Delft University of Technology
Faculty of Architecture and the Built Environment

Master’s Thesis

Neuro-adaptive Architecture in Extreme Environments

Investigating Visual Quality as Countermeasure to Stressor Exposure affecting Heart Rate Variability

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Abstract

Continuous or repetitive exposure to physical and psychological stressors can lead to a range of health problems caused by resulting malfunctional allostasis. The field of neuroarchitecture focuses on the relationship between architecture and neuroscience, and the specific neurological changes shown in biomarkers that can result from the built environment. In extreme environments, where exposure to stressors is heightened, the deliberate use of physical architecture and indoor environmental quality - for a positive influence on short and long-term stress response - is of even greater significance. Previous research investigated architecture as cause for stress, post-stress relaxation and for physical recovery. Still, architecture as acute countermeasure (reducing relative stress reaction) based on individual neuroendocrine response to prevent a shift to malfunctional allostasis is not well investigated. The thesis aims to help closing that gap by investigating the effectiveness of visual quality features as countermeasure to stressor exposure shown in biomarkers. It focuses on inter-individual reaction and the alignment of neuroarchitecture with functional requirements of architecture in extreme environments. The methodology for this is three-fold. A research framework was developed considering study design (including necessary infrastructure, stressor simulation, study conduction and data collection), and study outcomes (data analysis and data application). The framework was applied to a pilot study with human subjects focussing on colour correlated temperature (CCT) and heart rate variability (HRV). In addition to HRV, basic physical data, the participant's stress over the last month, chronotype, perceived stress/workload during the experiment and test performance were recorded. The study data were processed through different computational models (including multi-criteria decision analyses and Bayesian linear effects models) analysing inter-individuality, the effect of confounding variables and the use of transient stressor simulation. The findings - while not generalizable due to the small data sample – indicate baseline-, stress-, and recovery-HRV were higher under warm CCT, but the HRV-change from stress to recovery was greater under blue CCT. Despite this, CCT did not show a significant counteracting effect reflected in the change from baseline-HRV to stress-HRV. The most relevant findings relate to the development and exploration of the methodology, providing directions to address inter-individuality of stress-response and cause-effect ambiguity in cross-sectional research on the effect of visual quality as countermeasure. The data were further used for the demonstration of a future application - using a microgravitational space station as case study - detailing Multi-Sensor Data Fusion and Bayesian Reinforcement Learning for a system that considers confounding influences, spatial limitations, functional requirements, accessibility, individual- and group-needs and long-term trends in biomarkers. The research framework can be extended and applied to future neuroarchitectural studies, the results of which could inform the development of adaptive systems in extreme environments. The aim of this thesis was the development of research methods and their preliminary validation that can contribute to future research on neuro-adaptive architecture as countermeasure to physiological stress response.

Preface

The following manuscript is the result of my Master's thesis conducted between mid-November 2024 and June 2025 as part of the Master of Science in Architecture, Urbanism and Building Sciences (track Building Technology) at the University of Technology Delft.

I would like to express my sincere gratitude to my two supervisors Dr. Michela Turrin and Dr. Henriette Bier for their support, time and encouragement throughout the course of this thesis. I am very grateful to Prof. Dr. Yvonne de Kort from TU Eindhoven who made this research possible by giving me access to the HTI Lighting Lab in Eindhoven. I very much appreciate having had that great opportunity. Further, I want to thank Xinwei Gao from TU Eindhoven for sharing her expertise and advice on evaluating the ECG data collected as part of this research. Also, I want to thank Dr. Xiangzhen Kong, with whom I had the pleasure of sharing the lab during my study conduction. His help with technical matters and participant recruitment was greatly appreciated. I am thankful to Lisa-Marie Mueller from TU Delft for sharing her expertise on machine learning and for providing such helpful, encouraging feedback. Further, I want to thank Dr. Sarah Piechowski and Prof. Dr. Katharina Utesch from the German Space Agency (DLR) for their valuable insights on the role of psychology in my thesis research. I also want to thank my former supervisor at the European Space Agency, Pablo, for always having an open ear and providing helpful advice on many of my projects. Finally, I want to thank the participants without whom this thesis would not have been possible.

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1. Introduction

1.1. Background

The historical rise of health problems resulting from chronic stress has reached the level of a widespread challenge (Piao et al., 2024). In recent decades, architectural research has begun to address many challenges including the urgently needed changes to reduce the environmental impact of the built environment, but it's potential to inform health-supporting decisions has still not been fully explored. Research regarding the impact of indoor environmental quality on human health (Bluyssen, 2019; C.-C. Jung et al., 2014), the concept of healing architecture influencing recovery processes (Ghazaly et al., 2022; Lawson, 2010; Simonsen et al., 2022), architectural elements for post-stress recovery (Ho & Chiu, 2021; Minguillon et al., 2017) and certain features of architecture that temporarily induces stress (De Paiva & Jedon, 2019; Evans & McCoy, 1998; Litscher et al., 2013; Niza et al., 2024; Valentine, 2024) has addressed some of those questions. Nevertheless, it is not understood yet if and how architecture can counteract physiological response to stressors to prevent long-term consequences. This gap limits the full utilization of architecture's potential to enhance and protect human health, particularly in conjunction with reduced resource and energy use.

Environmental limitations and the relevance of human needs are amplified in extreme environments. Researchers in remote locations like Antarctica or astronauts in microgravitational space stations are exposed to amplified sets of stressors including limited resources, volume and mass restrictions, potential physical stressors like microgravity or ionizing radiation, altered dark-light cycle and psychological stressors like isolation, confinement, monotony and high workload (Kanas & Manzey, 2008). This makes it a suitable use-case for exploring architecture as countermeasure to stressor exposure. While in extreme environments like the International Space Station (ISS), a life support system is addressing the most relevant physical needs (Seedhouse, 2020) and a countermeasure system is working on the preservation of the astronauts' health (Petersen et al., 2016), the set of changes resulting from this environment still demands complex physiological and psychological adaptation, that can transpire differently in each individual. Adaptive architecture offers a way to address evolving individual and group needs (Urquhart et al., 2019), but the specific objectives guiding the output of the adaption must be defined first.

One example for an objective metric relevant for the physiological and psychological changes and representative for the interplay between them, is allostasis (Romero et al., 2009; Rusanov et al., 2023), which can cause severe negative health effects when cumulative stress turns into allostatic overload. Allostatic overload describes a total measure of dysregulation involving several multiple physiological systems due to a continuous or repetitive stress-inducing environment leading to malfunctional allostasis and resultingly an increased risk for many health downsides (Bobba-Alves et al., 2022). Biomarkers like heart rate variability, blood pressure and cortisol not only play a relevant role in evaluating the functionality of the body's allostasis (Beese et al., 2022) but also in the adaption process to the environment e.g. microgravity. Past studies suggest that decreased heart rate variability or increased cortisol could be related to problems regarding the physiological adaption in extreme environments and be a cause of resulting health problems (Finseth, n.d.; Otsuka et al., 2016).

Part of the solution for improving the adaption process in extreme environments and supporting functional allostasis is the emerging research field of neuroarchitecture, an interdisciplinary area concerned with the impact of architecture on the human brain and therefore on the whole body (Ghamari et al., 2021). The findings of this research can inform future adaptive systems that can counteract allostatic load and stress-induced health decline, thereby acting as a part of the countermeasure system. Neuroarchitecture has the potential to ease adaptation to stressors, prevent chronic stress, counteract adverse neurological changes, and enhance the overall accessibility of interior spaces by acting is an acute intervention to help prevent long-term consequences (shown in **Figure 1**). This thesis aims to make a first step in this direction by investigating the following hypothesis: Acute physiological stress reaction resulting from stressors in extreme environments, that negatively influence biomarkers relevant for allostasis can be counteracted by adaptive architecture focusing on visual quality.

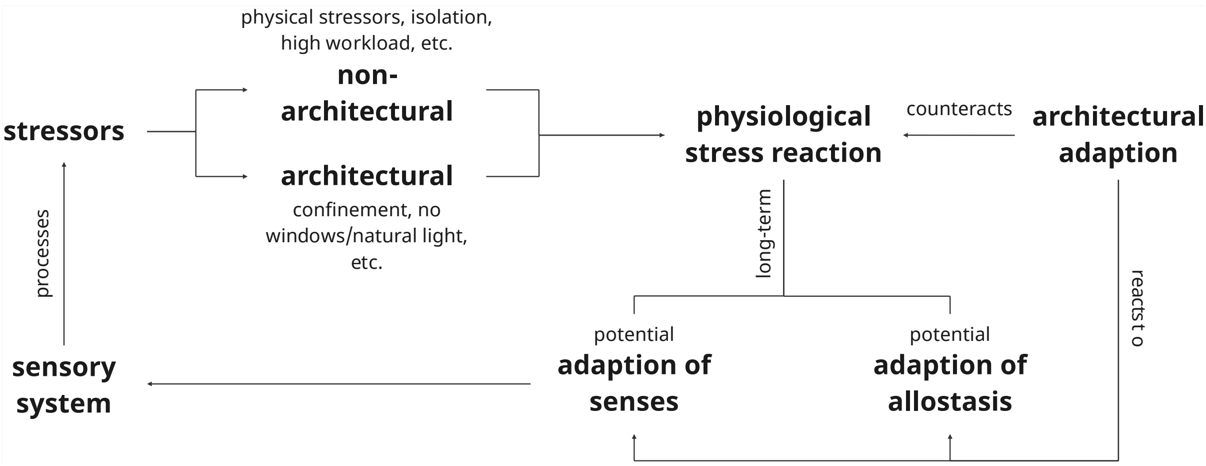

Figure 1 *Visualization of the Long-term Vision: showing the interaction loop between (adaptive) architecture and physiology, and the influence of changes to the senses or allostasis - resulting from stressor exposure in the environment – on the perception of the environment.*

1.2. Problem Statement

The unavoidable stressors occurring in extreme environments can have severe impacts on the individual's health and potentially lead to dysregulation of physiological systems. Adaptive architecture that is reacting to individual needs has the potential to act as countermeasure to stressor exposure and mitigate immediate stress to reduce allostatic load and prevent long-term health consequences. However, reliable data on the physiological and psychological effects of architectural and environmental features on individual stress reaction shown in biomarkers is needed. The investigation of this is complicated by the high degree of individual variability, cause-effect-ambiguity and challenges resulting from cross-sectional data collection. For the investigation of the hypothesis, the following research questions are raised.

1.3. Research Questions

The research questions were selected to support methodology development for future investigations on the topic and are formulated as follows:

1. How can neuroarchitecture be used in the investigation and application of visual quality as countermeasure to stressors in alignment with functional requirements of architecture in extreme environments?
   - 1.1 How can dynamic biomarkers and their inter-individuality in combination with stress be investigated in cross-sectional design studies?
   - 1.2 How can computational analysis be used to manage cause-effect ambiguity resulting from the dynamic nature of biomarkers for an increasement of result reliability?
   - 1.3 How can the findings be further developed in longitudinal research and applied in extreme environments?

1.4. Methodology

The contribution of this thesis is three-fold. The parts and corresponding research questions are as follows.

Part 1: Research framework for neuroarchitectural studies investigating visual quality as countermeasure (Chapter 4)

This part draws upon the literature research (Chapter 2 and 3) and uses the findings about gaps and challenges in this research to formulate a partial plan for the execution of future research on the topic. Therefore, it relates to the main research question:

1. How can neuroarchitecture be used in the investigation and application of visual quality as countermeasure to stressors in alignment with functional requirements of architecture in extreme environments?

Part 2: Neuroarchitectural pilot study (Chapter 5) investigating the influence of colour correlated temperature (CCT) on heart rate variability (HRV).

The study implements a small fragment of the research gap focusing on one biomarker and one parameter of visual quality as well as one of the possible stressor simulations (an overview of the study design is provided in **Table 1**). Therefore, in Part 2 of the thesis, sub-question one is answered:

1.1 How can dynamic biomarkers and their inter-individuality in combination with stress be investigated in cross-sectional design studies?

Study Aim	Investigating the influence of colour correlated temperature (CCT) on heart rate variability (HRV) during stressor exposure
Participants	8 students in an age range from 20 to 28 years old
Study Setting	The study took place in the Lighting Lab of TU Eindhoven with two lighting settings: 2700 K/1000 lux and 6000 K/1000 lux
Study Duration	April 2025, 2 hours per participant
Process of each Experiment Run	Each participant took part in the experiment twice at the same time of the day each of the two runs. The experiment was divided into three phases: a 10-minute baseline phase, 10-minute stress phase - in which participants performed a mental arithmetic test (MAT) - and 20-minute recovery phase.
Investigated Biomarker	Heart rate variability (HRV): Not commonly used in past studies related to allostatic load and architecture (Beese et al., 2022); but shown to be one of the five biomarkers that are highly associated with AL (Mauss & Jarczok, 2021) and specific health outcomes (McCrory et al., 2023); used in past studies as indicator for adaption to microgravity (Otsuka et al., 2016; Yamamoto et al., 2015).
Data Collection Methods	Electrocardiogram (ECG) Questionnaire about demographic/physical data, usual stress perception, chronotype and perceived stress/workload during the experiment Cognitive performance shown in the MAT results Spectroradiometer and temperature sensors

Table 1 *Synopsis of the Pilot Study on CCT and HRV*

Part 3: Computational analysis and application of study results (Chapter 6)

Part 3 focuses on how computational analysis and automized data processing pipelines can reduce the uncertainty in research involving dynamic biomarkers, inter-individuality and limited data due to cross-sectional study designs. Further, a future data application is presented. Resultingly, in Part 3 of the thesis the sub-questions two and three are answered:

1.2 How can computational analysis be used to manage cause-effect ambiguity resulting from the dynamic nature of biomarkers for an increasement of result reliability?
1.3 How can the findings be further developed in longitudinal research and applied in extreme environments?

1.5. Limitations and Considerations

As part of this thesis research, clear limitations in its execution must be considered due to the limited time frame and complexity/interdisciplinarity of the research. The limitations and their effects on study design and result reliability are as follows.

General limitations: The small number of participants limits the generalizability of findings. Additionally, confounding variables (in the study set-up as well as regarding the participant's individual circumstances) can affect physiological data, making it difficult to isolate the effects of the independent variables under study. Minimizing influencing factors was implemented through certain restrictions for participants (see Chapter 5.3). The influence of confounding variables that cannot be eliminated in short-term studies is addressed and investigated in Chapter 6.1.4.

Limitations regarding the chosen biomarker (HRV): Each experiment lasted 40 minutes, resulting in a 40-minute ECG recording per participant per CCT setting. While the reliability of HRV measurements increases with recording duration (with 24-hour recordings providing up to 90 percent reliability) depending on the HRV feature, the usual length for short-term recordings entails 5 minutes. The 40-minute recordings of this study are divided and analysed in different sequences, which is detailed in Chapter 6.1.1. Generalizable HRV results for each individual cannot be provided by this study.

Limitations regarding the chosen VQ feature (CCT): Investigating CCT poses potentially more challenges than other visual quality features due to its relationship with human's circadian rhythm, which is why each person participated in both of their experiments at the same time of day. Additionally, it should be mentioned that the baseline phase has been recorded in the CCT under investigation. This means that the baseline phase is already correlated with the CCT which makes it not possible to draw conclusions about the difference between the person's HRV baseline (in "average" lighting) compared to the HRV during stress with a certain CCT. On the other hand, it provides information about the neutral stress state of participants in each CCT and makes the influence of stress clearer as only one variable changes (stressor simulation) instead of two (stressor simulation and CCT).

Limitations regarding the stressor simulation: It is worth mentioning that while the MAT is an approved, standardized psychological test, changes in the stress response cannot just be a result of individual physiological response (and individual personal circumstance of the person) but also small variations in the conduction of the test cannot be ruled out completely. This effect was mitigated through the use of standardized procedures as explained in Chapter 5.2. Further, the use of the MAT twice for one person can lead to changes in the stress reaction (see Chapter 5.2), which is an important factor in the methodology investigation.

Limitations in the data analysis and application result from the small size of the dataset collected as part the study. The models developed in this thesis, have resultingly only been trained on little data. While this proves the functionality of the models, the reliability of the results is limited.

