Pan et al. and Miki et al. also demonstrated optimization for multiple users using a wireless sensor network [109, 103]. Chen et al. used energy efficient, colored lighting in addition to dimming in unoccupied areas [26]. Motion and imaging sensors were installed in the workspace to detect a set of predetermined activities. Expert rules were used to state adaptive lighting behavior. Users were able to overwrite rules in the second day of the two-day experiment, and all users changed at least one rule.

Some of these technologies have moved into the commercial domain and have been subject of several academic field studies. Existing implementations both in the commercial and research space, repeatedly demonstrated that controllability for the end user is core to the success of the system. From a technical perspective, manual input is required for user feedback, correction, or manual control during the learning phase [106, 24]. From the user's perspective it is essential to maintain a feeling of being in control [37, 148, 16]. Especially in the case of failure, the source of frustration is the experience of loss of control. Failure often happens because of poor understanding of technical limitations and reasoning behind system decisions [161]. For this reason, it is crucial to provide transparency. Additionally, it is important to acknowledge that it is in human nature to be spontaneous, expressive, and unpredictable. An intelligent interface should, therefore, support exceptions and improvisations [37]. Along these lines, Hallnäs and Redström call for a shift in the design considerations for pervasive computing from *use* to *presence*, from a use- to experience-driven design. Presence, in this case, describes how we invite and accept technology as a part of our everyday live [54].

2.2 Multimodal Media Environments

Spatial Augmented Reality - video projection on the surfaces of a room - is used for a range of applications such as gaming, entertainment, education, remote collaboration, and interaction with virtual objects. Michael Naimark's film installations in the 1970s and 1980s are early examples of Spacial Augmented Reality. In *Displacement* Naimark painted an entire room white including furniture and objects. A rotating image previously filmed inside the rooms is then projected back onto the white surfaces showing the original colors and people interacting with objects. For a brief moment, the image brings the space back to life and then reveals its white emptiness again when it moves on. Spatial projection aligned to the geometry of the space is today referred to as projection mapping. It is often used in performances, for example, the contemporary dance Apparition by Obermaier and Ars Electronica Futurelab in 2004 [39] and later Mortal Engine by Chunky Moves [157]. The dancer's position is captured in real-time and patterns, shadows or a halo is projected on the dancer's body and the background to create stunning effects.

In line with Underkoffler's vision of the IO bulb from 1999, a light bulb that can sense and create visual images [142], contemporary research in spatial augmented reality sometimes use a combination of a depth camera and ultra short throw projection. In the RoomAlive project, Jones used several projector camera units working in concert. The environment tracks the user's position to create an immersive game experience in a living room. In the illumiRoom Jones et al. used the mapping capabilities to extend the image from a television screen into the uneven surface of the environment, creating an overall more immersive experience. A simpler, commercial example of this idea is Philips Ambilight, a lighting system on the edge of the television to illuminate the surrounding area and to enhance the displayed image [111].

Another class of display technology, one that can easily fade into the background, is referred to as ambient display [68, 36] or peripheral display [90]. These implementations aim to calmly deliver information to the user. The notion of calmness was used by Weiser to characterize a technology that empowers the periphery [156]. Similarly, Buxton describes the calm computer as one that engages the user on two levels, at the center and the periphery of her attention [20]. The ambientRoom for example by Ishii et al. is equipped with various ambient displays, such as spotlights, a projection of water ripples, ambient sound, air flow and tangible objects, each connected to a digital source of information. Inspired by how we develop a sense of the weather or the liveliness of a building through subtle cues in the environment, these displays are designed to communicate both in the fore and background of the attention [68]. Tomitsch et al. are especially interested in the ceiling for ambient information display, *Information Sky* navigation, context information, and storytelling [139]. Other implementation offer shape-changing properties, such as the ExoBuidling, which can expand and contract [124].

Although sympathetic response detection has been used in biofeedback-driven meditation/relaxation systems for decades [53], a new generation of applications has been enabled by more advanced context recognition methods that incorporate affective state. Examples outside the domain of building control include cars that respond to driver fatigue [73] or games for relaxation training [27]. Physiological information can also benefit user preference modeling for smart homes [86]. The Sonic Cradle and ExoBuilding are examples of physiological signals controlling the build environment. In the Sonic Cradle the user's respiration pattern generates sound to help her to immerse in a meditative state [149]. The ExoBuilding transforms its physical shape to visualize several streams of physiology recordings [124].

2.3 Experiential Control

An *experiential controller* is one that describes the control capabilities using a human-centered representation that organizes the available actions according to a model of perception. Such models could be obtained from observations, sensing, or user ratings. Flynn et al. were pioneers in applying multivariate statistics to discover latent dimensions along which people make aesthetic judgments of lighting [47]. The authors reasoned that environmental cues facilitated or altered through illumination should be measurable as a consistent change of impression under varying lighting conditions. They exposed study participants to six lighting scenes and asked them to rate the conditions using semantic differential scales, for example spacious/cramped and sociable/unsociable. Applying factor analysis on the ratings, Flynn found five perceptual factors that would explain the variance in impression and named them evaluative, perceptual clarity, spatial complexity, spaciousness, and formality. This work has been influential for contemporary lighting research [147]. In the area of design, researchers used comparable methods to describe objects for procedural modeling, a method which allows a designer to tune the features of a model by specifying a set of parameters, such as how friendly or aggressive the object should appear [25, 163].

Aldrich used this technique for perceptual modeling to create an intuitive user interface for lighting control [1]. This interface visualizes the control capabilities according to human perception of aesthetics, a lower dimensional representation derived from user ratings. And indeed, this simplified representation, which has only two dimensions named Color Temperature and Appearance, was much easier for the user to understand and produced a map-like graphical user interface that was faster to use than the existing control panels. Ross et al. investigated possible user interfaces for home atmospheric control [118]. The authors created atmospheric scenes with music, video-art, and lighting. Using a mood board and the semantic differential method, they constructed a controller with three dimensions, *activity, warmth* and *attention*. Seven atmospheric scenes were subsequently projected onto the three-dimensional representation. The coordinates were derived from user-ratings. Finally, the authors studied how the user's interaction with a tangible interface, built on the perceptual model, could potentially express her intentions along the control dimensions. Using the same setup Vastenburg et al. compared the tangible device with a speech and visual interface [146]. The authors concluded that a different or extended model might better reflect the user's intention in a different context.

Other methods to construct a perceptual model is through observation and experience prototyping. In a series of experiments, Magielse et al. investigated adaptive lighting scenarios for social and work contexts [93, 92]. Through the demonstration and evaluation of different design techniques, the authors aim to offer a "growth plan" for dynamic lighting, a technology that is still in the incubation phase. In one scenario, they invited a group of human operators to simulate adaptive control. In another experiment, they gave participants a goal-oriented lighting design problem and compared the results. Furthermore, they prototyped sensor-driven interactions, for example, to direct the light to the active speaker in a group conversation. The authors did not recommend any specific dynamic lighting scenarios but noted that a private-public control dimension is potentially worth further investigation [93]. Offermans et al. implemented a recommendation system for colored lighting scenes using supervised learning [108]. Users were not convinced of the intelligence of the system because it was limited to only eight lighting scenes and the reasoning behind the recommendation was unclear to them. The system neither implemented online learning nor adapted dynamically. In an effort to measure experience and its relationship to gender, Wang et al. investigated and confirmed the impacts of speed, saturation and brightness of dynamic lighting on the perceived atmosphere. They found significant gender difference and three categories of perception: coziness, liveliness and tenseness [152].

Building on these findings my research aims to discover additional perceptual dimensions and a model suitable for context-aware control of the workspace. I expect the resulting dimensions to be different than the ones suggested in previous work because these new control axes represent work activities rather than aesthetics or impression. The resulting dimensions might be social/alone, formal/informal, and creative/executive. In review, my research advances state of the art in two aspects. First, building on existing work for energy conservation, comfort, and information delivery, my experiments aim to demonstrate additional possibilities for adaptive environments to influence productivity and physical wellbeing. Second, my experiments establish a human-centered representation for context-aware applications, which can control multiple outputs and media sources simultaneously based on measurements of the user's actions in a closed-loop fashion.

Chapter 3

Context-Aware Lighting

Adaptive lighting control promises better user experience, increased comfort, higher productivity, and energy savings compared to static uniform illumination. However little is understood about how to determine the relevant activities for context-aware control. Do we need different lighting for reading a magazine and reading a book, or maybe just different lighting for reading versus talking on the phone? How do we identify the relevant situations, what are the preferred lighting attributes, and how do they map to any given lighting system?

This chapter introduces three experiments on context-aware lighting, following the IRB protocol # 1308005863 and # 1507132660. The first two studies intended to construct a control map from user ratings. Building on previous work for perceptual modeling of impression these experiments introduced a new set of measures to capture task-depended variance of lighting preference. The derived map organized lighting scenes according to their perceived suitability for different office activities. The first study was conducted using a virtual simulation, whereas in the second experiment this method was repeated for a physical prototype. A context-aware lighting system was implemented in the physical prototype using the control map. It was evaluated in the third experiment.

3.1 Experiment in a Virtual Environment

A human subject study was conducted to prove the feasibility of using user ratings to generate contextual control dimensions and mapping for context-aware lighting. This section describes our method including data acquisition, mapping, and evaluation, followed by the results and discussion. In the discussion section, the derived control map is compared to lighting design guidelines suggested in existing lighting research.

3.1.1 Method

Data Acquisition and Mapping

First, we created a virtual conference room using a 3D game engine (*Unity Technologies, Unity*) and rendered six lighting scenes or the landmarks of the control map using *Unity's Global Illumination* capability. The simulated, windowless conference room was furnished with ten chairs and one large table in the center. On the walls, there were three decorative paintings and a white board. Furthermore, the room was equipped with four groups of luminaires: overhead down-lighting, wall-washing on the short wall, wall-washing on the long wall, and diffused overhead (see Figure 3-1). We varied light intensities of these groups while keeping the color temeprature constant to create the lighting scenes (see Table 3.1). In order to give the viewer enough context to understand how light affected activities such as reading, writing, computer work, and meetings, we placed objects, such as a whiteboard, decorative paintings, pencil, writing paper, newspaper, and laptop computers in the virtual room. These objects were simulated with the appropriate light diffusing, reflecting, and self-illuminating properties. In concurrent work of the Responsive Environments Group, this virtual space was examined using Flynn's measures of perception [1].

We developed a questionnaire, which measured perceived suitability of lighting scenes for 14 office tasks, to assess context-related dimensions of lighting preference. We chose 14 tasks according to our guesses of potentially relevant contextual dimensions in the space. They could be classified as creative, executive, restorative, demanding, social, individual, visual, non-visual, formal, informal, presentations, and work with and without displays (see Table 3.2 to find the complete list of tasks). Repeated measurements were collected from a panel of participants for the six lighting scenes. Participants recorded their opinions on a five-point Likert scale from *strongly disagree* to *strongly agree*, including an option to give *no answer*.

A dimensionality reduction method, PCA, was then applied to generate contextual control dimensions and mapping. Dimensionality reduction aimed to discover latent dimensions of user judgment. This analysis was performed using the PSYCH package in R [136] and

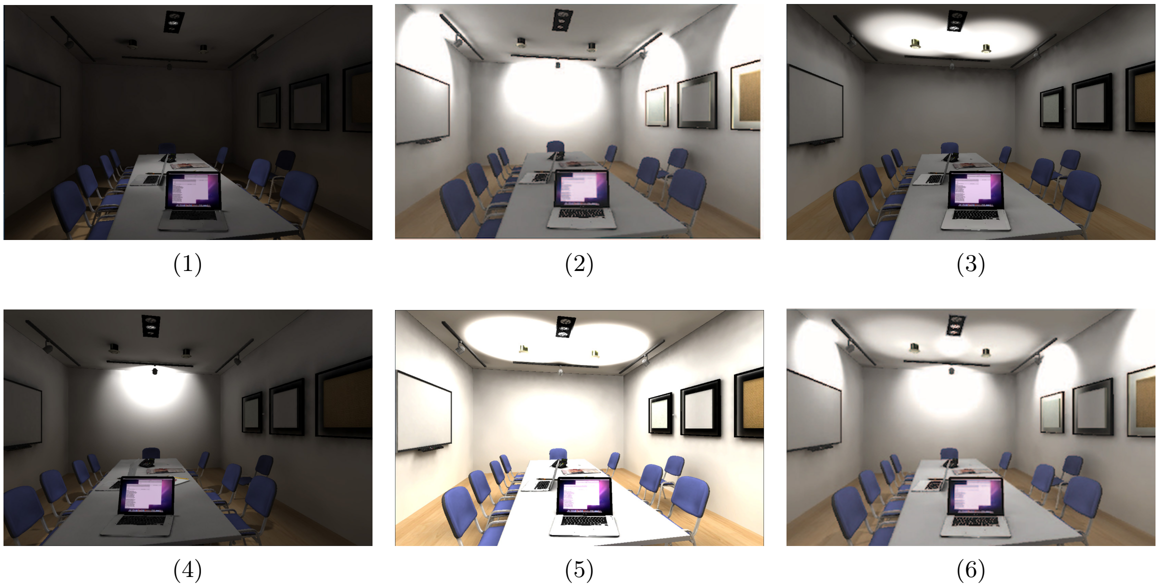


Figure 3-1: Virtual lighting scenes.

the Varimax rotation method [75]. The rotated principal components were considered the contextual control dimensions. Furthermore, the component scores of each lighting scene were used as their corresponding positions on the control map.

Participants

The panel consists of 40 participants, 21 women and 19 men, between 21 and 45 years old. The participants were staff and students from the university, thus familiar with the technology we used and the tasks in the questionnaire.

Procedure

The experiment was conducted in a dark, windowless office (4.2 m in length, 2.8 m in width, and ceiling height of 2.6 m). Participants sat at a desk and looked at a 3D display (*Asus, VG236H*) with active-shutter glasses (*Nvidia, P854*) at a distance of 0.5 m. The lighting scenes were presented in random order. For each lighting scene, participants filled out the questionnaire (see Appendix A.1), where they rated the suitability of the current scene for each task. The tasks were also shown in random order. During the study, participants were able to move around as an avatar in the virtual room and examine the effect of lighting on the available objects.

	Settings					
Lighting group	**Scene 1**	**Scene 2**	**Scene 3**	**Scene 4**	**Scene 5**	**Scene 6**
Overhead down-lighting	Medium	Off	Off	Off	Off	Low
Wall-washing (long wall)	Off	Medium	Off	Off	Off	Low
Wall-washing (short wall)	Off	Medium	Off	Medium	Off	Low
Diffused overhead	Off	Off	Medium	Off	High	Low
	Brightness [cd/m2]					
Measurement position	**Scene 1**	**Scene 2**	**Scene 3**	**Scene 4**	**Scene 5**	**Scene 6**
Table midpoint	1.3	2.6	2.7	2.4	10.7	5.2
Long-wall midpoint	0.3	5.0	2.4	0.5	11.8	7.1
Short-wall midpoint	0.2	7.4	2.5	5.9	10.0	6.5
Ceiling midpoint	0.3	2.4	9.1	0.6	11.2	5.4

Table 3.1: Lighting scene configurations and brightness.

3.1.2 Result

Parallel analysis is a method for determining the number of components to retain from PCA [85]. The outcome of parallel analysis suggested 3 principal components (see Figure 3-2). We named these components: *restorative, presentation, and visually demanding* (see Table 3.2) according to the clusters of tasks. Taking into account the 4th component, the visual component split into tasks *using computers* and *not using computers*. Figure 3-4 illustrates the resulting control space. Participants preferred a mix of light sources and indirect lighting for restorative contexts. If the situation is restorative but also involves visually demanding work, participants chose to increase the brightness of the wall-washers over the defused down-lighting (see Figure 3-4 - 2, upper right corner). In a less restorative but visually demanding context, participants wanted primarily down-lighting (see Figure 3-4 - 2, upper left corner).

3.1.3 Discussion

User ratings highlighted three contextual dimensions, *restorative — demanding, presentation, and visual — non-visual* from the set of possible dimensions embedded in the questionnaire.

The *restorative* dimension could also be named *casual* or *relaxing*, as it includes activities, which mainly occur in a break or relaxed setting. This dimension explains 41% of the total

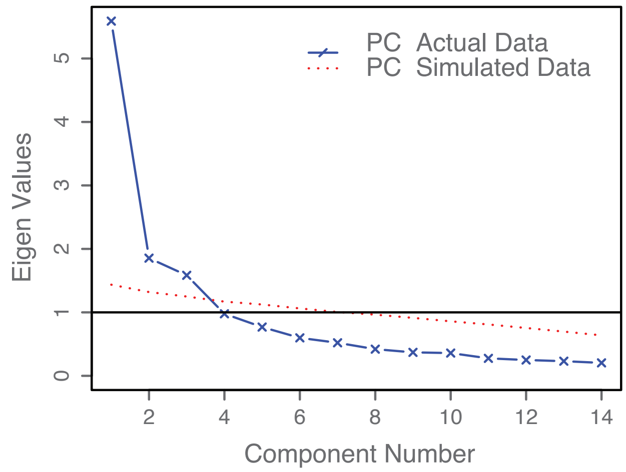


Figure 3-2: Result of the parallel analysis. Parallel analysis determines the number of components to retain from PCA by comparing the original dataset with a randomly generated, simulated dataset with the same number of observations. A component is considered significant if the corresponding eigenvalue is larger than the mean of the eigenvalues from the simulated data [85].

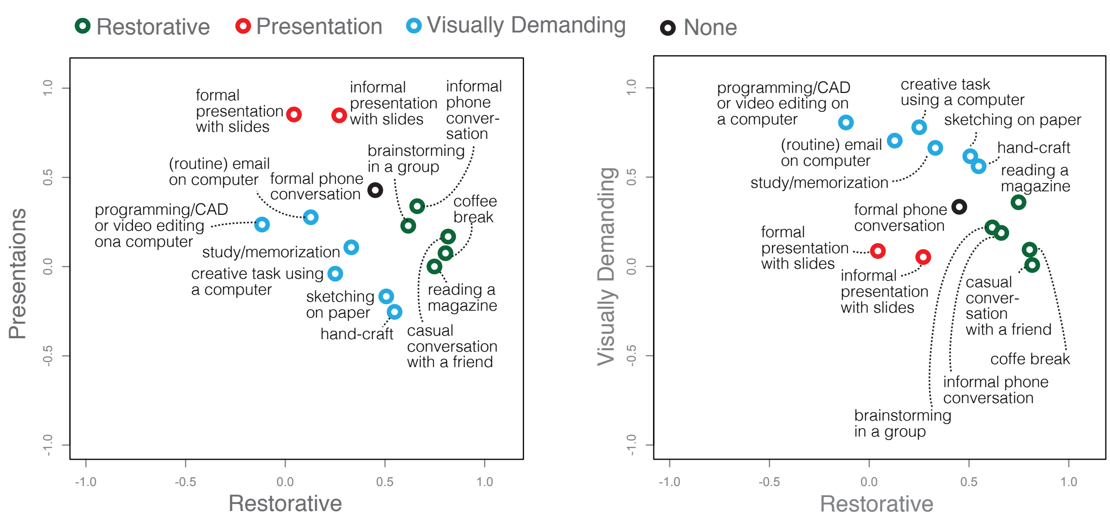


Figure 3-3: Factors (work tasks) in the control space according to their average loadings.

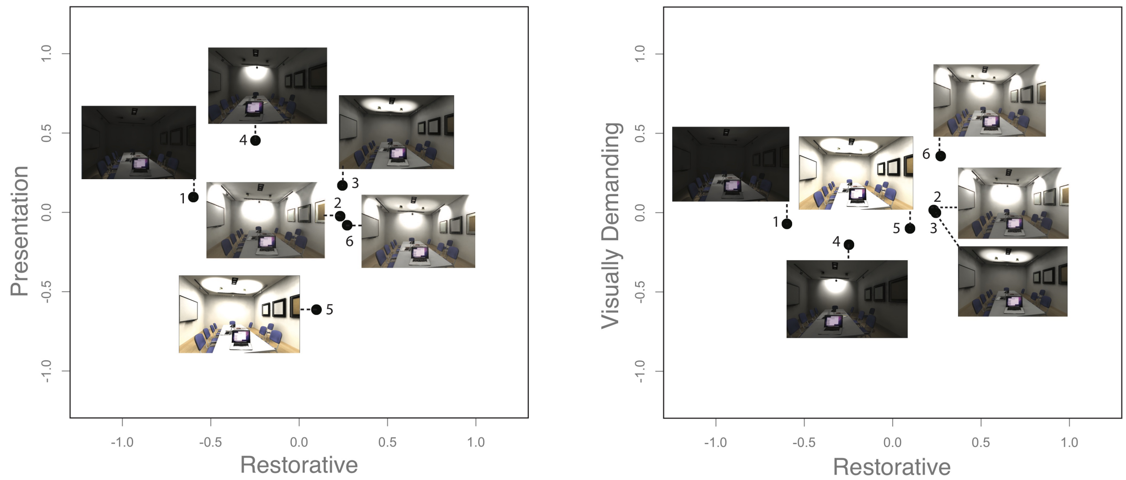


Figure 3-4: Lighting scenes in the control space according to their average component scores.

Task	RC1 Restorative	RC3 Visually demanding	RC2 Presentation
casual conversation with a friend	0.82		
coffee break	0.80		
reading a magazine	0.75		
informal phone conversation	0.66		
brainstorming in a group	0.62		
formal presentation with slides			0.85
informal presentation with slides			0.85
programming/CAD or video editing on a computer		0.81	
creative task using a computer		0.78	
(routine) email on computer		0.70	
study/memorization		0.66	
sketching on paper		0.62	
hand-craft		0.56	
formal phone conversation			
Proportion explained	0.41	0.36	0.23

Table 3.2: Rotated component (RC) loadings of the 14 tasks. Only loadings above a 0.5 criterion are shown, we named RC1, RC2, and RC3 *restorative*, *presentation*, and *visually demanding*.

variance in the data, which indicates that in this conference room lighting is an important factor for restoration. A common practice is to introduce nonuniformity — variation of brightness — to create a relaxing and visually appealing atmosphere. This method, for instance, is suggested in the IESNA Lighting Handbook [116] and prior research [58, 120, 87, 47]. Accordingly, in our study, a mixture of light sources and wall-washing fixtures were preferred for restorative tasks in the windowless conference room.

The second dimension is *presentation*. This lighting option is commonly available in today's conference rooms. Our result revealed nuanced differences for formal and informal presentations. For the latter, participants preferred higher vertical surface illumination using diffused over head fixtures.

The last dimension distinguishes between *visual and non-visual* tasks. It has been shown in many prior studies that lighting preferences vary with visual demand [147]. For instance, Butler et al. measured that a higher brightness level is preferred for visually demanding tasks such as reading and studying, and a lower level is preferred for relaxing activities such as talking to a friend or listening to music [19]. Biner et al. observed different preferences for varying levels of social intimacy [11]. This difference was more pronounced for non-visual than visually demanding tasks. Differences were also shown for video display terminal (VDT) and paper-based tasks [126, 145]. However, for this particular conference room, this dimension only explained 23% of the variance. A possible explanation is that the 3D display, which had limited dynamic range of brightness, inhibited the effect of glare. Another explanation is that the participants did not consider this dimension as important for a conference room.

Over all our results were in agreement with previous findings in lighting and psychology. The derived contextual control dimensions were aligned with preference differences discussed in prior studies. Our method was able to highlight the most relevant dimensions for the conference room.

3.2 Experiment in a Physical Environment

Following the proof of concept in the virtual environment, a human subject study was conducted in a physical office space with computationally controllable lighting. This study served several goals. First, it confirmed our approach to use user ratings to generate contextual control dimensions and control mapping for context-aware lighting. The results were compared to the outcome of the previous study, which used a virtual conference room. This comparison indicated sensitivities and robustness of our approach to new environments with different dimensions and setup. Lastly, the derived control map was used for the development and evaluation of a closed loop system, which controlled lighting dynamically based on user activity. This section describes our method including data acquisition, mapping, and evaluation of the physical prototype, followed by the results and discussion.

3.2.1 Prototype Office

The study was conducted in the *Lighting Lab* located in the Responsive Environments Group area in the MIT Media Lab. The Lighting Lab was installed after the proof-of-concept experiment using the virtual environment. It facilitated multiple projects at the Responsive Environments Group. For a detailed descriptions of the lighting system, I refer to a pervious dissertation of my research group [1], Chap. 5.2.1 and Chap. 5.2.3. The Lighting Lab is a windowless office (4.2 m in length, 2.8 m in width, and ceiling height of 2.6 m) with 20 individually controllable, internet-connected lighting fixtures. Each fixture has five channels, Red, Green, Blue, Warm White and Cold White. Six wall-washing type fixtures (*Philips, Color Kinetics Skyribbon IntelliHue Wall Washing Powercore*) are installed along the long edges of the room, and two downlight luminaires (*Philips, Color Kinetics Skyribbon IntelliHue Linear Direct Powercore*) are installed in the center. Building on the lighting capabilities, we introduced additional sensing and computation for my experimentation.

3.2.2 Method

Data Acquisition and Mapping

For this physical prototype, we collaborated with a lighting designer to create six lighting scenes — the landmarks of the control map (see Figure 3-5). Light fixtures were divided into six lighting groups as illustrated in Figure 3-6. Different intensities and color temperatures (CCT) were assigned to each group to create lighting scenes. CCT was uniform across all groups in each scene.

The Lighting Lab was setup as a small meeting room with two tables in the center and chairs along their edges facing each other. The table height was 0.7 m. There were books,

Lighting group	Settings					
	Scene 1	**Scene 2**	**Scene 3**	**Scene 4**	**Scene 5**	**Scene 6**
Wall-washing back	Off	90%	Off	90%	20%	Off
Wall-washing center	Off	90%	90%	90%	20%	Off
Wall-washing front	Off	90%	Off	90%	20%	40%
Downlight back	60%	4%	Off	65%	100%	Off
Downlight center	60%	4%	65%	65%	100%	Off
Downlight front	60%	4%	Off	65%	100%	40%
Color temperature	3000 K	3000 K	3000 K	6500 K	6500 K	3000 K

Table 3.3: Lighting scene configurations.

objects, sketching paper, pens, an office phone, a mug, a laptop computer, and some other office supplies on the table. Additionally, there were three decorative paintings on the walls and a white file cabinet with books.

Similar to the previous study in the virtual space, we used our questionnaire containing the 14 tasks to collect user opinion on the six lighting scenes. We adopted a repeated measure design, with lighting scene as a within-subject variable. Finally, we applied PCA to derive the contextual control dimensions and used the component scores to establish the map. The analysis was performed using the PSYCH package in R [136] and the Varimax rotation method [75].

Participants

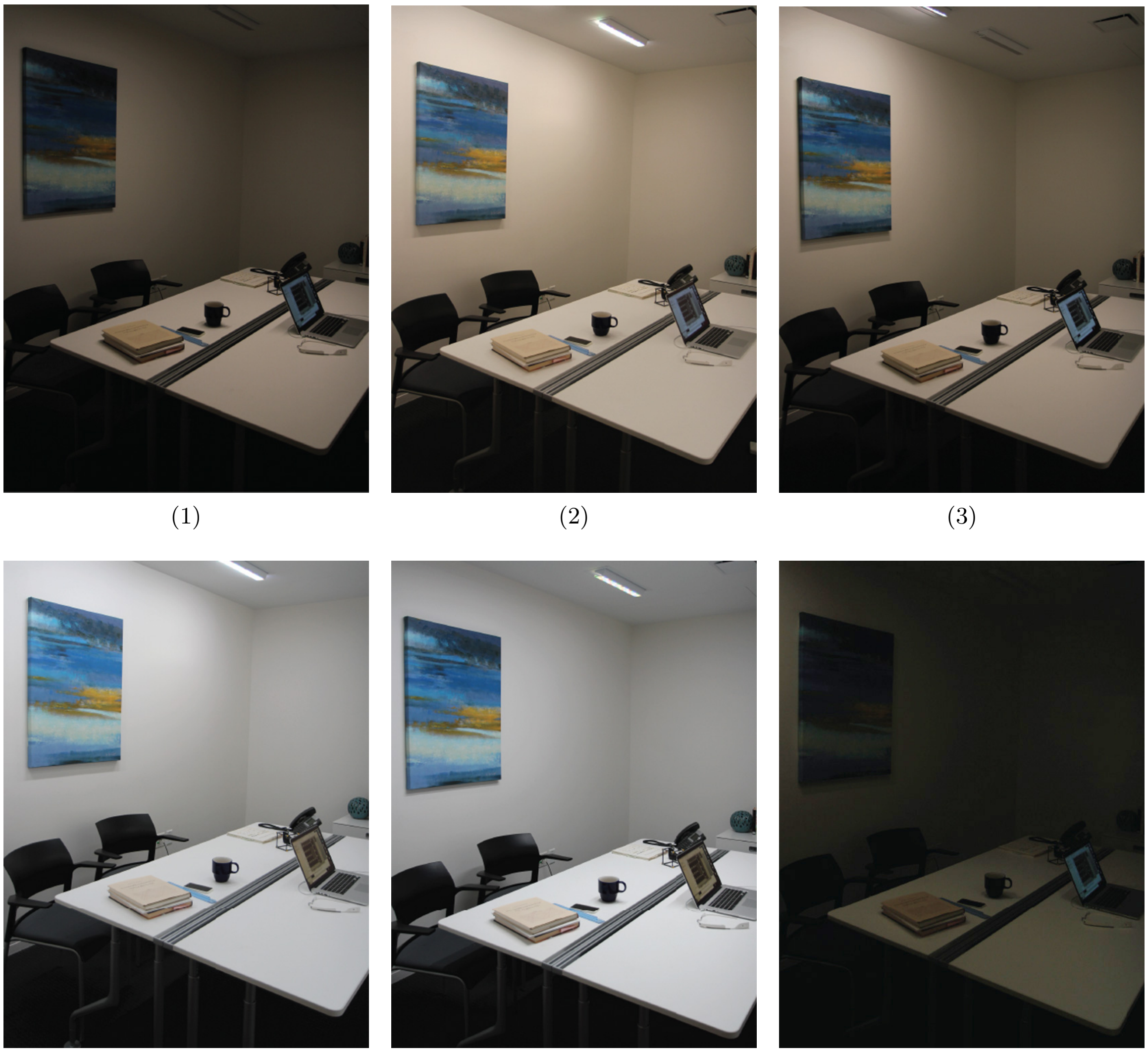
The panel consisted of 17 participants from 20 to 35 years old. The participants were students and staff of the university.

Procedure

The scenes and questions were presented in random order. Participants were able to move around and interact with objects, make sketches, work at the computer, and talk to the instructor to simulate the tasks. A neutral scene was shown between each test scene.

3.2.3 Result

Parallel analysis suggested 3 principal components (see Figure 3-7). We named the components: *focus*, *restorative*, and *work with displays* (see Table 3.4). Figure 3-8 visualizes the



(1) (2) (3)

(4) (5) (6)

Figure 3-5: Lighting scenes in the Lighting Lab.

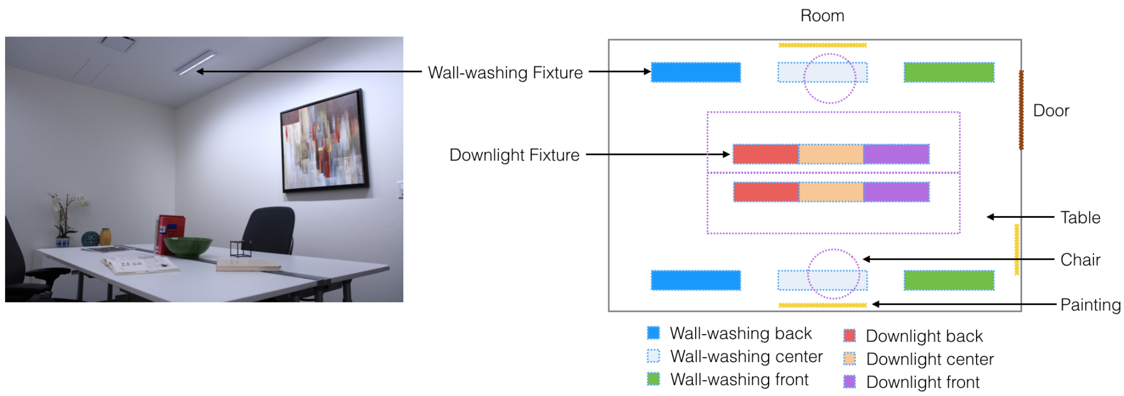


Figure 3-6: Lighting Lab setup and groupings of lighting fixtures.

factors (work tasks) along the component axes. The factors are colored according to their highest loading.

Participants preferred cold high-intensity lighting, such as scene 4 and 5, for focused and non-restorative tasks (see Figure 3-9 - left). For restorative activities, they preferred warm scenes and spotlights on the paintings, such as scene 3 and 2. For tasks at computers, wall-washers were preferred over down-lighting, for example, scene 4 was preferred over scene 5 (see Figure 3-9 - right).

3.2.4 Discussion

User ratings in the physical setup highlighted three contextual dimensions, *focus — non-focus, restorative — demanding*, and *work with displays* from the set of possible dimensions embedded in the questionnaire.