Despite these limitations, the thesis intends to contribute a fraction to the question if visual quality can counteract allostatic load in extreme environments. The framework details a potential approach for future work on the topic considering the state of the art and identified challenges. By applying the framework in the pilot study, the proposed methods were demonstrated and tested and revealed improvements for further research. Further, the tested statistical models in combination with the study design showed different strategies to analyse the data for an enhancement of result reliability on the participant level (due to the experiment repetition per person) as well as inter-participant level. Hereby, the focus of the analysis is on inter-individuality, the repeated use of the same stressor simulation and the effect of confounding variables on the results. Thus, the data collection and analysis as part of this thesis were conducted considering and addressing the different limitations while investigating the raised research questions.

2. Architecture in Microgravity

While the research questions of this thesis are broadly relevant to architectural settings in extreme environments – or any situations in which occupants are exposed to physical or psychological stress, a concern increasingly relevant given the global rise in chronic stress (Piao et al., 2024) - the literature review primarily focuses on human spaceflight in microgravity. Microgravitational space stations provide a high stressor exposure, confinement in the architectural space, and resultingly challenges in balancing different needs (Häuplik-Meusburger & Bishop, 2021), while leading to physiological changes (Seedhouse, 2020). Therefore, it was chosen as a suitable case study guiding this research.

Crewed space missions as implemented by NASA and the European Space Agency (ESA) contribute to our understanding of fundamental processes in physics, chemistry and biology. They are part of ongoing research about the planet, its origin, and climate change as well as medical research, as for example conducted in the Columbus laboratory on the International Space Station (ISS) (Benefits of Human Spaceflight, n.d.). The International Space Station is the most prominent example (and next to the Chinese Tiangong Space Station the only current example) of a human outpost in space. With the ISS reaching its end of life in the next years, new space outposts and missions are planned, as for example shown by the Artemis mission (Creech et al., 2022). Despite the growing interest in surface and sub-surface settlements, reflected in an increasing body of research, the next immediate outpost in space will be the Lunar Orbital Platform-Gateway (short Lunar Gateway or Gateway), another station in microgravity. In contrast to the gravitational force of 1 g that we know from Earth, microgravity describes 'an environment in which the apparent weight of a system is small compared to its actual weight due to gravity, creating a feeling of weightlessness' (Pletser & Russomano, 2020). Other than the ISS, the Gateway will not be in Low Earth Orbit (LEO) but instead will orbit the Moon. Also, in contrast to the ISS, the Gateway won't be permanently occupied by astronauts with occupation times lasting up to 90 days in a row. Its purpose will be to support a sustained, long-term human return to the lunar surface, serve as a steppingstone to further destinations (Fuller et al., 2024; M. Smith et al., 2020) and to replace the ISS as platform for microgravitational research.

Due to the focus of this thesis, this section is concerned with the interior architecture of a space station but won't detail the architecture of the structure/enclosure (including aspects like the protection from ionizing radiation, energy generation through solar cells, airlocks, etc.). The interior configuration of a space station is challenged with the task to create the highest level of habitability, defined as 'the suitability and value of a built habitat for its inhabitants in a specific environment including operational, physical, psychological and socio-cultural factors in a confined space' (Häuplik-Meusburger & Bishop, 2021) with many limitations regarding volume, mass or material choice (e.g. due to air pollution or flammability risks). Therefore, for the overall system engineering for space systems, NASA recognizes Human System Integration (HIS) as a vital part of it. The HIS domains include human factors engineering, operations, maintainability and supportability, safety, training and – most relevant for this research – habitability and environment - defined as 'ensuring system integration with the human through design and continual evaluation of internal/external living and working environments necessary to sustain safety, human and mission performance, and human health' (*HSI Handbook v2.0 092121_FINAL COPY*, n.d.). These standards build on decade-long experience in human spaceflight and are used for new constructions (Silva-Martinez et al., 2023). The guidelines are based on a range of factors evolving around the users like anthropometry, biomechanics, physical workload, sensorimotor function, visual/auditory perception, cognition and workload (*Human_integration_design_handbook_revision_1*, n.d.). Due to the growing inclusiveness in the astronaut profession, accessibility in space station designs is reaching an increasing relevance and will continue to do so with mission durations increasing, rising the risk for injury and placing even greater autonomy on the crew. This development is also leading to new innovations and research methods in the interior architecture and usability of devices, that might end up increasing the user experience for everyone (Molaro et al., 2024). Current concepts for future space habitation that will succeed the ISS, include a large variety of habitability measures. For example the use of Mixed and Virtual Reality has been suggested to make the available small space more versatile (Basu et al., 2021). Other research investigated senses centric-design guidelines for designs that are better tailored to the human senses responsible for balance and orientation (visual, vestibular, proprioceptive) and for avoidance of the sensory deprivations (Lipińska et al., n.d.). Modular systems like the one introduced by (Konstantatou, 2023) use specific colour palettes and flexible internal partitions to increase visual stimulation of astronauts and spatial efficiency of the station. Since the focus of this work is on indoor environmental quality, the following chapters will detail the life support system and the indoor environment in a space station.

The ecosystem that is sustaining life on Earth must be artificially created in space. This is achieved through the Life Support System (LSS) which handles the water management, waste management and atmosphere regeneration in the space station, with its energy supply resulting from large solar arrays outside the station (Seedhouse, 2020). For the fulfilment of mass restrictions on space stations, these systems must be closed-loop, reusing resources to the highest degree possible. The Environmental Control and Life Support System (ECLSS) onboard of the ISS is 93 % circular with some subsystems being regenerative and some being non-regenerative. They include 1) the Atmosphere Control System entailing the Manual Pressurization Equalization Valve; 2) the Air Revitalization System containing the Carbon Dioxide Removal Assembly, Oxygen Generating Assembly, Trace Contaminant Control Assembly, and Oxygen Recharge Compressor Assembly; 3) the Temperature and Humidity Control System Assemblies including the Inter-module Ventilation and Common Cabin Air Assembly 4) the Fire Detection and Suppression System Assemblies/Components consisting of the Portable Breathing Apparatus and Portable Fire

Extinguisher; 5) the Water Recovery Management System Assemblies entailing the Urine Processing Assembly; and 6) the Vacuum System (Seedhouse, 2020). For over two decades, research efforts like the Micro Ecological Life Support System Alternative (MELISSA) work on further closing the loop of the LSS by eliminating the re-supply of food, water and oxygen, which is especially relevant for deep space missions (Gòdia et al., 2002). Similar research effort s like LIAR, a selectively programmable bioreactor, that uses building waste as a fuel and produces clean water and electricity, aim to establish closed loop building systems on Earth as well (Imhof, n.d.).

2.1. Indoor Environmental Quality On- and Off-Earth

Indoor environmental quality (IEQ) is the term used on Earth to describe the sum of acoustical quality, air quality, thermal quality and visual quality (sometimes also called light quality). It is important to mention, that even though IEQ is often assessed in a linear way for "average occupants", the four factors combined result in a complex system characterized by interrelations and discontinuous non-linear relations depending on many factors like the specific situation, other stressors or interactions between variables (Bluyssen, 2019). On the ISS, while IEQ is partly integrated into the LSS (Atmosphere Control System and Air Revitalization System taking care of the air quality; Temperature and Humidity Control System Assemblies taking care of the thermal quality) (Seedhouse, 2020), acoustical quality and visual quality are addressed separately, which will be further detailed below.

2.1.1. Acoustical Quality On- and Off-Earth

Acoustical quality: The most common indicators for acoustical quality are reverberation time and background noise (D. Zhang et al., 2023). Sound itself is defined through the sound waves amplitude (sound pressure in decibel) and frequency (sound pitch in hertz) and perceived very differently depending on individual human conditions (effectiveness of hearing, personal preferences and associations, psychological state) and environmental conditions (sound insulation, sound absorption, materials used, distance to source, etc). In recent years experts in the field claimed that for the definition of acoustic comfort, the focus on dose-related (like sound pressure levels) or building-related indicators (like sound absorbing walls) should switch to occupant-related indicators focussing on physiological response. This is already applied in work surrounding the term 'soundscape' which is defined by the International Organization for Standardization (ISO) 12913-1, as 'acoustic environment as perceived or experienced and/or understood by a person or people, in context' (Hamida et al., 2023a). It describes 'the individual's perceptual construct of an acoustical environment including seven perceptual construct elements of soundscapes: context, sound source, acoustical environment, auditory sensation, interpretation of auditory sensation, and human responses' (Hamida et al., 2023b). The harmful consequences of unwanted, frequent noise exposure can be auditory (e.g. hearing loss, tinnitus, hyperacusis) and non-auditory (e.g. elevated blood pressure, elevated heart rate, stress reaction). Further, noise can have a global effect on physiological health, affecting several non-auditory systems like the cardiovascular system, neuroendocrine system, and central nervous systems (Gannouni et al., 2024; Passchier-Vermeer & Passchier, n.d.).

Acoustical quality in space: In space, noise remains a significant challenge, with elevated levels contributing to mental health declines for astronauts. On the ISS, allowable acoustic levels are exceeded 45% of the time, highlighting the difficulty in mitigating noise in such environments. Noise levels on the ISS regularly exceed 65 decibel (dB) in the laboratory modules, with the recommended value being 55 dB or below (Goodman, 2000). In the sleeping quarters, the recommended value is 35 dB or below and while a report in 2013 claimed astronauts are satisfied with the sound insulation (Schlesinger et al., n.d.-a), recent surveys show that sound levels in the sleeping quarters average around 50 dB (Begault, n.d.). Frequencies span a large range due to the number of different sources (C. Allen & Denham, 2011). Regulations preventing the use of hazardous or flammable materials for acoustic treatments, make noise reduction even more challenging. In a recent survey, 93% out of 33 astronauts stated that noise levels on the ISS should be lower, underscoring the relevance of this issue. (L. Smith, 2024) states that effective solutions require designing onboard systems with minimal noise output, as passive acoustic treatments are limited due to material restrictions. Further, to mitigate noise-related stress, strategies should include offering astronauts' personal control over their acoustic environments through tools like noise-cancelling headphones, white-noise machines, and music. Measures like these can help reduce stress and minimize the mental health risks associated with elevated noise levels in space stations.

2.1.2. Air and Thermal Quality On- and Off-Earth

Air and thermal quality: Due to the strong overlap between the two domains, they are addressed collectively in the following. The most common indicators for air quality are ventilation rate, concentration of indoor pollutants and odour type (Hamida et al., n.d.). According to AHRAE (American Society of Heating, Refrigerating, and Air-Conditioning Engineers) good indoor air quality is achieved 'by providing air in occupied spaces in which there are no known or expected contaminants at concentrations likely to be harmful and no conditions that are likely to be associated with occupant health or comfort complaints and air with which virtually no occupants express dissatisfaction' (Hewett & Pratt, n.d.). For thermal quality, air temperature, relative humidity and air velocity are commonly used as indicators of quality (D. Zhang et al., 2023). Thermal quality additionally significantly depends on the occupants clothing and metabolism. Thermal comfort is by definition the state of mind, which expresses satisfaction with the thermal environment (Hoof, 2010). Thermal comfort is influenced by both physical environmental factors and subjective human experiences, such as emotions. To analyse indoor comfort and design ventilation systems, various thermal comfort indices have been developed, among which Fanger's Predicted Mean Vote"(PMV) and Predicted Percentage of Dissatisfied (PPD) are the most widely used and understood (Seyit &

Umaroğulları, 2018). More recently, the concept of thermal landscapes which emphasizes occupants' perception of spatial thermal environments including the human body's capacity for temperature adaptation, spatial layouts and the use of materials with specific heat-storing capacities has been established (Hasan et al., 2023). Indoor air affects occupants' health, comfort and productivity and can cause serious health effects. Concentrations of volatile organic compounds (VOCs) for example can lead to sensory irritation in the eyes and airways as well as inflammatory effects e.g. in the lungs while a high CO2 concentration can potentially cause headaches, fatigue, decrease in cognitive abilities (Marques et al., 2019), or even more severe health problems like kidney calcification, oxidative stress and endothelial dysfunction (Jacobson et al., 2019). Research on thermal discomfort shows similar influences on human health, psychological response, and performance due to unsatisfaction with the thermal environment (G. Li et al., 2021).

Air and thermal quality in space: On the ISS, air temperature, air pressure, air humidity, air velocity and gaseous contents in the air are controlled and defined through recommended thresholds (L. Smith, 2024). Maintaining air quality in a space station is energy-intensive and relies on systems to filter air, remove toxins, recycle moisture, and maintain safe conditions. This is illustrated for example by the allowed CO2 concentration on the ISS. Standards for the built environment recommend CO2 concentrations between 400–1000 ppm above outdoor levels, with outdoor CO2 concentration at sea level usually being around 400 ppm. On the ISS, CO2 levels range from a minimum of 3000 ppm to over 6500 ppm. Studies indicate that astronauts develop variable levels of tolerance to high CO2 levels, but for safety, it is recommended to keep the upper limit as low as possible (Georgescu et al., 2020). Odor control is another particularly important aspect, as odours can affect mental health during spaceflight and have been a frequent source of complaints. Odors may arise from mould due to unsafe humidity or temperature levels, or from organic or gaseous contaminants. (L. Smith, 2024). In addition to the challenges arising from limited energy availability and mass constraints for devices and resupplies, the airflow distribution is challenged by the microgravitational environment. On the one side, the thermal load of a space station is high due to the equipment and intense occupancy. On the other side, natural convection does not exist and forced convection is a weaker removal of human heat, which is why the design of efficient airflow distribution remains challenging (F. Li & Wang, 2014; Wang et al., 2018). It is known that on the ISS the crew can modify the temperature settings in certain modules with the average temperature ranging between 21 and 23 degree Celsius (Thirsk et al., 2009). Further, astronauts can choose between three different ventilation settings in their private cabins to influence their thermal comfort, though complaints about the noise levels resulting from the ventilation were reported (Schlesinger et al., n.d.-b).

2.1.3. Visual Quality On- and Off-Earth

Visual quality: Definitions for visual quality or lighting quality vary usually encompass illuminance, luminance ratios, colour correlate temperature, colours, reflection, or view (Bluyssen, 2010). Many efforts have been made toward the development of an overall IEQ index defining the weight of the different factors. For VQ in particular, (Zanon et al., 2019) developed an index for the quantification of VG throughout the whole year. It includes five primary aspects (daylighting, electric illumination distribution, glare probability from daylight and from electric illumination, and colour correlated temperature) and four aspects for personal evaluation (view, shading, flexibility and control) (Zanon et al., 2019). For the investigation of visual quality, usually illuminance level and lighting uniformity are used (D. Zhang et al., 2023), although other parameters like view luminance ratios, reflection, colour, and glare play a relevant role as well (Bluyssen, 2010). Visible light is defined as the range of electromagnetic radiation that can be detected by most human eyes. Typically, the lower limit for wavelengths that can be recognized by the human eye is between 360 and 400 nanometres and the upper limit between 760 and 830 nanometres (nm) (Sliney, 2016). Light is commonly measured in intensity (Lux) and colour correlated temperature (degrees Kelvin) which is the colour appearance of a light source (on-dimensional from warm/yellow to cold/blue) (Durmus, 2022). The influence of light on human health has been well established. It is known that natural light is important for human's natural circadian rhythm, and if light exposure is low, melatonin is produced by the body which causes drowsiness and sleep (L. Smith, 2024). Studies, like the one by (Zhu et al., 2024) show the impact of artificial light on cognitive performance and individual comfort. Attention must also be given to blue light, which has a wavelength that can negatively influence sleep quality/quantity, reaction time, and mental alertness (Silvani et al., 2022).

Visual quality in space: On the ISS, solid-state light LEDs that emit white light are used, they can change light intensity and colour according to NSBRI's circadian lighting research (*Lighting in a Bottle | NASA Spinoff*, n.d.) and have been tested regarding their influence on melatonin production and visual performance of astronauts (Brainard et al., 2013). The light temperate range spans from 2700 K to 6500 K. The general illumination mode delivers 4500 K white light at an intensity of 210 candelas (cd) (*Ochmo-Tb-026-Lighting-Design.Pdf*, n.d.). (Lu et al., 2021) investigated the work efficiency and fatigue of the ISS's lighting system in a terrestrial user study (n=18) recommending a color temperature of 7500 K as result of their research. Since the astronauts are completely deprived of a natural day-night rhythm induced by cyclic changes of natural light, studies like the one by (Jiang et al., 2022), investigated the influence of light on an astronaut crew in a space analogue environment. During this 7-day simulation, one group lived in an artificial habitat with white lighting typically found in current space stations, the other group experienced changing light colours every three hours, with all other factors being identical between the two groups. The results show increasing negative emotions and anxiety only in the group with the white light, which was attributed to the fact that lighting colour can help prevent negative psychological effects. (L. Smith, 2024) observed that different research recommends very different lighting for space stations. While (Caballero-Arce et al., 2012) suggests the use of bright, cool light, (Burattini et al., 2016) on the other side recommends warmer, dimmer light, with the second research having used a larger body of data from previous research than (Caballero-Arce et al., 2012). Not only does the comparison show the deviation in intensity and temperature but also the opposite rhythms e.g. in the contradictions of light intensity in the morning as seen in **Figure 2**.

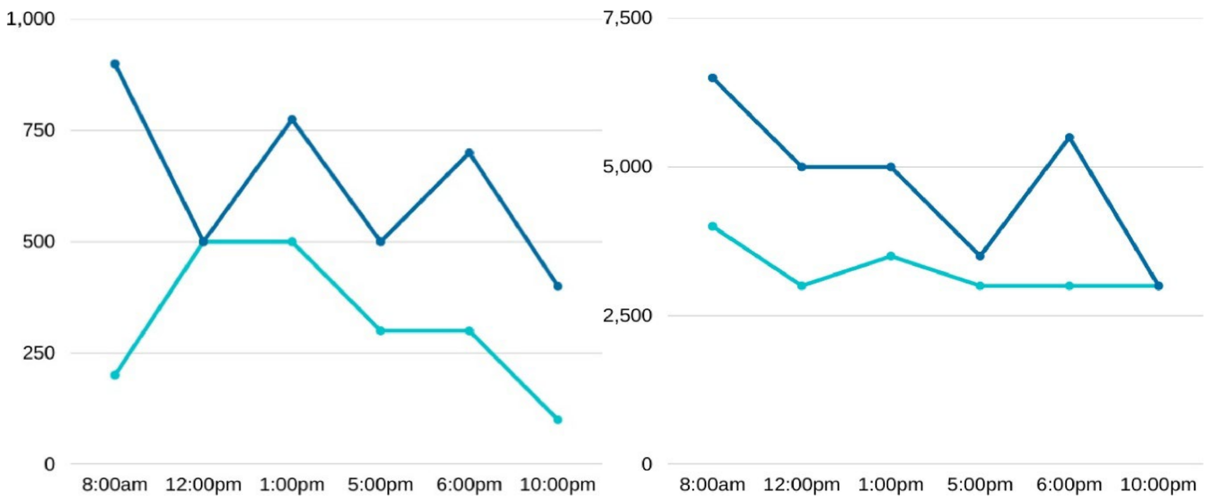

Figure 2 *Comparison of Light Intensity in Lux (left) and CCT in degrees Kelvin (right) derived from two different studies; dark blue: (Burattini et al., 2016); light blue: (Caballero-Arce et al., 2012); source: (L. Smith, 2024)*

2.2. Physiology and Psychology in Microgravity

A space station in microgravity is an extreme living environment for which the human body is not adapted, therefore demanding complex psychological and physiological adaptation. Human spaceflight entails inevitable stressors for the astronauts ranging from physical ones like acceleration, microgravity, ionizing radiation and the altered dark-light cycle to psychological ones like isolation, confinement, monotony and high workload (Kanas & Manzey, 2008). These stressors have severe consequences on the human body. The consequences and their interplay are complex and not fully investigated yet, therefore the following section will provide a non-exhaustive overview of common physiological (related to the physiology, the branch of biology that deals with the functions and activities of life or of living matter (such as organs, tissues, or cells) and of the physical and chemical phenomena involved (*Definition of PHYSIOLOGY*, 2024)) and psychological (belonging to psychology, the scientific study of mind and behaviour (*Definition of PSYCHOLOGY*, 2024)) changes in the human body.

2.2.1. Adaption Processes

Human spaceflight and the correlating microgravity and radiation exposure have severe consequences for the human **nervous system**, divided in central nervous system (CNS) consisting of the brain and spinal cord and peripheral nervous system (PNS) consisting of the nerves (Seedhouse, 2020). The nervous system receives stimuli from external sources as well as from the internal organs and it commands the responses to those same stimuli, by sending electrochemical impulses through the body's nerve fibre network (Kourtidou-Papadeli, 2022). The nervous system is affected by spaceflight in many ways including biological, functional and psychological ones. A fragment of which will be detailed in the following. Due to the complex and dynamic interplay between physiological and psychological effects, it was decided against a strict separation of the two categories. Directly affected by the space environment is the vestibular system which consists of the non-auditory parts of the inner ear, which include the three semicircular canals and the otolith organs (Kanas & Manzey, 2008) and provides information about motion, head position, and spatial orientation. (Seedhouse, 2020). The combination of the sudden absence of gravity and movements of the head or the whole body lead to space motion sickness (SMS) as a result of the two underlying mechanisms fluid shifts and sensory mismatch. Neuro-vestibular changes observed in a microgravity environment are primarily linked to two factors: (1) structural and functional modifications caused by physical forces or functional reorganization, and (2) altered perception and interaction with the surrounding environment. (Kourtidou-Papadeli, 2022). SMS can not only harm the physiological wellbeing but also the mental one, causing malaise, drowsiness and a lack of initiative (Kanas & Manzey, 2008). As a result of microgravity, body fluids shift from their natural distribution to a higher concentration in the upper body. Recent research shows changes in neuroplasticity (Van Ombergen et al., 2017), an upward shift of the brain (Roberts et al., 2017) in astronauts who completed long duration missions on the ISS. (Kourtidou-Papadeli, 2022) summarized recent studies on the subject, stating that local, nonlinear brain structural changes and tissue volume changes in astronauts follow spaceflight. "Spaceflight-Associated Neuro-ocular Syndrome" (SANS) leads to altered visual acuity amongst other effects (as further described below) and causes clear changes in the brain structure as well. These brain changes, clearly visible through MR images taken pre- and post-flight, are associated with behavioural effects, including postural adjustment and reaction time during cognitive tasks (Roberts et al., 2019). Microgravity also disrupts cerebral networks, affecting spatial navigation, sensory-motor processing, cognition, and multisensory integration. (Roberts et al., 2017) compared the brains of 18 astronauts from the Space Shuttle Programme before and after flight including long and short duration missions. Especially for the long-duration group, the results show significant narrowing of the central sulcus (the prominent groove on the lateral surface of the cerebral hemisphere), and an upward shift of the brain and narrowing of cerebrospinal fluid (CSF) spaces at the vertex (Roberts et al., 2017). Cognitive abilities are endangered through the potential reduction of grey matter. (Kourtidou-Papadeli, 2022) also addresses potential cognitive effects like losses in an astronaut's memory and judgment and biological effects like space-related neurological potentially negatively affecting DNA replication or protein transportation. The same way some physiological effects can lead to psychological consequences, psychological events can affect physical health. While some positive mental effects of spaceflight have been reported by astronauts like a new appreciation for the planet/life or increased personal strength (Kanas & Manzey, 2008), the above-mentioned stressors pose a serious challenge for psychological wellbeing. For example, the social isolation that leads to psychological prodromes that instigate functional neurological illness (Gupta et al., 2023). Sleep disturbances (as often experienced by astronauts due to the microgravitational environment), the disturbed circadian rhythm and stress can lead to decreased performance and alertness. Insufficient sleep quantity or quality has shown to negatively impact immune defence, increase the risk of inflammation and contribute to all-cause mortality (Barger et al., 2014; Coco et al., 2019; Irwin et al., 2016). (Palinkas et al., 2004) summarized the findings of a study investigating the psychiatric disorders of a crew living in isolation at an Antarctic research station during an austral winter. It revealed that 12.5 % of crew members showed symptoms that meet the criteria for one or more DSM-IV disorders (Diagnostic and Statistical Manual of Mental Disorders). The research of (Desai et al., 2022) summarize that from four selected stressors (radiation, microgravity, confinement/isolation, and sleep deprivation), between two and four of them impact astronauts' cognitive abilities in the categories, learning, memory, cognitive flexibility, cognitive control, attention/vigilance and depression/anxiety (Desai et al., 2022). **Proprioception** (the spatial orientation of the body resulting from sensory information from muscles, skin, and joint receptors) is significantly affected as well. In the absence of gravity, the body responds differently to stimuli. Astronauts reported a lack of eye/hand coordination and situations in the dark where they had no awareness for the position of their legs. **Vision ability** is affected in a large number of ways. Short term space flights have shown to correlate with reduced near sight in approximately 23% of astronauts during the mission and 48% of astronauts after return. Recent studies have shown that around 20% of astronauts on long-duration missions experience optic disc edema, globe flattening, choroidal folds, hyperopic shifts, and elevated intracranial pressure, both during and after spaceflight. While some of these changes are temporary, others persist and result in varying levels of visual impairment (Clément, 2011). Related to these effects is the so-called Vision Impairment and Intracranial Pressure (VIIP) which results from flattening of the eye bulb and mildly elevated pressures of the cerebrospinal fluid and consequently the eye chambers (Mader et al., 2011). Another phenomenon is the spaceflight-associated neuro-ocular syndrome (SANS) (Gupta et al., 2023). According to (Kourtidou-Papadeli, 2022) upon astronauts return to Earth, visual field decreases, retinal blood vessels constrict, and visual motor task performance and contrast discrimination decline. Additionally, orbital astronauts reported difficulties in evaluating distances (Clément, 2011), which can be particularly dangerous for docking manoeuvres, potentially further increasing stress levels. The two-week study with 32 participants of (Garaszczuk et al., 2025) simulating the life in a space station documented clear effects on binocular vision parameters. This could mean that not only microgravity and radiation are responsible for vision problems of astronauts but that isolation, specific lighting conditions or cognitive load could be contributing factors too. **Hearing ability** on a space station can be effected by several aspects like constant noise level (as detailed in Chapter 2.2.2) resulting from the life support system and the headward fluid shifts that may attenuate sound by way of the middle-ear structures (Nicogossian et al., 2016).

Olfaction and taste are affected as evidenced by astronauts disliking their food, describing it as blend and requesting more spices (Nicogossian et al., 2016). This is credited not to changes in the olfactory function or taste threshold. Instead it is a result of SMS, passive nasal congestion and the headward fluid shift (Kourtidou-Papadeli, 2022). **Haptic perception**, which relies on sensory input from skin and muscle mechanoreceptors, may be altered in microgravity. Cosmonauts were tested after short (15 days) or long (6 months) missions. On the day of landing their haptic performance was already improved and by 2 days after landing haptic performance returned to preflight levels, suggesting an enhanced role of proprioceptive input and movement feedback in microgravity. Continuing with the **cardiovascular system** that mainly consists of the heart and blood vessels, with its main function being the blood circulation for oxygen and nutrient delivery to all parts of the body. The above-mentioned body fluids shift to the upper part of the body cause temporary increases in central blood volume and intracranial pressure. These changes trigger complex adaptive responses in the cardiovascular, endocrine, and blood systems. Through a reduction of blood plasma volume, the body can adapt to restore the volume of fluid in the upper body closer to normal levels. Before this adaption, this shift of body fluids leads to astronauts complaining about nasal stuffiness and headaches during the first hours or days in weightlessness (Kanas & Manzey, 2008). Further, the **musculo-skeletal system** (consisting of muscles and bones) is affected. Astronauts in microgravity experience significant bone loss as well as muscle loss. The brain detects the removal of load and as a result the process of bone remodelling starts by decreasing the osteoblasts and increasing the osteoclasts. The result is a reduction in bone mass density of between 1.0 and 1.2 percent every month, thereby increasing the risk of fractures significantly (Seedhouse, 2020). While around 50 % of all muscles in the human body are needed to deal with gravity, specifically the muscles in legs and lower back are affected (Kanas & Manzey, 2008). Muscle atrophy in microgravity is similarly seriously with astronauts losing about 25 percent of their total muscle mass in 6 months (Seedhouse, 2020), which is why appropriate countermeasures are pivotal.

As shown above, physiology and psychology are intertwined in space the same way they are on Earth. One highly relevant example for this is allostatic overload. Allostatic overload describes a cumulative measure of dysregulation across multiple physiological systems due to continuous or repetitive stress-inducing environment. While allostasis describes the maintenance of physiological stability through adaption of the internal parameters (Romero et al., 2009; Rusanov et al., 2023), its counterpart homeostasis is the ability of an organism to maintain internal constants (Rusanov et al., 2023). The process of allostatic response between two states of homeostasis illustrated by (Valentine, 2023) in **Figure 3**. Allostatic load describes the added energetic coast that allostatic states of different physiological systems impose on the body as a result of stress (Bobba-Alves et al., 2022). But in the case of allostatic overload, the initially protective, physiological responses become damaging over time due to prolonged neural responses, which compromises the immune response, resulting in long-term damage to organs and tissues (Karlamangla et al., n.d.; Valentine, 2023). The research of (Finseth, n.d.) claims that allostatic load of long duration spaceflight impacts the intensity of negative physiological adaptions through steroidal hormones, such as cortisol and dehydroepiandrosterone (DHEA). They summarized a correlation between increased cortisol/DHEA and space-flight related health downsides like muscle loss, weight loss, immune system suppression, bone loss, cardiovascular changes, insomnia, depression, asthenia and anxiety. While the exact compilation of drivers may not be clear yet and research indicates different extends of it, it has been established that astronauts show increased salivatory cortisol levels during spaceflight (Mehta et al., 2014, 2017) and cortisol spikes in plasma and urinary post-flight (Capri et al., 2023). These results were more pronounced after long duration missions compared to short duration ones (Stowe et al., 2011). Research studying subjects in terrestrial settings has long established the existence of negative effects of allostatic overload on the human body. Dysfunctional allostatic response can result in a constant production of inflammatory antigens, which can lead to chronic systemic inflammation increasing the risk for cardiovascular diseases, immune system malfunction, metabolic syndrome and many more (Dhabhar, 2008; Guidi et al., 2021; Logan & Barksdale, 2008).

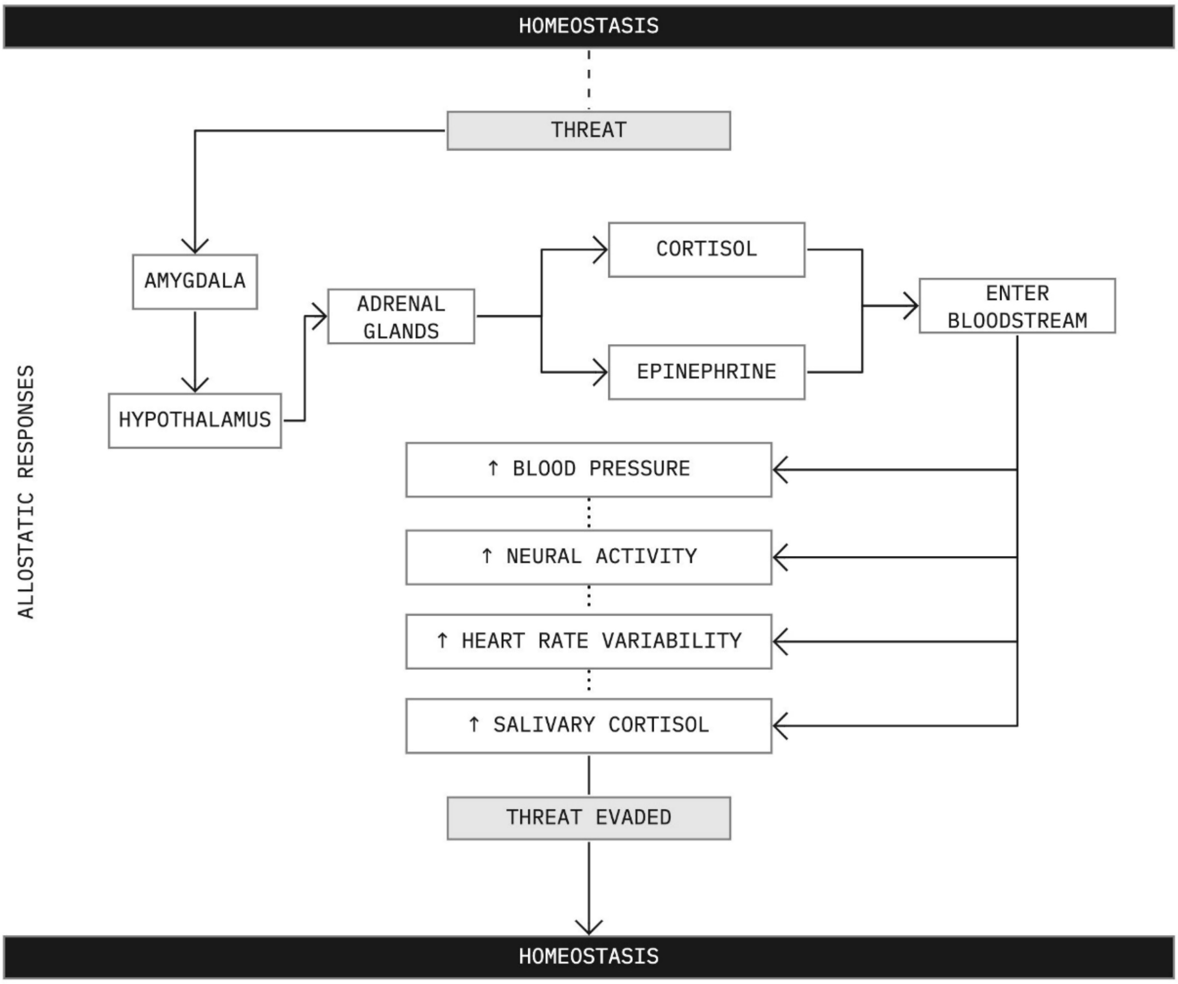

Figure 3 *Overview of Allostatic Response to reinstate Homeostasis; source: (Valentine, 2023)*

(Crucian et al., 2020) states that operational improvements and biomedical countermeasures onboard ISS have significantly improved astronauts' immunity and stress levels. This finding is based on the clear decrease in astronauts' cortisol levels since 2012 which coincides with improvements on the ISS like cargo delivery, resupply frequency, personal communication, exercise equipment, food quality, food diversity, nutritional supplementation, and schedule management (Crucian et al., 2020). Further direct or indirect measures that can counteract negative health effects are explained in the next chapter.