As shown in Table 3.4, the *focus* dimension included tasks such as *study/memorization, hand-craft*, and *formal phone conversation*. Participants preferred high color temperature and high-intensity lighting for these kinds of tasks. Accordingly, it has been shown in prior research that high brightness lighting in cooler color temperatures can increase attention, subjective alertness, cognitive performance, and psychomotor performance [128, 45, 105, 23, 22, 151]. In contrast, low intensity and warm color temperature lighting can introduce drowsiness and relaxation [162]. Furthermore, warm colored lighting has been shown to cause a positive shift in mood, and behavioral changes [8, 6]. However, Knez et al. observed interactions with gender and age, which might alter this effect [81, 82]. In agreement with

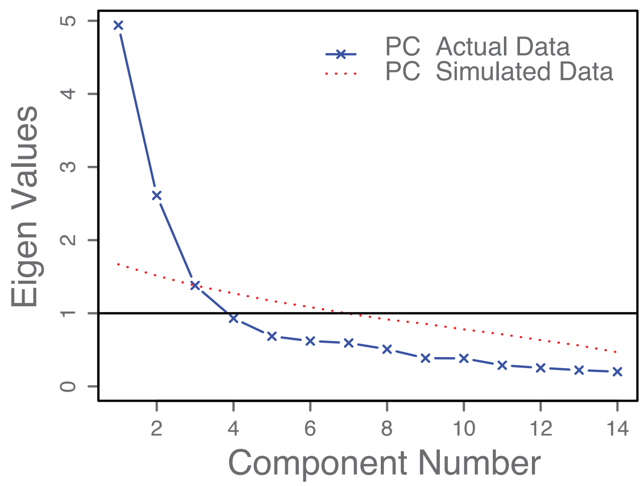


Figure 3-7: Result of the parallel analysis. Parallel analysis determines the number of components to retain from PCA by comparing the original dataset with a randomly generated, simulated dataset with the same number of observations. A component is considered significant if the corresponding eigenvalue is larger than the mean of the eigenvalues from the simulated data [85].

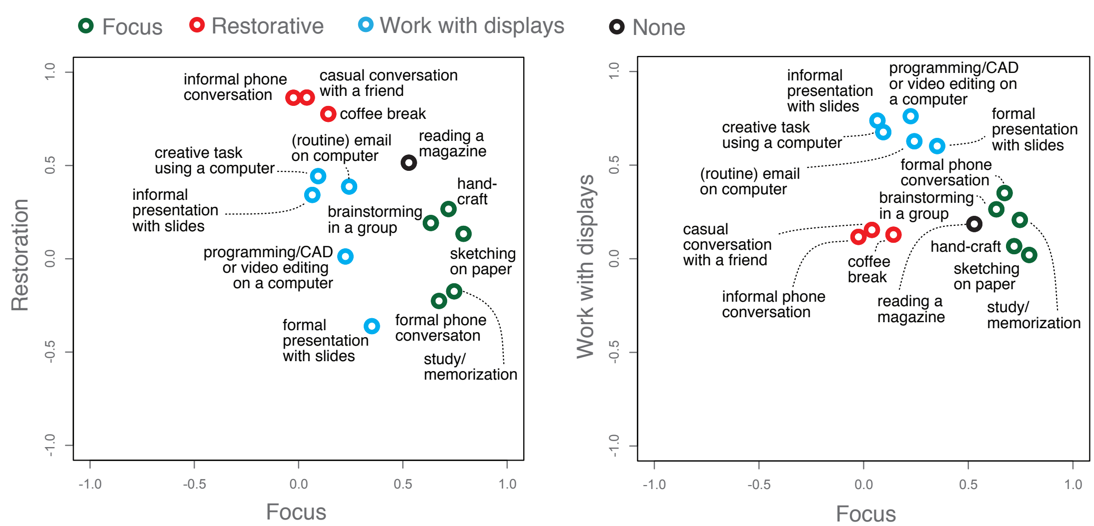


Figure 3-8: Factors (work tasks) in the control space according to their average loadings.

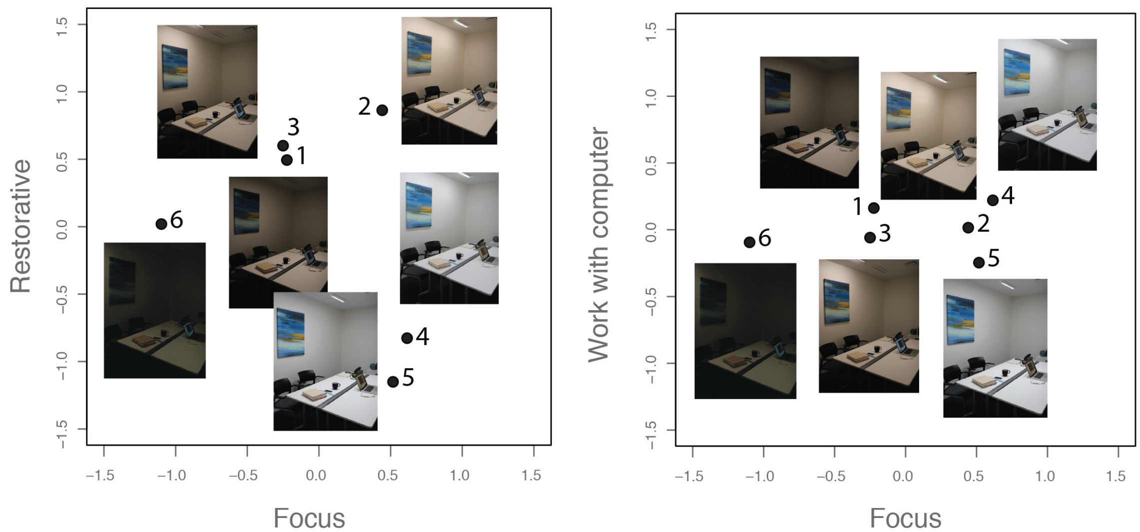


Figure 3-9: Lighting scenes in the control space according to their average component scores.

Task	RC2 Restorative	RC1 Focus	RC2 Work with computers
casual conversation with a friend	0.86		
informal phone conversation	0.86		
coffee break	0.78		
sketching on paper		0.79	
study/memorization		0.75	
hand-craft		0.72	
formal phone conversation		0.67	
brainstorming in a group		0.63	
programming/CAD or video editing on a computer			0.76
informal presentation with slides			0.74
creative task using a computer			0.68
(routine) email on computer			0.63
formal presentation with slides			0.60
reading a magazine			
Proportion explained	0.35	0.35	0.30

Table 3.4: Rotated component (RC) loadings of the 14 tasks. Only loadings above a 0.5 criterion are shown, we named RC1, RC2, and RC3 *focus*, *restorative*, and *work with displays*.

these findings, lighting conditions with warm color temperature and low intensity were rated as less suitable for focus and more appropriate for *restorative* tasks. Furthermore, lighting scene number 3, which highlighted the paintings on the wall, was considered more restorative than other low light, low color temperature scenes. This result is in agreement with a common lighting practice, which uses contrast and spot-lights to create an interesting and relaxing atmosphere [116]. For tasks that are both restorative and focused, participants favored warm color temperature and high-intensity lighting.

The third contextual dimension was named *work with displays*. Participants expressed preference differences for work with computers and displays, such as *programming/CAD or video editing on a computer, informal presentation with slides*, and *creative task using a computer*. This variance of preference could be related to *discomfort glare* [71]. Especially for VDT work, glare is an important lighting design criteria [107, 71]. It is recommended to select luminaires which do not produce light in angles that cause a bright, visible light source directly or through reflection [107, 71]. Field research, such as conducted by Hedge et al. observed that computer workers reported fewer screen glare problems, and fewer and less frequent problems with tired eyes and eye focusing when using indirect lighting compared to parabolic down-lighting [59]. Similarly, researchers found in a comparison of different types of lighting that visual fatigue was lowest for indirect lighting systems [159] and that workers favored indirect lighting [63]. Glare could be an explanation of the third contextual dimension, which accounted for 30% of the variance in the data. In this experiment, participants also preferred indirect wall-washing type lighting over down-lighting for computer work in bright scenes.

The study in the physical office highlighted different contextual control dimensions than the previous experiment in the virtual conference room. In the virtual conference room, the derived dimensions were named *restorative, presentation* and *visual*. One similarity among the simulated and physical room was the *restorative* component, which in both cases was associated with activities such as *casual conversation with a friend, coffee break*, and *informal phone conversation*. This outcome indicated that this group of activities was relevant for lighting design in both types of rooms.

The remaining components were unique for the virtual conference room and physical two-person office. In the physical space *work with computers* accounted for 30% of the variance, whereas in the virtual conference room, this component was not significant. As

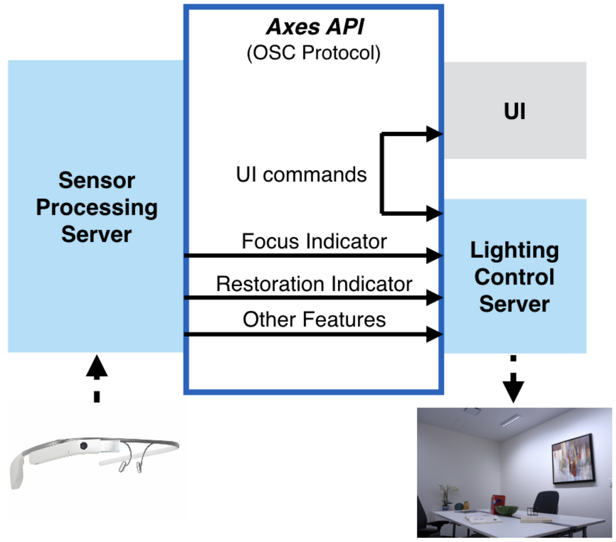


Figure 3-10: Diagram of the system architecture.

discussed above, glare is a determining factor for visual comfort for work with displays. The simulation did not realistically reproduce glare. This limitation might have reduced the effect of glare and biased participants experience. Another plausible explanation is, that computer work is less common in a conference room and therefore was less important for the users.

In contrary to the results of the conference room, participants' ratings of the physical space did not produce a *presentation* dimension. A possible explanation is that the two-person office does not accommodate presentations in the same way as the conference space with ten seats. Therefore, lighting for presentations was more relevant in the conference room than in the small office. Similarly, we could argue that focus tasks are more frequent in offices, therefore received more considerations in the small office setting. User's interpretation of lighting attributes notably depended on the affordance of the space. Our method of data acquisition and mapping embedded these differences in the contextual control dimensions.

3.3 Study of the Completed Prototype System

We conducted a pilot study to evaluate the closed-loop, context-aware lighting system in the Lighting Lab. This section describes the experimental method and result of the human

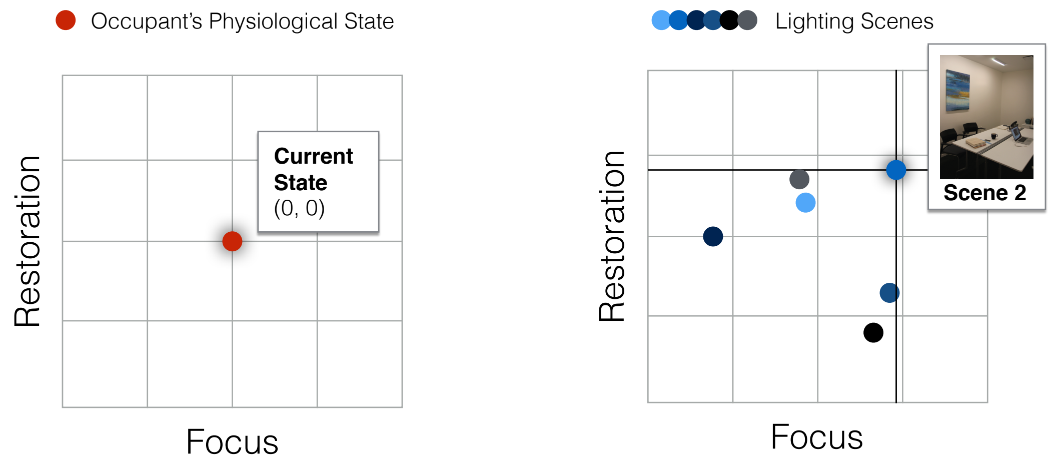


Figure 3-11: The control map divided into an input and output map. Left: the input map shows the occupant's physiological state. Right: the output map shows the map positions of the lighting scenes.

subject experiment. Besides a qualitative survey, we recorded system behavior and compared the total power consumption of the adaptive controller to a static illumination system.

The context-aware lighting system was implemented using the control map framework as introduced in chapter 1.4. We applied the previously established contextual control dimensions and mapping to create the output map (see Figure 3-11 - right). The output map is a representation of the landmark lighting scenes according to the control dimensions. Section 3.3.1 introduces the algorithm for the computation of a *continuous* control map using the landmark lighting scenes. This continuous map allows seamless transitions between any positions of the map.

For context inference, we implemented an activity recognition pipeline using a wearable sensor platform (*Google, Google Glass*). Figure 3-10 illustrates the control system architecture. Using this pipeline, we measured the user's level of engagement in focus and restorative tasks. These measurements established the user's activity state on the input map (see Figure 3-11 - left). Section 3.3.1 describes the activity recognition pipeline with Google Glass and the implementation of the control system.

3.3.1 Method

Continuous Mapping

The continuous map fills the gaps between the landmark lighting scenes. We introduce the vector $v = [v_1, v_2, ..., v_7]$, $v \in \mathbb{R}^7$, to describe the settings of lighting scenes. Each dimension in v represents one degree of freedom for lighting design. In this case, the lighting system was divided into six individually controllable groups, and the color temperature was only changed uniformly for all fixtures. This setup resulted in seven degrees of freedom. As an example v_1 is the intensity setting of the first luminaire groups and v_7 is the color temperature of the lighting scene. The settings of the ith landmark lighting scene is named $v_{0i} \in \mathbb{R}^7$.

We define the current activity state or *operating point* in the input map as $u \in \mathbb{R}^n$, where n is the number of control dimensions. In this case, we use two control dimensions $n = 3$. u_1 is the user's level of engagement in focus activity and u_2 is the extent of restoration. u_2 represents work with displays.

The continuous map is computed based on the positions of the landmark lighting scenes, v_{0i}, and their Euclidean distances to each other. More specifically, we calculated a superposition of v_{0i} with Gaussian decay as a function of distance. The mapping function between the operating point u and lighting setting v is

$$F(u) = \frac{\sum_{i=1}^{6}(a_i(u) * v_{0i})}{\sum_{i=1}^{6} a_i(u)} = v \tag{3.1}$$

The factor $a_i(u)$ describes the relevance of the ith lighting scenes for the current operating point. We define

$$a_i(u) = a(\|u - p_i\|) = \exp(\frac{-\|u - p_i\|^2}{2 * \sigma^2}). \tag{3.2}$$

The coordinates of the landmark scenes v_{0i} were already established in the previous study. $p_i \in \mathbb{R}^3$ is the component scores of the ith lighting scene and $\|u-p_i\|$ the respective Euclidean distance to the operating point. $a(\|u - p_i\|)$ is the Gaussian Function with $a(0) = 1$ and $a(\overline{\|u - p\|}) = 0.01$. $\overline{\|u - p\|}$ is the average distance between all landmark lighting scenes.

Figure 3-12 shows the resulting intensity setting of the downlight center lighting group. This lighting group is very dim for non-focus and non-restorative tasks and the highest for

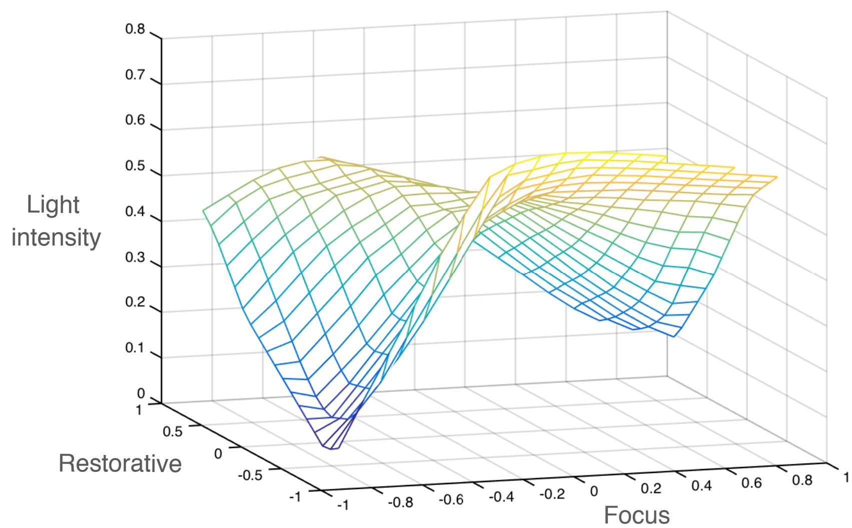


Figure 3-12: Light intensity setting of downlight center for various levels of focus and restoration, the first two rotated principal components. The third component was set to 0. Possible range of intensity is from 0 to 1, where 1 is the brightest.

focus and non-restorative activities.

Activity Recognition Pipeline

For activity recognition, we implemented a real-time processing pipeline, which computed a focus and restoration indicator using sensor streams from Google Glass's microphone and inertial measurement unit (IMU). The focus and restoration indicators determined the position of the operating point along the first and second contextual dimensions respectively. Subsequently, lighting settings were computed as a function of the operating point using Equation 3.1. In order to contain the complexity of the experiment, we focused this study on the first two contextual dimensions. We thus did not introduce sensor automation for the third contextual dimension — work with displays. However, a graphical control interface was implemented to configure this dimension manually.

We chose Google Glass as our sensor platform because head-mounted sensors have been shown to be suitable for recognizing gaze-related activities. For instance, Ishimaru et al. analyzed both eye-blinking frequency and head motion using the embedded IMU and infrared proximity sensor of Google Glass and was able to distinguish activities such as reading, watching TV, mathematical problem solving, and talking [69]. Furthermore, Kunze et al.

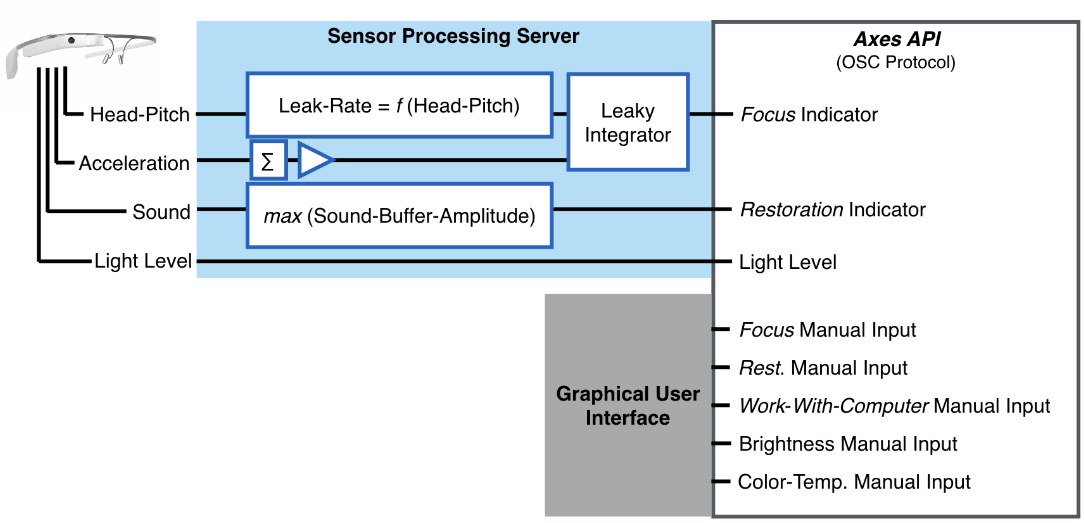


Figure 3-13: Diagram of sensor and manual inputs.

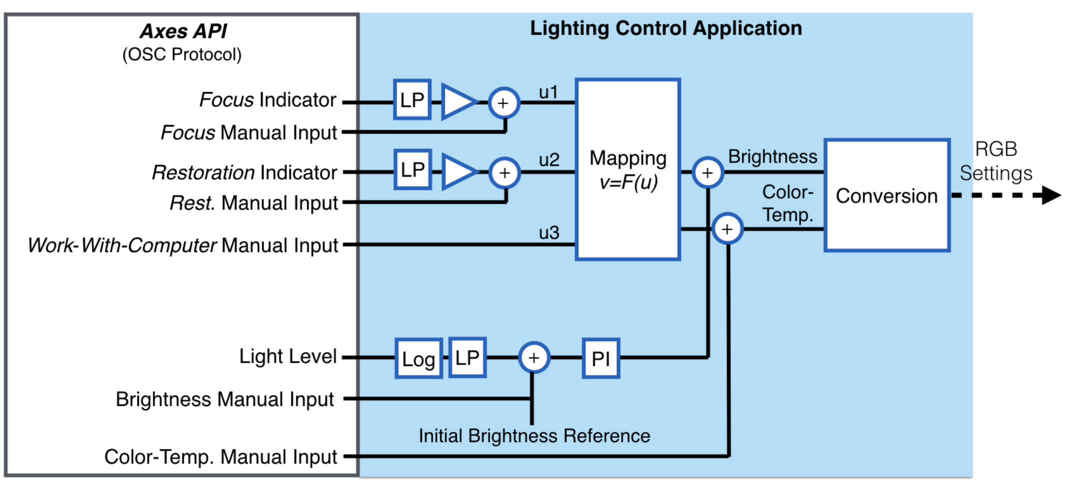


Figure 3-14: Diagram of sensor processing and mapping.

were able to distinguish subtle differences, which occur while reading different types of documents, for example, novels, mangas, magazines, newspapers, and textbooks using a wearable eye tracking system [83]. In another example, Head-mounted motion sensors were used to measure physiological signals, such as heart rate [61]. These examples are possible future directions of context-aware computing for the Lighting Lab. In our experiment, we developed two contextual indicators, head motion and sound.

We used Google Glass's IMU to compute a focus indicator (see Figure 3-13). The focus indicator was calculated by integrating the magnitude of head acceleration with a variable leak rate. We made the assumption that while performing a focused task with high visual attention, the head is more likely to remain steady and look down generally at paper work or displays. In contrast, during a conversation or other non-visual activities, the user is more likely to move, e.g. gesture or look around. We, therefore, considered the motion as a measure of focus. The leak rate was a function of head pitch angle. It was reduced by 0.5% for a lifted head compared to a dropped head. Comparison with a threshold value determined between the two head positions.

The restoration indicator determined the position of the operating point along the second contextual dimension. Here we made the assumption that restorative activities also involve social interactions. In the previous experiment, we discovered that the second, restorative, dimension included tasks such as casual conversation with a friend, casual phone conversation, and a coffee break. We focused our study on these kinds of restorative tasks and therefore, we chose sound level as an indicator for the second component (see Figure 3-13). The microphone on Glass is most sensitive to the wearer's voice, because of its location.

In this experiment, we did not automate the third contextual dimension, work with displays. In the future, an indicator of work with displays could be derived from an activity tracking application on the user's personal computer or using the first person camera on Google Glass.

Lastly, we used the embedded light sensor on Google Glass for closed-loop brightness feedback over the background context-based setting. This design choice reduced the context-dependent variation of brightness. It, however, only affected the illumination of close-by objects rather than the overall lightness of the room, because of the directional sensitivity of the light sensor. A proportional-integral (PI) controller kept brightness level in the field of vision at a constant (see Figure 3-14). Reference brightness level was initialized with a high value. During the experiment, the user was able to adjust brightness manually.

Both indicators were processed locally on Google Glass and streamed wirelessly over WiFi and in real-time to a *Lighting Control Server* using the OSC protocol [160]. In the Lighting Control Server, low-pass filters were applied to the incoming data streams (see Figure 3-14). The filter constants determined the responsiveness of the adaptive system and were chosen empirically.

A graphical control interface was available to the user for manual correction. This interface consisted of three sliders and a 2D pad. Using the 2D pad the user was able to adjust the position of the operating point along the first two contextual dimensions. Using the three sliders, the user was able to independently adjust brightness, color temperature, and the third contextual dimension, their engagement in work with displays. User input was treated as an offset to the sensor-driven operating point.

Finally, the Lighting Control Server computed brightness and color settings, which means the RGB values for each light fixture, and send these commands to the hardware.

Energy Estimation

In order to examine the potential for energy saving, we estimated the energy consumption of the lighting system. The power consumption model was the result of a joint collaboration with the lighting equipment suppliers established in [1]. The power consumption P of each light fixture was estimated from data obtained from the OEM during the analysis stage of this project.

$$P(v_R, v_G, v_B, t) = v_R(t) * \alpha + v_G(t) * \beta + v_B(t) * \gamma. \tag{3.3}$$

The coefficients α, β, γ were determined with linear regression using 16 power measurement points at two different color temperatures, 3000K and 6500K, and eight different brightness levels, from 20lx to 600lx. This linear model gave us a fair estimation of a limited range of intensities and colors. We defined the symbol $\overline{P}$ as the average power over time for the span of an experiment session.

Semi-structured Interview

A semi-structured interview was conducted with each participant individually, at the end of the study. The interview is a common way to collect verbal data and also considered well suited for understanding participants' perceptions and experiences [12]. Different than a structured interview, a semi-structured interview can diverge from the predetermined script to follow up on interesting, but unexpected aspects as they come up. The interview script contained the following questions:

- How would you describe the mechanism of the control system?
- Did the system support your work activities and why?
- Did the system distract you and why?

Participants

The panel consisted of 5 participants from 20 to 36 years old. The participants were affiliated with the university and familiar with wearable technology. We chose scholars that have used wearable technology before to avoid any novelty effects related to Google Glass or the concept of a responsive environment. These participants were able to compare our context-aware lighting system to their previous experience with such technology and thus provide educated feedback.

Procedure

Each participant experienced the context-aware lighting system for 30 to 60 min. During this time, the participant worked on her normal work tasks, e.g. programming, reading, writing, being on the phone, or crafting. She was also able to have casual conversations with the study personnel, who was present in the office. The study personnel was either working independently or interacting with the participant in a colleague-like fashion.

The Participant wore Google Glass throughout the study. She was also allowed to adjust the lighting conditions manually. At the beginning of each study, the control interface was explained in detail, and the participant was asked to familiarize herself with it. In the introduction, the participant was told that Google Glass controlled the lighting in the space according to the contextual control dimensions. However, she was not informed about which sensors were used to do so. Google Glass was processing their activities in the background, and no visual feedback was provided on the head-mounted display. The study personnel did not wear Google Glass or change the lighting manually. At the end of each study, the study personnel held a semi-structured interview with the participant.

	Scene 1	Scene 2	Scene 3	Scene 4	Scene 5	Scene 6
Color Temperature [K]	3000	3000	3000	6500	6500	3000
Average horiz. illuminance [Lux]	176	376	224	568	636	60
P **[W]**	57.20	235.09	108.69	303.46	167.93	46.52

Table 3.5: Estimated power consumption and average horizontal illuminance level measured at table height. Due to lower intensities the casual and not focused scenes (scene 1 and 3) used less energy.

	Experiment
$\overline{P}$ **Mean [W]**	145.40
$\overline{P}$ **Standard Deviation [W]**	24.07

Table 3.6: Average estimated power consumption and standard deviation recorded during the experiment.

3.3.2 Result

Power Consumption

The average estimated power consumption $\overline{P}$ across all subjects is 145 W with a standard deviation of 24 W. We compared this outcome to two non-adaptive scenarios, one where scene number 2 and another where number 4 would be used. Scene number 2 was suitable for both attentive and casual tasks (see Figure 3-9). It was, therefore, the most likely to be chosen scene in a non-adaptive scenario. Compared to scene 2, the adaptive controller enabled 38.15% estimated energy savings. Compared to the brightest scene, which was scene 4, we achieved 52.09% estimated energy savings.

Semi-structured Interviews

In the interview, we learned that participants overall agreed with the dynamically chosen lighting conditions. The adaptive process was described as subtle, natural, and slow. One participant said that "it remind[ed]" her "of the summer when clouds pass by." Dynamic changes were overall not considered distracting. In rare cases, the system performed fast transitions, which was more noticeable for the participants. Two out of 5 participants used the manual controller to correct the lighting settings. In both cases, the participant explained that they preferred a different color temperature.

All participants found that the dynamic changes supported their work activities. They described different reasons, which fall in one of two categories: behavioral feedback and adaptive lighting.

Subject 1 described the lighting as an indicator for social interaction. The lighting configuration revealed the state of social interaction in the shared office space. When both interviewer and participant were focusing on individual tasks and not interacting, the system chose a cold, high-intensity lighting scene which was suitable for focus, but was less restorative. In this situation, the participant felt encouraged to keep on focusing on her own task and to not disturb the state of interaction and lighting that both users of the office had implicitly agreed on. This effect was enhanced by the slow adaptation, which created *contextual inertia*. Similarly, subject 2 saw the lights as a reminder to go back to work, when the lighting slowly adapted to a more restorative setting.

Other subjects noted that they found the adaptive mechanism helpful. Subject 4 mentioned that conversations felt nicer with the adaptive changes, but showed concerns that there might be a situation where that is not the desired effect, for example in a very formal conversation. The same participant also noted that she enjoyed that the light focused on the table when she looked down to work. Subject 3 expressed similar experiences and said that it was comfortable, when the light responded to talking and change of work modes, for example, when she looked at the computer. Subject 5 referred to the brightness feedback control and described, that "the light [system] understood the gap between the light source and the light arriving at my eye." The same participant also noted: "when I am multitasking, the lights are not trying to do something in particular, but trying to compensate for multitasking, therefore the effects are subtle. Maybe, if I spend more time in here, I will notice the effect more". Similarly, subject 1 also suggested that more time in the office would help her to better understand the effects on productivity.

3.3.3 Discussion

The experience study revealed a high potential for energy savings. Energy conservation is an objective of building automation. Previous research on lighting control has shown the possibility to save energy through occupancy sensing, basic activity detection (e.g. trigger of a light switch), and preference settings [106, 40, 158]. Our result suggests that besides these methods, significant energy savings can be achieved through real-time control based on wearable sensors and advanced activity recognition (e.g. level of engagement in focus and social activities). The savings were accomplished using our continuous mapping approach with the appropriate arrangement of scenes on the control map. We did not specifically optimize for energy savings, however our framework took advantage of changing lighting needs for different office tasks. In the derived map, the brighter scenes were positioned towards the edge of the control space. High brightness settings were activated only during attentive tasks. In contrary, social activities and less focused tasks called for settings with less energy consumption such as scenes 1 and 3. Participants performed both restorative and focused tasks, a mix of activities common for office work, which triggered the system to alternate between high and low energy scenes. This kind of system behavior could be intentionally embedded into the control map to further improve energy consumption.

The continuous map enabled seamless transitions from high to low energy settings without disturbing the participant. This was confirmed through the semi-structured interviews. The transitions were perceived as supportive towards the participant's activity. The lighting transitions in our prototype were derived from user ratings and therefore in sync with the user's actions. Dynamic lighting changes could easily cause an unpleasant experience if not chosen carefully. Related research on adaptive lighting has emphasized the importance of subtlety and the ability of the system to move into the background [92]. In our study, pleasant transitions were described as subtle, natural, and slow. Fast transitions, on the other hand, were more likely to cause a negative response. The speed of adaptation is an important variable and should be further investigated in the future.

We determined that the speed of adaptation was a key factor for behavioral feedback. Our study revealed that adaptive lighting functioned as a feedback indicator. Some lighting transitions were described as especially pleasant or supportive, because they indicated the social state in the room, for example as a focus indicator. The speed and continuity of adaptation made participants aware of the *level* of focus and social interactions in the space, which had an influence on the participant's behavior. Existing research on lighting systems for shared environments has investigated how lighting preference modeling [150] and different tangible and graphical interfaces [91] could mediate between different users' lighting needs. However, potential dynamic properties of lighting were not discussed in these previous works. This aspect deserves more emphasis in future research.

3.4 Discussion and Outlook

A physical prototype and series of experiments for context-aware lighting were introduced in this chapter. The first two experiments evaluated a method to discover contextual control dimensions using preference ratings. This was applied to a multi-channel lighting network in both a virtual and a physical office. The third experiment investigated the usability of the derived control map for context-aware control. The adaptive system was able to save energy and revealed promising directions for behavioral feedback.

The adaptive potential of a digitally controllable space is the product of the space properties, the capability of the lighting system, its layout, and last but not least, the users' preferences and activities. In our experiments, we mapped the adaptive potential for two kinds of spaces, a virtual conference room and a small office. The two spaces produced different orders and types of contextual control dimensions. This outcome suggested that there is more than one valid mapping. In agreement with this outcome, we can observe in related work in lighting and psychology that researchers struggled to find consensus on concrete luminance levels, distributions, or degree of luminance contrast for office lighting, despite similarities among research outcomes [147]. Researchers also noted that, even if this information would be available, the results are only useful as general guidance for an "acceptable range" [147]. To find meaningful solutions for a particular space would still rely on the expertise of a lighting practitioner.