A few studies about HRV in space exist, including different methodologies and objectives. Two previous studies on the influence of microgravity on HRV were analyzed in detail and compared to each other. The first study, by (Otsuka et al., 2016), monitored the HRV **of 10 astronauts during a 6-month mission** to the ISS. Measurements were taken five times. Control: before flight (days 234.4 ± 138.4); ISS01: approximately after the first weeks on the ISS (days 20.8 ± 2.9 after launch); ISS02: approximately after the second month on the ISS (days 72.5 ± 3.9 after launch); ISS03: approximately after the fifth month on the ISS (days 152.8 ± 16.1 after launch); and After flight: after return to Earth (days 77.2 ± 14.4 after return). On average, no differences were found in HR (or NN) or in SDNN among the 10 astronauts. Nevertheless, a **distinguishment in two groups** was noticed resulting from the two types of reactions shown in the consistent differences in several HRV endpoints. In 7 astronauts (group 1), **the 24-hour SDNN was significantly lower than in the other 3 astronauts**. **Group 1 and group 2 also differed in their average NN intervals**. (group 1 showed increases in their average NN interval, group 2 showed decreases). While the 24-, 12-, and 8-hour components of HRV stayed unchanged during the mission, the 90-min amplitude became about three times larger in space compared to Earth in the subgroup of 7 astronauts. The study concludes that while the effect of spaceflight on cardiovascular health is clear, the influence of individual daily routines before and during flight or different sleep patterns is unclear and needs more investigation. A significant finding is that amplitudes of all 4 anticipated components clearly increased in astronauts of group 1, while the same components primarily decreased in the second group.

The second study, conducted by (Yamamoto et al., 2015), measured the HRV of **7 astronauts each of which participated in a mission of around six months** as well. Similarly, as in the study by (Otsuka et al., 2016), HRV data were collected five times. Pre: before launch; DF1: one month after launch; DF2: two months after launch; DF3: two weeks before return; and Post: three months after landing. At each measurement point a 24-h electrocardiography was performed. In 2 of **the 7 astronauts the HF component increased**, while it **decreased in 3 astronauts and remained almost unchanged** in 1 astronaut at DF1. During DF3, towards the end of the six months, the **HF component of 5 out of the 7 astronauts recovered from the decrease after launch**, showing a clear improvement of over 20% in 3 astronauts. Changes for example in r-MSSD, CVRR or SDNN were very individual with no distinct pattern for all 10 astronauts. The study concludes that regular sleep–wake and eating schedules act as helped in restoring proper circadian rhythms after 6 months at the ISS and that the adaption process differs among individuals.

2.2.2.Countermeasure Systems

According to (Kanas & Manzey, 2008), countermeasures can be roughly divided into two aspects. Category one is about adapting humans to the environment: This approach views the environmental conditions as fixed and focuses on preparing and shaping humans to perform optimally under these constraints by finding well suited individuals, considering group dynamics in the selection process and providing the right training. Category two is the opposite and about adapting the environment to humans: This involves adjusting environmental conditions during space flight to meet human psychological needs and capabilities. It includes all aspects of habitability like hardware/software design, work design, and work-rest schedules considering ergonomics and human factors (Kanas & Manzey, 2008).

Current methods to adapt humans to the environment by lowering the effects of the space environment either include physical exercise or the intake of medication/vaccine (Petersen et al., 2016) as well as pre-flight healthcare measures like training, therapeutics, and psychological support protect crew health before launch (Nicogossian et al., 2016). To counteract microgravity-induced adaption (decreases in body mass, muscle strength, bone mass, etc. as explained in Chapter 0), astronauts on the ISS perform a daily physical countermeasure program, that is tailored individually to each astronaut depending on the individual fitness level, personal preferences and ISS exercise hardware specifications (Petersen et al., 2016). In addition to physical countermeasures, psychological training, medication to mitigate fatigue, pre-flight vaccinations (to counteract virus reactivation), anti-inflammatory drugs (to counteract inflammation), biomarker monitoring, and pre-/pro-/postbiotics can help according to (Capri et al., 2023). Further, they suggest the integration of wearable sensors to measure e.g. stress hormones and the use of artificial gravity. (Fink et al., 2014) and other research proposes real-time health monitoring and condition-based health maintenance that allow for early self-diagnosis of early health issues through autonomous identification of negative trends. Their proposal includes extending the current system that is heavily based on exercise as countermeasure through data analysis, and statistical methods to astronaut health maintenance, unobtrusive and non-invasive sensors/devices for health monitoring, algorithms and models for large-scale health data processing. Similar concepts of autonomous healthcare have been developed for example by (Popov et al., n.d.), suggesting the integration of a human-centred and intuitive design of health monitoring and the use of computational biomarkers to stratify health-related risks and match them to a corresponding individual-based health maintenance.

On the ISS, the Crew Health Care System (CHeCS) is a collection of devices that provide the needed medical and environmental capabilities to ensure the crew's safety during long-duration missions. The CHeCS consists of three subsystems: the Countermeasure System (CMS), the Environmental

Health System (EHS), and Health Maintenance System (HMS). While the EHS oversees monitoring the atmosphere for contaminants, acoustics and radiation levels and the, the CMS and HMS are particularly relevant for the scope of this chapter. The CMS consists of equipment and protocol for regular operations like exercise to counteract the deconditioning effects of living in microgravity. Further, it monitors exercise sessions, reduces vibrations during them, and enables periodic fitness evaluations. The HMS offers in-flight life support and resuscitation, as well as medical care, and health monitoring (Clement, 2011; *Crew Health.Pdf*, n.d.).

While it is a known fact that the habitability of a space station interior is imperative for the health of astronauts (Childress et al., 2023), the harm resulting from it as a consequence of resource limitations is not well investigated, specifically the harm that does not follow a linear connection—such as hearing damage directly caused by loud noise—but instead arises as a cumulative result of multiple factors, leading to a chronic condition with widespread, non-localized effects. Resultingly, the potential of architecture and the indoor environment as countermeasure is not well understood.

3. Neuroarchitecture

Humans spend a very significant part of their time inside buildings, in developed nations up to 90 %. Therefore, it is crucial to know the influence of their surroundings on human physiology (Valentine, 2024). In recent years, the study of neuroarchitecture has gained increasing attention as an interdisciplinary field concerned with the effects of architecture on the human brain incorporating that the influence of architecture goes beyond just psychological effects e.g. emotions. Reactions in the brain can have physiological effects like heart rate fluctuations or changes in blood pressure to surrounding stimuli before we consciously process them (Bower et al., 2019). Further, health effects that start as purely psychological can lead to severe physiological ones, like for example allostatic overload as detailed in Chapter 2.3.3. Definitions of the term neuroarchitecture vary between focusing on human wellbeing as a whole (including physically (body), intellectually (brain), emotional (emotions), social wellbeing (behaviour)) (Medhat Assem et al., 2023) and focusing on the human brain including function, cognition, psychological well-being and behaviour (Valentine & Mitcheltree, 2024). In short, neuroarchitecture can be understood as the joining of forces between architecture and neuroscience (the study of the human nervous system and brain (*Neuroscience*, 2025)). Therefore, neuroarchitecture is closely related to environmental neuroscience which focuses on how different physical environments - such as natural, urban, or built settings - affect the structure and function of the human brain (Kühn, 2024).

3.1. Allostatic Load

Many examples of research exist that investigated architecture or specifically visual quality as cause to stress responses and health downsides and how this effect can be avoided (De Paiva & Jedon, 2019; Evans & McCoy, 1998; Litscher et al., 2013; Niza et al., 2024; Valentine, 2024), as tool to foster post-stress relaxation (Ho & Chiu, 2021; Minguillon et al., 2017) or support to physical recovery after an injury/sickness (Ghazaly et al., 2022; Lawson, 2010; Simonsen et al., 2022) (with significant overlaps between the research due to interaction effects). Some examples, like the study by (Fich et al., 2014), have investigated the influence of the environment of cortisol concentration during stress tests. In recent years, allostatic overload (as described in Chapter 2.3.3.) has been subject to research in the field of neuroarchitecture. Prior to detailing the current research situation on the subject, the methods to evaluate allostatic overload and the influence of architecture on it, must be explained.

3.1.1. Biomarkers for Allostatic Load

The two primary methods of measuring health conditions like allostatic overload include biomarkers and clinimetric assessment. The first method comprises biological markers that are connected to chronic stress and that can be measured from different parts of the body over time (Valentine, 2023). Initially, allostatic load was measured through primary mediators (representing biochemical changes in the neuroendocrine system as a result of stress) and secondary mediators (remodelling of receptor sites in the cardiovascular, immune, and metabolic systems as a result of stress). The original primary mediators entailed cortisol, noradrenaline (norepinephrine), adrenaline (epinephrine), and dehydroepiandrosterone (DHEA). In recent years, the use of biomarkers for allostatic load became much more diverse (Beese et al., 2022). An overview of the different neuroendocrinal, immune, metabolic and cardiovascular biomarkers for allostatic load and the number of studies using them (up till July 2021) can be seen in **Figure 4**.

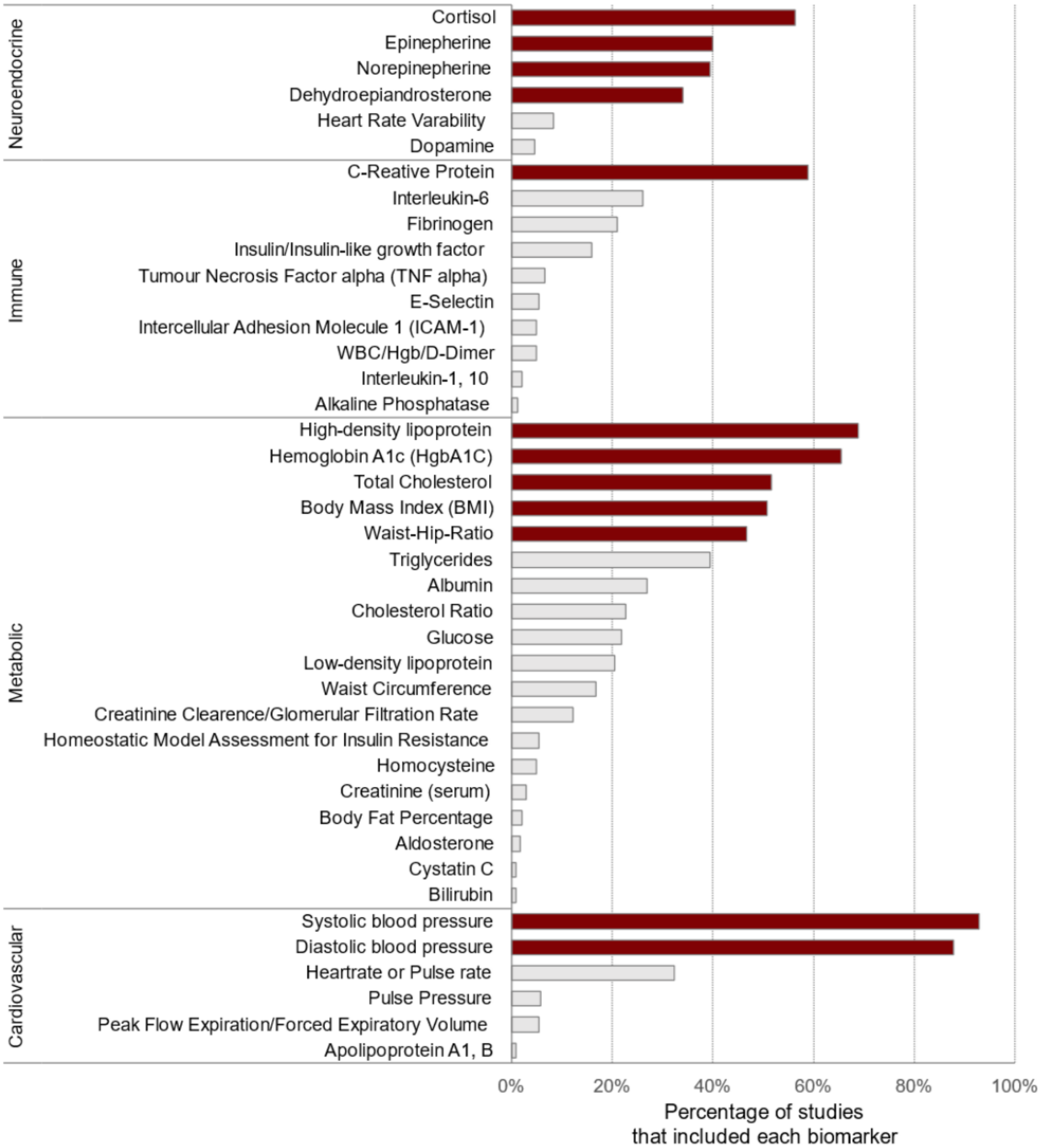

***Figure 4** Allostatic Load Biomarkers (the darker shaded biomarkers refer to the original primary and secondary biomarkers; source: (Beese et al., 2022)*

(Valentine, 2023) analyzed the interrelationship between the biomarkers that were employed in previous studies on allostatic load and those employed in the investigation of neuroarchitecture in a diagram, a seen in **Figure 5**. A relevant observation by (Valentine, 2023) is that none of the biomarkers used in studies about allostatic (over)load were employed in neuroarchitecture studies. This suggests that while the stress responses observed in neuroarchitectural research indicate allostatic activity, they do not automatically confirm the presence of allostatic overload.

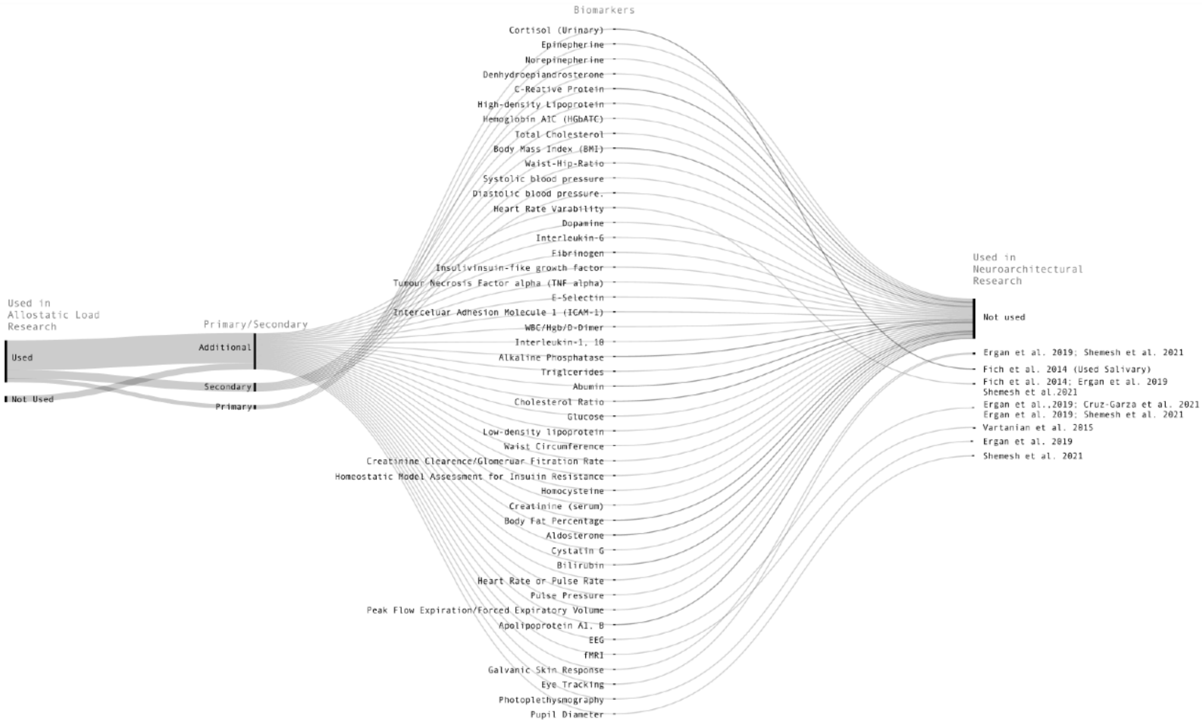

Figure 5 *Interrelationship Biomarkers used in Allostatic Load Research and Neuroarchitecture research; source: (Valentine, 2023)*

For the investigation of regular physiological stress responses in form of biomarkers, different techniques are employed and will be discussed in the following. One common method is the **Electroencephalography** (EEG), a technique to measure electrical signals produced by neurons in the brain (Medhat Assem et al., 2023). Different wavelengths are associated with different types of brain activity including delta, theta, alpha, beta, and gamma (Abhang et al., 2016b, 2016a). Other methods include **Functional Magnetic Resonance Imaging** (fMRI) detects changes in blood flow and oxygenation to measure brain activity by generating images through magnetic fields and radio waves and **Functional Near Infrared Spectroscopy** (fNIRS) that uses near infrared light to spot variations in blood oxygenation. **Heart rate variability** (HRV) is a measure of the variation in time between each heartbeat and an indicator for activity in the autonomic nervous system. The high frequency band (0.15 - 0.4 Hz) represents predominantly parasympathetic activity and the low frequency band (0.04 - 0.15 Hz) represents sympathetic activity with a parasympathetic component (Medhat Assem et al., 2023; Valentine, 2024; Viljoen & Claassen, 2017). **Galvanic skin response**

(GSR) (sometimes also referred to as Skin Conductance Response (SCR)) measures the electrical conductance of skin, which is known do vary depending on emotional and physiological stimulation e.g. stress causing sweat glands to increase activity**. Pupil dilation** is another method and known to be an indicator of potential threats (related to the body's fight or flight reaction) with the physiological purpose of allowing more light to enter the eye. Finally, **cortisol**, a steroidal hormone that is released as part of the body's stress response and can be measured in salivary, urine or sweat as a non-invasive way to understand and track stress-induced health outcomes (Medhat Assem et al., 2023; Valentine, 2024). Other than the other biomarkers, cortisol is not only used in neuroarchitecture research about stress resulting from architecture, but it is also one of the most common biomarkers for allostatic load. As seen in **Figure 4**, the most popular biomarker used in allostatic load research is systolic/diastolic **blood pressure**, the force on the walls of your arteries as your heart pumps blood through your body, (Valentine, 2023). Systolic pressure describes the highest arterial blood pressure of a cardiac cycle occurring during a heart heartbeat (*Medical Definition of SYSTOLIC BLOOD PRESSURE*, n.d.) and diastolic pressure describes the lowest arterial blood pressure of a cardiac cycle occurring between two heart beats (*Medical Definition of DIASTOLIC BLOOD PRESSURE*, n.d.).

The majority of studies doesn't use single biomarkers but instead relies on composite biomarkers that entail combined assessment of multiple biomarkers (Valentine, 2023). For this, one common technique includes uniformly assigning weightage to all biomarkers (categorised as "0" for low values and "1" for high values, as per nationally standardised ranges) and summing the score to evaluate the level of allostatic load. Another technique, that according to (Valentine, 2023) is most commonly used, applies extreme quantiles of biomarkers like the 10^{th} and 90^{th} percentile to evaluate the acceptable range (Beese et al., 2022; Valentine, 2023). The last common method using biomarkers is the Mahalanobis Distance Method, which investigates allostatic load by using biomarker data to calculate the statistical distance from the covariance of biomarkers (Cohen et al., 2013; Valentine, 2023). While biomarkers offer a good way for the objective evaluation of biological thresholds resulting from allostatic overload, they don't consider patient experience. Clinimetrics on the other side consist of objective and subjective measures by including patient-reported symptoms in connection with biomarkers. The physiological symptoms are situated in the context of the person's experience through questionnaires or interviews that track the patient's perspective over time (Valentine, 2023). Within clinimetric assessment, outcome-based evaluation uses a specific health outcome (e.g. a cardiovascular disease) that is tracked over time to attribute the level of allostatic load experienced by the person to it (Guidi et al., 2021). Latent-profile analysis on the other side can increase our understanding of allostatic load by using observed variables as indicators of the unobserved latent variables (Valentine, 2023). This can for example help predict the likelihood of health effects resulting from allostatic overload due to the exposure to certain events (e.g. childhood trauma) (Johnson et al., 2019; Spurk et al., 2020).

Limitations of research in the field of architectural allostatic load include 1) the cross-sectional nature of many studies: Most research on allostatic load is cross-sectional, limiting the ability to understand temporal relationships between stress and health outcomes, although longitudinal studies are increasingly addressing this gap; 2) the lack of standardized measurement methods: There is no consensus on how to measure allostatic load, with variations in the selection of biomarkers, combinations used, and assessment techniques, which hampers cross-study comparisons and reduces measurement validity and reliability; 3) the limited scope of biomarkers: Current biomarker-based methods might not be able to describe the complexity of physiological responses to stress, and clinimetric approaches, while comprehensive, may lack specificity and sensitivity; 4) the variability in stress responses across populations: Differences in stress response mechanisms between individuals, influenced by factors such as age, health conditions, and genetics, complicate comparisons of allostatic load across populations; and 5) the influence of external factors: External variables like age, biological sex, and socioeconomic status significantly affect allostatic load measurements, making it challenging to isolate specific factors, though clinimetric approaches can provide contextual insights into these influences (Valentine, 2023). The development of algorithmic tools that can use biomarkers to predict allostatic load is one possible solution to create the needed consistency and comparability of results using the same biomarkers with the same magnitude. (Carbone et al., 2022) analysed existing algorithms, detailing the relevant considerations of such tools, like the question if biomarkers should be treated as continuous or dichotomous variables, how biological systems should be taken into account when calculating allostatic load, or what score on the scale of this tool would represent high allostatic load. The research concludes that most work has used an overall score if dichotomized biomarkers indicated high risk, but that more nuanced, sophisticated tools are needed if reliable examination of allostatic load is the goal.

3.1.2. Architecture and Allostatic Load

While the focus in the following chapters (beginning in Chapter 4) will be on visual quality (light quality) of architecture which relates to physical architecture as well as IEQ, this subchapter summarizes the state of the art of research on architectural allostatic load on physical architecture but mainly on the four different subdomains of IEQ. (Valentine, 2023) explored architectural allostatic overload by reviewing literature on stress-inducing architectural shapes. The work summarizes past research on different architectural shapes and their influence on human health. Certain room proportions (Cruz-Garza et al., 2021), wall curvature (Vartanian et al., 2021), and window arrangement/size (Cruz-Garza et al., 2021; Ergan et al., 2019) have shown to cause stress reactions in humans without them consciously noticing. These studies used a combination of biomarkers including heart rate and heart rate variability, salivary cortisol, electroencephalogram (EEG), galvanic skin response, photoplethysmography, eye tracking, pupil dilation, and functional magnetic resonance imaging (fMRI) (Valentine, 2023). Since these studies used biomarkers referring to general stress (not specifically to allostatic load), the observed stress reaction could be temporal and mean that the participants returned quickly to homeostasis, or it could mean that if they are exposed to stress-inducing architectural features frequently they develop allostatic overload. For this distinguishment, further research is needed.

Regarding the influence of indoor environmental quality on allostatic load, the research of (C.-C. Jung et al., 2014) conducted between July 2011 and December 2012 offers relevant results. The study investigated the relationship between air quality/illumination and allostatic load using a range of eleven biomarkers including cortisol and heart rate through a multiple linear regression model. While no direct connection between the total allostatic load and indoor environmental factors was demonstrated, it revealed that the allostatic load on specific body systems was associated with specific environmental indexes. For example, an association between CO2 levels and the allostatic load on the endocrine system was proven. Other work, like the one of (Thach et al., 2020) looked at IEQ as countermeasure for temporary stress and observed a relevant reduction in stress at the workplace in association with higher satisfaction of perceived acoustic, air, thermal and light quality. This implies that good IEQ can potentially counteract stress resulting from work-related stressors. It is relevant to mention that this study didn't collect data through biomarkers but used the OFFICAIR questionnaire for participants to evaluate the IEQ and self-report questionnaires for stress. Table 3 shows an overview of findings from recent studies about the influence of IEQ on the biomarkers most relevant for this thesis. The studies used in **Table 2** investigated general associations between IEQ and the chosen biomarkers but did not focus on allostatic overload.

Blood Pressure	Extreme temperatures affect blood pressure (D. Xu et al., 2019); Elevated blood pressure can be a result of ambient air pollution (Y.-J. Choi et al., 2019); association between light exposure and increased blood pressure (Gubin et al., 2017); small blood pressure differences were found in relation to noise exposure (van Kempen et al., 2002)
Heart rate variability	Increased temperature is strongly associated with lower HRV (with inverse relationships for cold and warm) (H. Li et al., 2023), temperature extremes are associated with low HRV (Mowery et al., 2011); Recent exposure to poor air quality (particulate matter and ultrafine particles) changes HRV (Breitner et al., 2019); different findings about the influence of light on HRV exist, (Petrowski et al., 2023) revealed no significant influence of light intensity on HRV parameters, light colour significantly influenced all HRV parameters except the low frequency; (Veternik et al., 2018) revealed no significant effect of sounds under different frequencies on the HRV parameters, other studies found an effect e.g. Resulting from low frequency sound (Vilímek et al., 2022)
Cortisol	(Indoor air) temperature and exposure time influence cortisol concentration (X. Zhang et al., 2023); Moderate association between (traffic) air pollution and salivary cortisol (Hajat et al., 2019), long-term ambient air

	pollution levels are associated with increased chronic stress levels (shown in hair cortisol) (Verheyen et al., 2021); Direct and positive relationship between noise annoyance and cortisol secretion (Yaghoubi et al., 2020); Light exposure has been reported to produce contradicting results (no effect, increase, or decrease cortisol levels) (C. M. Jung et al., 2010), bright light exposure increases the cortisol level the most compared to dim white, red or blue light (Petrowski et al., 2021)

***Table 2** Past Research Results on the Influence of IEQ on Biomarkers relevant for Allostatic Load*

3.2. Neuro-adaptive Architecture

The term neuro-adaptive architecture introduces a novel and largely unexplored interdisciplinary field that aims to create a built environment responsive to human emotions, cognition, and health. While the term is not well defined yet, a recent publication describes neuro-adaptive architecture as 'structures and settlements capable of adapting discretely to human cognitive and affective states in real-time' (Makanadar, 2024). The term 'cognitive state' can be described as a person's cognitive processes, encompassing mental actions like memory, attention, reasoning, problem-solving, comprehension, and language organization (Thakor, 2023). 'Affective state' is a psycho-physiological construct linking mental and physical processes, represented by arousal and valence in Russell's model, and inferred from physiological changes in the body (Cittadini et al., 2023). In the context of this thesis, neuro-adaptive architecture is understood as smart architecture able to respond to physiological and psychological states of its inhabitants, resulting in a response loop between architecture and human. This distinguishes it from neuroarchitecture, that is concerned with a more linear investigation of the effects of architecture, as described in Chapter 3. Due to the extreme novelty of the field of neuro-adaptive architecture and the resulting lack of research, the following two chapters will detail past work on adaptive architecture off-earth that could be complemented through neuroarchitecture in the future and adaptive architecture that already applied biomarkers or automation/machine learning.

3.2.1. Adaptive Architecture Off-Earth

A few decades ago, the increasing interest in the creation of spaces that respond to changing environmental conditions, user behaviours, and functional demands led to the research field of adaptive architecture. Adaptive architecture is not a precisely defined field with varying and overlapping definitions like smart architecture, responsive architecture or cyberphysical architecture (Liu Cheng & Bier, 2016). These terms have in common that they each refer to a 'multi-disciplinary field concerned with buildings that are designed to adapt to their environments, their inhabitants and objects as well as those buildings that are entirely driven by internal data' (Schnädelbach et al., 2016) with some definitions including the use of artificial intelligence. Another relevant term in this context is ambient intelligence, which describes an environment's ability to apply intelligence through sensor networks, pervasive computing and artificial intelligence (Cook et al., 2009), therefore describing another concept relating to adaptive architecture. In the following, the potential use of adaptive architecture in space stations is described.

On the ISS, the sleeping quarters provide the crew with the possibility for minor adaptions. For instance, they can choose between three different ventilation settings and make small adjustments to the light through fabric shades (Schlesinger et al., n.d.-a). Current examples of adaptive architecture in extraterrestrial settings aim for a higher level of adaptiveness. One example is the study by (Oungrinis et al., 2014) detailing an Intelligent Spacecraft Module (ISM) that represents a spacecraft interior by addressing the physiological and psychological needs of astronauts during long-duration missions through adaptiveness. The ISM utilizes ambient intelligence to adapt environments to human activities and emotional states. The researchers divided the spacecraft into modular spaces with transformable features allowing the spaces to dynamically adapt based on activity and efficient space use. The concept includes an Activity Evaluation System (AES) that uses sensors and machine learning to monitor physiological and psychological indicators such as perspiration, movement, and facial expressions; a Dynamic Building Program (DBP), an application that examines the relation between the optimum and existing conditions to visualize the deviations; and a Responsive System (RS) that adjusts environmental factors like lighting, sound, and tactile stimuli. These systems operate across three spatial zones—personal, peri-personal, and navigational—to create tailored comfort and mitigate stressors associated with confinement. The authors concluded that while the application of their proposed system has relevant benefits in theory, the parameters of the application must be tested within a high-fidelity analogue.

Another example includes a study by (Pischulti et al., 2024) that examines the integration of commercial-off-the-shelf (COTS) smart technologies to enhance habitability, autonomy, and crew performance in deep-space exploration. Recognizing the self-sufficiency required for missions e.g. to Mars, the researchers investigate the alignment of terrestrial smart home technologies with the functional needs of space stations. The study identified physiological and psychological challenges of long-duration missions and emphasizes the importance of advanced systems capable of reducing reliance on Earth-based support. The authors categorized over 90 smart devices, ranging from lighting and climate control systems to fitness and hygiene tools, and assessed their potential to address NASA's Moon-to-Mars habitat objectives. While most COTS devices lack full autonomy, their integration into smart systems offers significant benefits, such as personalized environmental settings, health monitoring, and automation of routine tasks, enhancing overall habitability. By analysing the functional overlap between smart devices commonly used on Earth and astronauts' needs, the study identified gaps where innovation is needed, particularly in medical care and maintenance.

3.2.2. Biomarker Use in Machine Learning for Adaptive Architecture

The investigation of an adaptive system for a space station that uses biomarkers as inputs and outputs environmental conditions that change the biomarkers' state is challenged by many factors as mentioned in Chapter 1.5. Machine learning (ML) can not only be applied for the actual implementation of the adaptive system but also for the data analysis and interpolation. ML is a subcategory of artificial intelligence, that is concerned with a computer observing a given dataset to generate a model based on the data to solve a certain problem. (Baduge et al., 2022). In combination with neuroarchitecture, the needed data can result from biosensors like EEG signals, as explained in Chapter 3.1.1. As mentioned in Chapter 2.2, the focus in IEQ research shifts from dose-related indication to physiological response. Therefore, past research focusing on biomarkers as indicators for IEQ and the use of machine learning to improve IEQ including wearable technology will be discussed in the following.