Context-aware lighting is an interdisciplinary challenge, which is not yet supported by today's practice. In public or office buildings, lighting is part of consultants' work, which can be led by the architect or specialist lighting designers and specifiers. It is important to ensure an aesthetic appearance in line with the design of the building. Lighting designers have in-depth knowledge of guidelines and best practices determined by professional bodies such as the Illuminating Engineering Society. However in most cases, the design process happens before the inhabitants of the space are known; as a result, there is often no communication between designer and user, and the level of customization is limited. Despite attempts to provide flexibility with re-configurable lighting tracks, pre-programmed lighting scenes, and zones, it remains difficult to meet the dynamic, modern meeting and work requirements. This challenge is growing as more spaces are used as Loose Fit, programmable spaces, with no single program. Different than the lighting designer and architect, the application creator, e.g. the producer of the Google Glass application, might not know the space at all and probably was also not involved during the space design process. However, in order to create a meaningful, personalized experience, space design is an important aspect of the context-aware application.

The experiments introduced in this chapter were developed with this challenge in mind and attempted to bridge these gaps in today's practice. Accordingly, we invited a lighting designer to create lighting scenes based on limited information about the use of the space, given as the 14 example tasks. Using the preference questionnaire, the user was then able to rate the pre-programmed scenes according to their needs and preferences. As a result, a customized solution was created based on the lighting designer's initial suggestions. To take this idea a step further, the level of customization can be increased, for example by allowing users to add or subtract items from the questionnaire, the list of relevant tasks, or provide tools that enable users to design additional lighting scenes.

The application creator can implement a context-recognition solution using only the derived contextual dimensions without any other knowledge about the space. The strength of this approach is that it enables a simple set of sensors to manipulate complicated lighting scenarios by indirectly simplifying and reducing the complexity of the sensor-lighting control space. The prototype system integrated Google Glass and implemented manual control using a two-dimensional touch pad and sliders. However, other kinds of sensors or control methods, e.g. gesturing, pointing, etc. can be easily mapped to the control space and opens up many possibilities for the application creator.

A different space or lighting setup might require new measurements. This process at present relies on user ratings. Even though data could be collected in a less instructed way, it remains a bottleneck. A sensor-based solution to assist the process would dramatically increase deployability. Ideally, the process would combine all of the above-mentioned players — expert knowledge, sensor based initial calibration, and user input over time — to achieve the best fit with maximal customization.

Chapter 4

Sensor-based Mapping for Context-Aware Lighting

The objective of sensor-based mapping is to estimate human-derived criteria and to minimize the required user input for the construction of the control map. One important question for the deployment of the control map is its generalizability. A different room setup would require new measurements because the arrangement of lighting fixtures and room attributes, e.g. size and furniture, might affect the lighting outcome. This part of my research aims to enable a scenario, where new control maps are established using an automated calibration process — sensor-based mapping. In previous work, Aldrich [1] tested the feasibility of sensor calibration through distributed probing of color and intensity on various room surfaces. However, the resulting map was not useful, because it organized the scenes (landmarks) in contradiction to how users perceived them. I believe that camera imaging can prompt a better result because the captured light-field is more representative to how people experience the room. In this chapter, I introduce two approaches, one using photography and another using rendering of simulated spaces.

We envision these two methods being used at different stages during the installation of a lighting system. 3D rendering could be used during the planing phase to decide how to position the lighting system and to discover which settings would maximize the adaptive potential. Photography could be used during the configuration phase after the installation of the lighting system is finished. This is especially relevant when there is no control over the position of the lighting fixtures, for example, if the installation is a retrofit or upgrade of an existing system. Another reason why we experimented with both photography and 3D rendering is that using the later we were able to examine many kinds of spaces, whereas for photography we were limited to the Lighting Lab. A series of tests explored different attributes for data acquisition, e.g. camera view dependency and image resolution. The sensor-derived maps are compared to the human-derived model and for different kinds of spaces.

4.1 Dataset

Datasets for sensor-based mapping were generated using images of six lighting scenes. In order to compare with the previous outcome, we implemented the same lighting scenes that were used for the human subject study (see Table 3.3). Data were collected in two ways: High Dynamic Range (HDR) photography and 3D rendering. The two data acquisition methods are described in detail in section 4.1.2 and 4.1.1.

In addition to the images from photography and 3D rendering, we generated supplemental samples through the linear combination of the original images. The supplemental samples artificially inflated the sample size. For each pair of images, we performed a number of linear interpolation steps. For each step, the multiplicator of one image was increased, and the other was decreased.

For HDR images we used Radiance RGBE Encoding (.hdr). RGBE is an image format introduced by Gregory Ward [154]. This encoding is an improvement over the RGB standard, both regarding precision and regarding dynamic range. Each color channel — red, green, and blue — has the precision of 32 Bit floating point values instead of 8 Bit in the standard RGB encoding.

We converted RGB channel values to luminance values according to the human visual response curve [65] using

$$L = 179 * (0.2651 * R + 0.670 * G + 0.065 * B) \tag{4.1}$$

Furthermore, we took into account the logarithmic relationship of human perception and stimulus intensity as stated in Fechner's Law [44, 104]. Thus, we used the logarithm of the weighted channel intensities in the dataset.

Lastly, the RGB pixel matrix ($Height \times Width \times 3$) was reshaped to a vector ($1 \times$

$(Height * Width * 3))$. The image vectors were concatenated to form an image data matrix $(NumberofImages \times (Height * Width * 3))$. The labels of the images were stored in a separate matrix $(1 \times NumberofImages)$. In a final step, the order of the image vectors in the image data matrix, and the associated labels in the label matrix were jointly randomized. The randomized matrices together produced a dataset.

4.1.1 Photography

For photography, we used a DSLR camera (*Canon, Canon D5*) with a wide angle lens (*EDIT*) and a HDR capable firmware (*Magic Lantern, Magic Lantern for Canon* [84]). In the firmware settings, we configured the camera to use 9 brackets and 2 Exposure Value (EV) increments, which means that for each HDR photograph the camera took 9 images and after each image, the exposure was increased by 2 stops. A 2 stop increase is, for example, a change in shutter speed from 1/8 of a second to 1/2 of a second, from 1/2 of a second to 2 seconds, and so on. ISO and Whitebalance settings were fixed to 100 and Daylight respectively. The image resolution was 5616 by 3744 pixels.

HDR images were computed using 9 photographs for each image, and the Photosphere command line tool (*Anyhere Software, Photosphere 1.8.7U* [153]). We provided the software with a calibration file, which was generated using our camera setup and a luminance meter. The output HDR Images were stored with the Radiance RGBE Encoding. A color correction was applied to the images. Furthermore, they were centered, cropped and re-sized to 512 by 512 pixels (see Figure 4-1).

4.1.2 Simulation

For the simulation, we chose three types of spaces: One Person Office, Conference Room, and Small Office. The One Person Office has the smallest footprint. It is a private space that allows one person to work comfortably. The Small Office is a slightly bigger room that could facilitate two people. This space could be used for one-on-one meetings and collaborative work. The Conference Room is a large room that could host a group of people for meetings, presentations, group discussions, etc.

In order to build examples of the three types of spaces, we collaborated with Steelcase, a leading company producing office furniture and interior architecture. Steelcase created 3D models of the three types of offices, with three variations for each type. The variations were

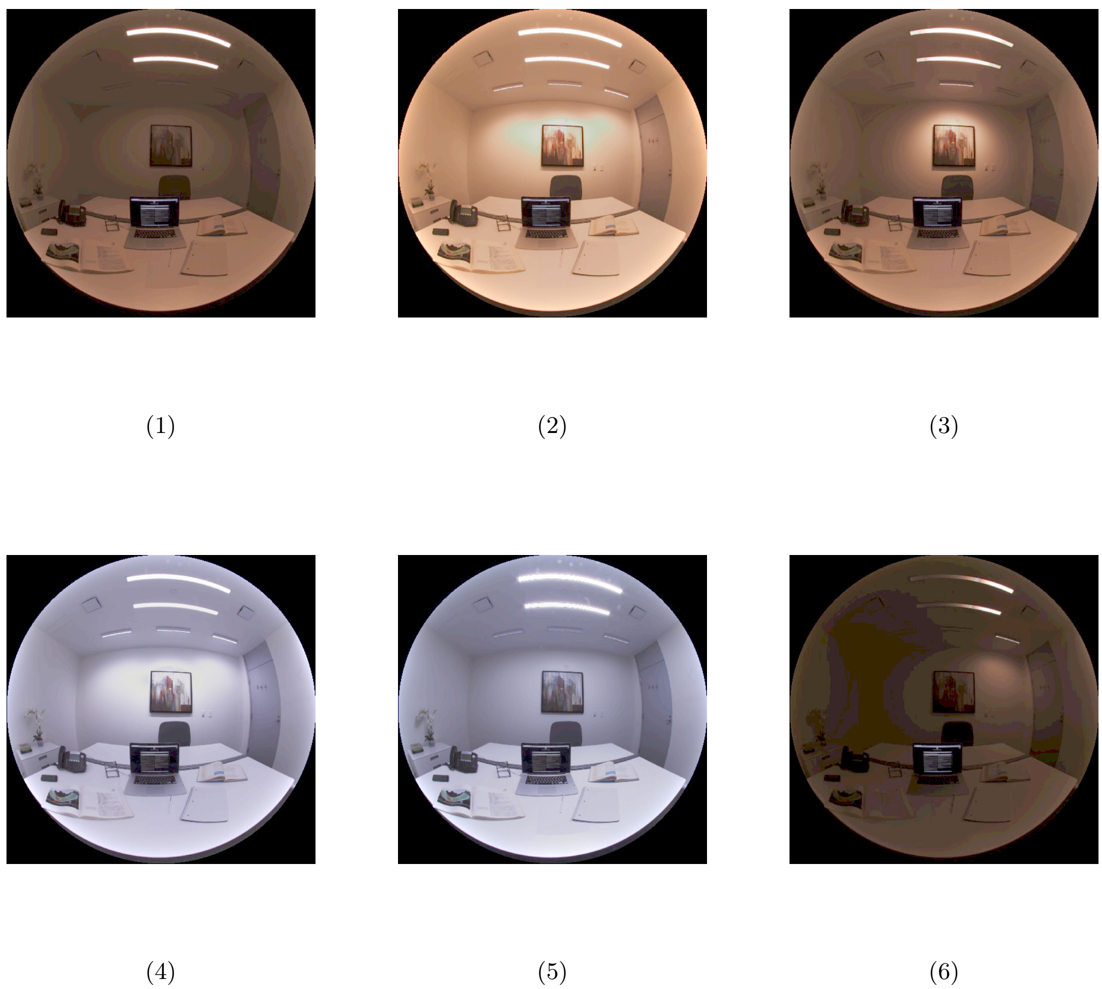


Figure 4-1: Photographs of the six lighting scenes.

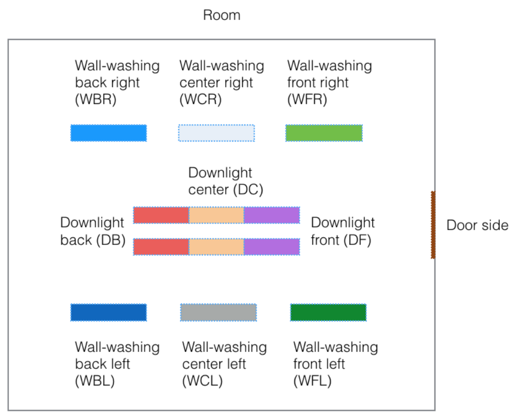


Figure 4-2: Naming of lighting groups.

Windowless, With Window, and Lounge Setting. The Lounge Setting was furnished with a couch and coffee table instead of a work desk. These models, comprised of Steelcase's furniture, accessories, and space division products (see Figure 4-3, 4-4, and 4-5).

Next, we added a ceiling lighting system to these spaces. The lighting system was modeled after the system in the Lighting Lab using wall washing fixtures (modeled after the *Philips Color Kinetics SkyRibbon IntelliHue Wall Washing Powercore*) with dimensions $0.56\ m \times 0.10\ m$ and recessed downlights (modeled after the *Philips Color Kinetics SkyRibbon IntelliHue Linear Direct Powercore*) with dimensions $1.2\ m \times 0.10\ m$. The position and quantity of the lighting fixtures were adapted for each space. As a constrained, the distance between the wall washing fixtures was constant and the downlights were always grouped as a continuous strip of lights. In total, 16 sample offices were created based on the 9 variations of spaces by altering the layout of the lighting installation.

HDR renderings were created using the 3D Rendering and Animation Software KeyShot (*KeyShot, KeyShot 6* [79]). Keyshot is a commercial software for 3D rendering and animation [122]. It has been used to render architectural interiors [79]. This software offers several illumination textures, e.g. Diffused Area Lights, Point Lights, and IES Profiles. It also provides an option for interior lighting. We used the Diffused Area Light textures and configured it by specifying a color temperature and output intensity in Lumens. The resulting configurations of each space and lighting scene are summarized in Table 4.1.

		Settings									
Spaces	**Scene**	**CCT**	**WFL**	**WFR**	**WCL**	**WCR**	**WBL**	**WBR**	**DF**	**DC**	**DB**
1	1	3000	Off	Off	N/A	N/A	Off	Off	60%	60%	60%
1	2	3000	90%	90%	**N/A**	**N/A**	90%	90%	4%	4%	4%
1	3	3000	Off	Off	**N/A**	**N/A**	Off	Off	Off	65%	Off
1	4	6500	90%	90%	**N/A**	**N/A**	90%	90%	65%	65%	65%
1	5	3000	20%	20%	**N/A**	**N/A**	20%	20%	100%	100%	100%
1	6	3000	**40%**	**Off**	**N/A**	**N/A**	**40%**	**Off**	Off	**Off**	Off
7	1	3000	Off	Off	Off	Off	Off	Off	60%	60%	60%
7	2	3000	90%	90%	90%	90%	90%	90%	4%	4%	4%
7	3	3000	Off	Off	90%	90%	Off	Off	Off	65%	Off
7	4	6500	90%	90%	90%	90%	90%	90%	65%	65%	65%
7	5	6500	20%	20%	20%	20%	20%	20%	100%	100%	100%
7	6	3000	**20%**	**Off**	**20%**	**Off**	**40%**	**Off**	Off	Off	**Off**
11	1	3000	Off	Off	Off	Off	Off	Off	60%	60%	60%
11	2	3000	90%	90%	90%	90%	90%	90%	4%	4%	4%
11	3	3000	Off	Off	90%	90%	Off	Off	Off	65%	Off
11	4	6500	90%	90%	90%	90%	90%	90%	65%	65%	65%
11	5	6500	20%	20%	20%	20%	20%	20%	100%	100%	100%
11	6	3000	40%	40%	Off	Off	Off	Off	40%	Off	Off

Table 4.1: Example lighting scene configurations. Deviations from the original lighting scenes used in the Lighting Lab are highlighted. For the naming of the lighting groups see Figure 4-2.

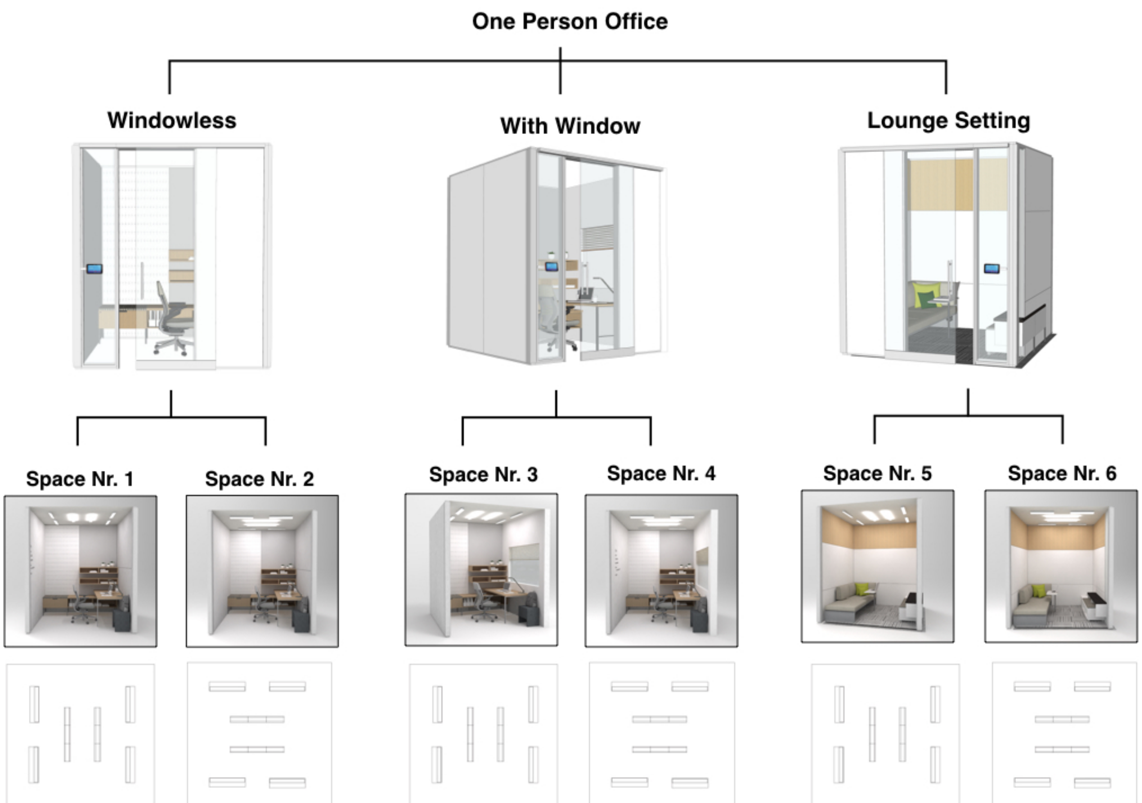


Figure 4-3: Models and renderings of One Person Offices. The first row of images shows 3D models of the three variations, Windowless, With Window and Lounge Setting. The middle row of images shows renderings of the spaces with the lighting system in place. Finally, the last row of images illustrates the layout of the lighting system. The top edge of the illustration corresponds to the back wall in the rendering.

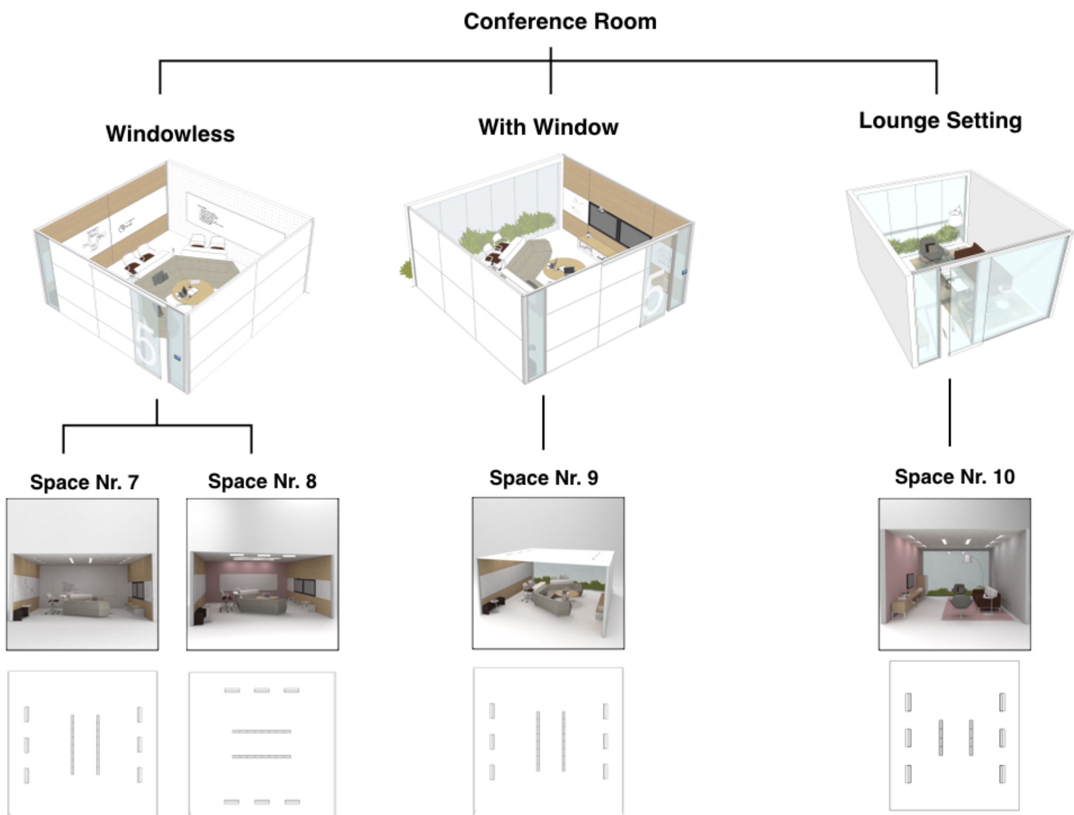


Figure 4-4: Models and renderings of Conference Rooms. The first row of images shows 3D models of the three variations, Windowless, With Window and Lounge Setting. The middle row of images shows renderings of the spaces with the lighting system in place. Finally, the last row of images illustrates the layout of the lighting system. The top edge of the illustration corresponds to the back wall in the rendering.

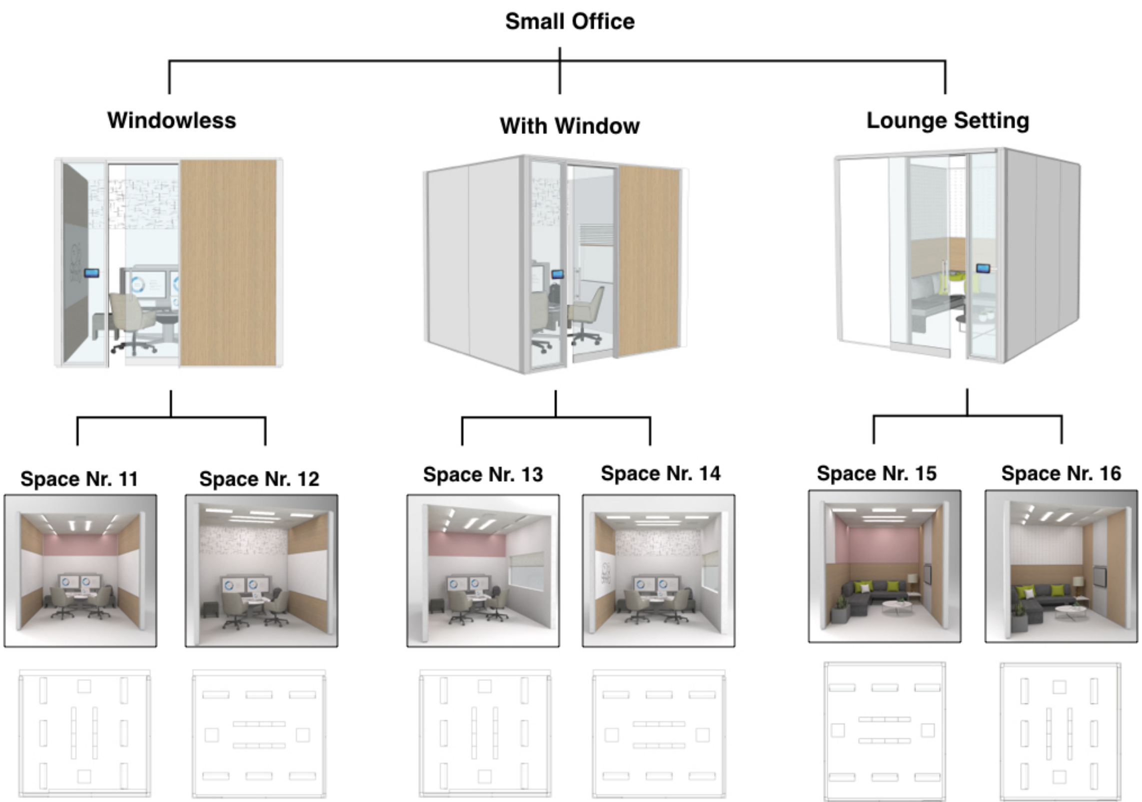


Figure 4-5: Models and renderings of Small Offices. The first row of images shows 3D models of the three variations, Windowless, With Window and Lounge Setting. The middle row of images shows renderings of the spaces with the lighting system in place. Finally, the last row of images illustrates the layout of the lighting system. The top edge of the illustration corresponds to the back wall in the rendering.

4.2 Algorithms

Dimensionality Reduction Methods

For the definition of dimensionality reduction, I refer to van der Maaten [144], who wrote:

> "Dimensionality reduction is the transformation of high-dimensional data into a meaningful representation of reduced dimensionality. Ideally, the reduced representation has a dimensionality that corresponds to the intrinsic dimensionality of the data. The intrinsic dimensionality of data is the minimum number of parameters needed to account for the observed properties of the data [...] Dimensionality reduction is important in many domains since it facilitates classification, visualization, and compression of high-dimensional data [...]".

In this experiment, I considered three methods: PCA, Isomap, and t-SNE. The calculations were carried out using the Dimensionality Reduction Toolbox for MATLAB [144]. Principal Component Analysis or PCA is a linear dimensionality reduction method, which computes a lower dimensional subspace in which the variance of the data is maximal. It uses the unit eigenvectors of the covariance matrix to establish the base of the subspace [114]. PCA is a popular algorithm commonly used for face recognition and feature detection in machine learning applications. One characteristic of this method is that it focuses on preserving the global structure of the data, meaning the large pairwise distances between samples and is less effective at conserving local structures, keeping samples with small pairwise distances close together [114].

Isomap, on the other hand, aims to preserve local structures by retaining the geodesic rather than the Euclidean distance between data points. The geodesic distance is measured over the manifold on which the data points lie. It is the shortest path between two points in a neighborhood graph [114]. In the neighborhood graph, every data point is connected with its k nearest neighbors in the dataset. This algorithm performs well on datasets that form a curved manifold such as the Swiss Roll Dataset [134]. However, it also has several weaknesses such as topological instability and problems with holes in the manifold [114].

Lastly, t-SNE is a variation of Stochastic Neighbor Embedding. This method was developed to visualize data that lie on several related manifolds, such as images of objects, which for example could be grouped by color and the shape of the objects. This algorithm can reveal both a global and local structure in the data at several scales [88]. A quality of this algorithm is that it models dissimilar data points using large pairwise distances, and models similar data points using small pairwise distances, which results in well-separated clusters for data visualization [88]. This algorithm calculates a probabilistic measure representing the pairwise similarity of data points. This similarity measure is calculated for both the high and low dimensional representations, where for the later the Student-t distribution instead of the Gaussian distribution is used. An optimization method is then applied to find a lower dimensional representation that minimizes the difference of similarity values between the two representations [88].

Computation of Dissimilarity

In order to compare the maps of two different spaces, we computed a dissimilarity value. The computation was done using MATLAB. The dissimilarity value is a measure of the distances between landmarks in two lower dimensional representations. The distance was calculated after the two representations were aligned to each other through a linear transformation, in a way that minimized their dissimilarity.

In a first step we calculated the centroid of the landmark lighting scenes for both 2D representations using

$$[C_x, C_y] = [\frac{1}{N}\sum_{j=1}^{N} S_{j,x}, \frac{1}{N}\sum_{j=1}^{N} S_{j,y}] = [\overline{S}_x, \overline{S}_y] \tag{4.2}$$

N was the number of scenes and $S_j = [S_{j,x}, S_{j,y}]$ was the xy-coordinate of the j-th scene in the 2D representation. We applied an offset to the 2D map so that the centroid became the origin. We then normalized the map so that the coordinates of the landmark lighting scenes were between -1 and 1. This was achieve by dividing the xy-coordinates with the maximum x- and y-value respectively.

Next, we performed procrustes analysis [78] to determine the linear transformation that would minimize the dissimilarity between the two representations. Finally, the dissimilarity value was the sum of squared errors of the transformed landmarks, standardized by a measure of the scale of S, given by:

$$\sum_{j=1}^{N} (S_{j,x} - \overline{S}_x)^2 + \sum_{j=1}^{N} (S_{j,y} - \overline{S}_y)^2 \tag{4.3}$$

4.3 Result

4.3.1 Photography

The analysis using photographs established a lower dimensional representation that was a close approximation ($DissimilarityValue < 0.05$) of the human-derived contextual map. Among the three dimensionality reduction methods, PCA achieved the lowest dissimilarity value. A linear transformation (e.g. translation and orthogonal rotation) was necessary to align the principal components with the human-derived contextual dimensions. However after a simple transformation, the human- and sensor-derived representations exhibited obvious similarities. This outcome demonstrated that it is possible to approximate human judgment of lighting scenes with the analysis of photographs of the lighting scenes. The following paragraphs discuss how different dimensionality reduction methods and parameters of the dataset affected the outcome.

Comparison of Dimensionality Reduction Methods

The results of the three dimensionality reduction methods are visualized in Figure 4-6. The upper half of the Figure shows the two-dimensional projections of the data. The lower half shows the side by side comparisons of the sensor- and human-derived maps after the linear transformation was applied to align them. It also shows the normalized dissimilarity value between the aligned maps.

For this analysis, we used six HDR photographs of the six landmark lighting scenes in the Lighting Lab. We created supplemental samples using 100 interpolation steps, which generated a final sample size of 1491 data points. Furthermore, we reduced the resolution of the photographs from 512 by 512 to 52 by 52 pixels.

PCA achieved the lowest dissimilarity value. After the linear transformation, the human- and sensor-derived representations exhibited obvious similarities. One remaining difference was the relative distance between scene 1 and scene 3. These two scenes were considered alike when rated according to their suitability for different work tasks, but the photographs of these scenes were comparatively distinct.

Isomap performed nearly as well as PCA. The positions of the landmark lighting scenes after the transformation were similar to the PCA result and the human-derived representation. The interpolated samples formed a non-linear pattern visualizing the approximated

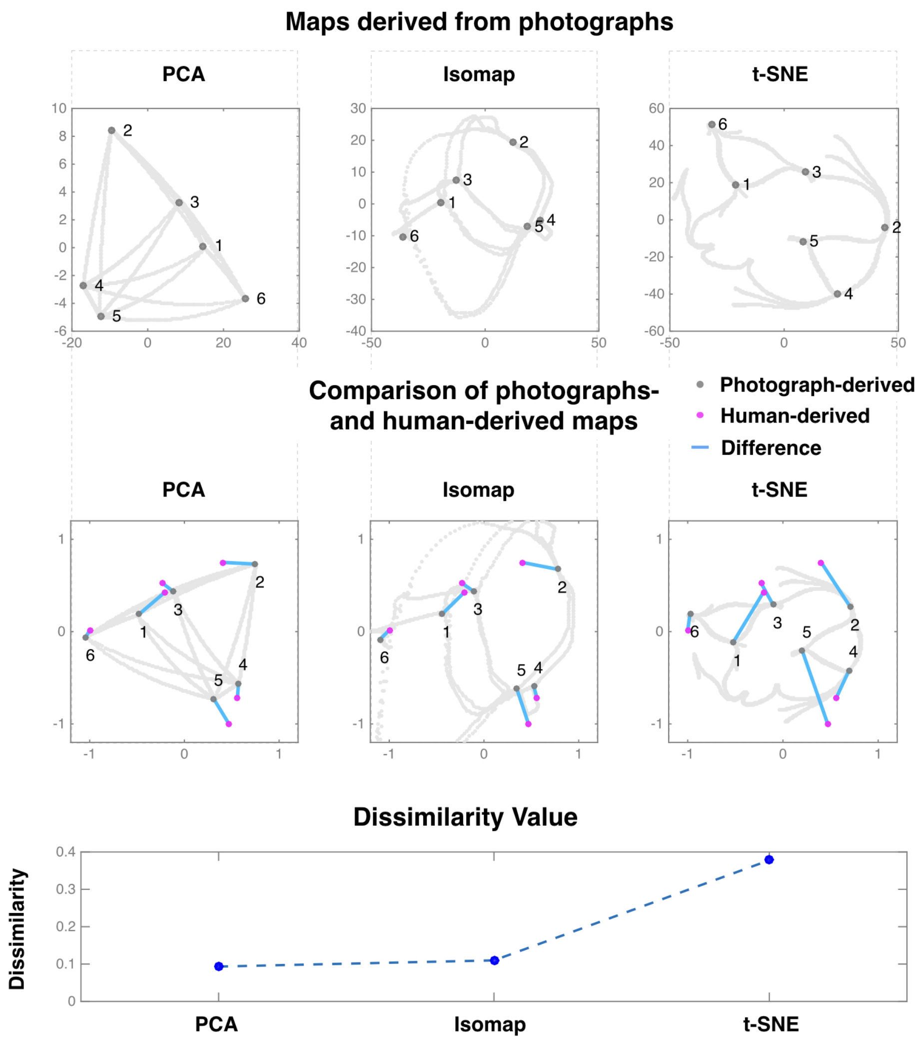


Figure 4-6: Comparison of three dimensionality reduction methods: PCA, Isomap, and t-SNE. Each method was applied to a dataset of 1491, 52 by 52 HDR images of the Lighting Lab.

geodesic distance between samples. This pattern was different for PCA. For PCA the interpolated samples formed slightly curved lines between the landmark lighting scenes. Curved instead of straight lines were to expect because pixel intensity scaled logarithmically, whereas the supplemental samples were generated with linear interpolation steps.