Adaptive acoustical quality: Adaptive acoustic comfort is described as a model that connects indoor acoustic conditions to outdoor ones, influenced by other environmental, contextual, and personal factors. However, due to the lack of research about global indoor/outdoor acoustic exposure coupled with various contextual information, it is not comparable to the ASHRAE thermal comfort database (Torresin et al., 2024). The work of (Harvie-Clark et al., n.d.) looks at the interdependence of ventilation and heating systems (which naturally produces sound that is often considered as a disturbance) and acoustic comfort, which could potentially be synergized in a smart, adaptive system. Other work uses soundscape augmentation (an emerging approach for noise mitigation by introducing additional sounds so-called 'maskers' to increase acoustic comfort) like the IoT system for an adaptive in-situ soundscape augmentation developed by (Wong et al., 2023). In this system the soundscape, as explained in Chapter 2.2.1, is augmented through a deep learning model creating an autonomous reaction to changes in the acoustic environment. Thereby, the maskers are not defined post-hoc in a time-consuming and sometimes arbitrary process but instead react in real-time to the current acoustic situation. A recent study by (Bagheri et al., 2024) looked into acoustic and visual comfort and their impact on persons with and without ADHD through EEG, eye tracking, health monitoring bracelets and self-reports of participants. The study revealed that observed activation of a specific brain activity – a defence system - in uncomfortable environmental conditions only occurred in the participants without ADHD and was lacking, slow, or weak in participants with ADHD. The need for adaptiveness that considers individual sensory experiences is further underlined by this difference in neuro-responses.

Adaptive air and thermal quality: As countermeasure for harmful indoor air, many adaptive concepts exist to prevent negative health impacts. Examples include AI-enabled prevention systems that use real-time forecast to predict the level of carbon dioxide by determining the likelihood based on past data and external indicators for different CO_2 patterns, like the example by (Alavi et al., 2022) shows. Other work used ambient assisted systems consisting of sensors, mobile devices, wireless networks and different software for personal healthcare and tele-health systems that track blood pressure, glucose, oxygen, temperature, location, etc. (Marques et al., 2019) presented a concept for CO2 real-time monitoring based on IoT architecture that in the future can be accessed by doctors in order to support medical diagnostics. The work by (J. Kim et al., 2020) explored the application of machine learning based on EEG signals for automated classification of indoor air quality by analysing the characteristics of building occupants' adaptive behaviours for future behaviour prediction. Although this study included only a very specific demographic group and therefore doesn't provide data relevant for all building occupants, it showed that for the chosen group of subjects, brainwave indices depend heavily on IEQ conditions. The study suggests that an IEQ condition control is possible through EEG signal analysis and that it could improve task performance and reduce drowsiness.

Solutions for adaptive thermal control are well studied and utilize a range of different machine learning techniques like fuzzy-based control, adaptive neuro-fuzzy inference system-based control, artificial neural network-based control (Moon et al., 2011), and K-nearest-neighbour algorithms. The goal of these systems is a thermal comfort model that can adjust the thermal experience for one specific person according to the changing environmental conditions, often incorporating considerations about reduced energy usage (Xiong & Yao, 2021). The idea of local heating is becoming more prominent due to the hope that it can balance humans' wish for individual comfort and the needed reduction of energy consumption. The study of (Liu et al., 2022) showed that personalized local heating can reduce the heart and proofed a user acceptance of 81%. Other examples investigating IEQ and their influence on biomarkers like the research of (Pan et al., 2023) showed how thermal comfort (temperature, relative humidity, air velocity) influences the individual's experience through an EEG-and questionnaire-based study. The results suggest that at 22 ◦C and 25 ◦C, theta, beta (1 and 2), and gamma waves were highly similar, and at 0.5 and 1 m/s for velocity highly similar results were reported for all EEG waves, indicating similar brain reactions to the same settings.

Adaptive visual quality: Many examples from the industry and scientific community of systems for adaptive lighting exist and the topic has been of interest for a mentionable timespan. For example, as part of the European project, ALADIN, which is intended to support elderly in their daily lives through light. The developed concept uses a simulated annealing optimization algorithm and has shown to induce a state of relaxation in participants (Grigore et al., 2008). A more recent example by (Mostafavi et al., 2024) demonstrated an association of higher illumination with higher arousal levels, but the study also showed the high variance in user preferences regarding lighting changes and the influence of demographic factors on it. (Tong et al., 2023) investigated the relationship between illuminance and efficiency (through a task state) and comfort (through a rest state) using absolute power of EEG (a direct measure of the total brain activity within a band, without comparison to other bands or regions). Results indicate that the lighting levels influence comfort through neural activity in specific brain regions and that specific brightness levels (500 lux and 750 lux) optimize task performance including accuracy and reaction time without significantly altering EEG power.

Wearable sensor technology: Through the use of wearable and portable sensors in cooperation with architectural infrastructure, the advantages regarding personalized adaption and health tracking of a study situation are brought to occupants' daily lives, though this poses risks e.g. regarding data protection. One example for this is the illumination system by (Cheng et al., 2017) that uses Support Vector Machine (SVM) and k-Nearest Neighbour (k-NN) classification models for an ad-hoc response to occupants needs intending to improve their wellbeing via continuous regulation of intensity and colour of illumination. The integrated Human Activity Recognition system aims to detect fatigue of the user by clustering and analysing the data coming from the body sensors (in this case a fitness watch). A challenge remained the differentiation by the system between a fatigued gait and a slow yet healthy one. The authors suggest extending the system through facial-recognition and visual detection methods for an increasement of accuracy. Other work specifically investigated the effectiveness of unobtrusive wearable sensors for stress monitoring using cortisol as biomarker trained with four different machine learning algorithms. Electrodermal activity and blood volume pulse signals were recorded using a fingertip sensor during the so-called Trier Social Stress Test, which is an established experimental protocol to cause stress in participants. In this study, the logistic regression performed the best and achieved a very good AUC score of 0.81 (Nath et al., 2022). (Kadian et al., 2023) summarized recent developments on non-invasive portable and wearable biosensors for health monitoring in conjunction with machine learning. They conclude a high effectiveness of ML-enabled wearable devices to predict probability of injury or cardiac arrhythmia and their feasibility for remote healthcare. In addition to challenges regarding data privacy, consistency, stability, accuracy, and adaptive learning capacity, it is also mentioned that the use of a single biomarker is not sufficient for the understanding of some diseases, therefore the integration of multiple sensors and novel machine learning algorithms that can extract multidimensional features was proposed. (Ojha et al., 2019) proposed a research framework to analyse physiological changes as reaction to the urban environment. The research includes a range of environmental factors like illuminance, field of view or sound level (measured through wearable sensors) to provide a comprehensive picture of the relationship between built environment and human health. The results of the corresponding machine learning models that were used to process the study data showed the dominance of certain features (temperature, humidity, illuminance) over others (sound level and dust concentration) (Ojha et al., 2019). The study – that was conducted for a specific route in Zurich is an example of example of how environmental sensing data can be leveraged to identify key influencing factors in architecture. Further research could generalize these findings across diverse architectural environments and for a diverse range of users.

4. Neuroarchitectural Studies on Visual Quality as Countermeasure to Stress

While the previous chapters explained the context and state of the art of relevant research areas, this section will first summarize the research gaps and challenges and detail how these can be addressed by introducing the research framework as used for this thesis.

4.1. Research Gap and Challenges

The unavoidable stressors occurring in extreme environments (as well as in everyday situations) can have a severe impact on the individual's health and can potentially lead to dysregulation of physiological systems (Chapter 3.1). A relevant example for the interplay between psychological and physiological mechanisms and the consequences is allostatic overload, which demonstrably can have very severe impacts on human health. A relevant example is human spaceflight. A strong body of research about habitability and its relevance has been established, though this research partly depends on subjective data collection methods that can deliver unreliable or contradicting results. Current health countermeasure systems consist of exercise and medical equipment utilized to counteract effects on the human body for instance resulting from microgravity but still leave a range of health-related problems unsolved (Chapter 2.3.3). Adaptive architecture that is reacting to individual needs has the potential to react to acute, individual changes resulting from past or real-time data. While preliminary research about the inclusion of smart and adaptive systems in space exists, they need extensive development and testing time to ensure reliability and to prove their feasibility in conjunction with the mentioned limitations of a space station (Chapter 3.2.1). These challenges at the intersection of architecture and healthcare can potentially be addressed by the field of neuroarchitecture through the use of biomarkers as indication for adaption of environment. Architecture has been explored as cause to stress responses and health downsides and how this effect can be avoided as tool to foster post-stress relaxation or support to physical recovery after an injury/sickness (Chapter 3.1). However, architecture as an individual countermeasure to stressor exposure in extreme environments to prevent repeated or continuous physiological (stress) responses manifesting in long-term health consequences is not well investigated. It is also unknown how this knowledge translates to a stressor-intense environment including limited resources, spatial limitations, individual needs and abilities and their consideration in the group. Further, methodological limitations in the field of neuroarchitecture must be considered including the distinguishment of biomarkers suggesting current stress and the concentration of these biomarkers over a long duration, inter-individuality of baseline-biomarkers, cause-effect ambiguity (confounding variables effecting results), and representative stressor simulation. As highlighted by previous research (Aguilar et al., 2024), a consistent research framework can help increase the reproducibility of findings in studies on the interaction between architecture and occupants, which is even more pressing if the research entails the integration of dynamic biomarkers.

4.2. Research Framework

This chapter introduces the context for the research framework on cross-sectional lab experiments (implemented on a pilot study in Chapter 5).

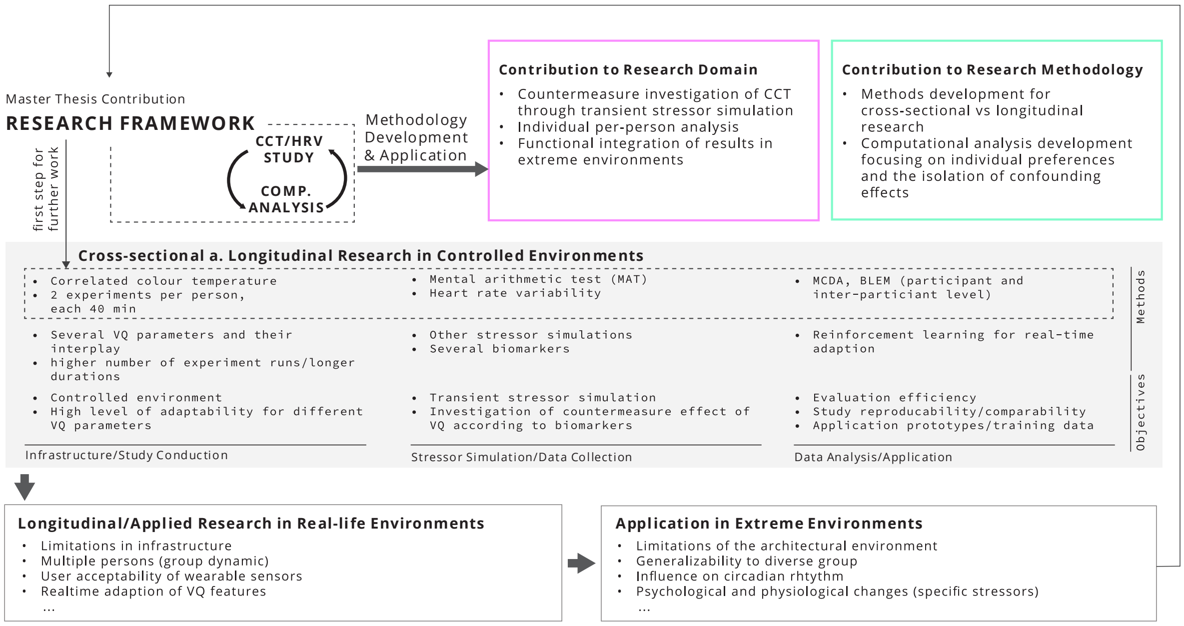

Figure 6 *Visualization of the Research Context and the Thesis Research located in it showing Longitudinal/Applied Research and the future Application as Motivation for the Framework and Cross-sectional Research developed as part of this Thesis*

Architecture as individual countermeasure to stressor exposure in extreme environments to prevent continuous physiological (stress) response manifesting in long-term health consequences is not well investigated. The proposed research framework focuses on the investigation and application of visual quality as countermeasure to stressors in alignment with functional requirements of architecture in extreme environments by investigating dynamic biomarkers and their inter-individuality in combination with stress in cross-sectional design studies and by using computational analysis to manage cause-effect ambiguity resulting from the dynamic nature of biomarkers. Different approaches, stages and timelines were considered including lab experiments, field experiments and the potential application of research results in the future. Challenges occurring in the investigation of visual quality (VQ) features as countermeasures to stressors in cross-sectional lab experiments are addressed in this framework. By running the experiment twice per participant (Chapter 5.3) - focusing on inter-individuality of HRV and stress response -, using a psychological stress test as stressor simulation (Chapter 5.2) – providing the setting for the investigation of a countermeasure -, and by applying computational analysis (Chapter 6.1) – focused on interaction effects between confounding variables and independent variables and the consequences for individual results – the framework uses a bottom-up approach to navigate this field. As seen in **Figure 6**, the thesis study is a small fragment of the wider research context focusing on one VQ feature (color correlated temperature) and one biomarker (heart rate variability) during short-term stress (a roadmap of potential future research is provided in Chapter 7.2.2).

5. Study Design - CCT and HRV

The framework is applied to a pilot study focusing on CCT and HRV to demonstrate the methods defined as part of this thesis (**Figure 7**) and explore its hypothesis. The study took place in the Lighting Lab of the Human-Technology Interaction group at Eindhoven University of Technology which also provided the ECG. The study was approved by TU Delft's Human Research Ethics Committee.

To ensure focused research within the scope of the thesis, the study was streamlined to examine colour correlated temperature (CCT) (as a representative VQ parameter) and heart rate variability (HRV) (as a relevant biomarker). Light, especially CCT - the colour appearance of a light source (Durmus, 2022) - plays a versatile role in architecture by not only rendering spaces visible but also influencing perception, mood, and spatial hierarchy. As explained in Chapter 2.2.3., it is an integral part of indoor environmental quality (IEQ), specifically of visual quality, and not only serves an aesthetic function and but is also a physiological necessity, impacting circadian regulation and overall occupant well-being. HRV is a relevant biomarker for allostatic load and as indicator for stress reaction and stress adaption as mentioned in Chapter 3.1.1. Further, HRV has been investigated during microgravitational spaceflights as indicator for adaption to the new environment (see Chapter 2.2.1).