Lastly, the t-SNE produced the most distinct map. Using this algorithm, the distant data points were positioned with large distances between each other. Therefore, on the 2D projection, each landmark lighting scene became an intersection of several sequences of samples. Landmark scenes formed independent islands surrounded by their closest variations. Despite this representation being very different than the human-derived map, it has potential to enable an alternative interface, which would allow the user to easily find and select the preset scenes and to fine tune the selection using its neighboring cluster.

Number of Images

To evaluate the required sample size and the usefulness of the supplemental images for PCA, we generated 5 datasets with different total numbers of images. Each data set consisted of the 6 HDR photographs of the landmark lighting scenes and 0 to 100 interpolation steps between unique pairs of lighting scenes. The image resolution was 52 by 52 pixels. PCA was performed for all 5 datasets. Figure 4-7 visualizes the comparisons. The result suggested that when using PCA, the supplemental images did not increase the similarity to the human-derived representation. This outcome was plausible because the most distinct samples, in this case, the landmark lighting scenes were also the most influential samples for PCA.

Image Resolution

We examined the effect of image resolution using 8 datasets with resolutions ranging from 1 by 1 to 512 by 512 pixels and the dimensionality reduction method PCA. 512 by 512 HDR images were resized using a bicubic interpolation algorithm to create lower resolution images. No supplemental images were added to the datasets. Figure 4-8 visualizes the dataset and result. The outcome revealed that a resolution as low as 6 by 6 pixels was sufficient to preserve the information in the image.

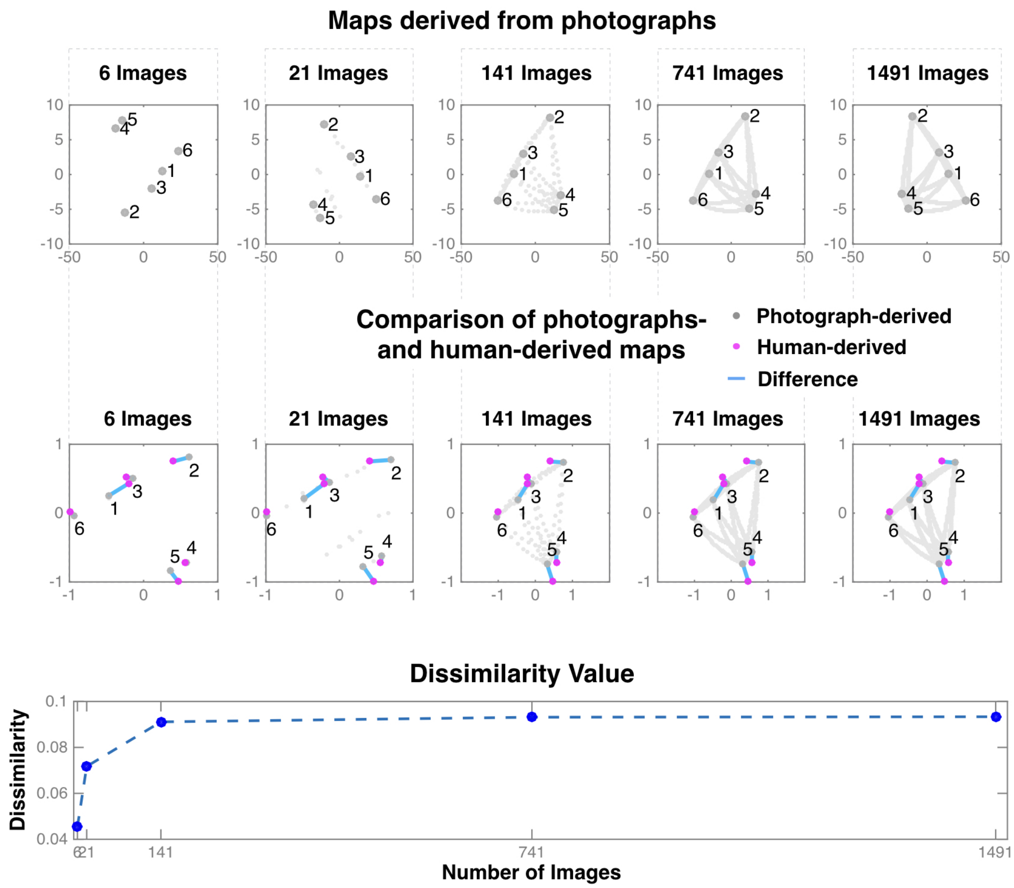


Figure 4-7: Comparison of 5 datasets with different total numbers of images. Each image shows a different lighting setting. Images were 52 by 52 HDR images of the Lighting Lab.

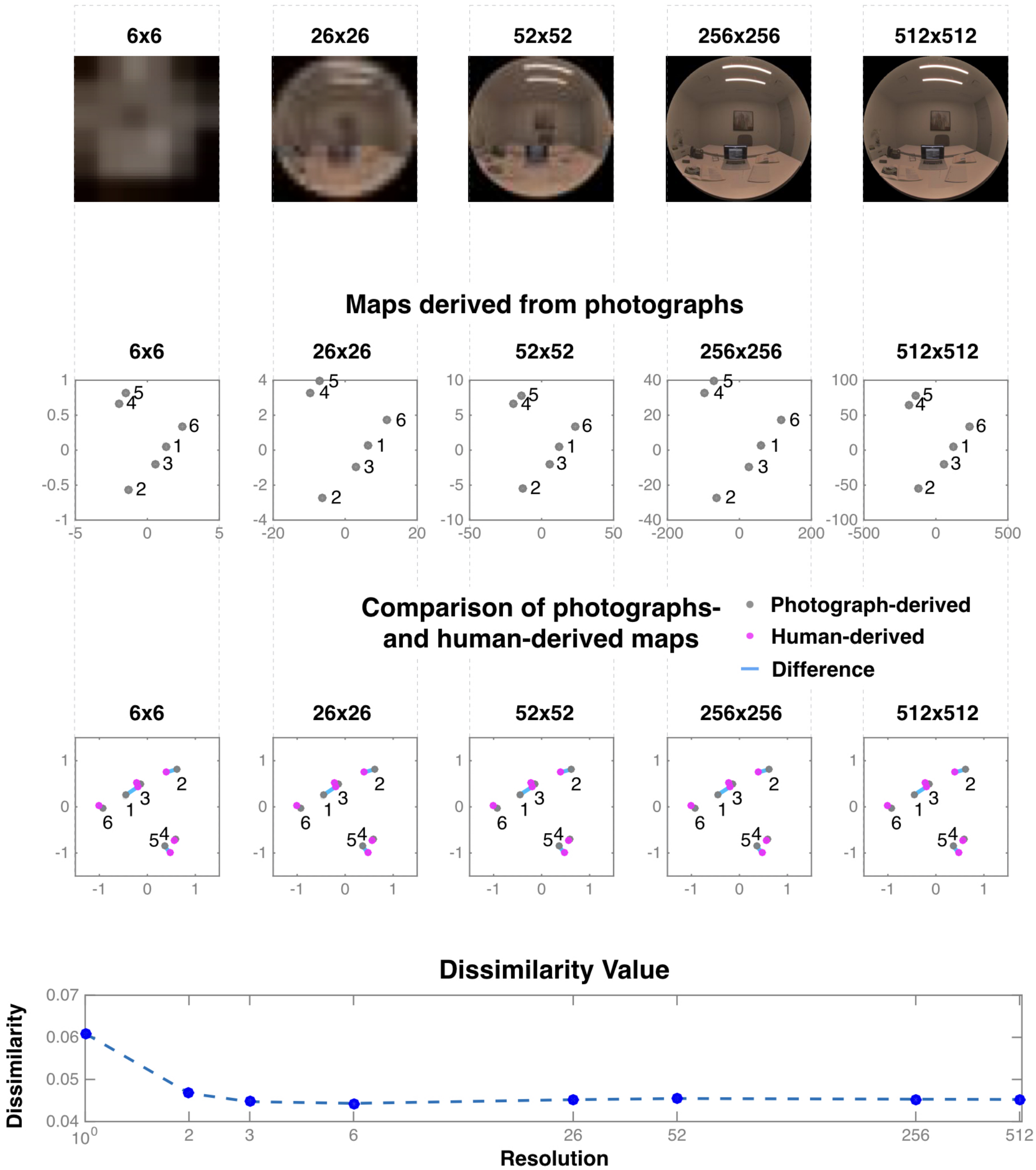


Figure 4-8: Comparison of 5 datasets with different levels of image resolutions. Each dataset contains 6 radiance HDR photographs of the Lighting Lab with resolution from 6 by 6 pixel to 512 by 512 pixels.

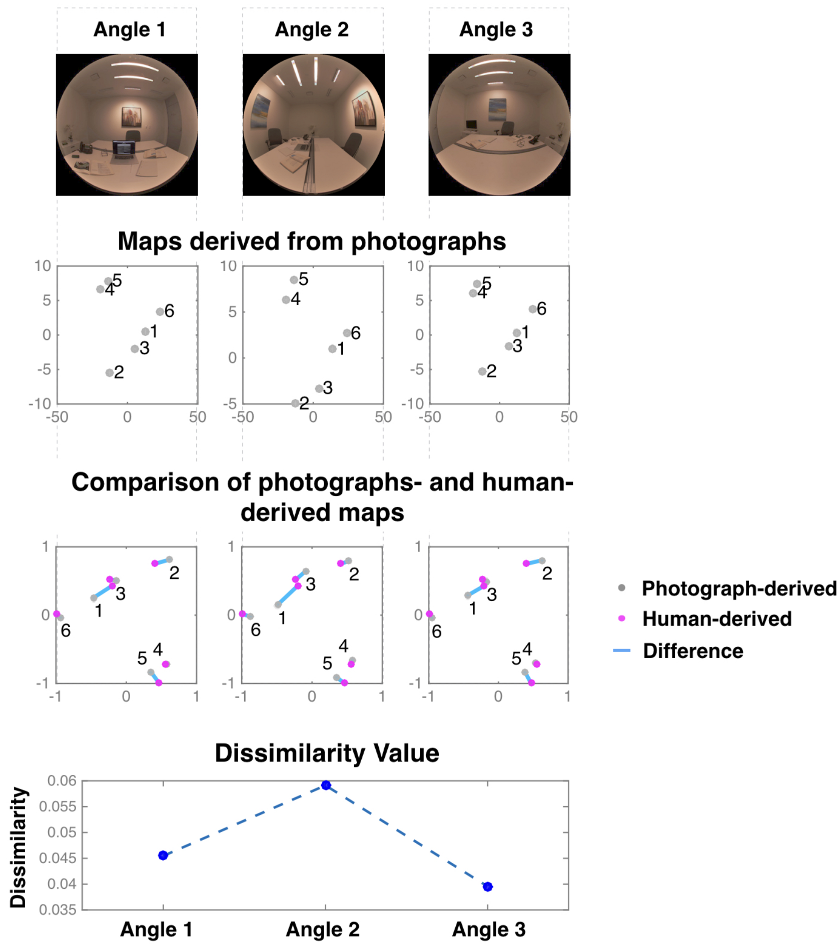


Figure 4-9: Comparison of 3 datasets with different angles of view. Each dataset contained six 52 by 52 HDR photographs of the Lighting Lab taken from different angles.

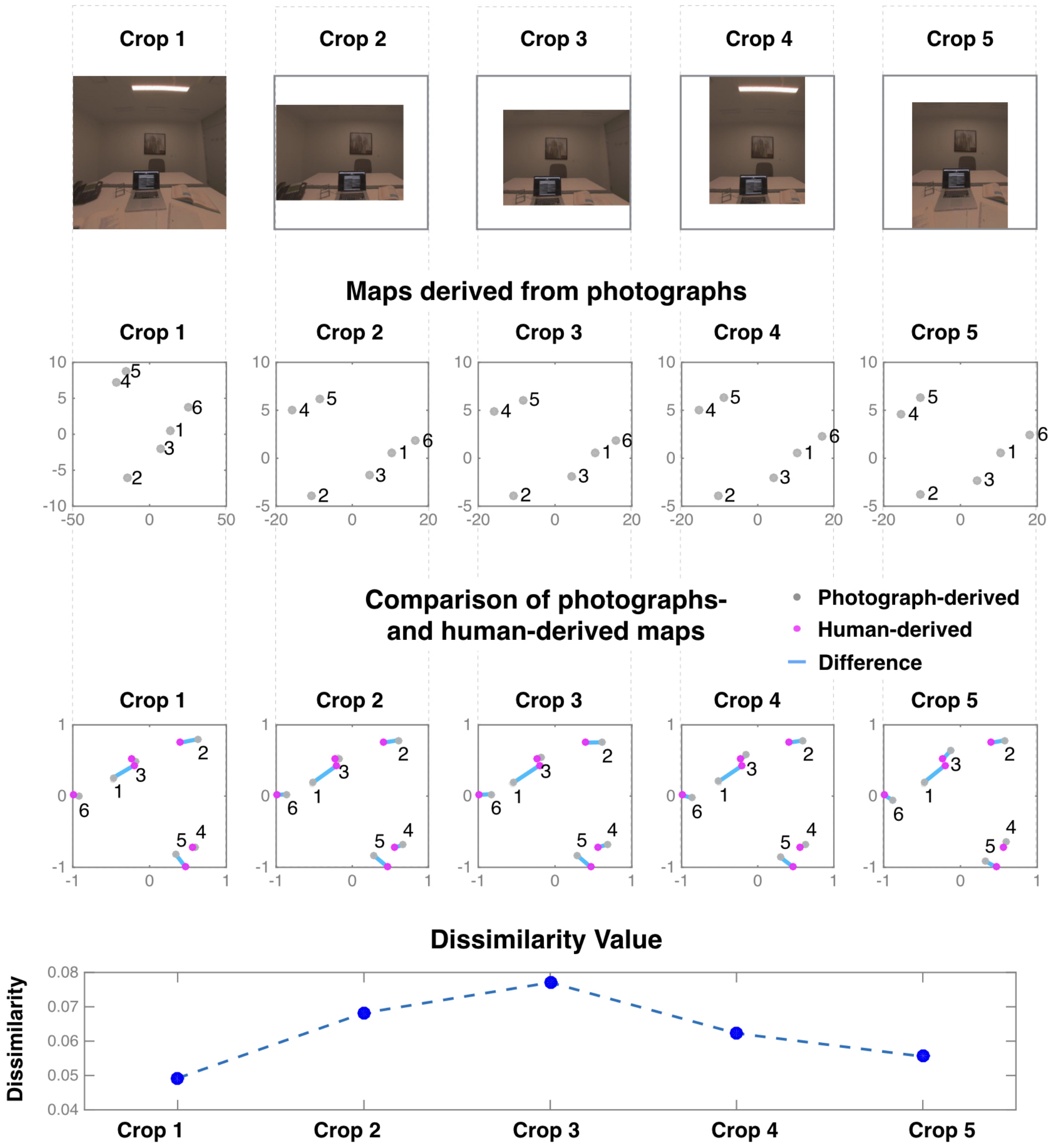


Figure 4-10: Comparison of 5 datasets with different simulated fields of view. Each dataset contained 6 HDR photographs of the Lighting Lab. An algorithm was applied to the photographs to remove lens distortion. Undistorted images were cropped in 5 different ways to approximate 5 different camera angles of a narrow (field of view) lens.

Angle of View

The human field of vision is limited, so is the field of view of most types of cameras. One would need to decide the position and orientation of the camera to collect sample photographs. What angle of view is the most suitable for the analysis of interior lighting? To address this question, we generated datasets using three different camera positions and five uniquely cropped images. We took photographs from the following three positions using the wide angle lens: an overview position that showed both workstations at the shared table and two different seated positions on each side of the table. For the cropped images, we generated pictures with a narrower view by cropping 20% along different edges of the undistorted photograph. We used the MATLAB Camera Calibration App (*MATLAB Single Camera Calibration App, Mathworks* [94]) to create a custom calibration file for the wide angle lens and to undistort the original photographs. Figure 4-9 and Figure 4-10 present the photographs from the three camera positions and the undistorted, cropped images.

Figure 4-9 and 4-10 show result of the different camera angles. The outcome of this experiment indicated that the choice of camera view should be similar to the first person view of the worker. Among the three different camera positions, the dissimilarity value was the lowest for Angle 3. Interestingly, Angle 3 was the same position where the study participants sat during the human subject study (section 3.2). This relation to the previous user study might have contributed to the increased similarity with the human-derived result. The photographs taken from this angle were a better representation of the participants' experience than the other camera angles. This angle showed a unique painting which was illuminated differently than the painting visible from the other seated desk position (Angle 1). A filter attached to the wall-washing fixtures created a soft rather than hard spotlight on the painting. The dissimilarity value of the desk position (Angle 1) was lower than the overview position (Angle 2), which indicated that approximating the first person experience is more important than capturing the entire space. Similarly, among the cropped images of the picture that best represented the worker's view (Crop 1 followed by Crop 5) achieved the lowest dissimilarity value.

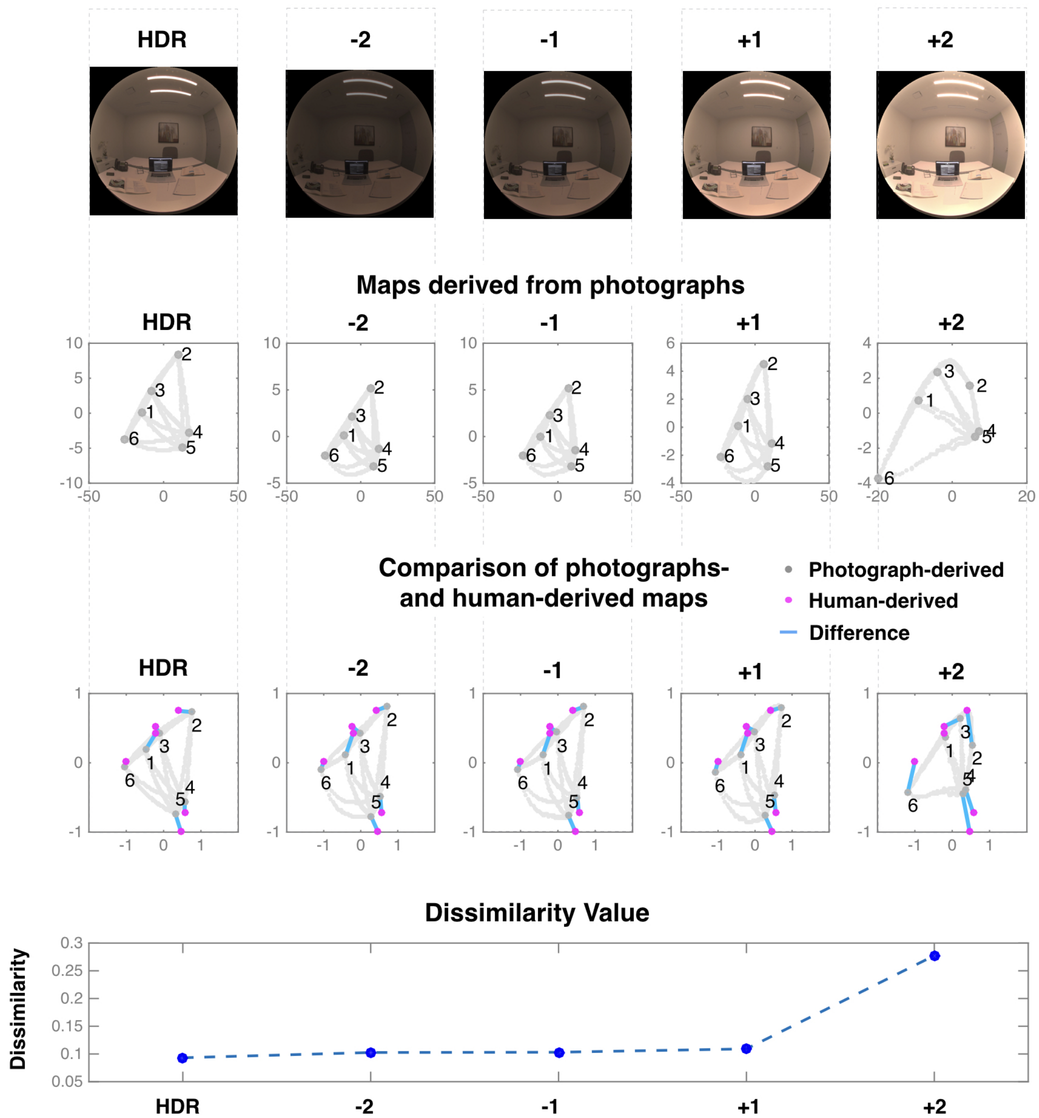


Figure 4-11: Comparison of 5 datasets with different dynamic range and exposure settings.

Dynamic Range

Lastly, we analyzed how HDR images compared to 8-Bit RGB encoded images. Using Radiance, a lighting simulation and rendering software (*University of California, Radiance* [155]) we generated JPEG images with 4 different exposure levels from the HDR photographs. The image resolution was 52 by 52 pixels. In order to visualize the distortion caused by the saturated pixels, we also added supplemental samples with 100 interpolation steps. As shown in Figure 4-11, the HDR dataset achieved the lowest dissimilarity value. Furthermore, dissimilarity was lower for underexposure than overexposure.

4.3.2 Simulation

The simulation results indicated that modification of interior attributes in large spaces (Conference Room and Small Office) created a greater variance in lighting outcome than in small spaces (One Person Office). There were also more differences in lighting outcome among the three types of rooms than within the variations of one type (see Figure 4-12).

For the One Person Office, we reduced the number of light sources to adapt to its small footprint. We used 4 wall-washing and 6 downlighting fixtures instead of 6 wall-washing fixtures and 8 downlighting fixtures as were originally installed in the Lighting Lab. Furthermore, we made two changes to the lighting scenes to accommodate for the new layout and the small space. For scene 3, the gallery lighting scene, which formally used a combination of 2 wall-washing spotlights and 4 downlights, was reduced to only using 2 downlights. Scene 6, the low light presentation mode, which previously used 2 wall-washing fixtures and 2 downlighting fixtures, was reduced to only 2 wall-washing fixtures and half of the output intensity (see Table 4.1).

The resulting maps for the six One Person Offices were skewed in comparison to the human-derived map ($DissimilartiyValue < 0.1643$). Figure 4-13 shows the result for this type of space. The relative distance between scene 6 to scene 3 and scene 1 was smaller in all versions of the One Person Office than in the human-derived map. This outcome indicated that scene 6 created a dim diffused effect similar to scene 3 and scene 1, despite using half of the light output from the original design. Furthermore, scene 3 became more similar to scene 6 than scene 2 because we removed the wall-washing spotlights. Among the three types of spaces, the maps of the 6 One Person Offices were the least different from each other ($DissimilartiyValue < 0.0041$). We calculated the dissimilarity value for each variation of One Person Offices in comparison to the windowless version, the version that was the reference for the other spaces. We can reason that because this type of office has a small footprint, light can bounce off nearby wall surfaces and create a uniform diffused illumination with little contrast. Therefore the position of luminaires and the interior attributes had diminished impact on the resulting effect.

For the Conference Rooms, we added 8 downlighting fixtures to the existing 8 and doubled the output capacity of the wall-washing fixtures in Spaces Nr 8-10 to compensate for the size of the room. Figure 4-14 shows the result for this type of space. In this case dissimilarity values were computed in comparison to the windowless Space Nr. 7. Because of the large footprint, despite the increase in brightness and number of light sources, the system produced high contrast, spotty illumination patterns in the space. Among the variations, the lounge setting caused the greatest difference, larger than the diffusely lit window. The different variations of Conference Rooms generated more distinct maps than the One Person Offices ($DissimilartiyValue < 0.0582$). The resulting maps for the Conference Room also showed reduced similarity to the human-derived map ($DissimilartiyValue < 0.2381$).

The Small Offices were the most alike to the Lighting Lab in size and shape. Hence, we were able to use the same number of lighting fixtures as the original setup in the Lighting Lab. Because of these similarities, the maps of the Small Offices were the most similar to the human-derived map among the three types of spaces ($DissimilartiyValue < 0.1363$). Figure 4-15 shows the result for this type of space. The comparison of the variations of Small Offices showed that the modification of lighting system layouts caused larger divergence than a diffusely lit window or change of furniture. For the Small Offices, we computed dissimilarity values for Spaces Nr 11-16 in comparison to the windowless Space Nr. 11 ($DissimilartiyValue < 0.0201$).

4.4 Discussion and Outlook

In this chapter, we demonstrated that it is possible to create an approximation of the human-derived contextual map using images of the lit environment, either photographs or 3D renderings. Furthermore, we identified several parameters that influenced the dissimilarity to the human-derived map and established recommendations for them. We experimented with

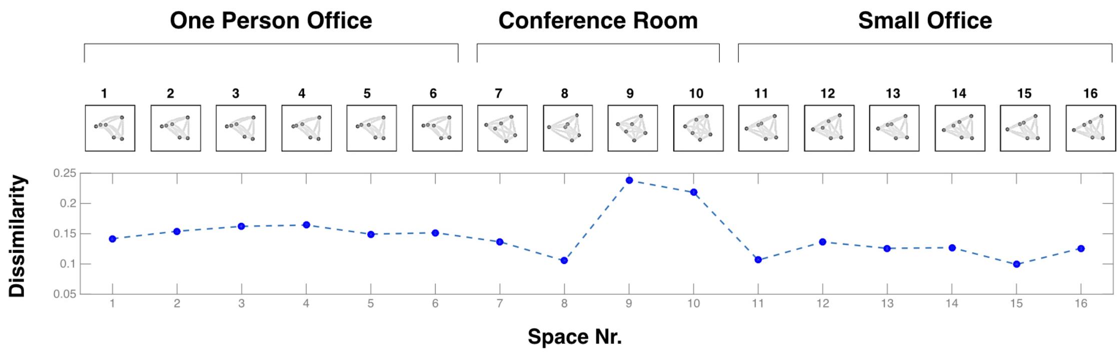


Figure 4-12: Maps of all simulated offices and dissimilarity values in comparison to the human-derived map.

three-dimensionality reduction methods and identified PCA as the most suitable method. Fortunately, this was also the fastest technique and required the least number of samples, e.g. six samples for the six landmark lighting scenes. Image resolution as low as 6 by 6 pixels were sufficient to preserve the information in the picture. Using low-resolution images could further increase computation speed. Regarding image format, HDR encoding was the preferred encoding. Underexposure is recommended if the standard 8-Bit RGB encoding was used instead. Lastly, the images should show a first person view of the office as close as possible to the experience of a person.

The lower dimensional representation derived from images requires a linear transformation (e.g. translation and orthogonal rotation) to align with the contextual dimensions. In our experiment, we computed this transformation using the human-derived map. However, normally this map would not be available. We envision three ways to acquire the transformation without the human-derived map.

The first possibility is to collect additional data through user ratings. The required human input is reduced compared to the approach in the human subject study (as described in section 3.2) because the distances between landmark scenes can be established through sensor-based mapping. Given that the contextual dimensions are known, as little as three coordinates would be sufficient to align the sensor-derived map with the contextual dimensions. Data could be theoretically collected for three instead of six lighting scenes, which would reduce the amount of human input to half.

The second possibility is to use the human-derived map generated from our experiment

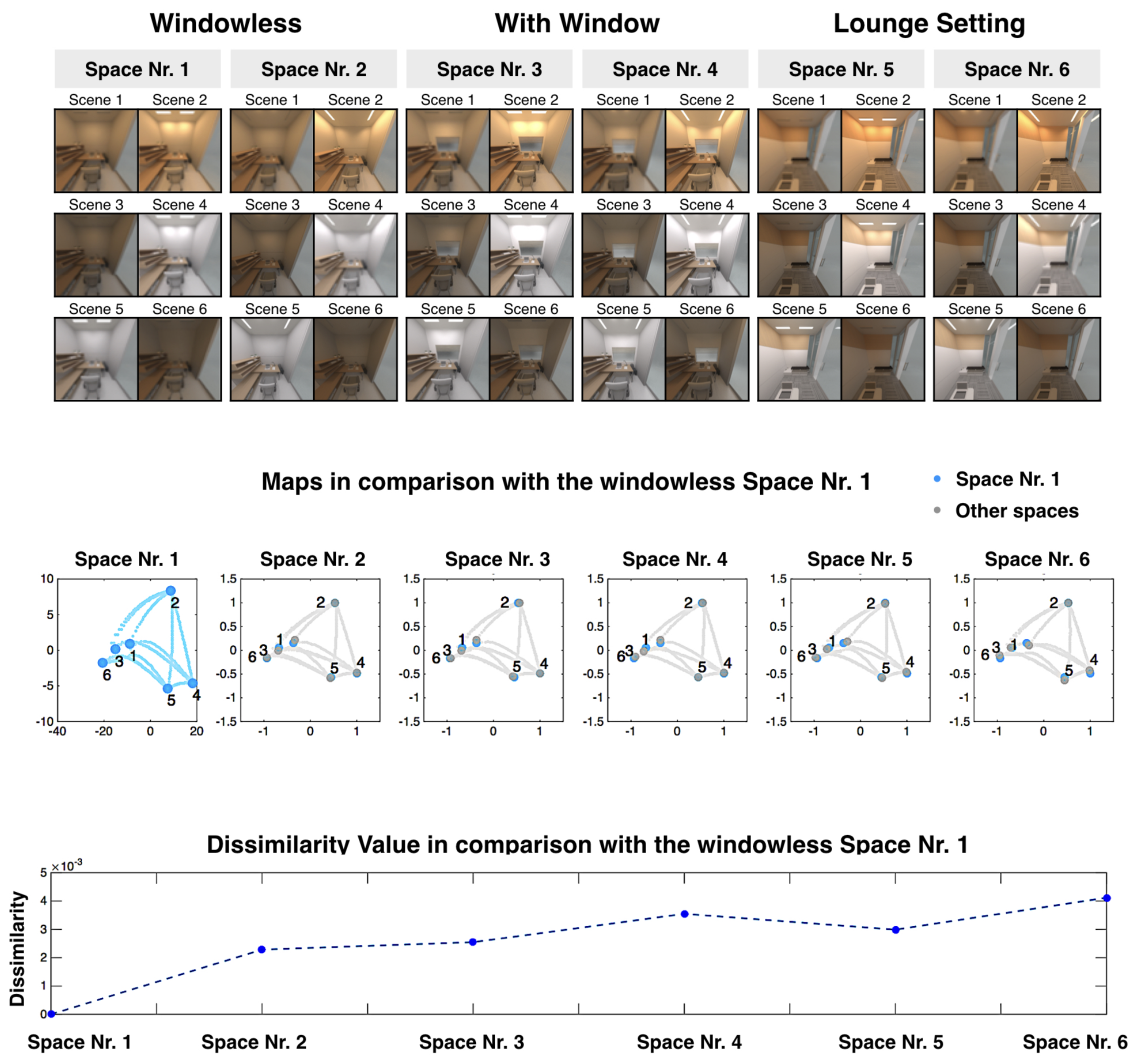


Figure 4-13: Results of One Person Office simulation. At the top, the rendered images are the six lighting scenes of the simulated spaces. In the center, the sensor-derived maps for each variation of the space are shown in comparison to space Nr. 1. The bottom graph shows the dissimilarity value of all variations in comparison to space Nr. 1.

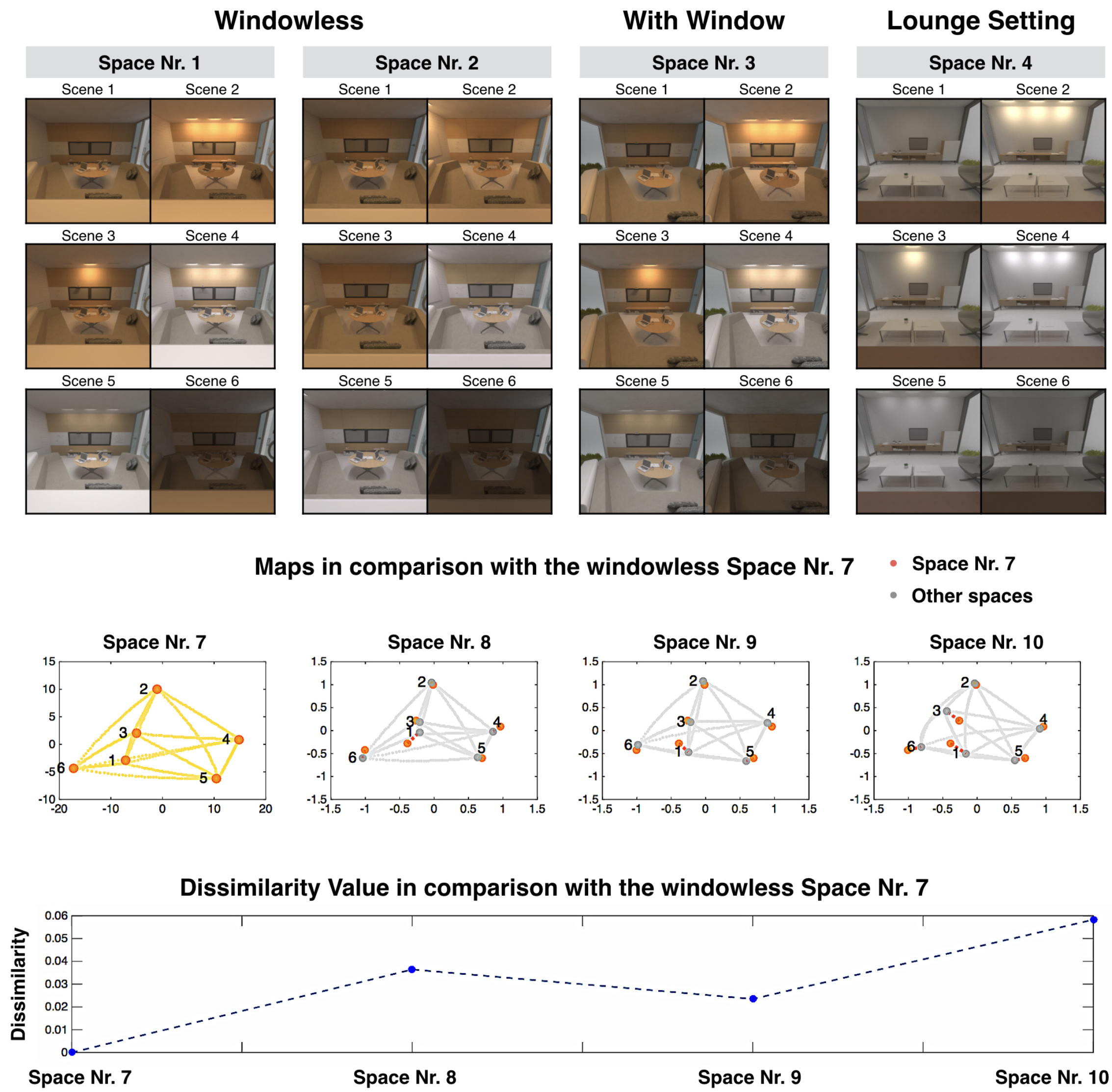


Figure 4-14: Results of Conference Room simulation. At the top, the rendered images are the six lighting scenes of the simulated spaces. In the center, the sensor-derived maps for each variation of the space are shown in comparison to space Nr. 7. The bottom graph shows the dissimilarity value of all variations in comparison to space Nr. 7.

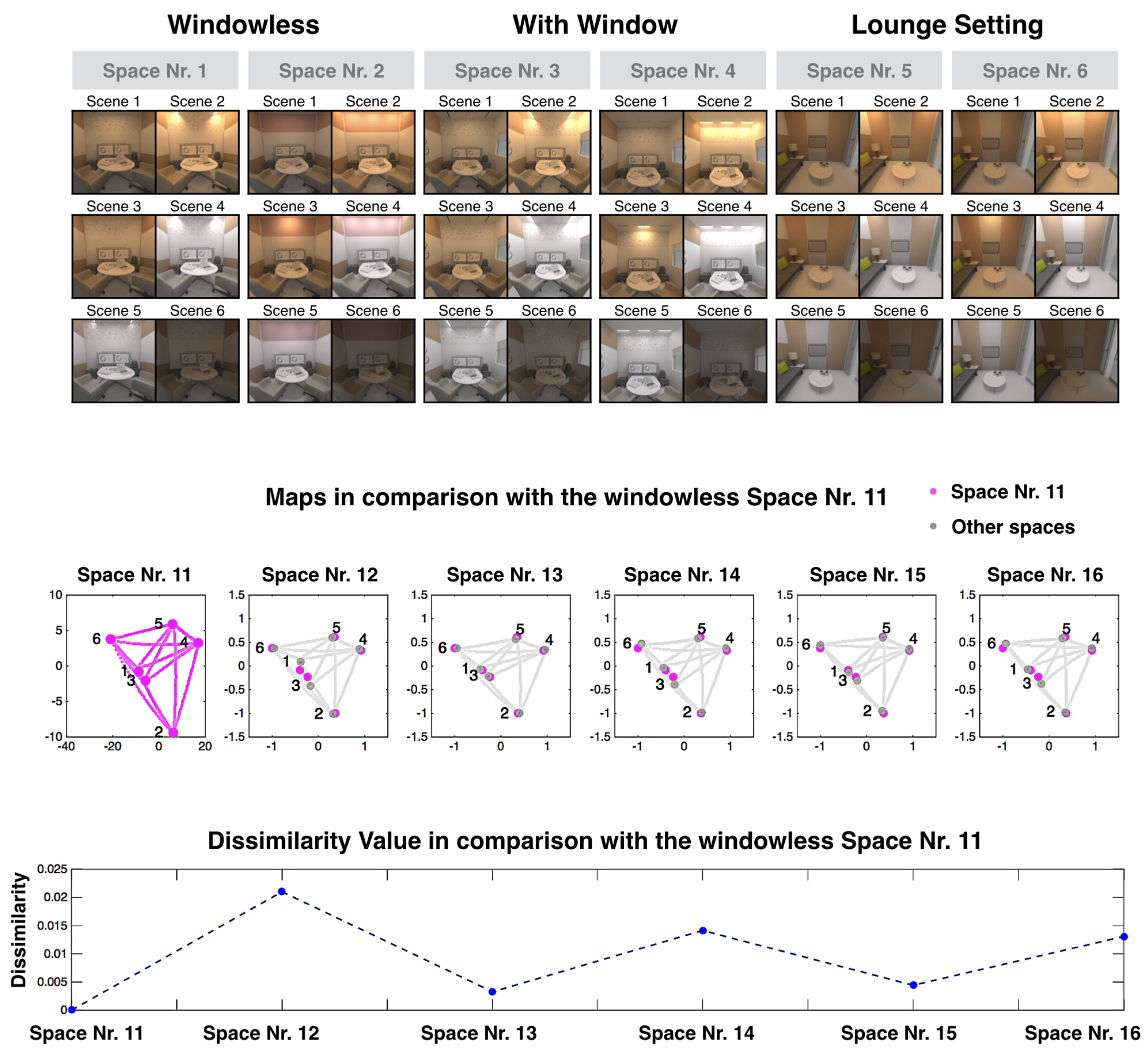


Figure 4-15: Results of Small Office simulation. At the top, the rendered images are the six lighting scenes of the simulated spaces. In the center, the sensor-derived maps for each variation of the space are shown in comparison to space Nr. 11. The bottom graph shows the dissimilarity value of all variations in comparison to space Nr. 11.

as a template for the linear transformation. The simulation study revealed that a general pattern was present in all 2D representations, despite differences in room size, the layout of the lighting system, furniture, scene configurations, etc. In particular, the dissimilarity was the lowest between variations of the same type of office. The commonalities among the simulated spaces were the kind of lighting fixtures and the basic arrangement pattern, e.g. the distance between wall washing fixtures, and a few fundamental attributes of the scenes. Within these constraints, a template could be used to align the sensor-derived map with the contextual axes. Such template could be created for each type of space. The human-derived map appears to be most suitable for the Small Office.

The third option is to use machine learning on a large set of space- and perception data. Our current results are encouraging for this option because we were able to see prominent features in the image data.

Besides the application in context-aware lighting, the sensor-based mapping approach is also applicable for interior planning and simulation. Through the simulation of the three types of offices, we demonstrated means to visualize the adaptive potential of the lighting system before its installation. During the planning phase, this kind of visualization could assist in decision making. Furthermore, it could be used to optimize the layout and lighting scenes in a way that produces the largest perceptual difference between scenes to ensure a rich and interesting experience. Such tool could be integrated into an architectural planning- and simulation software. Using a processing pipeline similar to the simulation study the control maps could be generated in real-time while the architect or lighting designer constructs the interior.

Chapter 5

Context-Aware Multimodal Media

Besides light, many other aspects of the ambient environment have an impact on work experience. Recent technological developments have enabled immense progress in Augmented Reality and displays. Besides academic research [68, 72, 115], companies such as Microsoft and Sony laid out their vision for ubiquitous displays, which are embedded in tables, furniture, and wall surfaces [102, 129]. Many surfaces in our living and workspaces will become screens. If they are not displaying information, such as data visualization, games, movies, they could be used in a composition with the ambient environment. For example, Sony's Life Space UX products [129] and the Apple TV [33] offer modes that show landscape images or photos from the user's album as screen savers. Given the impact of the ambient conditions on health and productivity, dynamic control can unlock new opportunities for these technologies. This chapter introduces a multimodal approach that uses projection and sound in addition to lighting for Mediated Atmospheres.

Section 5.1 describes the multimodal media prototype. It explains the reasoning and implementation of the sensing and output systems, the atmospheric scenes, and the overall software architecture. The subsequent sections present the setup, methods, and results of two experiments, following the IRB protocol # 1601357773. In the first experiment (Study I), I assessed the effect of the atmospheric scenes on users' physiology and perception of the space. The results of this study were published in the academic journal Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies [165]. Building on the findings of the first study, I implemented two context-aware application modes that form a closed loop between the user and the dynamic environment. These modes are named

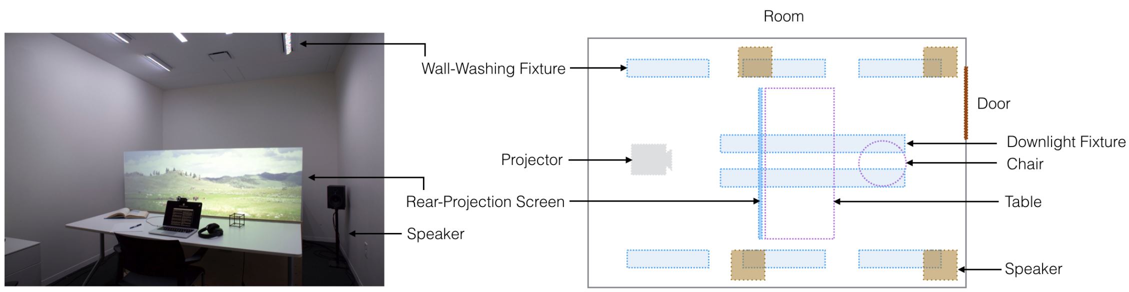


Figure 5-1: Physical layout of the room.

Biofeedback and Goal Mode. In the second experiment (Study II) I evaluated the impact of these application modes on work experience in a life-like work scenario and examined their differences and unique advantages.

In this implementation, instead of deriving a control map from data, an approach demonstrated in a previous experiment (see section 3.2), the control dimensions were selected to be *Focus* and *Restoration*. These axes were established in the experiments on context-aware lighting, which were carried out in the same office space using a different setup. Additionally, related research also identified these activities as the main work modes that commonly require changing of work settings [48]. Therefore, these contextual control dimensions were used for the multimodal media setup.

5.1 Prototype Office

The prototype office was implemented in the *Lighting Lab*, a windowless rectangular room, 4.2 m by 2.8 m with a ceiling height of 2.6 m, located in the Responsive Environments Group area in the MIT Media Lab. The space design process was guided by frequent exchange with office furnishing and lighting professionals. By doing so, we expect our research to be relevant to modular office and cubicle design in the future. The prototype's physical layout is sketched in Figure 5-1. This prototype was also used in concurrent research in my research group [5], which was an initial study of how the affective influence of imagery and lighting could be measured and determined, and [117], which explored the use of conversational agents in these environments. This section provides an overview of the prototype's components and features.

5.1.1 Outputs

We consider lighting as a central factor of our design, given its wide-ranging effect on the human body. Illumination technologies provide high-quality light, e.g. high dynamic range, and Color Rendering Index, whereas display technologies can create immersive illusions. Images enable additional design possibilities, for example, the environment as a behavioral cue or as the facilitator of restoration as described in the Attention Restoration Theory. Related research has shown that the feeling of presence or immersion is an important factor for the effectiveness of digitally generated stimuli [64, 130]. We, therefore, synchronize light and visual images with sound to heighten the sense of presence. Sound is able to alter our sense of the environment beyond the limited visual window, for example, to convey the spaciousness or openness of a place [55].

Accordingly, our prototype used controllable lighting, projection, and sound, which were installed in the room and furniture. For lighting, we used the 20 individually controllable multi-channel fixtures of the Lighting Lab. For sound we implemented two options, an ambisonic sound system using four speakers and alternatively a pair of wearable noise canceling headphones (*Bose, QuietComfort*). The headphones offered control of ambient noise and were used during user studies. For video projection, we used a high-luminosity output projector (*NEC, NP-PA571W*) with short throw lens (*NEC, NENP30ZL*). A custom rear projection display was built using a 1.83 m by 0.76 m light-diffusing acrylic. The final design as shown in 5-1 is the result of many design iterations [5].

5.1.2 Sensors

We integrated a set of sensors in the office prototype. These sensors were used to evaluate occupants' physiological response to atmospheric changes. They were also used for real-time activity recognition and context-aware dynamic control. A Sensor Collection Server [5] manages and stores incoming sensor data streams. Using the Sensor Collection Server, sensors can be easily added or removed from the system.

We selected several commercial, low-to-medium price range wearable sensors for physiological monitoring. The current setup includes a heart rate and physiological monitor chest strap (*Zephyr, Bioharness 3* [164]), a wrist worn monitoring device (*Empatica, E4* [42]), and EEG headband (*InteraXon, Muse Headband* [42]). These sensors provide physiological mea-

Figure 5-2: Two amospheric scenes side by side.

surements, such as ECG, BIB, and GSR, which are frequently used for affective computing and especially relevant for our application.

Additionally, the prototype office incorporates facial feature tracking using the *Intraface* software library (*CMU Human Sensing Laboratory and University of Pittsburgh Affect Analysis Group, Intraface*) [38]. A standard USB camera (*Logitech, Quickcam Vision Pro* or *Genius, WideCam F100*) is placed in front of the occupant, on top of the occupant's computer screen. It captures the occupant's face and part of the upper body. The complete list of sensors is shown in Table 5.1.

5.1.3 Atmospheric Scenes and the Scene Library

The scene library currently contains over 30 atmospheric environments based on real places. These include beaches, natural landscapes, indoor spaces such as libraries, cafes and museums, and scenes of metropolitan cities, train rides, and even a roller coaster ride. These scenes were chosen to cover a wide range of effects and perspectives. They have different themes (nature, urban, indoor) and experiential attributes (motion, repetitiveness, color, brightness). Each scene contains video and sound data, a lighting configuration file and meta information of key characteristics. The lighting design of the scenes were inspired by

Table 5.1: Sensors and their featured measures.

Sensor	*Measurements (Reporting Frequency)*
Zephyr Bioharness 3	Heart Rate (1 Hz), RR Interval (18 Hz), ECG (250 Hz), Respiration Rate (1 Hz), Breathing Waveform (25 Hz), Posture (1 Hz), Activity Level (1 Hz), Peak Acceleration (1 Hz), 3 Axis Acceleration (100 Hz), Sensor Confidence, Device State and Debugging Information (1 Hz)
Empatica E4	3 Axis Acceleration (32 Hz), Blood Volume Pulse (64 Hz), Inter Beat Interval, Electrodermal Activity (4 Hz), Skin Temperature (4 Hz)
Intraface	49 facial feature points 3D head orientation 3D viewing orientation Prediction of 6 emotions (neutral, angry, disgust, happy, sad and surprised) videos are recorded and processed at approximately 10 fps with a resolution of 1280 by 720 pixels
Muse Headset	EEG alpha theta band entropy, EEG gamma beta band entropy

the video content, either using light measurements of the space the video was recorded at or using the video content itself. A description of recoding and light measurment tools we used is detailed in [5].

The lighting configuration file, in JavaScript Object Notation (JSON) format [14], contains position, size, intensity, and color information of virtual light sources. Virtual light sources, different than the actual physical installation in the space, can be positioned anywhere on the ceiling. The virtual ceiling is an infinite x-y-plane. A room model of the physical setup converts the virtual light information to actual light settings. This separation of lighting configurations and the physical lighting layout aims to make the configuration file applicable for any space that can be described with a room model.

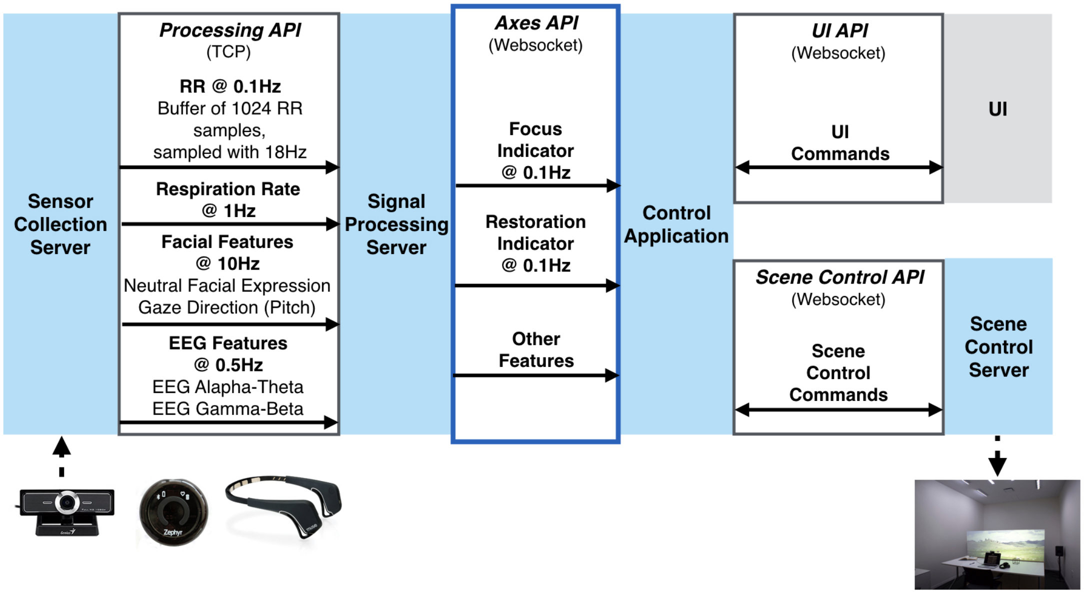
Meta information, in JSON format, includes sound level, brightness level, light color temperature, light direction, keywords, dominant colors, descriptive name, ID, length, etc.

5.1.4 Software Architecture Overview

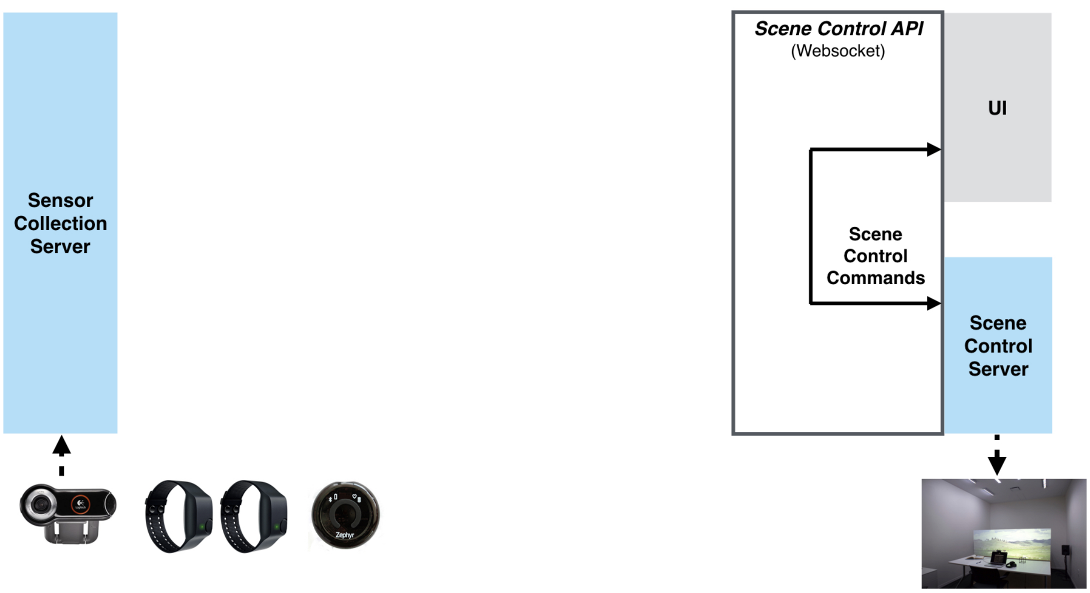
The software has a modular architecture, which allows agile modification and expansion of the system's functionality. It consists of modules with specialized services and API's. These modules can be combined and customized for the desired application.

(1) (2) (3) (4) (5) (6)

Figure 5-3: Example Scenes



(1) Closed-loop configuration as used in Study I



(2) Open-loop configuration as used in Study II.

Figure 5-4: Software architecture in two configurations.

Figure 5-4 shows two configurations, a closed-loop and open-loop configuration. In the open-loop configuration, the outputs are controlled independently from the occupant's physiological response. Sensor streams are recorded for offline analysis. This configuration was used in Study I and is described in detail in section 5.2.

In the closed-loop configuration, the Control Application forms a closed-loop with the occupant's physiological response. This design incorporates results from the first experiment. It was used in the subsequent Study II and is described in section 5.4.

5.2 Open-Loop Software Architecture

This section describes the open-loop configuration as illustrated in Figure 5-4-2.

5.2.1 Sensor Collection Server

The Sensor Collection Server manages incoming data streams and data logging to storage. This module was developed in [5] and modified for this research. It is implemented in Python using the Twisted library - an asynchronous, event-driven networking engine [80]. This network engine builds on the reactor pattern, in which a reactor loop multiplexes incoming requests to the appropriate request handler. Request handlers were implemented for each sensor with the service to parse, format and log incoming data for example as .csv files.

In this configuration, we used the physiological monitor chest strap (*Zephyr, Bioharness 3*), the wrist-worn devices (*Empatica, E4*), and the facial feature tracking library (*CMU Human Sensing Laboratory and University of Pittsburgh Affect Analysis Group, Intraface*) in combination with a standard USB camera (*Logitech, Quickcam Vision Pro*), for physiological monitoring.

5.2.2 Scene Control Server

The Scene Control Server implemented in Python facilitates real-time control of all output capabilities and manages transitions between atmospheric scenes. It consists of two main parts, a *Room Model* and a *Transition Handler* as shown in Figure 5-5.

Upon a scene transition request, the Transition Handler, loads the target scene from the Scene Library and initiates a fading effect with the specified transition speed. Subsequently,

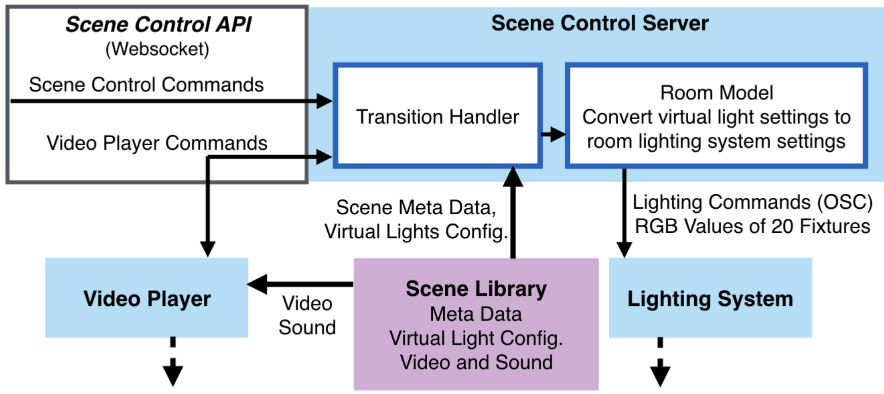


Figure 5-5: Top-level design of the Scene Control Server.

the Video Player, which is responsible for video projection and sound, executes the desired transition. The transition typically means that video and sound of the current scene are gradually faded out and, after a short break in a neutral state, video and sound of the new scene are faded in. When the transition is completed, the Video Player sends a status update to the Scene Control Server. The Video Player is implemented in Javascript and displayed through a web browser. Video and sound are played in a loop. At the end of the video and sound file, typically an H.264 encoded .mp4 file, a cross-fade is initiated to a specified or random position in the video and soundtrack.

For lighting transitions, the Transition Handler needs the Room Model. The Room Model is a transfer function from an abstract space to the actual lighting installation in the prototype office. We introduced the concept of an abstract space and virtual light sources to separate the desired lighting result from the physical lighting system and its layout in the room. Hereby we aim to make lighting configurations reusable for other lighting systems (see section 5.1.3). The Room Model contains information of the physical lighting installation and maps the virtual light sources to the existing lighting system. The resulting RGB channel brightness settings are then sent to the lighting server, which controls the lighting systems in the prototype space.

5.2.3 Scene Control API

The Scene Control API is a Websocket interface that facilitates Scene Control Commands and Video Player Commands. It allows rapid prototyping of web-based applications for manual or sensor-driven control. Using this interface, we developed a set of tools for scene design and experimentation. API commands are in JSON format. They typically contain a command type and several parameters. The command for a standard scene transition is for example

```
{
    "type": SCENE,
    "name": Forest ,
    "id": 1,
}
```

5.2.4 User Interfaces

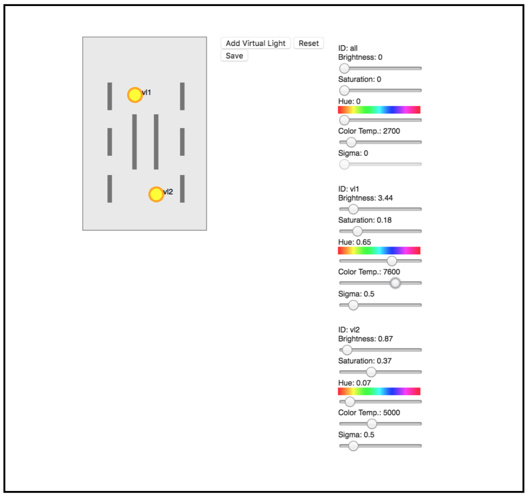
For this configuration, we developed three sets of graphical user interfaces: design tool interfaces, a demo interface and an experiment interface. Figure 5-6 shows screen-shots of the three kinds of interfaces. Design tool interfaces allow the designer to explore lighting attributes for scenes design. It facilitates the creation of virtual light sources and manual configuration of light fixtures. The demo interface visualizes and provides access to the scene library. It also facilitates turning on and off the entire system and displays the status of the Scene Control Server. Lastly, the study interface provides instructions and tasks for the experiment (Study I). It guides the study participant through the experiment, collects ratings from the participant, and manages sensor data acquisition and scene transitions in the background.

5.3 Study I

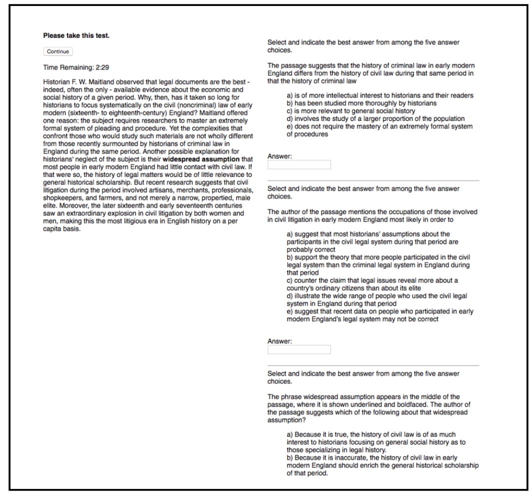
The goal of the Study I was to assess the effect of Mediated Atmospheres on the perceived ability to focus and restore from a stressful situation, and to evaluate its influence on physiology. This experiment was performed using the open-loop configuration of the prototype system.

5.3.1 Experiment Design

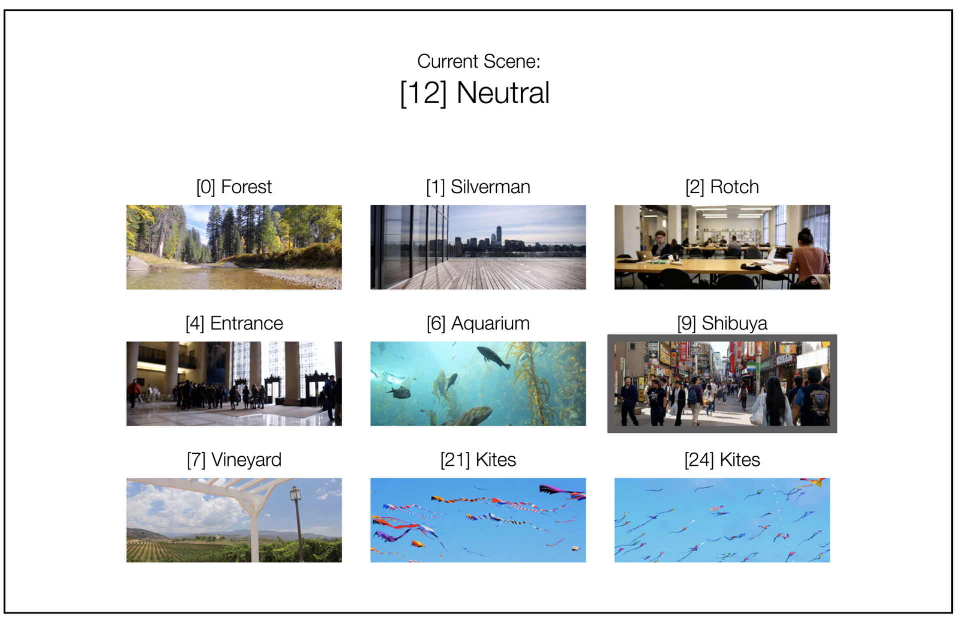
In this experiment, we adopted a repeated-measures design, with the type of atmosphere as a within-subjects variable. We used five atmospheric scenes as the experimental conditions. The conditions are described in detail in Section 5.3.1. Furthermore, we defined



(1) Virtual Lighting Tool — to explore lighting attributes and create lighting designs



(2) Study Interface — guides the study participant through the experiment, collects ratings from the participant, and manages sensor data acquisition and scene transitions in the background



(3) Demo Interface — visualizes and provides access to the scene library

Figure 5-6: User interfaces for open-loop configuration.

two measures to determine participants' perception of the room's suitability for focus and restoration activities. Section 5.3.2 explains the design of these measures. For each measure, a Friedman's Test and post-hoc comparisons using the Wilcoxon Signed Rank Test were conducted to examine any significant changes. The calculations were carried out using MATLAB's Statistics Toolbox.

For the analysis of physiological effects, we took personal bias into account and labeled each physiological measure according to the associated perceptual rating of the scene in which they were recorded. Each scene was given two labels: restorative/non-restorative and focus/non-focus, which represented their perceived suitability for restoration and focus respectively. A series of paired t-tests, one for each physiological measure, evaluated the significance of mean differences between the two levels of restoration and focus. The analysis was carried out using three features from the recorded physiological data: Heart Rate Variability, Head Orientation, and Neutral Facial Expression. These features were selected in a preliminary analysis and are explained in detail in section 5.3.3.

In each condition, participants performed several cognitive tasks using a laptop computer. The study procedure is described in section 5.3.1. The activities included a focused, stress-eliciting work assignment and a break for recovery, which simulated a work day with alternating activities. The variation of tasks forces our processing algorithm to distinguish physiological changes that were introduced by the scenes from the higher fluctuations caused by the user's activity.

Conditions

We designed five atmospheric scenes. Each scene introduces a different context that is often associated with focus or restorative activities. Their key characteristics are summarized in Table 5.2. The video lengths vary, but they are all longer than the duration of the study. If a video reaches the end, it dissolves to the beginning.

Forest The video projection shows a forest in autumn. A clear, shallow mountain stream flows though a dense, partially red-colored forest. There is no camera motion. The perspective suggests that the viewer is resting, elevated over the stream. One can hear the sound of the river and occasionally birds in the background. Low intensity, warm lighting completes this scene. Two virtual light sources in the center of the ceiling correspond to the forest opening and direction of lighting in the video.

Library The video shows a study room in a university library. A number of students are present. They are sitting at tables and studying independently. There is no camera motion. The viewer appears to be sitting at one of the tables in the library. One can hear the ambient sound of the space, such as movements, or when someone enters or leaves. High intensity, white light characterizes the ambiance of the room. A virtual light source in the center of the ceiling corresponds to the fluorescent ceiling lights in the image.

Kites The video shows three kites against the background of a blue sky. The horizon is not visible. Each kite has a unique shape, flying speed and trajectory. The third kite appears and disappears from the screen depending on its movement. There is no camera motion, but compared to the Library and Forest scene, there is significantly more visual action. The camera perspective suggests that the viewer is resting and looking up to the sky. One can hear ocean waves crashing in the background. For this scene, we choose cold, high intensity, primarily indirect lighting which complements the color and openness of the sky.

City The video shows a walk though the Shibuya district in Tokyo, Japan. The camera moves steadily at walking speed through crowds of pedestrians. The video captures the activities of a busy walking district with colorful billboards, shops, and buildings from a first-person-perspective. One can hear the sound from the street, some illegible speech, music coming from the stores, etc. We choose a mix of direct and indirect, high-intensity white light, which corresponds with the weather in the video image.

Neutral Finally we created a "Neutral" scene, which is the office without augmentation. The projection screen is white and the projector displays a black screen. Lighting is uniform, white and at medium intensity. There is no additional sound. This scene represents the original office context.

(1) Neutral

(2) Kites

(3) City

(4) Forest

(5) Library

Figure 5-7: Images of the test conditions

Table 5.2: Conditions and characteristics.