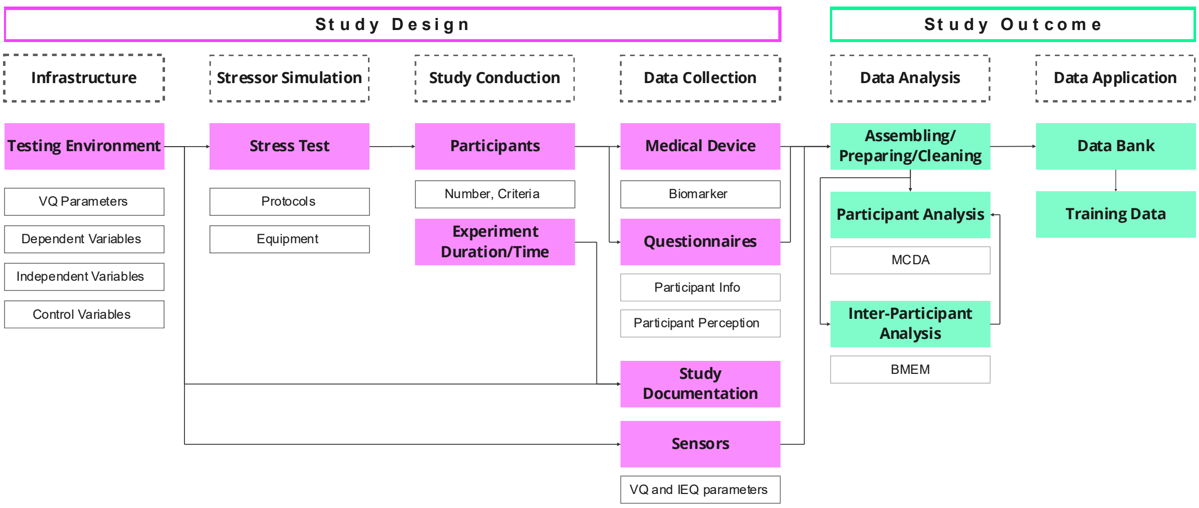

Figure 7 *Research Framework applied on the Pilot Study on CCT and HRV: showing the main pillars of the study design and study outcome (each pillar including its different components is further detailed in the following chapters)*

The influence of blue light (measured in wavelength) on HRV has been investigated in several studies with blue light showing an increase in HRV in individuals medically classified as healthy (Litscher et al., 2013; Petrowski et al., 2023; Schäfer & Kratky, 2006) and in individuals showing symptoms of anxiety and depression (C.-J. Choi et al., 2011) during different circadian phases. Further, small studies like the one by (Minguillon et al., 2017) indicate that blue light can positively contribute to post-stress relaxation. (Luo et al., 2022) specifically investigated blue-enriched light on the HRV of 20 participants for five hours in the afternoon, with one group being in bright, blue-enriched light (1200 lx, 6500 K) and the other to dim blue-enriched light (200 lx, 6500 K). The results showed clearly higher HRV in the dim light, though no relevant differences were documented in the frequency - domain indicators of HRV suggesting that the autonomic nervous system was more significant in the bright light (Luo et al., 2022).

The list of limitations and considerations regarding general aspects, the chosen biomarker, the chosen VQ features, and stressor simulation are found in Chapter 1.5. The study aimed to explore and demonstrate the proposed methodology, it did not aim to provide reliable, generalizable results on the relationship of CCT and HRV under stress.

5.1. Infrastructure

The pilot study as part of this thesis investigated cold CCT (also referred to as blue) and warm (also referred to as yellow) CCT as countermeasure to physiological stress reflected in HRV. Therefore, the effect of warm CCT and cold CCT were tested in combination with high illuminance (1000 lux measured horizontally on table height). In extreme environments - characterized by high stress exposure - elevated illuminance levels are often unavoidable for instance during emergency procedures, high-precision work like station repairs, or surgical operations in hospital settings. The illuminance of 1000 lux was chosen as it is the standard for high-precision work (ISO 8995 / CIE S 008 and EN 12464-1) used in many applications where visual acuity is required including -precision activities on the ISS (*Ochmo-Tb-026-Lighting-Design.Pdf*, n.d.).

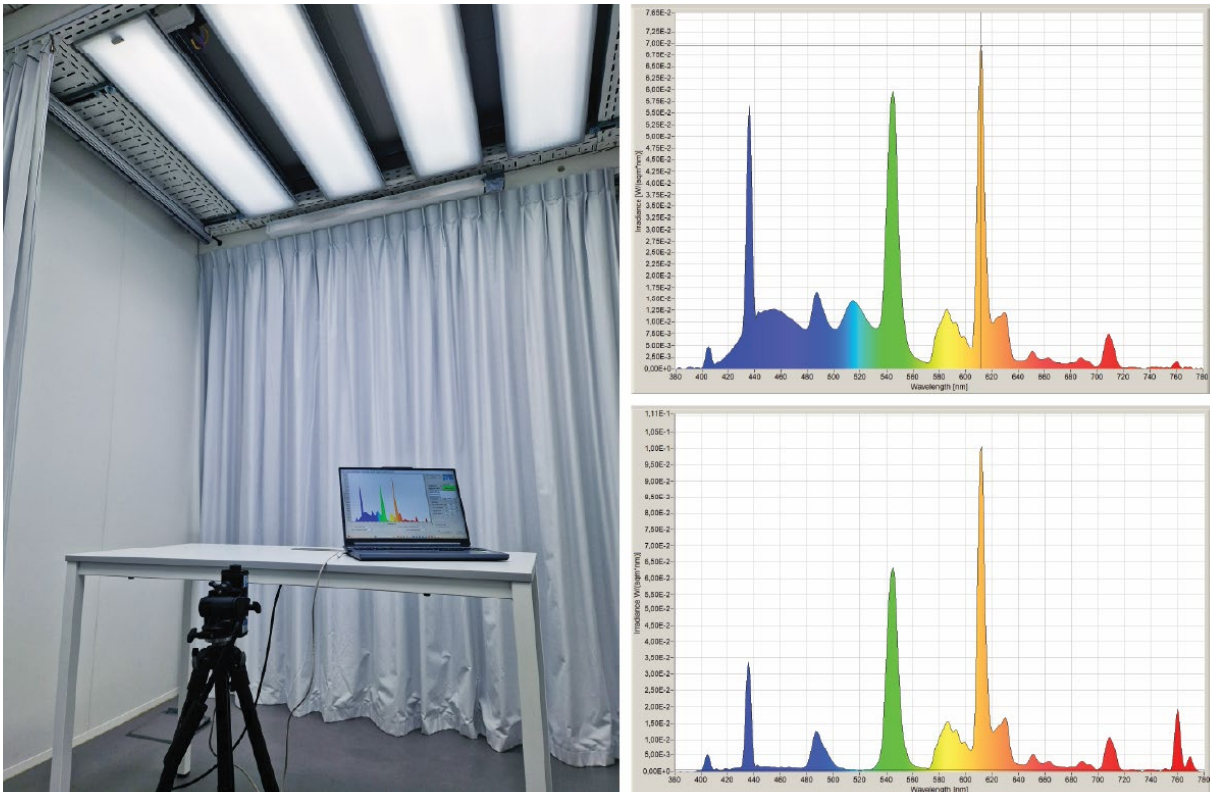

Figure 8 *Light Calibration in the Lab (upper right: blue CCT, lower right: yellow CCT)*

The ceiling of the HTI Light Lab at TU Eindhoven is equipped with sixteen lighting fixtures (Philips Savio TPS760 C), consisting of fluorescent tubes that allow CCT ranges between 2700 K and 6000 K. The lighting situation (illuminance and CCT) was controlled through DMX (Digital Multiplexing) protocols developed by researchers at TU Eindhoven. The two lighting conditions were calibrated using a JETI Specbos 1201 spectroradiometer, with measurements taken at two positions: vertically at the participants' eye level (130 cm above the floor) in the position of their chair, and horizontally at table height (approximately 75 cm above the floor). This is the more relevant measurement as it aligns with the standard reference for illuminance measurements. The calibration process and spectrum plot for the two settings can be seen in **Figure 8**.

While CCT measurements remained consistent across both settings (apart from minor fluctuations), illuminance was approximately 700 lux at eye level and 1000 lux at table height. It is important to consider that illuminance at the individual level may vary depending on the person's position, as measured illuminance varies depending on the exact position of the spectroradiometer and is further influenced by present materials, including surface reflectivity and colour, and room geometry (Cai et al., 2018; Katunský et al., 2022). Furthermore, as the laboratory is equipped with fluorescent lighting rather than LEDs, minor fluctuations can occur over the course of its use. This was controlled through repeated measurements with the spectroradiometer to enable consistent conditions for all experiments. Nevertheless, small fluctuations could not be ruled out completely. For each experiment run, the room temperature was kept at a constant 22 degree Celsius (± 0.5) monitored by two sensors on opposite walls of the room.

5.2. Stressor Simulation

While past studies focused on architectural simulation and the recreation of a space station mock-up to test different light situations, their user acceptance and physiological reactions (Jiang et al., 2020), this framework focuses on short-term stressor simulation. By combining the physiological (not architectural) simulation of the situation with the short time-term investigation of design research, this framework investigates psychological stress tests and their potential to simulate short-term HRV changes. This is possible because of the focus on countermeasure effectiveness. A cross-sectional study design might be sufficient for investigating a countermeasure because if the effect can be mitigated at a single point in time, it indicates that longer-term consequences spanning over a longer period can be prevented by timely intervention.

Nevertheless, for HRV specifically, it is important to mention that different measurement intervals are usually used to capture the inherently dynamic nature of heart rate variability. HRV is influenced by a wide range of physiological and environmental factors such as stress, sleep, physical activity, and even breathing patterns which can cause fluctuations over short and long timescales. As a result, short-term recordings (e.g., 5-minute intervals) are often used for assessing immediate autonomic responses, while long-term recordings (e.g., 24-hour monitoring) provide a broader view of overall autonomic function (Shaffer et al., 2020). This variability underscores the importance of context and consistency in HRV measurement and interpretation.

I. Established Stressor Simulations

For research on physiological adaption in human spaceflight a range of advanced, resource-intense simulation methods exist like Head-Down Tilt Bed Rest (entailing subjects lying in a bed tilted downward at a specific angle (usually 6 degree) to simulate the fluid shifts and cardiovascular deconditioning experienced in microgravity), and Lower Body Positive Pressure (which positive pressure to the lower body while subjects are upright, reducing body weight to simulate lunar or Martian gravity) to Dry Immersion (DI) (DI immerses subjects in thermoneutral water while protected by a waterproof layer, minimizing proprioceptive perception and simulating microgravity) (Fernandez-Gonzalo et al., 2024; Navasiolava et al., 2011). Each method offers specific insights into the body's adaptation to microgravity. The choice of simulation depends on the specific physiological aspects under investigation, such as cardiovascular, musculoskeletal, or neurocognitive responses. More accessible, low-tech methods to induce physiological stress response are psychological stress tests such like the Trier Social Stress Test, Mental Arithmetic Test and Maastricht Stress Test. These tests have shown to activate the sympathetic nervous system and hypothalamic-pituitary-adrenal axis, causing changes in biomarkers like cortisol and heart rate variability (Immanuel et al., 2023a; Spellenberg et al., 2020).

The direct comparison of stress test-induced changes in HRV and changes in HRV resulting from long-term stressor exposure in extreme environments like microgravity is clearly not possible due to the great discrepancy between measurement time (30 min vs. 24 h) and stressor-exposure time (10 min vs. a few months) and magnitude, and the resulting difference between chronic autonomic changes and transient effects. Nevertheless, with the definition of a countermeasure in this context being the reduction of acute stress response, short time improvements in HRV working against the effects of the stressor exposure can give suggestions of how light settings could positively contribute to healthy HRV in extreme environments. The results from this research could serve to design an individual light situation for each crew member (or depending on profiles). For this to be a reliable, feasible tool in the future for the development of individual health countermeasure systems using architecture, several data points contributing to the result must be considered as reflected in the research questions (Chapter 1.3).

Table 3 provides an overview of common stress tests and common findings on the effects on HRV which was used for the choice of a feasible stress test that triggers the relevant HRV features. While the high level of individuality in stress response is partial reason for this research, past results from studies applying different stress tests can still serve as orientation for the kind of HRV changes they trigger on average.

Test	Process Explanation	Effect on HRV
Trier Social Stress Test (TSST)	5-minute interview-style presentation and 5-minute surprise mental arithmetic test in front of an interview panel that doesn't provide feedback (A. P. Allen et al., 2016)	Decreased vagal tone, increased sympathetic activity (Specifically: HR increase, lower RMSSD, decreased SDNN) (Seipäjärvi et al., 2022; Spellenberg et al., 2020)
Maastricht Acute Stress Test (MAST)	Combination of the most stressful features from TSST and Cold Pressor Test (CPT), Participants immerse one hand in ice-cold water (0–3°C) for up to 90 seconds followed by a mental arithmetic task under time pressure (overall 10 min) (Smeets et al., 2012)	Lower parasympathetic tone, higher SNS activation (Specifically: decreased RMSSD) (Tervonen et al., 2023)
Mannheim Multicomponent Stress Test (MMST)	Several modalities (cognitive, emotional, acoustic and motivational stressors) are combined (overall around 12 min) (Reinhardt et al., 2012)	Decreased vagal tone (Specifically: decreased RMSSD, decreased SDSD, decreased pNN50, decreased NN50) (Ernst et al., 2023)
Cold Pressor Test (CPT)	The subject's hand is placed in ice water (0–4°C) (for e.g. 120 s) (Jarczewski et al., n.d.)	Sympathetic activity increased, baroreflex activity is still effective (Specifically: Transient increase in HR, increase in LF, HF power remained the same compared to baseline (Xie et al., 2017)

Mental Arithmetic Test (MAT)	Participants must mentally subtract a number from a four-digit number and verbally report results to the researcher (Yadav & Sahu, 2024)	Sympathetic activation, reduced vagal tone and parasympathetic withdrawal, decrease in baroreflex sensitivity (specifically: decrease in HF power, increase in LF power, decrease in SDNN) (Dimitriev et al., 2018; Xie et al., 2017)

Table 3 *Overview of the Effect of common Stress Tests on HRV*

II. Chosen Stressor Simulation as Part of this Study

After evaluating the HRV features that are influenced by the different stress tests it was decided to use the MAT, which has proven to cause sympathetic activation and parasympathetic reduction (Dimitriev et al., 2018; Xie et al., 2017) . Further, it is a feasible, easy-to-implement test that doesn't need a staff team or specialized equipment. Details about the execution of the test can be found in Chapter 5.3. Even though the MAT is an established psychological test to induce short-term stress in participants, the nature of a psychological test is very dynamic leading to individual results in different people. Especially, in the context of this study, that applied the MAT twice per person (using different arithmetic questions) prior to the experiment it was unknown if the second time participants will be less stressed because they already know the procedure. Past research found different results on the familiarity with the MAT during the second time of use second time (Barthel et al., 2025; Boesch et al., 2014; Jönsson et al., 2010; Pulopulos et al., 2018). While increasing the level of difficulty in the second MAT could potentially provide a way to trigger higher stress reaction, it also introduces more variance and effect-uncertainty that cannot be accounted for. The similarity between the two experiment was maximized by using an instruction protocol and standardized responses if participants made mistakes. Due to the collecting of the baseline-HRV for both experiment runs (in both CCT settings), the potential influence of the familiarity with the MAT the second time is less relevant, since each stress reaction is analysed relative to the baseline of that experiment run.

5.3. Study Conduction

Participants (n = 8) included international students (3 women, 5 men) from TU Eindhoven in an age range from 20 to 28 years old (23.6 ± 2.6) with proficient English skills. The majority of participants (7) had a form of vision impairment (including myopia, hyperopia or astigmatism) which is corrected through glasses. Following standard procedures for studies with this type of physiological data, they were advised to refrain from drinking alcohol for at least 24 h, from eating food for 1.5 h, and excessive physical activity for 12 h prior to the experiment. Before the study began, participants were briefed, gave their written informed consent and filled out the pre-study questionnaire on demographic data, physical data, usual stress perception and their chronotype (Chapter 5.4).

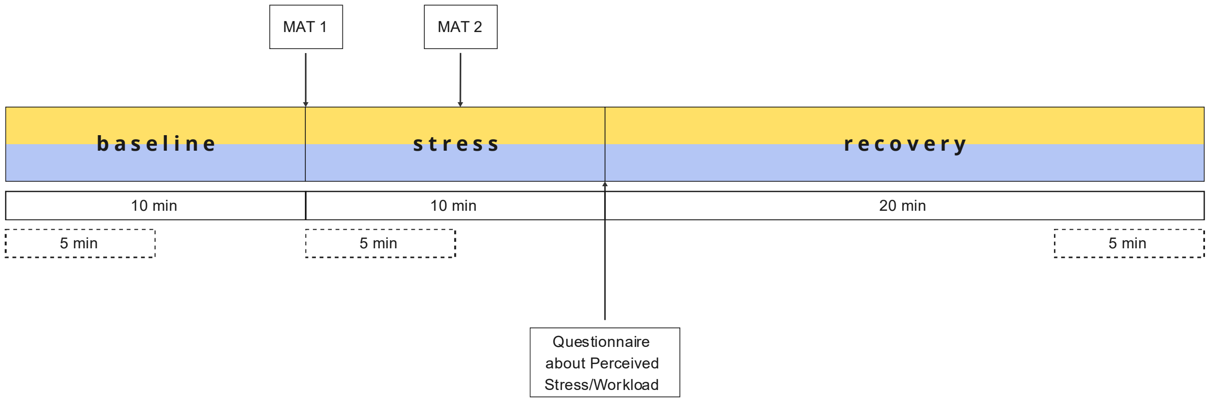

Figure 9 *Timeline for each experiment run showing the three Phases (baseline, stress and recovery), their Duration and Data Collection*

Each participant took part in the two settings including yellow light (2700 K, 1000 lux) and blue light (6000 K, 1000 lux). This approach controls for individual differences to determine whether any observed effects are truly due to the light temperature rather than inter-individual variations between participants. For better comparability, both study runs for each participant took place at the same time. The sequence of the experiments ensured that blue and yellow light are equally applied in the morning and afternoon timeslots and that each person has one day of break between the two experiments. The order in which participants were exposed to each CCT was switched (leading to 4 subjects first being in blue CCT and vice versa) and aligned with the 4 times of day during which experiments took place to ensure both CCTs were equally often used in the first experiment during each time of day. Each experiment run took 40 minutes per person per session. Each run entailed a pre-stress phase (to record the HRV baseline) of 10 minutes, a stress-phase of 10 minutes (using a mental arithmetic test), and a post-stress phase of 20 minutes. In the case of the pilot study, two 5-minute MAT sessions were completed by each participant per experiment. For this, the researcher stood in front of the seated participant giving them a 4-digit number from which they had to subtract a 2-digit number. The participants had to do the calculations mentally without getting anything to write or other supportive tools. They were told to do as many calculations as quickly as possible. If the answer was correct, they did not receive any feedback, if the answer was wrong, they were told that the reply is incorrect, and they should start from the beginning (the original 4-digit number). The researcher recorded the number of overall calculations the participant finished as well as the number of errors. Directly after the stress phase, participants answer the questionnaire about perceived stress and workload. An overview of the process can be found in **Figure 9**.