	Conditions				
Characteristic	*Forest*	*Library*	*Kites*	*City*	*Neutral*
Movement in video	Low	Low	High	High	None
People or Buildings in video	No	Yes	No	Yes	No
Nature in video	Yes	No	Yes	No	No
Light Color Temperature (K)	3500	5500	9000	6500	6500
Horizontal Illumination on the Desk (lux)	250	1000	800	1000	350
Sound	Forest, river	Ambient sound of the library (e.g flipping pages)	Ocean waves	Ambient sound of the city (e.g. illegible voices)	None
Expected Restoration	High	Low	High	Low	Low
Expected Focus	High	High	Low	Low	High

Participants

The population of interest is office workers. The experiment panel, therefore, consisted of university students and local office workers, N = 29, 40% Female. On average, participants were 31 years old (M = 30.8, SD = 6.7).

Procedure

Each session took approximately one hour and was divided into five identically-structured sub-sessions. Figure 5-8 visualizes the session procedure. At the beginning of each session, the study personnel explained the different parts of the study to the participant in a tutorial. Afterwards, the participants were left alone in the workspace, and a website — the study interface as shown in Figure 5-6, guided them through the experiment. The website also controlled the transitions between the scenes in the room and collected the participants' inputs. Both physiological signals and survey responses were recorded.

In each sub-session, the participants were shown a different, randomly selected scene. At the beginning of each sub-session, participants saw the Neutral scene for 30 s and the tested scene for 1 min in order to disconnect the sub-sessions from each other and to avoid

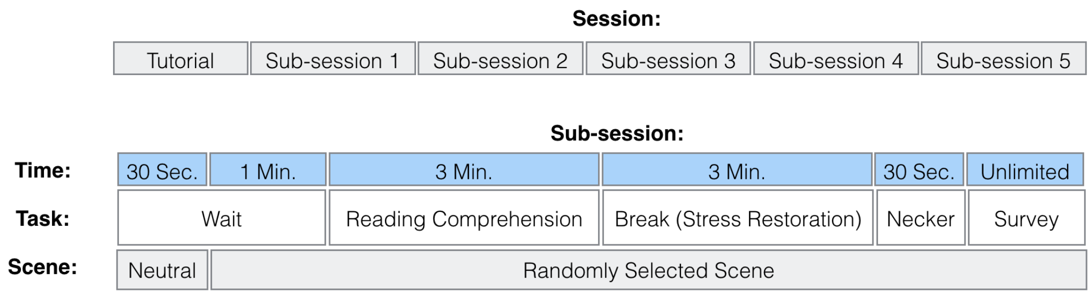


Figure 5-8: Schematic illustration of the study session procedure. Each participant was invited to one session. Sessions and sub-sessions were structured as illustrated above.

possible novelty effects. Afterwards, they performed a series of tasks: a GRE level reading comprehension assignment, a short break, the Necker Cube Test, which is explained in section 5.3.3, and the survey. During the break, participants were allowed to explore the space, but they were asked to remain seated.

5.3.2 Measures of Perception

We defined two measures to determine participants' perception of the workplace, *Perceived Focus Potential* and *Perceived Restoration Potential* and collected responses through direct ratings. All ratings used a five-point Likert scale ranging from -2 ("very low") to 2 ("very high"). Perceived Focus Potential describes the scene's suitability for demanding work tasks that require mental concentration, as perceived by the participant. Likewise, Perceived Restoration Potential describes how suitable a scene is for restoring from a stressful situation. Participants rated each atmospheric scene on seven variables. The survey is included in Appendix B.1.

Two questions in the survey asked participants to rate the suitability of the rendered scene for specific work scenarios. Prior research [62] used a similar approach to assess perceived restorative qualities and inspired our choice of questions. The first question invited the participant to imagine herself in a situation where she is full of energy and about to start a challenging task. This rating measured the Perceived Focus Potential. The second question asked the participant to imagine herself in a position where she needs to recover from the prolonged mental effort. This rating contributed to the Perceived Restoration

Potential.

For additional five questions, participants rated the atmospheric scene on five facets of a restorative environment, Compatibility, Coherence, Being-away, Fascination, and Scope, as suggested in the Perceived Restoration Score Questionnaire [110]. Finally, the Perceived Restoration Potential is the mean of all restoration-related ratings.

5.3.3 Measures of Physiology

Heart Rate Variability

Heart Rate Variability (HRV) is an established psycho-physiological measure for stress development and restoration e.g. in [135, 10]. High HRV is generally believed to indicate parasympathetic regulation [10]. Using the Zephyr Bioharness 3 [164], we recorded RR, which measures the time interval between consecutive heart beats. This signal was generated on the device using the ECG waveform sampled at 1000 Hz. For the calculation of HRV, the recorded RR interval series was converted to an equidistantly sampled series by cubic spline interpolation. The resulting sample rate was 18 Hz. We used the standard deviation of RR intervals (SDNN) method to compute HRV. SDNN was calculated for consecutive overlapping sections of 1 min of the resampled RR data. We then applied a moving average filter with a window length of 10 s. The result was set to the right edge of the window.

Head Orientation

Using the head orientation information we aim to estimate where participants directed their visual attention. A lifted head position was associated with attention towards the projection screen, which is tall and further away. Accordingly, looking at the table or laptop computer resulted in a dropped head orientation. A restorative environment naturally draws attention [77], whereas a focus environment should not create any distraction. Therefore, we expected a difference in visual interest between the different conditions. Participants' head orientation was generated by Intraface.

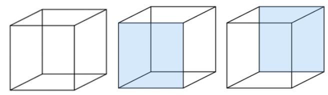


Figure 5-9: During the Necker Cube Test, participants were presented with the wireframe cube on the very left. The center and right images illustrate the two possible perceived orientations.

Facial Expression

Facial expression indicates whether the participant exhibited emotional changes during the experiment. We chose the Neutral feature, which was computed by the Intraface software library, because we were most confident about the interpretation of this feature compared to the other available emotional features. This feature was reported as a confidence level between 0 and 1, with a value of 1 indicating a confident detection of Neutral expression. It was therefore not normalized per person in post processing.

Direct Attention

The Necker Test is a psychological test designed to measure one's capacity to direct attention [29, 30]. A wire-frame cube can be seen in two different orientations (see Figure 5-9). After viewing the cube continuously for several seconds, the perceived orientation reverses spontaneously. The duration of time between perceived reversals, which could be measured as the number of reversals within a certain amount of time, has been shown to correlate with one's ability to direct mental effort [137]. In our experiment, an increase in reversals implies a decline of the participant's ability to focus their attention in the rendered scene. Each reversal was recorded through mouse clicks.

Signal Processing

Physiological recordings were divided into samples. A *sample* is the time series signal of one physiological measure from one sub-session. Each sample is therefore associated with one participant and one atmospheric scene and has the length of 8 minutes or longer. Samples were labeled according to the associated perceptual rating. If the participant rated the Perceived Focus Potential of the scene as above average, the sample was labeled with *focus* otherwise, it was labeled as *non-focus.* Likewise, a sample with Perceived Restoration

Potential rating above average was considered as a restorative and non-restorative otherwise.

We defined two kinds of metrics to compare the time series samples, one using the aggregated mean value and another based on probabilistic modeling, which could potentially describe trends in the data that are not apparent in the aggregated mean. Each sample produced several metrics for comparison: (1) mean, (2) probability to be higher than mean (Prob. > 0), and (3) probability to be more than one standard deviation higher than mean (Prob. > 1). We computed the probability metrics for HRV and Head Orientation. For Neutral Facial Expression, because of the format of the data, we instead calculated the likelihood of a confidence level above 0.5 (Prob. > 0.5). Because the Necker Cube Test did not produce a time series signal, we only compared its mean values.

For the probabilistic metrics, we constructed a probability density function *pdf*: $p(x)$ for each sample using Kernel Density Estimation (KDE) with a Gaussian Kernel and by considering the data points as random variables. We can interpret the *pdf* as an estimation of the likelihood to observe the physiological state x. Accordingly, the probability that an observation will fall within a certain range, $p(x \in [a, b])$, is the area under the curve of the estimated *pdf*. Let's assume that the data is normalized, which means that $x = 0$ is the personal average. Then, the probability to observe a physiological state higher than average is $p(x \in [0, \infty])$ and more than one standard deviation higher than average is $p(x \in [1, \infty])$.

Before the analysis, all recorded samples were inspected visually to identify and sort out sessions with sensor failure. Outliers that were higher than five times the standard deviation of the sample were removed. Unless otherwise specified, samples were normalized per person. We expected differences of the physiological signals among the participants. To make the comparison more meaningful, we transformed each data point to its z-score. Before we computed the metrics, data points that were recorded during the 30 s Neutral time and 1 min adjustment time at the beginning of each session were removed.

5.3.4 Results

Effects on Perception

Perception differed significantly ($p < 0.05$) among the atmospheric scenes for both Perceived Focus Potential (PFP), $\chi(25) = 29.8, p = 5.33 \cdot 10^{-6}$ and Perceived Restoration Potential

Table 5.3: Perception test mean scores (M) and standard deviation (SD) of five atmospheric scenes for Perceived Focus Potential (PFP) and Perceived Restoration Potential (PRP). Scenes that were perceived significantly different than Neutral are highlighted.

	Forest		*Library*		*Kites*		*City*		*Neutral*	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
PFP	1.07	0.96	0.76	1.18	0.46	1.40	**-1.00**	**1.25**	0.64	1.13
PRP	**1.21**	**0.72**	-0.06	0.87	**0.67**	**0.84**	**0.53**	**0.99**	-0.44	0.99

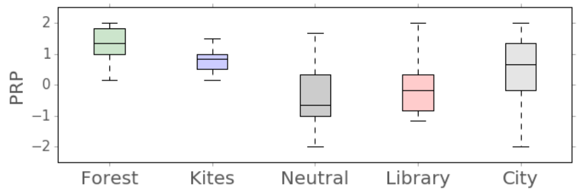
(PRP), $\chi(28) = 42.3, p = 1.45 \cdot 10^{-8}$.

Post-hoc comparisons of individual mean differences showed that PRP for Forest, Kites, and City were significantly ($p < 0.05$) higher than for the Neutral office atmosphere. There was also a significant difference in PRP between Forest and Library. Concurrently, the PFP for City was significantly reduced compared to all other tested scenes. The mean scores and standard deviations of the ratings as summarized in Table 5.3 and the data is visualized in Figure 5-10.

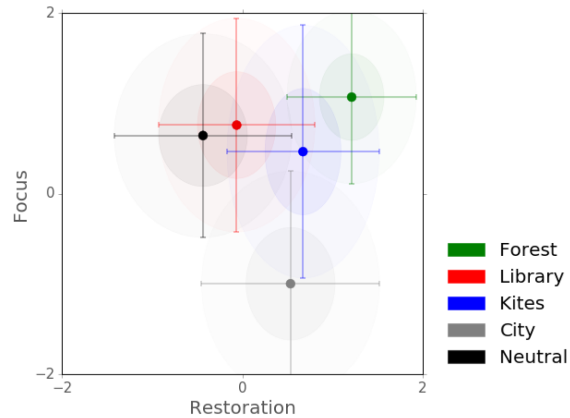
These results suggest that our prototype is able to affect the user's perception of the office's suitability for restoration and focus as defined by our measures. Specifically, Forest and Kites atmospheres were considered as suitable for both restorative and focused activities. On average, the City scene was considered as promoting restoration but not focus. Library and Neutral scenes were considered as less restorative, but suitable for focus, see Figure 5-10. These trends overall agree with our design-intentions. However, high variance indicates strong personal and context-specific differences in atmosphere preference.

Heart Rate Variability

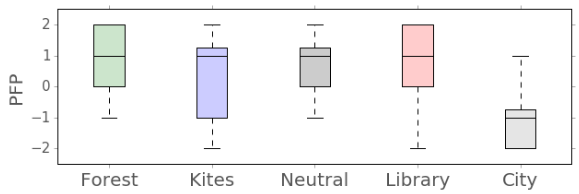
Paired t-tests revealed significant ($p < 0.05$) differences between restorative and non-restorative scenes (labeled according to user ratings as defined in section 5.3.1) in all metrics: aggregated mean HRV (Mean: $t(28) = 3.2, p = 0.003$), probability of high HRV (Prob. > 0: $t(28) = 2.6, p < 0.014$) and probability of very high HRV (Prob. > 1: $t(28) = 2.7, p = 0.013$). On average, mean HRV in restorative conditions were 1.5 times higher than in non-restorative scenes. HRV was also on average 20% more likely to be above personal mean and 36% more likely to be more than one standard deviation higher in restorative conditions (see Table 5.4). There were no significant differences of HRV between focus and non-focus conditions.



(1) Boxplot of perceived restoration



(2) Mean scores of perceived focus and restoration visualized in a x-y-diagram. The ellipses represent personal variances in the focus-restoration-space. The error-bars have the length of two standard deviation.



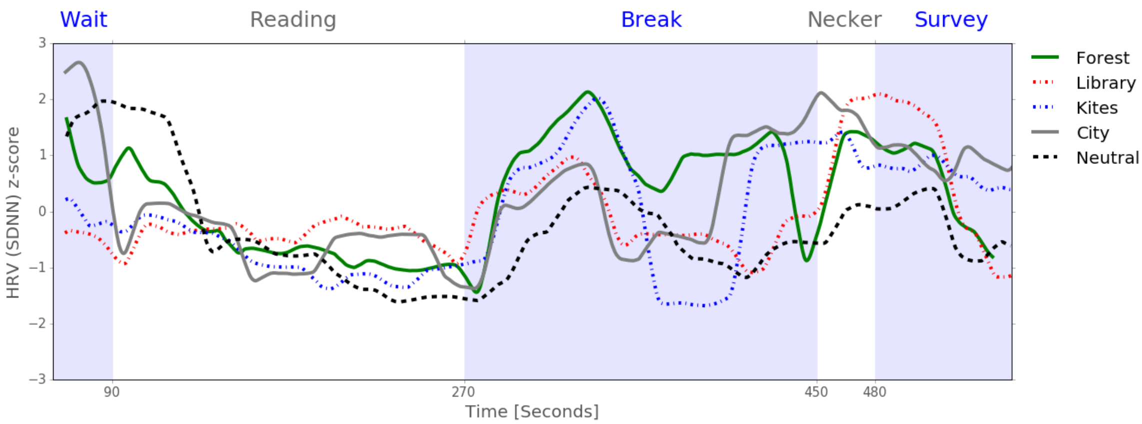
(3) Boxplot of perceived focus (central mark - median; box - 25th and 75th percentile; whiskers - maximum and minimum which are not considered outliers)

Figure 5-10: Visualizations of perceptual ratings

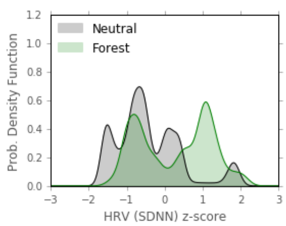
Table 5.4: HRV mean scores (M), standard deviation (SD), and difference between conditions. Statistically significant ($p < 0.05$) changes are highlighted.

HRV

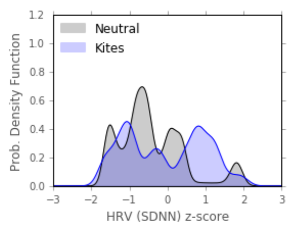
	Focus		*Non Focus*			
	M	*SD*	*M*	*SD*	*p*	*Diff. of mean (%)*
Mean	0.03	0.18	-0.07	0.20	0.17	140.9
Prob. > 0	0.45	0.09	0.40	0.09	0.09	11.4
Prob. > 1	0.16	0.05	0.14	0.07	0.50	9.1
	Rest.		*Non Rest.*			
	M	*SD*	*M*	*SD*	*p*	*Diff. of mean (%)*
Mean	**0.08**	**0.15**	**-0.14**	**0.24**	**0.003**	**158.6**
Prob. > 0	**0.47**	**0.08**	**0.39**	**0.11**	**0.014**	**20.2**
Prob. > 1	**0.17**	**0.05**	**0.13**	**0.06**	**0.013**	**36.8**



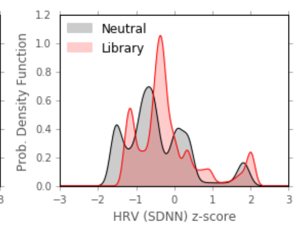
(1) HRV Time Series of one typical participant. Steady decline of HRV can be observed for all environments during the reading assignment. However the initial slope varies between atmospheres. Similarly, the speed and amplitude of HRV recovery are different among the scenes.



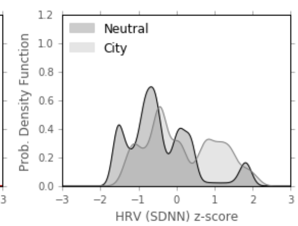
(2) Forest



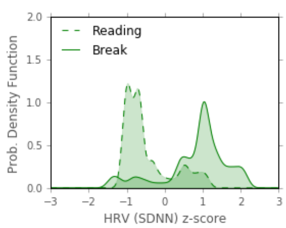
(3) Kites



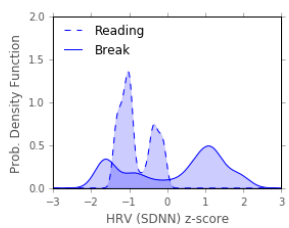
(4) Library



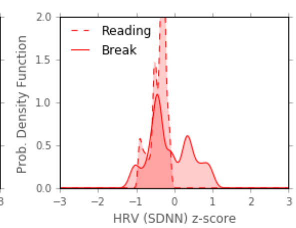
(5) City



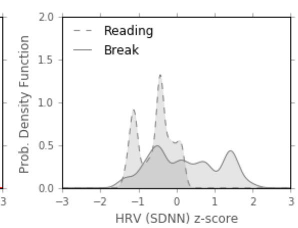
(6) Forest



(7) Kites



(8) Library



(9) City

Figure 5-11: Visualization of HRV of one typical participant. (1) Time Series Signal. (2)-(5) Estimated Probability Density Functions of Forest, Kites, Library, and City in comparison to the Neutral Setting. (6)-(9) Estimated Probability Density Functions for reading and break activities separately.

Table 5.5: Head Orientation mean scores (M), standard deviation (SD), and difference between conditions. Statistically significant ($p < 0.05$) changes are highlighted.

Head Orientation

	Focus		*Non Focus*			
	M	*SD*	*M*	*SD*	*p*	*Diff. of mean (%)*
Mean	**-0.22**	**0.19**	**-0.01**	**0.33**	**0.016**	**-1504**
Prob. > 0	**0.38**	**0.08**	**0.43**	**0.11**	**0.021**	**-13.7**
Prob. > 1	**0.10**	**0.05**	**0.18**	**0.12**	**0.011**	**-44.7**
	Rest.		*Non Rest.*			
	M	*SD*	*M*	*SD*	*p*	*Diff. of mean (%)*
Mean	-0.12	0.19	-0.24	0.23	0.11	50.0
Prob. > 0	0.41	0.07	0.37	0.13	0.15	11.8
Prob. > 1	**0.14**	**0.05**	**0.13**	**0.05**	**0.011**	**62.0**

Head Orientation

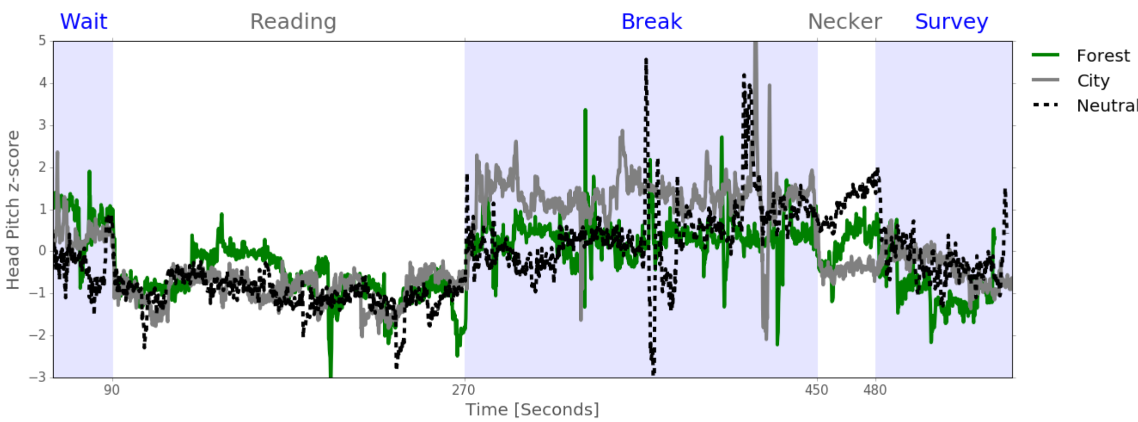
Participants' head orientations were facing significantly more downwards in focus than non-focus environments according to all three measures (Mean: $t(23) = -2.6, p = 0.016$, Prob. > 0: $t(23) = -2.1, p = 0.021$, and Prob. > 1: $t(23) = -2.8, p = 0.011$). For the two levels of restoration, the difference was only significant for distinctively lifted head orientation (Prob. > 1: $t(20) = 2.8, p = 0.012$). The mean scores, standard deviation, and difference between conditions are summarized in Table 5.5.

Facial Expression

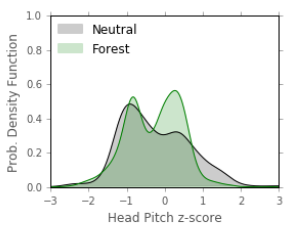
Neutral facial expression was significantly more often detected in focus than non-focus environments (Mean: $t(23) = 2.2, p = 0.042$, Prob. > 0.5: $t(22) = 2.4, p = 0.040$). This was not the case for the two levels of restoration. The mean scores, standard deviation, and difference between conditions are summarized in Table 5.6.

Necker Test

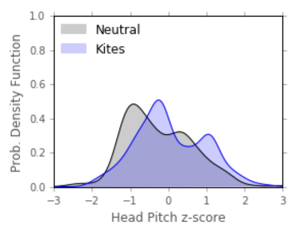
Differences in Necker Test results were not significant, neither for focus nor restorative conditions. However, on average Necker results were lower (Mean and standard deviation of difference between conditions $M' = -0.23, SD' = 1.01$) in focus than non-focus environments and higher ($M' = 0.25, SD' = 0.91$) in restorative than non-restorative conditions.



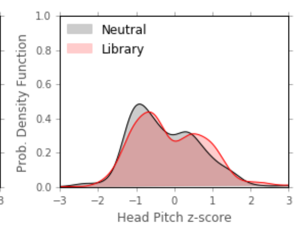
(1) Head Orientation Time Series of one typical participant. During the reading assignment, Head Orientation in the City and Neutral setting were similar. In the Forest scene subject look up more often. During the break participant's head was lifted higher and more steady in the City Setting.



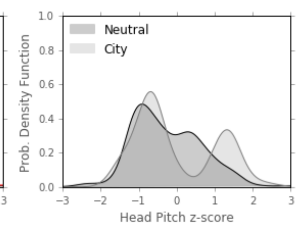
(2) Forest



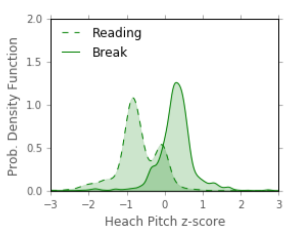
(3) Kites



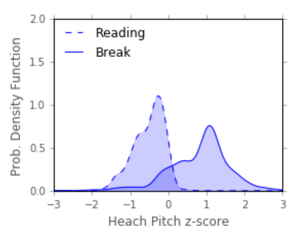
(4) Library



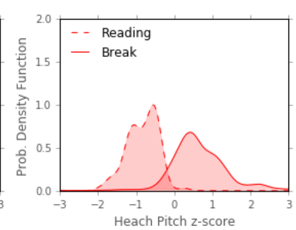
(5) City



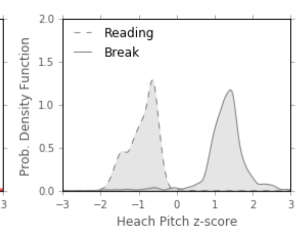
(6) Forest



(7) Kites



(8) Library



(9) City

Figure 5-12: Visualization of Head Orientation of one typical participant. (1) Time Series Signal, for visibility only two scenes are shown. (2)-(5) Estimated Probability Density Functions of Forest, Kites, Library, and City in comparison to the Neutral Setting. (6)-(9) Estimated Probability Density Functions for reading and break activities separately.

Table 5.6: Facial Expression mean scores (M), standard deviation (SD), and difference between conditions. Statistically significant ($p < 0.05$) changes are highlighted.

Facial Expression

	Focus		*Non Focus*			
	M	*SD*	*M*	*SD*	*p*	*Diff. of mean (%)*
Mean	**0.64**	**0.25**	**0.57**	**0.24**	**0.042**	**10.7**
Prob. > 0.5	**0.65**	**0.25**	**0.58**	**0.23**	**0.040**	**11.1**
	Rest.		*Non Rest.*			
	M	*SD*	*M*	*SD*	*p*	*Diff. of mean (%)*
Mean	0.60	0.27	0.63	0.25	0.31	5.1
Prob. > 0.5	0.61	0.27	0.64	0.25	0.31	5.4

A follow up analysis to examine whether there were any notable differences for the five tested conditions revealed that participants performed significantly (p<0.05) better in the Library than the City scene (Wilcoxon signed-rank test: $X(26^1) = 44.0, p = 0.022$, t-test: $t(26) = 2.53, p = 0.018$).

Sensor Reliability

Heart rate monitoring worked reliably with 99.3% success. Only one sample was dropped due to missing data. A few samples of RR contained outliers that were removed according to the procedure described above. In comparison, no sensor failure was detected for respiration, activity level, and posture.

Facial recognition depended on the presence of facial features in the image. This data stream was disturbed when the participant turned away from the camera, moved outside the frame, or when her face was partially occluded, for example by her hands. This limitation led to spotty and missing data. We dropped in total 37 sessions from 10 different participants, which accounted for 25.5% of all recordings, and used the remaining for analysis.

[1] Due to an error we lost the Necker Test results from two participants.

5.3.5 Discussion

Effects on Focus and Restoration

The study results suggest that our prototype workspace and the design choices we have made successfully influenced participants' perception of the room's suitability for restoration and focus. Accordingly, environments that were perceived as restorative also exhibited the desired physiological response. We identified two sensor features that corresponded to environments that were perceived as suitable for focus. This result is important as a first step to quantify the effect of our prototype. In previous research, the influence of restorative stimuli has varied depending on the specific setup [74, 130]. Furthermore, few studies have empirically investigated the relationship between restoration and preference [57]. Our results show substantial variance among participants' ratings, and that physiological response correlate with personal preference. This result confirms that personal appreciation for an environment had a significant influence on restoration outcome. Our findings agree with previous work on the restorative effect of nature [77]. Prior research has shown that nature scenes are more restorative than urban landscapes. This is reflected in the overall trends in the participants' ratings on restoration. Atmospheric scenes, such as the Forest or Kites, were perceived as more restorative than the Neutral office. We also note that these were not perceived as being less suitable for focus. On average, Forest and Kites were rated as more restorative than the City scene, and the City scene as more restorative than the Neutral office.

Despite significant motion of the kites in the image, the Kites atmosphere was overall not considered distracting. The City atmosphere, however, which has camera movement and peripheral image movement substantially decreased focus potential. This is an indication that there is higher tolerance of movement, when it mainly occurs in the center of the visual field, such as in the Kite scene.

Because the Neutral office setting is already an environment that is conducive to focus, the tested atmospheres did not significantly improve Perceived Focus Potential. Similarly, Necker Test results were not significantly different when compared with user ratings, confirming that most conditions were similarly suitable for focus. We only observed significant difference between the Library and the City atmospheres. In agreement, perceptual ratings exhibited trends of improvement for focus in the mediated Library. A long term study or a social study could further clarify this effect, whereby the atmosphere functions as a social cue to reduce distractions and noise.

For both restoration and focus, we observed physiological and behavioral changes. HRV was elevated, and participants paid more attention to the projected image, as indicated by the Prob. > 1 metric. In contrast, participants looked downwards more often and exhibited less facial expression in focusing conditions. This study was designed to test acute effects that occur within minutes. A future study could examine longer term effects, which is also very important for real use case scenarios.

High variance in the perceptual ratings suggests strong personal bias. A user's preference of ambiance depended on both the context and the individual. These results demonstrate the importance of personal preference modeling. While the City scene was restorative for some participants, it caused the opposite reaction for others. Participants' subjective ratings and physiological responses were in agreement. This supports the idea that it should be possible to use user ratings as an initial system configuration and rely on physiological monitoring in the background to further improve labeling of the atmospheric scenes in recommendation applications. We identified three physiological features that correspond well to user's ratings: HRV, Head Orientation, and Neutral Facial Expression. We used these features in our system to build personal response models, which is described in detail in section 5.4. A personal response model was generated for each atmospheric scene as part of the customized scene library.

Comparison of Signal Processing Approaches

During the experiment, participants performed a series of different tasks, which introduced significant changes in their physiological recordings. Despite the activity-dependent fluctuations, both metrics based on aggregated mean and probability density estimation correlated with the participant's ratings of the scenes. The results of the two methods were overall in agreement. This indicates the mean score is sufficient to approximate physiological changes in HRV and Facial Expression for tasks similar to the activities in the user study. However, the probabilistic metric detected nuanced differences in head orientation, which were less pronounced in the comparison of means.

The reason is that the estimated probability density functions describe multiple trends that occurred during the different tasks. For example, the signal illustrated in Figure 5-11-(2) shows two peaks in HRV, which indicates two main physiological states. In Figure 5-11-(6) the distribution is plotted for measurements during the break and the reading activity separately. Here we can see that one physiological state was more pronounced during the reading and the other during the break activity.

For Head Orientation, in a simplified scheme, there were three dominant head positions: dropped head, lifted head and distinctly lifted head. By applying the appropriate threshold, it is possible to separate between these states. In the study, we observed significant changes in restorative environments only for the distinctly lifted head. Therefore, as we expand the range of possible activities in the office, we expect the probabilistic method, which can identify multiple states, to be more powerful than using mean value alone.

The chest-worn wearable sensor reliably measured heart rate, respiration, and motion. Facial feature tracking was successful for approximately 75% of the cases. Hands occluding the face and moving out of the camera frame were the main causes. A camera with a wider angle or using multiple cameras could solve part of the problem.

5.4 Closed-Loop Software Architecture

This section describes the closed-loop configuration as illustrated in Figure 5-4-1. This configuration builds on the results of Study I and the modules of the open-loop configuration. The Scene Control Server for example remains the same for the open-loop configuration.

5.4.1 Upgraded Sensor Collection Server

The Sensor Collection Server was extended to facilitate a low-cost commercial EEG headband (*InteraXon, Muse Headband*). In the Evaluation study we used the Necker Cube test to measure participants' ability to direct attention. In order to measure occupants' cognitive state in real-time, we added EEG sensing to the system. 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) [138]. In our application, we use EEG monitoring to infer the occupant's cognitive state. This feature is further explained in section 5.4.3.

Other sensors in this setup are the physiological monitor chest strap (*Zephyr, Bioharness 3*) and the facial feature tracking library (*CMU Human Sensing Laboratory and University of Pittsburgh Affect Analysis Group, Intraface*) in combination with a wide angle USB camera (*Genius, WideCam F100*). The camera was upgraded to a wider angle camera, as we learned from the sensor reliability evaluation that faces moving out of the frame was a main reason for sensor dropout.

5.4.2 Processing API

The Processing API provides real-time access to sensor data from the Sensor Collection Server. A subscriber to this service opens a TCP socket to connect. Upon connection, it receives sensor updates at a specified update rate. Data packages typically contain a data type, timestamp and value vector in JSON format. Example data packages with dummy data are:


```
{
        "type": respiration ,
        "timestamp": 1493746492.0000,
        "value": [10]
}

{
        "type": rr ,
        "timestamp": 1493746493.0000,
        "value": [1,2,3 ... ]
}
```


5.4.3 Signal Processing Server

The Signal Processing Server computes real-time physiological state indicators from raw sensor values as shown in Figure 5-13. State indicators are high level features that describe the occupant's physiological state. They are aligned with the contextual control dimensions as defined by the control map. In this implementation we therefore have two indicators, the *Focus* and *Restoration* indicator. This service is implemented in Python and subscribes to the Processing API. This section describes components of the Signal Processing Server.

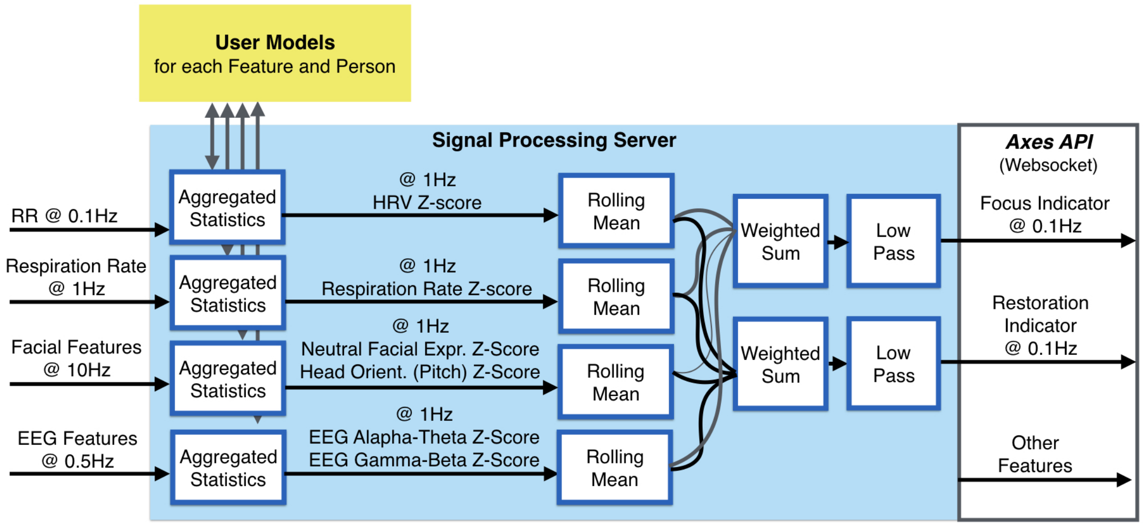


Figure 5-13: Diagram of the Signal Processing Server.

Physiological Measures

7 physiological measures were selected from over 30 recorded sensor features to compute the indicators; 4 measures for Restoration and 3 for Focus. In Study I, we observed that Heart Rate Variability, Head Orientation, Facial Expression qualify as indicators of focus and restoration. In addition to these sensor features, we also included EEG and Respiration Rate monitoring.

Heart Rate Variability (HRV) was processed as described in section 5.3.3. The Signal Processing Server received overlapping (92%) arrays of 1024 consecutive RR interval values through the Processing API with an update rate of 0.1 Hz. The array contains approximately 1 minute of RR interval values sampled at 18 Hz. Upon receiving the data, the RR interval array was converted to an equidistantly sampled series by cubic spline interpolation. We then used the standard deviation of RR intervals (SDNN) method to compute HRV.

Head Orientation was processed in two ways. The first variation, which we refer to as **Viewing Scene**, only used head pitch angle above average. As established in the results of the Evaluation Experiment (see section 5.3.4) for the two levels of restoration the difference in head orientation was only significant for distinctively lifted head. Therefore the Viewing Scene measure only considers lifted head positions and is used for the Restoration indicator. The second Head Orientation measure, which we refer to as **Viewing Desk**, included the full range of possible head pitch angles. Participants' head pitch angle were facing more downwards in focus than non-focus environments, which resulted in significant mean differences. This measure is therefore used for the Focus indicator.

Neutral Facial Expression is the raw confidence level for detected neutral facial expression. It lies between 0 and 1, with a value of 1 indicating a confident detection.

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 [49]. It is also traditionally part of exercises such as 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 [49]. Accordingly, in the Study I we observed lower respiration rates during the break activity then the reading activity. In this configuration, we included respiration rate as an component of the Restoration indicator.

EEG spectral analysis commonly divides the signal into five frequency bands that are associated with different mental states [31]. Table 5.7 shows the division used by the commercial Muse Headband. 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 [31, 138]. An increase of Theta activity, on the other hand, has been associated with a state of drowsiness in adults [123]. Beta and Gamma waves are of higher frequency and occur during focused mental activity [21, 119]. In our implementation, we used an entropy-based approach to compute Focus and Relaxation scores from relative spectral band powers. This method was introduced and evaluated in [117]. For the Relaxation score, which we also refer to as **EEG Alpha-Thata**, 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 *Tsallis entropy* H_{Ts} [140] is a non-logarithmic parameterized entropy measure defined as

Table 5.7: *EEG frequency bands provided by Muse headband [67].*

Name	δ (Delta)	θ (Theta)	α (Alpha)	β (Beta)	γ (Gamma)
Frequency range	1-4 Hz	4-8 Hz	7.5-13 Hz	13-30 Hz	30-44 Hz

$$H_{Ts} = \frac{1}{\alpha - 1} \cdot \sum_{i} \left(p_i - p_i^{\alpha}\right). \tag{5.1}$$

Signal Processing

The processing algorithm is built on the findings of Study I. That experiment revealed that aggregated mean is sufficient to detect physiological changes if the range of activity is limited. For example, we must assume that the participant remains sitting during the study and his tasks are similar to these performed in Study I. As we can make this assumption, we used the aggregated mean to compute the focus and restoration indicators. However, our software is set up to easily replace the mean values method with a quantiles or histogram type representation, which take into account the probability distribution.

In a first step, all incoming sensor data are added to the associated *User Models* (see Figure 5-13). Each occupant has several User Models, one for each sensor feature, e.g. RR, Respiration Rate, Neutral Facial Expression, etc. We used the P-squared algorithm [70] to construct the models. The P-squared algorithm is a heuristic method that dynamically calculates median and quantiles without storing the data. Its advantage is therefore that it requires a minimal, fixed data storage. The User Models are loaded when the Signal Processing Server is started.

Using these personal models, we then calculate the Z-scores for the incoming sensor data with:

$$x_{p,f} = (x - \mu_{p,f})/\sigma_{p,f} \tag{5.2}$$

where x is the sensor data point, p is the occupant's ID, and f is the sensor feature. Accordingly, $\mu_{p,f}$ and $\sigma_{p,f}$ are the mean value and standard deviation extracted from the User Model of occupant p and sensor feature f. The Z-score values are then low pass filtered and combined to a weighted sum to compute the state indicators as shown in Figure 5-15. If a feature is temporarily not available, then its weight is distributed to the other features.

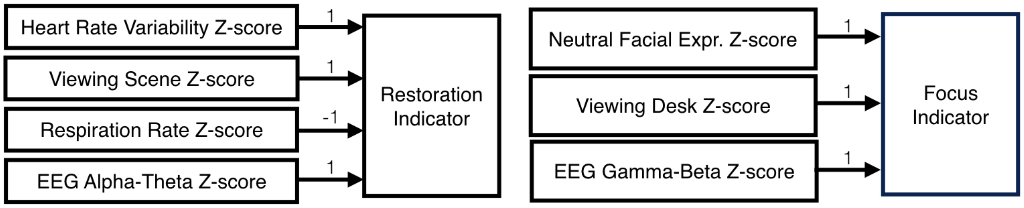


Figure 5-14: The components of the Focus and Restoration indicator.

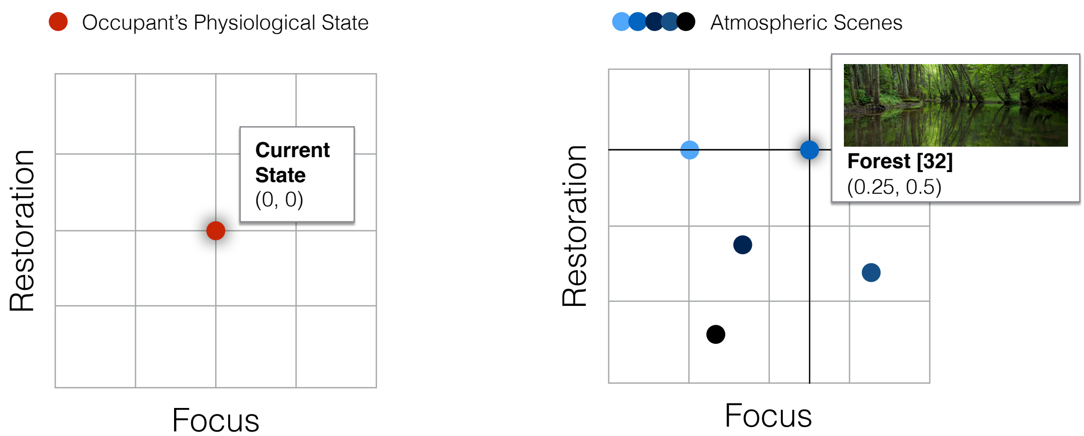


Figure 5-15: Sensor and output maps. Left: the sensor map shows the current occupant's physiological state. Right: the output map shows the scores of the atmospheric scenes. These maps combined is the graphical user interface that visualizes the scenes and physiological state to the user.

5.4.4 Axes API

The Axes API is the core API for the integration of sensing and output capabilities. A subscriber to this API receives regular updates of the Focus and Restoration indicators and physiological measures (features) formatted in JSON. The encoding of features is: 0 - Focus Indicator, 1 - Restoration Indicator, 2 - Heart Rate Variability, 3 - Viewing Scene, 4 - Respiration Rate, 5 - Neutral Facial Expression, 6 - Viewing Computer, 7 - EEG Gamma-Beta, 8 - EEG Alpha-Theta. A feature is *null* when it is currently not available. An example data package is

```
{
        features: {
                0: 0.16306872124934577
                1: −0.06279325041015098
                ...
                8: null }
        focus: 0.16306872124934577
        restoration: −0.06279325041015098
        type: "COORDS"
}
```


5.4.5 Control Application

The control application is the central intelligence of the closed-loop system. It determines how the system or the atmospheric conditions adapts to the occupant's physiological changes. We created two application modes, a biofeedback Mode and a Goal Mode (see Figure 5-16 and Figure 5-18). In the Biofeeback Mode the environment responds directly to occupant's physiological signals, whereas in the Goal Mode the user is able to specify a goal and the system selects the atmospheric scene that is most likely to guide the participant towards the desired state.

A web-based graphical user interface enables user interaction with the control application. Before the application can start, the occupant is required to select her profile. Upon login, the system loads the appropriate *Scene Models* from the scene library, which contains information about the occupant's preference settings and physiological response to each scene.

Each occupant has several Scene Models, one Focus Model and one Restoration Model for each available scene. To explain the underlying mechanisms of these models, I use the Focus Model as an example. All explanations are also valid for the Restoration Model. The Focus Model contains information about the scene's suitability for focus activities and determines its position in the control map along the focus axis. It accumulates physiological observations related to the user's level of focus and produces statistical measures, e.g. the observed mean level of focus, using the P-squared algorithm [70]. The mean value defines the scene's position on the control map.

Manual preference input initiates the model. While viewing the scene, the user specifies its suitability for focus by dragging it into the desired position on the control map. This input generates a dummy dataset with k datapoints using a narrow uniform distribution, where the mean is the selected level of focus. The dummy data is then added to an empty model using the P-squared algorithm. The resulting model simulates an ideal case, where the physiological observations are entirely in agreement with the user's prediction or preference. If no additional sensor observations are available, the manual selection determines the position of the scene in the control map. When physiological observations are added, the model slowly shifts towards the actual physiological response. The speed of adaptation depends on the size of the dummy dataset k. In this application, k is designed to reduce the influence of the initial selection by half after 15 minutes.

In the graphical user interface, the control map is shown as a two-dimensional graph (see Figure 5-17 and Figure 5-19). It visualizes the atmospheric scenes and the current physiological state or operating point derived from real-time sensor data. A bar-graph next to the control map displays the physiological features in real-time. Finally, the interface allows the user to start or stop the application and select scenes manually. The interface is implemented using Javascript and the application itself using Python.

Biofeedback Mode

In an update loop, the Biofeedback Mode searches for the scene that is the closes to the current physiological state or operating point in the control map. It calculates the distance to the operating point to all available scenes using the Scene Models. If the closest scene is not the current scene on display, then it tests whether the new scene is by a margin closer to the operating point than the current scene. This constant margin introduces a hysteresis or inertia to prevent instabilities caused by frequent changes. If this margin is achieved, then a request for the new scene is sent to the Scene Control Server.

Goal Mode

In the Goal Mode the user can select a goal by dragging the goal marker in the focus/restoration control map. The marker can be readjusted at any time. The system then selects the scene that is closest to the goal on the control map. During usage, more data is accumulated

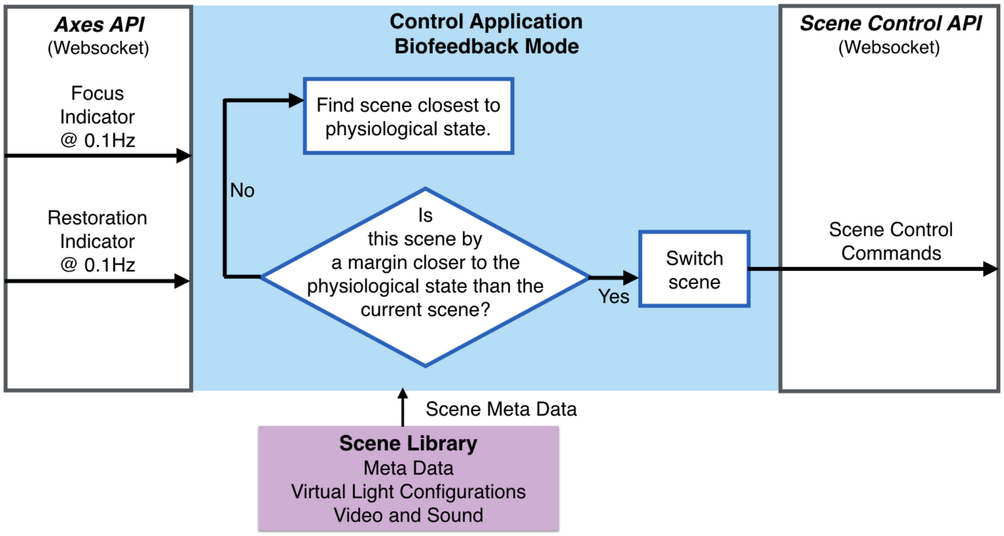


Figure 5-16: Diagram of Biofeedback Mode.

about the user's response to the selected scene, and the Scene Model updates according to the incoming data. As a result, the position of the scene on the control map relocates. If the scene is contributing to the goal, then the distance between the scene and goal will be decreased. Conversely, if the scene is not contributing to occupant's goal, the distance between the scene and the goal will increase. Eventually, if the distance becomes large enough, another scene will be selected for the user. This mode also offers a Skip button. This button allows the user to change to another scene that is also beneficial for their goal.

5.5 Study II

We conducted an human subject experiment to evaluate the closed-loop system. In order to create an experience as realistic as possible, participants were instructed to work on their own regular work tasks and were free to choose what to work on during the study. Furthermore, each participant spent in total more than 4 hours in the prototype office.

In this experiment, we compared two application modes, the Biofeedback and Goal Mode. Through this comparison, we aimed to gain insight on three aspects. First, we measured the usability of the system and compared the usability of the two modes. System usability measures how easy it was for the participants to understand the system and configure the system to achieve their goals. It also measures whether the system was error prone and how

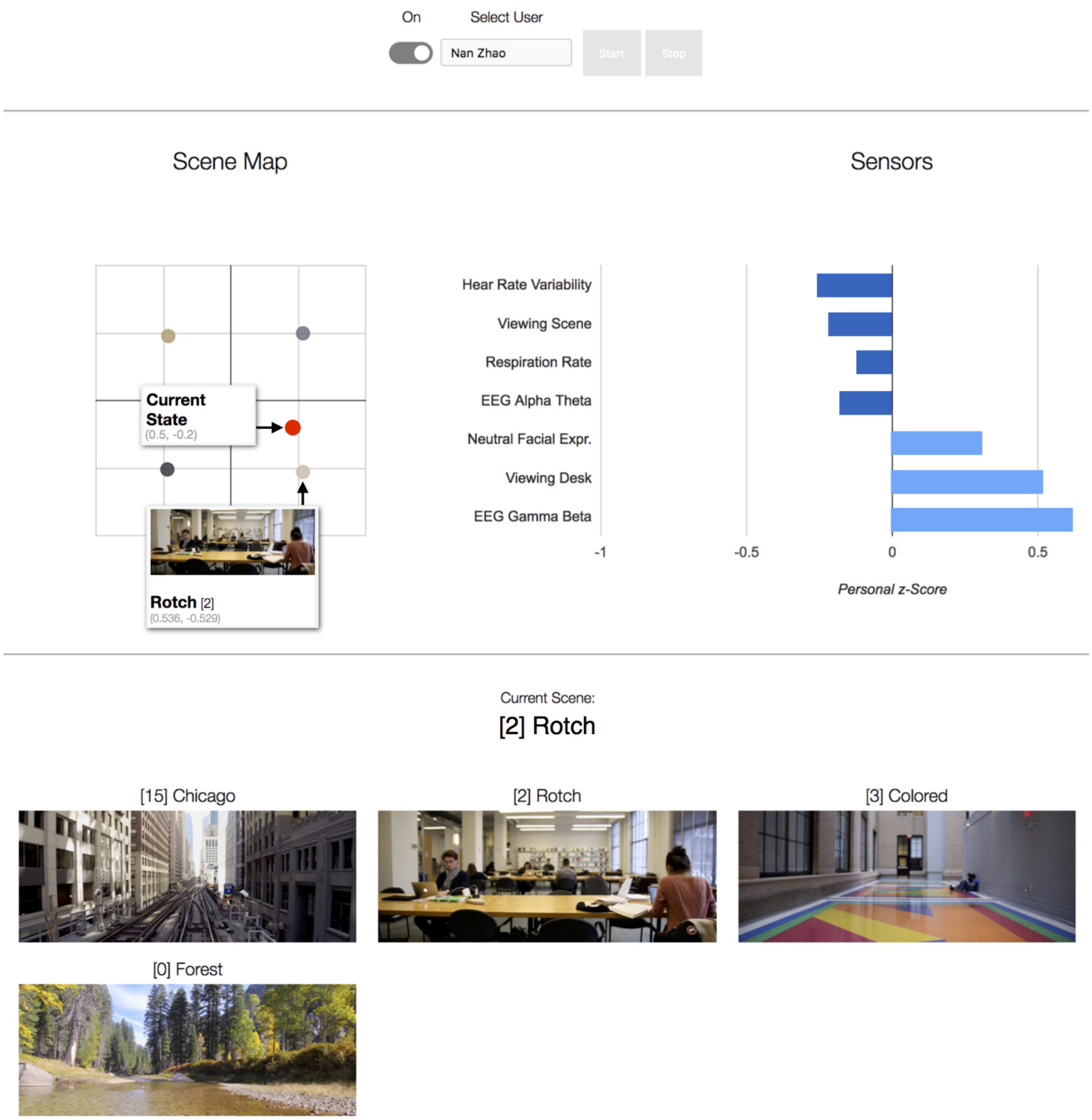


Figure 5-17: User interface for Biofeedback Mode.

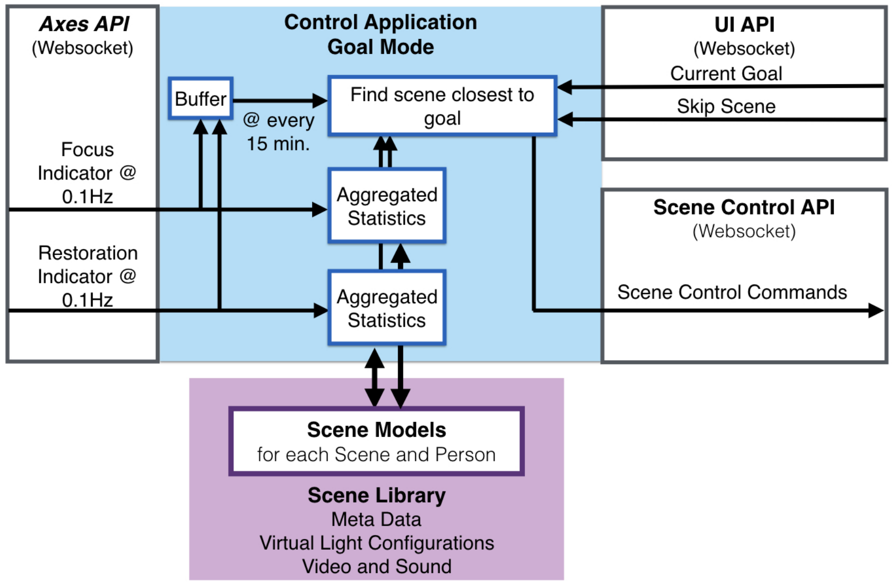


Figure 5-18: Diagram of Goal Mode.

well it fulfilled its service.

Secondly, the two application modes provided the user with different levels and types of control. For the Goal Mode, participants directly expressed their intention - the goal - through an user interface. They had high control and were able to specify the desired state scene at any time, but in this mode they also had more responsibility to configure the system. In the Biofeedback Mode, the system responded to the participants' physiological changes. Participants only had indirect control. They were able to influence the system by changing their behavior.

Through the comparison of these two modes, we wished to derive recommendations for the level and type of control for context-aware multimodal media environments. Having to make a choice of atmospheres could be overwhelming for users, especially in the work context, where already many decisions need to be made on a regular basis. However not having control could also cause distress and negative feelings, especially when control over aversive stimuli is not available [4]. This could lead to learned helplessness with emotional and behavioral impact [125].

Related research on lighting control discussed potential positive and negative effects of perceived control [147]. Having to make choices could cause concerns of self-presentation [18], especially if the user thinks that an expert could make better choices, or if there is a

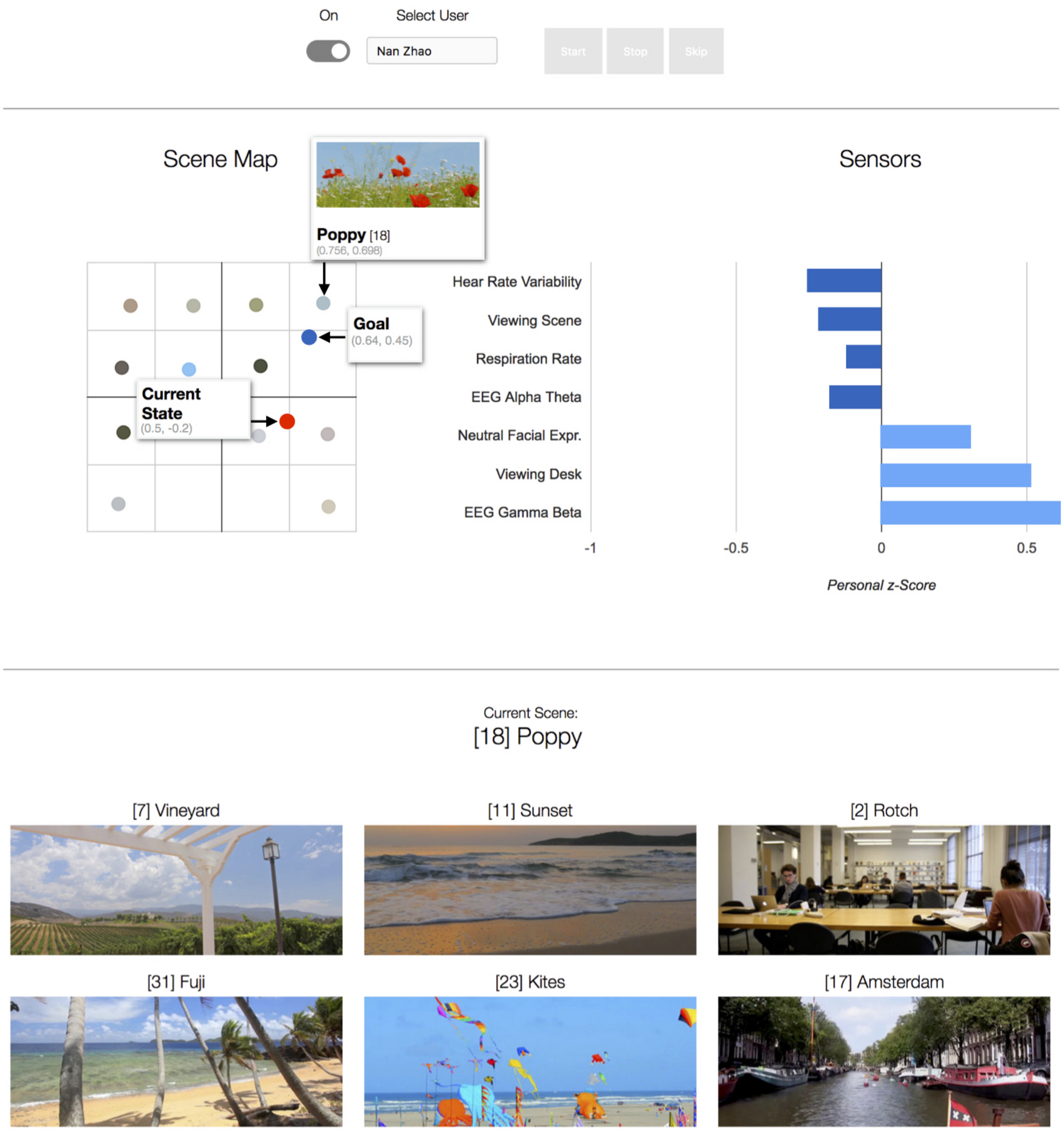


Figure 5-19: User interfaces for Goal Mode.

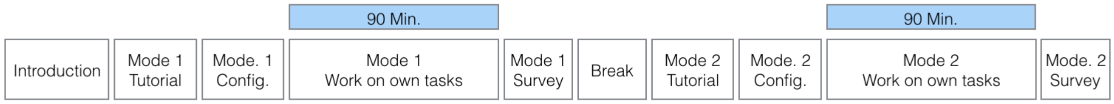


Figure 5-20: Overview of the experiment procedure.

risk to embarrass oneself by making the wrong choice. Having a degree of individual control of lighting, however, tended to maintain work motivation over the day [13]. In a multimodal setting, where, in addition to lighting, video projection and sound are also present, it will be especially important to find the balance of perceived control and system automation.

Lastly, through the comparison of the two application modes, we wished to gain insight on the participants' experience of support - which characteristics of the system were perceived to be supporting their activities. Possible characteristics were the atmospheric scenes themselves and the three output modalities; lighting, projection and sound. It could also be the timing and responsiveness of the system, the feedback on their physiological state, etc. Assessment of perceived support aimed to identify key characteristics for future development.

5.5.1 Method

Participants

The population of interest were knowledge workers, who mainly work in office type settings. Therefore, the panel (N=9) consisted of students and local professionals. Furthermore, the panel comprised of 30% technical experts with special interest in Internet of Things (IoT) and Affective Computing, 30% interior and furniture design experts, and 30% non-experts. This distribution of experts and non-experts allowed us to gather informed feedback about the system's technical performance, interior design, and usability.

Procedure

Each experimental session began with an introduction of the system. The study personnel demonstrated several atmospheric scenes and explained what physiological signals were collected. Subsequently, one of the two application modes was selected randomly. The user received an tutorial on the first application mode and was then left alone in the prototype office to configure the application. When the user was finished with the configuration, they worked for 90 minutes on their own work tasks using this application mode. After 90 minutes, they filled out a survey and were asked to take a break. The same procedure repeated for the second application mode. At anytime 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.

The configuration of the application was necessary to provide some initial information for the User Model and Scene Models. For the User Model. the system collected physiological data during the introduction phase and the configuration phase. Using this data, the system was able to determine a baseline for the user's physiological signal to accurately calculate the z-score values.

For the Scene Models, the users were instructed to place atmospheric scenes into the contextual map according to their preference. For the Biofeedback application, they were instructed to only choose 4 scenes and place them into the center of each quadrant. We constrained the number of scenes to 4 so it would be easier for participants to remember which scene was associated to which activity state. Here participants had the freedom to choose scenes to reflect their activity state, or on the contrary, to inhibit the activity state. For example, participants were free to choose both a calming scene or an exciting scene for the restorative state. In the Goal Mode, participants were allowed to place as many scenes as they wanted into the contextual map. In this case the coordinates of the scenes should reflect the associated activity state. For example, they were instructed to select a rejuvenating scene for the restorative state.

Measures

User feedback was collected using a survey. The survey consisted of 10 questions of the System Usability Score (SUS) [15] and 6 additional questions to be rated on a 5 point Likert scale. For another 12 questions, the users were able to write short paragraphs about their experience. The questions were, for example, what strategy did they use to configure the application, why did they feel or not feel in control, why did they enjoy or not enjoy the application, how would they further improve the application, etc.

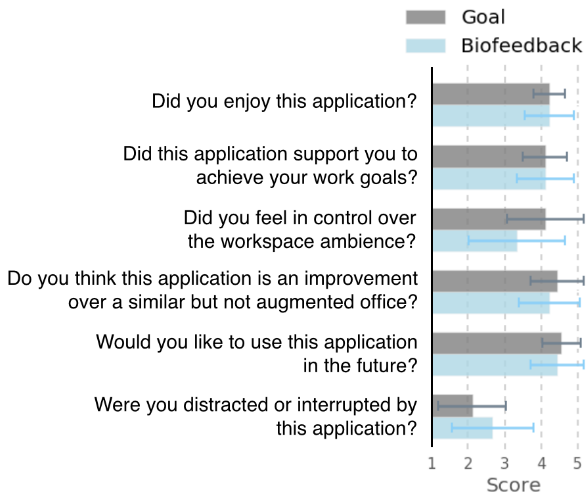


Figure 5-21: Results of the Experience Survey. The x-axis represents the user's ratings from 1 (Not at all) to 5 (Very much).

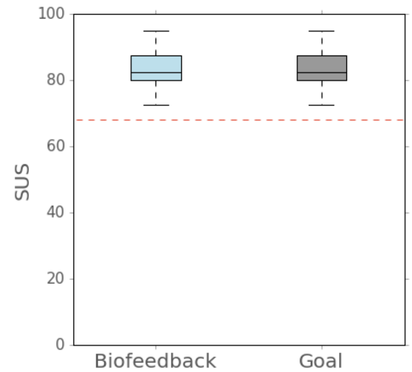


Figure 5-22: Results using the System Usability Scale (SUS). The x-axis shows the two applicaiton modes and the y-axis shows the SUS score. SUS above the red line (> 68) is considered above average.

5.5.2 Result

The SUS result is shown in Figure 5-22. Ratings from the additional 6 questions are visualized in Figure 5-21. For a in-depth analysis, to clarify what motivated the ratings, we split each written answer of the 12 essay questions into smaller statements. These statements contained either one subsentence, one sentence, or multiple sentences that described a single phenomenon. As a result, we identified six central topics: Scenes, Feedback, Adaptive Control, Outcome, Future Features, and Novelty. Figure 5-23 shows how many positive and critical or negative statements of each topic were made for each follow-up question.

Scenes The first topic, Scenes, related to effects and attributes of the atmospheric scenes. Here participants described how different media channels (lighting, projection or sound) the places they assembled, and how having access to them influenced their work experience. Positive statements under this topic were, for example, "I also like discovering the scenes[...]" (T1), "Overall ambient light was pleasant [...]" (S1), "[ambient light] was well matched to the video feed." (S1), "I liked the possibility of switching between different scenes to stay focused." (N1), "The immersing experience of relaxing

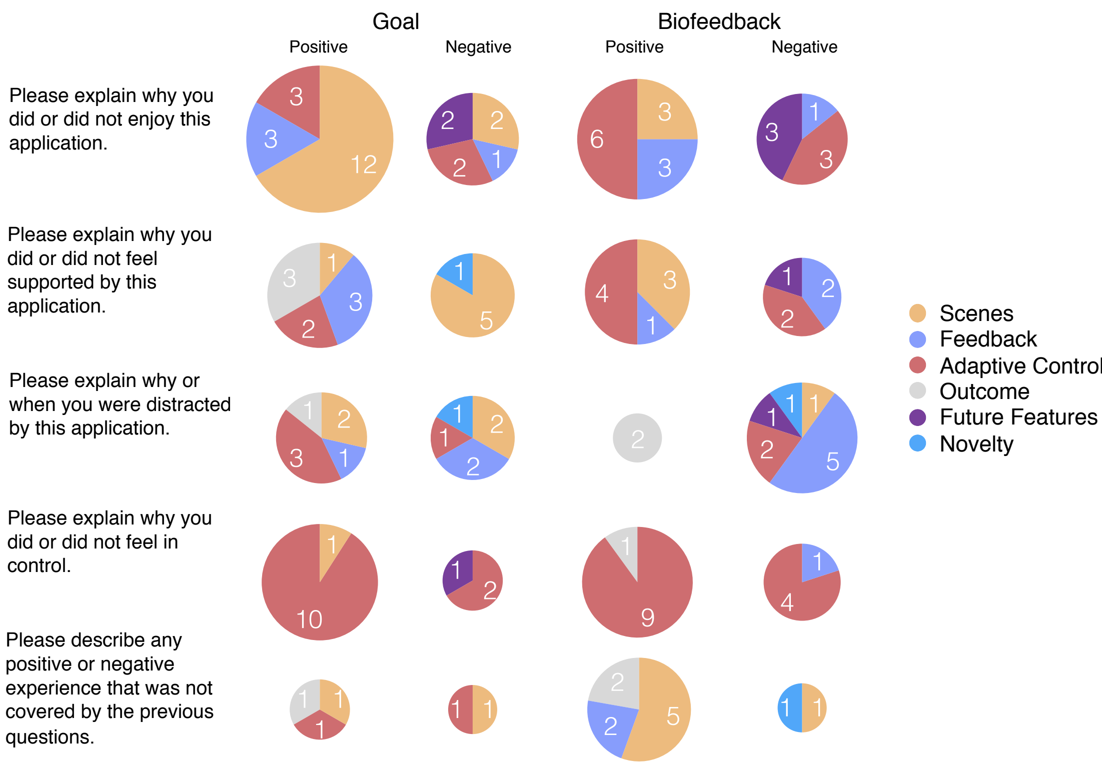


Figure 5-23: Pie charts of the percentage of six central topics stated in the answers of the experience survey follow-up questions. The pie charts show the distribution for positive and negative comments as well as the two application separately. The numbers in the pie charts are the corresponding numbers of responses.

in a forest while working was incredible." (N3), "I found that the environment also helped me stay on the focused side of the spectrum the majority of the time." (S2). Some examples of critical responses related to this topic were "it depends which scenes do we select, some of them prevent me from working well and reac[h]ing my goals" (T2), "This time around, [I] was a little more distracted. Maybe it's the stimulus, [...]" (N3), "Some movement in "calm" environments (library, reading room) distracted me. [T]hat student fiddling with his pen drove me nuts." (N1).

Feedback Feedback covered statements related to the experience of seeing one's own physiological state. The feedback was delivered either through the graphical interface or the environment reacting directly to physiological changes. Examples of positive statement were "I felt like I had a much better understanding of what environments actually do lend themselves to different work states." (S2), "[T]his allowed me to realize lots of things about my concentration." (N2), "I still felt supported by the application, and very supported when my goal and actual dot were nearby. I felt very "in the groove" when they aligned, [...]" (S3), "I found it interesting to watch my dot move around, particularly noticing where it didn't really want to go (e.g. quadrant 2). I most enjoyed taking big steps from one state to another." (T1). Examples of critical statements were "I am a procrastinator, so naturally I was interested to check regularly on what the application was doing or measuring, [...]" (T1), "I want the focused and relaxed scene[,] but the more I think about it, the less focused and relaxed [I] am." (N1), "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." (S2).

Adaptive Control Any comments about sensing, context recognition, and control algorithms were associated to the topic Adaptive Control. These comments discussed perceived logic, transparency and usefulness of the applications, as well as accuracy and timeliness. Positive statements were for example, "Getting to articulate what my goal is certainly helped the feeling of control." (S2), "the different setting helping feel that way [very focused and relaxed]" (T3), "Intentionally or not, the transitions between scene[s] supported my activity and allowed me to refocus. Intentionally or not, means that sometime[s] I start an activity and the scene would follow. For example[,] when I started sketching[,] the scene changed from the forest to the library, which was nice. [...] Sometime[s] the scene changes first and then I changed my activity" (S1), "Most of the time I deliberately took a break, the system did exactly the right thing (matched my break state with a nice scene)." (T1) "I felt like it had a better idea of what I needed than I did." (S3), "I felt that it reflected my state of mind [...]" (N3). Critical comments were for example, "[...] it sometimes changes between focused relaxed and focused energizing (while [I] feel [I] am the same). [I] don[']t know why" (T2), "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." (T1) "The transitions and light changes broke my concentration at times." (N3), "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." (S3).

Outcome In some comments, participants described the outcome as a measure of their experience. Positive comments are for example "[I] worked pretty well!" (T2), "[...] once the scenes were going, I felt like my work was greatly enhanced." (S3) "[I] think [I] had (in my view) 2 productive hours of work." (S1). The only critical comment of this topic was "[the scenes] sometime feel too much in contrast" (S1).

Future Features Future features includes comments that describe missing or desired features, and expansion of existing features. Comments of this topic were all considered critical, for example "I enjoyed the experience but as I only selected four scenes, it end up being a bit repetitive." (T3), "I felt somewhat more neutral on this one than the previous scenario. Most of all I missed having all the scene options from before, as it got somewhat repetitive after a few hours!" (T1), "would have been nice to add more scenes per zone." (S1), "I would have wished to further feel the wind [...]" (T3).

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), "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).

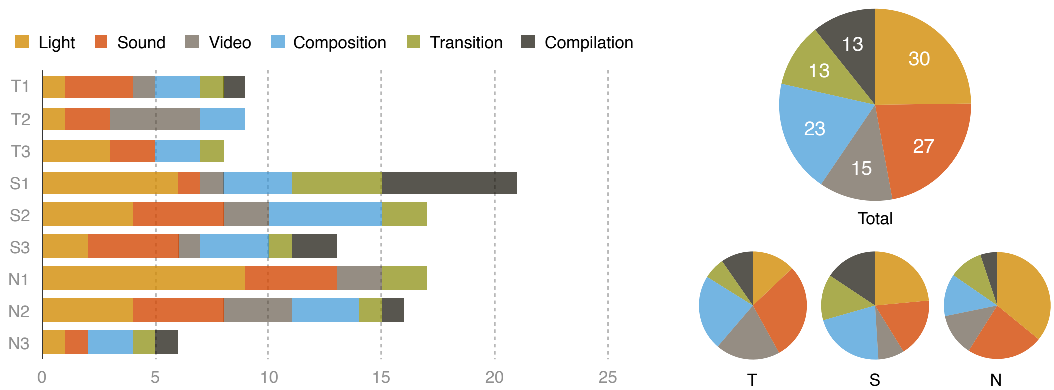


Figure 5-24: Left: Stacked Bar Diagram which shows which media properties participants used to described their experiences. The unit of the x-axis is the number of statements. Right: Pie Diagram showing the percentage of media properties found in the answers of all participants (Total), technical experts (T), space design experts (S), and non-experts (N).

Properties of Atmospheric Scenes

In another analysis, we investigated which properties of the atmospheric scenes were perceived as especially important for one's experience. We analyzed how often participants used certain properties to describe their experience; e.g. light, sound, video, the composition of these media, the transition between scenes and the compilation of multiple scenes (see Figure 5-24). This analysis was done for each participants, group of expertise, and for all participants together. Light and sound were considered more important than the video projection for nearly all participants.

Physiological Response

To analyze whether the Goal Mode led to the desired activity state, we computed the Mean Squared Error (MSE) for any environment that was used for more than 15 minutes. The MSE was 0.30 for focus and 0.39 for restoration. This outcome could be an indication of the subtle influence of the atmospheric scenes, but could also be the result of participants' decision to focus or relax. A change of atmospheric scene might prompt participants to consciously or unconsciously change their behavior.

Figure 5.5.2 illustrates the distribution of participants' activity state and a comparison with the selected goal. For each participant, we depicted two scenes, which are the scenes

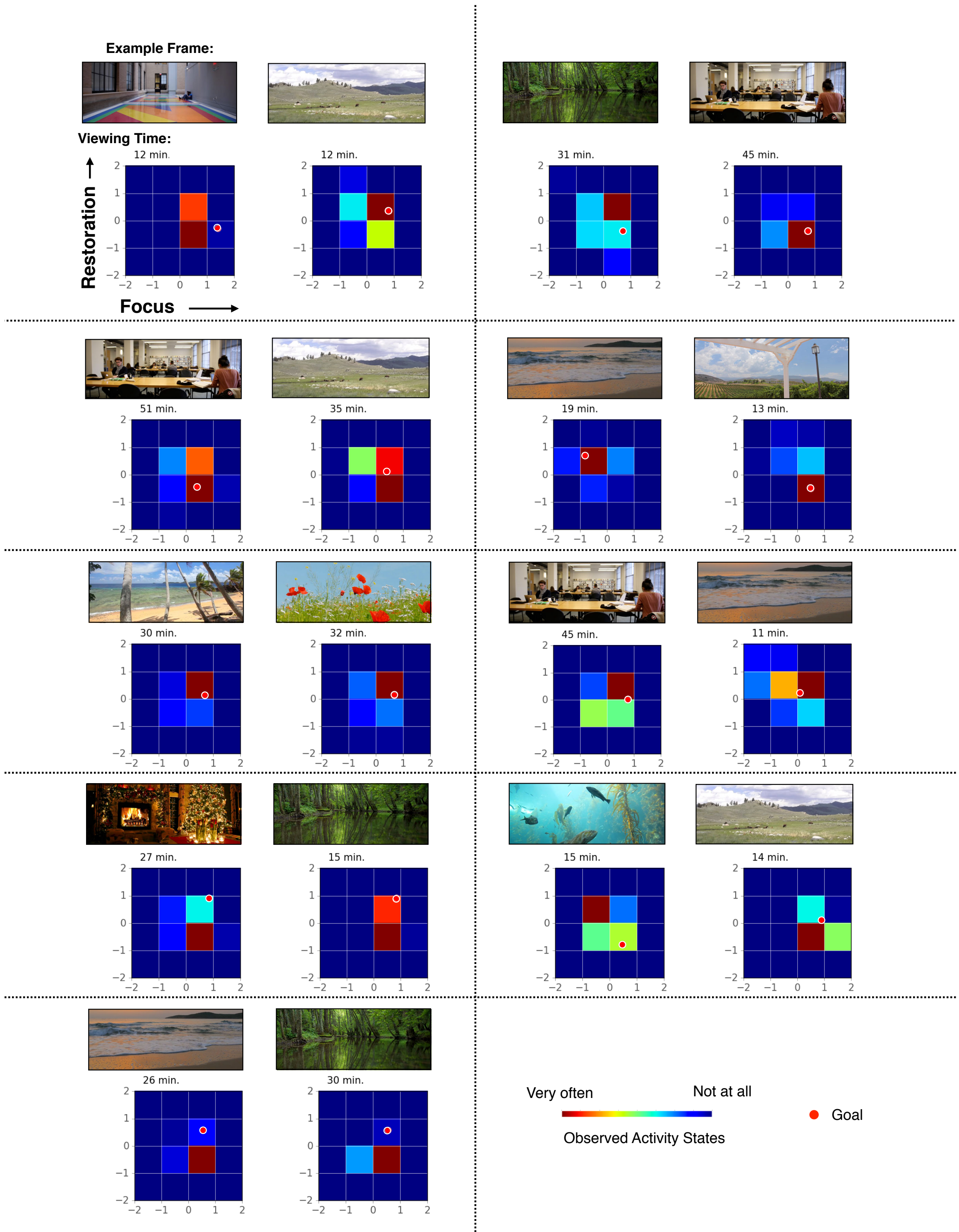


Figure 5-25: Diagram of participants' activity state as 2D histograms including the set goal. Two scenes are shown for each participant, which were the scenes where they spend the most time in. For each scene, a 2D histogram of Focus (x-axis) and Restoration (y-axis) indicators is depicted. In the left upper corner of each diagram, the duration of time spend in the scene is shown. The red dot represents the Focus and Restoration goal that was selected during the time.

that they spend the most time in. Some participants frequently changed the settings and never spend more than 12 minutes in one scene. Other participants spend up to 51 minutes without changing the scene. The longer a scene was used, the more observation we collected about a scene, hence the more confident was the measurement of the effect of the scene.

The histograms indicated that participants' activity state varied for different scenes. We can also observe similarities among participants, for example for the Library scene. The library scene led to a relatively more focused and less restorative state. The Bison scene, which showed a field with grazing bison, however caused rather distinct responses for different participants.

5.5.3 Discussion

For both Biofeedback and Goal Mode, participants reported that they enjoyed the application and would like to use it in the future. Both applications supported their work activity and were an improvement to the unaugmented office. In agreement with that, the SUS was above general average performance for both modes. In direct comparison, the Goal Mode scored higher on average than the Biofeedback Mode.

From the written answers, we learned that the participants enjoyed the two application modes for different reasons. The answers also revealed the two modes' unique shortcomings. Building on our results, we concluded three application design guidelines for context-aware multimodal work environments, which are discussed below.

Provide Positive Feedback

Participants received feedback in both application modes. In the Biofeedback Mode, they experienced the feedback as change of atmospheric scenes. In the Goal Mode, their activity state was displayed in a graphical user interface.

The Biofeedback Mode was more distracting for the participants (see Figure 5-21), because they were notified about every activity state change. This made them aware of their activity state, and sometimes even prompted them to check the visualization of their physiological signals to learn more. In the Goal Mode, this effect was reduced, although driven by curiosity, some participants nevertheless, checked the graphical interface regularly. We expect this kind of behavior and ensuing distractions to decrease over time, as the user become more familiar with the system. This was also pointed out in participants' comments.

Furthermore, feedback was often perceived as distracting only when it was negative feedback that indicated an undesired state.

While positive feedback - indication of a desired state - was perceived as a reward or a source of motivation, negative feedback caused further distress. This observation could be related to previous findings in psychology about interoceptive awareness. Interoceptive awareness defines a person's ability to perceive her bodily state. The relationship of introspective awareness and experience of emotion has been subject of numerous studies. It was found that people with heightened ability to perceive their bodily states, e.g. heart rate, also experienced emotions more intensely [113]. In recent reasearch, this effect has been used to create technology for emotion regulation. Such research has demonstrated the feasibility of using false (heart rate) feedback to trigger desired emotional effect [34].

A possible solution for Mediated Atmospheres to overcome this effect is to provide different delivery mechanisms for positive and negative feedback. In our current implementation both types of feedback follow the same activation mechanism. While this mechanism was suitable for positive reinforcement, it was less useful when the user was in an undesired state. In that case, the adaptive environment should provide guidance rather than notifications.

Participants' who were able to successfully regulate their activity state showed an recognizable pattern in their activity state signal. This pattern was composed of a sustained period of focus followed by short intervals of other states. This pattern could potentially indicate a rhythm or state of *flow*. Csikszentmihalyi, who has conducted many years of research on creativity and flow, definited it as "a state of heightened focus and immersion in activities such as art, play and work" [35].

A user who has difficulty to enter a desired activity state, for example a focused state, might benefit from the exposure to the rhythm of flow. The experience of their desired state might help them to gain motivation and confidence. Furthermore, the adaptive environment might help the user to overcome unwanted behavioral patterns. A related phenomenon was described in the participants' comments, which said that repetitions in the video or sound helped to break procrastination behavior. It provided a sense of time and a reminder to reflect on one's active task. Other participants reported that a change of atmospheric scenes prompted them to adapt their activities. Repetitions in the surroundings is an intuitive concept because humans evolved with repetitive cycles of ambient conditions, such as day and night. Future studies could further investigate the *frequency* or pattern of repetitions and their implication for work activities.

Avoid Overwhelming Control Choices

Both modes achieve above average usability. This result suggests that participants overall enjoyed the user interface and understood the system. The contextual dimensions effectively communicated the sensing and output capabilities as well as the intended use of the system.

Participants felt more in control in the Goal Mode. In this mode, participants were able to place as many scenes as they wanted into the contextual map. In some cases, they were not satisfied with their initial selection as they experienced them while working. Consequently, when asked about any reasons why they did not feel supported by the system, nearly all comments related to having made the wrong initial choices.

While making the initial selection, participants decided predominantly based on the video. When they were asked about what characteristics of the scenes defined their work experience, the video was the least important of all output media. While participants were working, sound and lighting moved more into the foreground. They facilitated their tasks and immersed in them with the feeling of being on a grass field, in the city, or a quiet library. Because participants visually focused on their work, they paid little attention to the projected video.

Participants who expressed regret about initial choices also mentioned that over time the system would learn and that the system seemed to understand better what they needed. Similarly, they also described that they enjoyed loosing control in the Biofeedback Mode. They felt especially supported when the system responded as they changed their work task and transformed automatically according to their activities. The adaptive system reduced the user's control responsibility and provided an attractive alternative to the manual system through context-awareness.

Scenes and Timing

In the written answers, participants expressed that they enjoyed the two application modes for different reasons. For the Goal Mode, participants referred to the quality of the scenes and access to the palette of scenes as the main reasons why they enjoyed the application. In this mode, they had access to many scenes and were able to switch between them by selecting a goal. In the Biofeedback Mode, participants had only 4 scenes. Consequently, several participants mentioned that they wished there were more scenes.

For the Biofeedback Mode, participants especially enjoyed the adaptive control. They often referred to the timing of scene changes when they described why they enjoyed and were supported by the application. Scene changes were triggered by the participants' activity state. The timing was therefore in sync with the participant's activity. In the Goal Mode, the scene changes were either activated manually or occurred after some time when the model updated. The update of the model was not in sync with the participant's activity. Therefore, despite the attempt to adapt to the user's physiology and learn from the user over time, the Goal Mode was not perceived as responsive as the Biofeedback Mode. It also received less positive comments about the adaptive behavior for why participants enjoyed or felt supported by the application. The written answers indicated that optimized timing for adaptation contributed to further understanding of system behavior and higher perception of system intelligence.

Chapter 6

Research Conclusions

In this dissertation, I introduced Mediated Atmospheres, a concept of a dynamically controlled room that can manipulate its ambient appearance to support the occupant's activities. This room responds to the occupant's actions and uses digitally controlled lighting, display technology, and sound to create atmospheric compositions in line with the user's context. The presented research examined this dynamic concept for the workplace. This research is justifiable, given the theoretical and empirical evidence that the ambient environment has an impact on physiology, cognition, and wellbeing; and that such influence is determined by the activity and occupant's preference in addition to the properties of the physical space. New digital control capabilities make it feasible to take advantage of these ambient influences and to augment the office interior for better performance and physical wellbeing. This work is relevant for today's practice because of a growing need for a flexible use of the available space and the concurrent decline in workplace satisfaction. Hence, the motivation of this work builds on three aspects: justifiability, feasibility, and relevance. Likewise, I conclude my research with respect to these three values and explain how the outcome confirmed the justifiability of Mediated Atmospheres, advanced the feasibility of this vision and showed the relevance of my approach.

6.1 Justifiability

While the scientific evidence suggests that physical manipulation can improve the work environment, it was yet unclear how the user would perceive a workspace with continuous, dynamic adaptive attributes. To evaluate the adaptive approach, I designed complete prototypes and conducted user studies. It was important for these studies to simulate real work scenarios and allow the user to spend adequate time with the system to form an opinion, which limited the studies to small numbers of participants.

The context-aware lighting system used a wearable sensor platform to control a lighting network. The user study (N=5) simulated a work scenario with two people in the shared office. During the study, the system achieved significant energy savings, estimated to be 38%, in comparison with the best static lighting condition and 53% as compared to the brightest static scene. Because work activities consist of multiple modes that have different illumination needs, the context-aware system was able to alternate between high- and low-energy settings based on a particular situation and placed more light where the user was dynamically working. Focus- and visually-demanding tasks required high-intensity lighting, whereas for other tasks the contrast and variety of light were more important. Participants overall considered the adaptive behavior as not distracting, On the contrary, they describe the changes as pleasant and supportive, because the transitions were subtle and in line with their actions.

The multimodal media prototype used additional outputs to create atmospheric scenes of real-world environments. The controller relied on physiological and affective sensing for context inference. The first user study (N=29) revealed that the atmospheric scenes had a significant ($p<0.05$) effect on the user's physiological response and their perception of the office's suitability for focus and restoration. Encouragingly, the physiological changes were correlated with participants' ratings. Furthermore, the ratings indicated that the scenes were an improvement over the non-augmented windowless office. In particular, the Forest and Kites scene, which displayed a creek in a forest and flying kites in the sky respectively, were perceived as restorative. Likewise, the City scene, which takes the occupant on a walk through a crowded pedestrian zone in Japan, was also rated as restorative, however with greater variance among participants. This result confirmed that the multimodal media prototype could improve the user's work experience. Given the high variance among participants responses, the results also emphasized the importance of personalization.

A separate user study (N=9) examined the context-aware implementation. In this experiment, participants worked on their regular work tasks instead of instructed exercises. The panel consisted of three expertise groups, technical experts, space design experts, and non-experts. The study outcome showed that all groups enjoyed the context-aware application.

They found the application supportive for their work activities and would like to use such a system in the future. In particular, they enjoyed the different scenes and their properties. Participants were also in favor of the context-awareness because it off-loaded configuration and maintenance responsibilities. Furthermore, the context-aware adaptations provided useful feedback about participants' work behavior. However, it is notable that while positive feedback boosted motivation, negative feedback sometimes enhanced unfavorable feelings. Therefore negative feedback should be a form of guidance, rather than notification. Participants' responses indicated that the system was able to provide guidance through rhythmic, repetitive stimuli and scene changes.

Both prototypes confirmed the justifiability of Mediated Atmospheres and demonstrated the benefits of continuous adaptive control to save energy and to improve work experience. This outcome supports further development of this vision.

6.2 Feasibility

The implemented controller both for context-aware lighting and the multimodal media environment built on a lower dimensional representation of the input and output capabilities. This representation or control map was essential for the feasibility of Mediated Atmospheres. The atmospheric compositions of multiple output sources established a complex, high-dimensional solution space with nearly infinite possible combinations. This level of complexity is challenging both for a human operator and for system integration. Accordingly, this dissertation introduced a solution using a human-centered representation, the control map, to reduce the dimensionality of control. This interface integrated input and output capabilities and visualized the underlying mechanisms of the system to the user. It provided a template of intent, that organized the idealized expert plan (scenes) along the contextual control dimensions according to the situated user's interpretation.

Building on prior work on perceptual modeling, a series of experiments established the contextual control map for context-aware lighting. The result revealed two most relevant dimensions for the office prototype: focus and restoration. The resulting control map enabled the context-aware lighting prototype and led to positive user responses in the user study for this application. Participants not only found the adaptation pleasant and supportive, but they also were able to understand the underlying mechanism of the system.

The multimodal media environment also used the focus and restoration control dimensions for context-aware control. Likewise, the user study of this application confirmed that the usability was above average according to the standard System Usability Score ($SUS > 68$). Participants were able to configure the system after a brief explanation. They overall agreed with the underlying control mechanisms and felt supported by the system. Another indicator of system transparency is that participants used the control map as a graphical visualization of their activity state for behavioral feedback.

Both context-aware lighting and the multimodal media environment demonstrated the feasibility of reducing the number of control dimensions using the control map with two contextual dimensions; focus, and restoration. The study results confirmed the usability of the control map for context-aware continuous adaptation. Both implementations revealed that by personalizing the expert scene design according to user's interpretation, this approach created a transparent and coherent control system.

6.3 Relevance

One constraint of this research is that the examinations were limited to the prototype office, where human studies defined the lighting control space. To ensure the relevance of the approach and findings for other spaces I, therefore, conducted research on sensor-based mapping.

For context-aware lighting, I used photographs of the physical prototype and simulations of several variations of offices to investigate how image analysis might construct a control map to approximate the rating approach. Firstly, this investigation assessed the possibility to use photographs of the room to reduce the amount of human input required to establish the control map. Secondly, the study examined how the lower dimensional representation might vary for different kinds of spaces with different furniture and ambient light conditions. The outcome suggested that it is possible to derive a close approximation ($DissimilarityValue < 0.05$) of the control map using photographs, which could theoretically reduce the required human input by 50%. Image analysis, which used six pictures of the six lighting scenes, could execute within seconds and thereby enable a quick calibration of new light installations.

The simulation of variations of offices demonstrated that there were consistent similarities ($DissimilarityValue < 0.06$ for the same type of space) among the derived lower-dimensional representations of lighting scenes. For all variations of offices, the lighting design followed a set of constraints. The results suggested that if the lighting design supports these constraints, then the human-derived map could be used as a template to establish new control maps for other spaces. This template approach could potentially further accelerate the calibration process for new spaces and make human input optional. Furthermore, the simulation method would allow practitioners to plan new lighting installations. The mapping approach might assist such processes by visualizing the expected perceptual difference between lighting scenes and thereby aid in optimizing the system for the maximal perceptual variance.

Through the experiments on sensor-based mapping, I evaluated the generalizability of the control map for lighting. The introduced calibration method using image analysis increased the deployability of this approach. This outcome could have a significant impact on how smart building system will be implemented in the future and how they are planned and calibrated for advanced control.

For the multimodal media environment, because of its increased complexity in comparison to the lighting network, I introduced an approach using physiological measurements for mapping. This sensor-mapping method established a probability distribution for each user and each atmospheric scene. I presented a technical implementation that would make this learning feature possible and evaluated the system in a user study. Using these models, the system selected scenes that would serve the user's focus and restoration goal ($MSE = 0.30$ for focus and $MSE = 0.39$ for restoration). However, this approach needs further investigation through a long-term study. Future research could explore how the user's reaction might alter over time and which adaptation speed would be appropriate to balance the acute and long-term effects.

6.4 Outlook

Looking forward, I imagine Mediated Atmospheres becoming a companion of everyday life and helping people to develop healthier work routines and restoration from fatigue. Accordingly, this dissertation demonstrated several related beneficial effects of this dynamic concept, e.g. the ambiance as a behavioral feedback, improvement for restoration, and personalized control. Using the prototypes presented in this work, further research should focus on obtaining data on work-flow and work patterns. Additional data is essential for further development. I envision applications for learning, which for example help students to memorize vocabulary or physics principles by creating a link between the environment and the learning tasks. I imagine applications that help to spark creativity by taking the occupant on virtual journeys to different places with different perspectives.

In the current prototype, the user wore several devices for monitoring. Some sensors were contact-free, for example, the face tracking camera setup. Other sensors required contact to the skin, such as the EEG headset and heart rate monitor. In a future implementation, the number of devices could be potentially further reduced for example by using camera or motion based heart rate and respiration monitor [96, 60]; and the required sensors could be better integrated and improved for the user's comfort.

As our everyday living and work spaces become increasingly mediated through video projections, screens, and wearable displays, many surfaces will become interactive. These surfaces will potentially transform the appearance of our existing interiors and create indoor environments optimized for the interaction with screens. This transformation will likely have in impact on our approach to interior design. When the displays in our surroundings are not actively presenting information, they could form a composition with the ambient lighting and sound to optimize the space for the user's experience. While images are important for the experience, my research also demonstrated that the auditory and light conditions tend to be the dominant experiential factors for office activities. During work, people are often visually focused on their tasks, which makes the sound, lighting and potentially other non-visual factors their prevailing connections to the surrounding environment.

In a future use scenario for Mediated Atmospheres, I envision the user designing their atmospheric scenes or recording scenes at their favorite locations. This work presented a blueprint for a multimodal environment that can display such recordings. It also introduced the technical implementation of the Scene Library, the scene data format, and design considerations. Building on these achievements, additional tools for scene design and recording could be created in future research. Ideally, each user would own a personal collection of scenes that contain meaningful places, which they have encountered in the course of their lives. As a result, users could revisit their childhood hideaway and other memorable places to enrich their everyday activities, to reduce stress, to stimulate imagination, and to feel connected to their memories and potentially a diversity of cultures and locations. Users would be able to share these augmented environments with each other and thereby share their experiences of the world.

Appendix A

Supplementary Materials For Context-Aware Lighting

A.1 Survey On Human Judgement of Lighting Scenes for Different Work Tasks

The survey outlined below was used in the experiments described in chapter 3.1 and 3.2.

Human Judgement of Lighting Scenes

We want to find out what are the basic ways in which we perceive and judge lighting scenes in a physical space. We ask for your cooperation in carrying out the following instructions.

A note on privacy: This survey is anonymous. The record kept of your survey responses does not contain any identifying information about you unless a specific question in the survey has asked for this. If you have responded to a survey that used an identifying token to allow you to access the survey, you can rest assured that the identifying token ist not kept with your responses. It is managed in a separate database, and will only be updated to indicate that you have (or haven't) completed this survey. There is no way of matching identification tokens with survey responses in this survey.

Procedure to follow

(a) You are now asked to imagine that you are performing an action or task in this space and answer the questions below.

(b) Please indicate how strongly you agree that the ambience of the scene is suited for the tasks below. You are asked to judge the ambience in relation to the task; do not focus on the objects in the space

(c) Judge each action by itself, do not worry about your previous responses. There is no correct answer, please select your initial impression

(d) Try not to base your judgements on your "likes" and "dislikes" of particular individual works of if you are "skilled" or "unskilled" for the particular task.

Mark only one option per row.
strongly disagree = 2, disagree = 1, neutral = 0, agree = 1, strongly agree = 2

1. *brainstorming in a group -2 | -1 | 0 | +1 | +2 | No Answer*
2. *study/memorization -2 | -1 | 0 | +1 | +2 | No Answer*
3. *informal phone conversation -2 | -1 | 0 | +1 | +2 | No Answer*
4. *formal presentation with slides -2 | -1 | 0 | +1 | +2 | No Answer*
5. *formal phone conversation -2 | -1 | 0 | +1 | +2 | No Answer*
6. *informal presentation with slides -2 | -1 | 0 | +1 | +2 | No Answer*
7. *programming/CAD or video editing on a computer -2 | -1 | 0 | +1 | +2 | No Answer*
8. *handcraft -2 | -1 | 0 | +1 | +2 | No Answer*
9. *sketching on paper -2 | -1 | 0 | +1 | +2 | No Answer*
10. *casual conversation with a friend -2 | -1 | 0 | +1 | +2 | No Answer*
11. *creative task using a computer -2 | -1 | 0 | +1 | +2 | No Answer*
12. *(routine) email on computer -2 | -1 | 0 | +1 | +2 | No Answer*
13. *coffee break -2 | -1 | 0 | +1 | +2 | No Answer*
14. *reading a magazine -2 | -1 | 0 | +1 | +2 | No Answer*

Appendix B

Supplementary Materials For Context-Aware Multimodal Media

B.1 Survey on Restoration and Focus Potential of the Space

The questions outlined below were used in the experiment described in chapter 5.3.

1. *Recall one of those times when you worked hard on a project that required intense and prolonged intellectual effort. Remember how it felt. You probably reached a point where you could tell that your ability to work effectively had started to decline and that you needed a break. You needed to do something during the break that would restore your ability to work effectively on the project. Put yourself in that mind set now and please rate, how good this setting would be to take a break and restore your ability to work effectively on your project.*

   (Not very good) -2 / -1 / 0 / +1 / +2 (Very good)

2. *You have just finished breakfast and have only one thing on your agenda for the day. You have a project that you need to think about. Thinking deeply and thoroughly about this project is your goal. Please rate this setting on how good a place it is to accomplish your goal.*

   (Not very good) -2 / -1 / 0 / +1 / +2 (Very good)

3. *How much do you like the setting? This is your own personal degree of liking for the setting, and you do not have to worry about whether you are right or wrong or whether you agree with anybody else.*

   (Not very much) -2 | -1 | 0 | +1 | +2 (Very much)

4. *Sometimes even when you are near your office it can still feel like you are far away from everyday thoughts and concerns. How much does this setting provide an escape experience or a feeling of being away?*

   (Not very much) -2 | -1 | 0 | +1 | +2 (Very much)

5. *Some settings have many interesting things that can draw your attention. How much does this setting easily and effortlessly engage your interest? How much does it fascinate you?*

   (Not very much) -2 | -1 | 0 | +1 | +2 (Very much)

6. *Sometimes a setting can feel like a whole world of its own. How much does this setting feel like there is much to explore and discover in many directions?*

   (Not very much) -2 | -1 | 0 | +1 | +2 (Very much)

7. *Some settings are confusing, have no organisation and have too much going on. Please rate how chaotic and distracting this setting feels?*

   (Not very much) -2 | -1 | 0 | +1 | +2 (Very much)

B.2 Survey on System Usability and User Experience

The questions outlined below were used in the experiment described in chapter 5.5.

1. *How did you go about positioning Scenes on the Map? Please explain which scene characteristics you considered in your decisions.*

2. *Did you enjoy this application?*

   (Not at all) 1 / 2 / 3 / 4 / 5 (Very much)

3. *Please explain why you did or did not enjoy this application.*

4. *Did this application support you to achieve your work goals?*

   (Not at all) 1 / 2 / 3 / 4 / 5 (Very much)

5. *Please explain why you did or did not feel supported by this application.*

6. *Were you distracted or interrupted by this application?*

   (Not at all) 1 / 2 / 3 / 4 / 5 (Very much)

7. *Please explain why or when you were distracted by this application?*

8. *Did you feel in control over the workspace ambience?*

   (Not at all) 1 / 2 / 3 / 4 / 5 (Very much)

9. *Please explain why you did or did not feel in control.*

10. *Please describe the work activity or process you pursuit during this study. Did you experience any changes or learned anything new about your work process or yourself?*

11. *Please describe any positive or negative experience that was not covered by the previous questions.*

12. *Do you think this application is an improvement over a similar but not augmented office?*

    (Not at all) 1 / 2 / 3 / 4 / 5 (Very much)

13. *Would you like to use this application in the future?*

    (Not at all) 1 / 2 / 3 / 4 / 5 (Very much)

14. *How would you further improve this application?*

15. *Please elaborate how sound, video, and lighting were or were not crucial for your experience?*

16. *What other kinds of sensory/output modalities would further improve your experience?*

17. *Do you think the sequence order of scenes is important? Do you remember any specific transitions that worked well?*

18. *Which other environments would you add to the list of scenes?*

System Usability Score

1. *I think that I would like to use this system frequently.*

   (Strongly Disagree) 1 / 2 / 3 / 4 / 5 (Strongly Agree)

2. *I found the system unnecessarily complex.*

   (Strongly Disagree) 1 / 2 / 3 / 4 / 5 (Strongly Agree)

3. *I thought the system was easy to use.*

   (Strongly Disagree) 1 / 2 / 3 / 4 / 5 (Strongly Agree)

4. *I think that I would need the support of a technical person to be able to use this system.*

   (Strongly Disagree) 1 / 2 / 3 / 4 / 5 (Strongly Agree)

5. *I found the various functions in this system were well integrated.*

   (Strongly Disagree) 1 / 2 / 3 / 4 / 5 (Strongly Agree)

6. *I thought there was too much inconsistency in this system.*

   (Strongly Disagree) 1 / 2 / 3 / 4 / 5 (Strongly Agree)

7. *I would imagine that most people would learn to use this system very quickly.*

   (Strongly Disagree) 1 / 2 / 3 / 4 / 5 (Strongly Agree)

8. *I found the system very cumbersome to use.*

   (Strongly Disagree) 1 / 2 / 3 / 4 / 5 (Strongly Agree)

9. *I felt very confident using the system.*

   (Strongly Disagree) 1 / 2 / 3 / 4 / 5 (Strongly Agree)

10. *I needed to learn a lot of things before I could get going with this system.*

    (Strongly Disagree) 1 / 2 / 3 / 4 / 5 (Strongly Agree)

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