5.4. Data Collection

Different biomarkers were considered for the study execution. Their relevance for allostatic load is explained in Chapter 3.1.1. While cortisol is the most frequently used primary mediator for allostatic load and fifth most used biomarker in past studies on this topic (Beese et al., 2022) it was decided against its inclusion in this research due to limitation of reliable, non-invasive, available measurement techniques. Heart rate variability (HRV) while it is not that commonly used in research related to allostatic load (Beese et al., 2022) has shown to be one of the five biomarkers that are highly associated with allostatic load (Mauss & Jarczok, 2021) and specific resulting health outcomes (McCrory et al., 2023). For the investigation of HRV, different aspects must be considered in cross-sectional studies due to the challenges arising from its high sensitivity to transient factors such as time of day (H.-S. Kim et al., 2014), recent physical activity, emotional state, and environmental conditions, which are difficult to control or standardize in a single-time-point measurement (Chen et al., 2020; Gullett et al., 2023; Shaffer et al., 2020) (addressed in Chapter 6.1.3). For the measuring of HRV an electrocardiogram (ECG) is commonly used. To provide context for the HRV data collected during the stressor exposure, the baseline HRV is taken prior to the study. This gives insight into the individual's regular HRV while the post-stress measurements provide data about the duration for the HRV to return to baseline. An overview of the most common HRV features and their interpretation can be found in **Table 4**.

The HRV data can be interpreted in combination with the data on regular stress, chronotype, and perceived stress/workload collected through the established tests. For the investigation of the participants' usual stress level (referring to the last month) the Perceived Stress Scale (PSS-10) (Pedersen et al., 2024) was used and for the investigation of the chronotype (to receive an approximate idea of the person's awake/sleep rhythm), the Morningness Eveningness Questionnaire (MEQ) (Shahid et al., 2011) was used. The questionnaire about perceived stress and workload entailed question of different psychological tests like the State-Trait Anxiety Inventory (STAI) (Shahid et al., 2011), NASA Task Load Index (TLX) (Hart & Field, n.d.) and Subjective Units of Distress Scale (SUDS) (Shahid et al., 2011). For the HRV recording the ECG Bionomadix from Biopac Systems was used. With this ECG, three electrodes were placed on the participant's right clavicle and right and left rip which were connected to the data logger.

Time-Domain Measures	
SDNN Standard Deviation of NN intervals (normal-to-normal interval) and **SDSD** Standard Deviation of Successive - Differences (short- term beat-to-beat variability)	• Measures overall HRV, reflecting both sympathetic and parasympathetic activity • Higher values indicate better autonomic balance.
RMSSD Root Mean Square of Successive - Differences between RR Intervals (inter-beat intervals between all successive heartbeat)	• Reflects parasympathetic (vagal) activity • Higher values suggest stronger vagal tone (better recovery, relaxation)
pNN50 - % of adjacent RR intervals differing by more than 50 ms	• Another indicator of parasympathetic activity. • Higher values suggest better vagal control
Frequency-Domain Measures (Spectral Analysis)	
HF - High Frequency, 0.15–0.4 Hz	• Linked to parasympathetic activity and respiratory-driven heart rate fluctuations • Higher HF power suggests better vagal (rest-and-digest) control
LF - Low Frequency, 0.04–0.15 Hz	• Reflects a mix of sympathetic and parasympathetic influence • Sometimes interpreted as a marker of sympathetic activation, but this is debated
LF/HF Ratio	• Used to estimate autonomic balance • A higher ratio suggests sympathetic dominance (stress response), while a lower ratio suggests parasympathetic dominance
Non-linear Measures	
SD1 and **SD2** - Poincaré plot standard deviation	• SD1 is related to parasympathetic activity, while SD2 reflects overall HRV
ApEn - Approximate Entropy and **SampEn** - Sample Entropy	• Measures of unpredictability of HRV
DFA α1 and **DFA α2**- Detrended Fluctuation Analysis	• Describe short-term and long-term fluctuations

Table 4 *Overview of Measurements for HRV derived from (Kleiger et al., 2005; Shaffer et al., 2020)*

A selection on HRV features (time-domain and frequency-domain) was made based on their suitability to be investigated in short-term measurements. For a detailed picture of physiological and perceived stress in relation to the study design, the data points as shown in **Table 5** were collected.

Data	**Datapoints**	**Data Collection Method**
Heart rate variability (HRV)	LF VLF HF SDSD R-MSSD pNN50	Electrocardiogram (ECG)
Cognitive performance (CP)	Errors and time at mental arithmetic test (MAT)	Post-study evaluation
Demographic and basic physical data	Age Gender/sex Height/weight Vision impairment (and correction if applicable) Chronotype (MEQ) Perceived stress levels of the last month (PSS-10)	Pre-study questionnaire
Perceived stress and workload (PSW)	Workload (NASA TLX) Stress (STAI, SUDS)	Mid-study questionnaire
Environmental data	Light illuminance Colour correlated temperature Room temperature	Spectroradiometer, lab sensors
Task and duration	MAT, 2 x 5 min	Study documentation
Stressor Simulation and Duration	MAT	Study documentation

Table 5 *Collected Data and Data Collection Methods as part of the Pilot Study*

6. Study Outcomes - CCT and HRV

This chapter applies the second part of the research framework to the pilot study on CCT and HRV. Focusing not just on group patterns but on individual participants - by comparing the two experimental settings within each person rather than relying solely on inter-participant analysis - allows for more meaningful conclusions. This approach reduces the number of confounding variables for some of the results that typically arise in between-subject comparisons. Further, it aligns with the research context of designing for a very specific user group. In the context of human spaceflight, light settings could be tailored to the individual and not rely on general findings, the same way exercise is tailored to the individual where also no one-size-fits-all solution is applicable. This approach would still need longitudinal data collection per person to deliver reliable results in the future.

6.1. Data Analysis

The data analysis included data preparation and the investigation of computational methods to find meaningful results. This was demonstrated on the dataset of this study, but the application of the developed computational models would be more meaningful with larger datasets and especially with longitudinal data collected through several points in time per participant. The process from data collection to results enabled by the computational analysis is shown in **Figure 10**. All scripts developed as part of this analysis were developed in Python using excel data files with standardized variable names as inputs. This allows for a semi-automated analysis process, easy change of variables that each model should analyse and easy modification when needed.

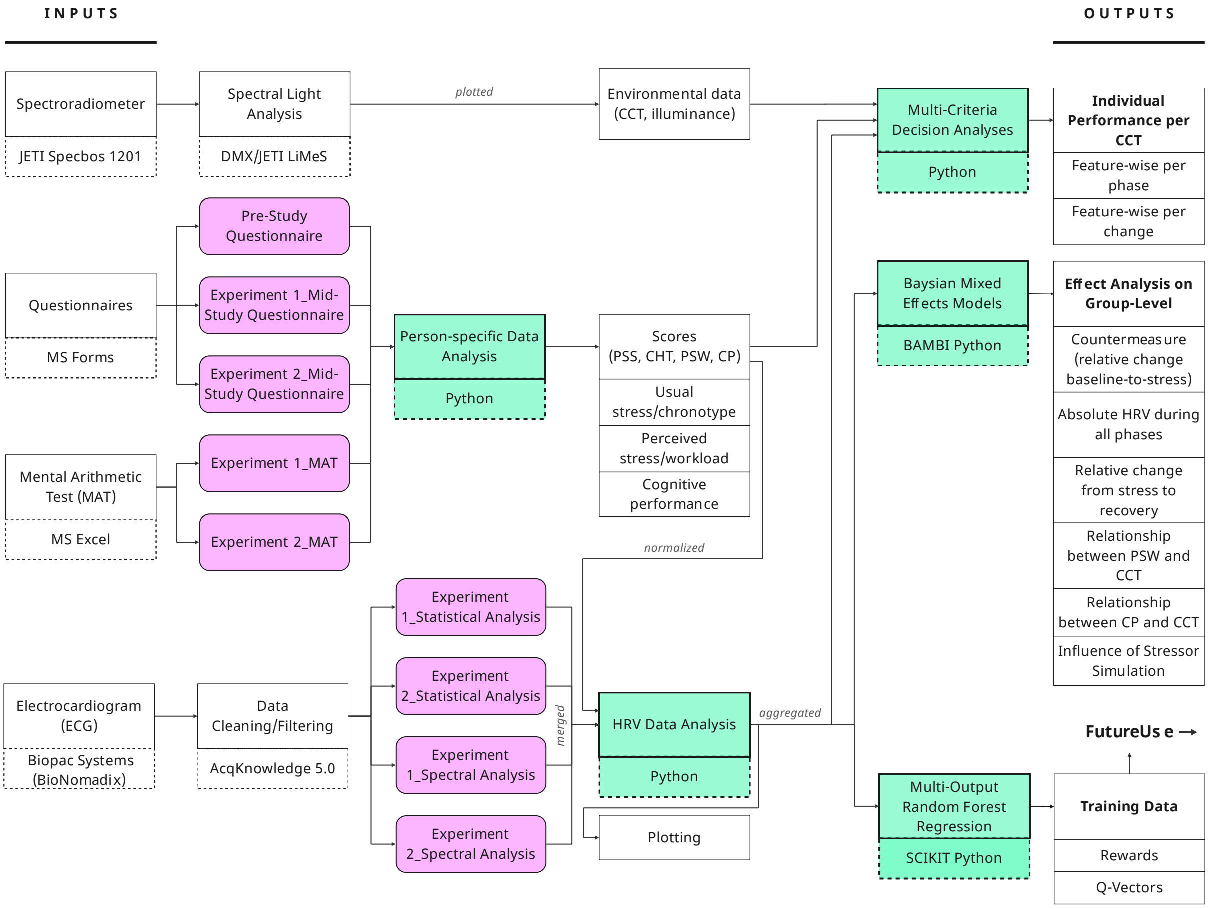

__Figure 10__ Data Pipeline from Data Collection to Final Results using specialized Software for Light Analysis and ECG Data Processing and different types of Computational Analysis developed in Python

6.1.1. Data Preparation and Overview

Cleaning and filtering ECG data is needed to ensure an accurate analysis and interpretation of the data. For this step, AcqKnowledge 5.0 was used which is the corresponding software of the used ECG device. A bandpass filter (between 0.5 and 35 Hz) was applied to remove high frequency noise. Through a tachogram, artifacts resulting from electrode movement/poor contact were removed. Overall, per participant 9 data files were collected (Pre-Study Questionnaire, Experiment 1_Statistical Analysis for the three focus areas, Experiment 1_Spectral Analysis for the three focus areas, Experiment 2_Statistical Analysis for the three focus areas, Experiment 2_Spectral Analysis for the three focus areas, Experiment 1_Mid-Study Questionnaire, Experiment 2_Mid-Study Questionnaire, Experiment 1_MAT Results, Experiment 2_MAT Results) and were processed through the analysis tools.

For the computational analysis, the 40 minutes of recording per experiment were divided into eight 5-minute sequences. 5 minutes are the standard HRV short-term measurement and were chosen due to better comparability with other research and allowed for short breaks between sequences to minimize overlaps between them. For the following, 5-minute datasets were used for each phase: the first 5 minutes of the baseline phase, first 5 minutes of the stress phase and last 5 minutes of the recovery phase (shown in **Figure 9**).

The questionnaires about participant's chronotype (CHT), usual stress (PSS), and perceived stress and workload during the MAT (PSW) were automatically evaluated and normalized (0-1) using a script created in Python for this research. For the perceived stress and workload (PSW), the item count of the questions from each questionnaire (STAI, NASA TLX) was used to define the weights for the overall-score. Coincidentally, the MEQ revealed that all participants are the chronotype "definitely evening", therefore the influence of different chronotypes on the results could not be investigated. For score for cognitive performance (CP) was defined by calculating the number of correct answers, attempted answers, and error, derive a normalized performance score using the number 80 as reference for the completion rate.

Due to the sensitive nature of the physiological data and the small number of participants, the full dataset (containing all datapoints in both CCTs and all three phases connected) is only presented in aggregated form in compliance with the ethical approval for this research.

I. Overview Yellow vs. Blue CCT

An overview of the HRV feature's mean value and standard deviation across participants is shown in **Table 6**. The comparison of the stress-HRV in both CCTs shows that on average RMSSD/SDSD, pNN50, High Frequency Power (HF), Low Frequency Power (LF) and Normalized High Frequency Power (HF/(LF+HF) were higher in yellow CCT. The ratio between High and Low Frequency Power (LF/HF) was on average lower during stress in yellow CCT. The same tendency is observed during the baseline phase and recovery phase with the only differences seen in the recovery phase for pNN50 (which is marginally higher in blue CCT) and High Frequency Power (HF) and Low Frequency Power (LF) showing higher values in blue CCT. It is relevant to mention that the standard deviations are high (especially for HF and LF/HF during recovery). The Perceived Stress and Workload (PSW) and Cognitive Performance (CP) are nearly identical in both CCTs with very similar standard deviations.

CCT	**2700 K (yellow CCT)**			**6000 K (blue CCT)**		
State	**baseline**	**stress**	**recovery**	**baseline**	**stress**	**recovery**
RMSSD mean [ms]	52.41	48.31	58.82	41.79	37.45	53.48
RMSSD sd [ms]	11.01	11.34	21.39	15.68	11.1	23.65
SDSD mean [ms]	52.41	48.31	58.82	41.78	37.45	53.48
SDSD sd [ms]	11.01	11.34	21.39	15.68	11.1	23.65
pNN50 mean [%]	29.88	24.63	29.87	16.48	14.35	30.87
pNN50 sd [%]	10.43	9.13	12.58	11.86	8.85	20.37
HF mean [-]	1139.9	864	1369.29	876.07	582.7	1496.44
HF sd [-]	615.57	475.31	1350.05	966.88	381.67	1835.15
LF mean [-]	1752.39	2400.12	2125.87	1490.34	2103.64	2170.53
LF std [-]	1425.92	1844.52	1419.69	1355.56	1571.15	1951.19
HF/(LF+HF) mean [-]	0.43	0.3	0.37	0.37	0.25	0.4
HF/(LF+HF) sd [-]	0.15	0.1	0.13	0.19	0.08	0.24
LF/HF mean [-]	1.76	2.66	2.05	2.45	3.68	2.93
LF/HF sd [-]	1.51	1.4	1.34	1.86	2.36	3.18
PSW mean [-]	-	0.55	-	-	0.54	-
PSW sd [-]	-	0.18	-	-	0.17	-
CP mean [-]	-	0.37	-	-	0.35	-
CP sd [-]	-	0.21	-	-	0.27	-

Table 6 *Mean and standard deviation of HRV features, Perceived Stress and Workload (PSW) and Cognitive Performance (CP) for all participants in both CCTs (2700 K and 6000 K)*

The HRV features for each participant were plotted against time of day to visualize temporal patterns (see **Figure 11**). The resulting graphs (baseline_blue, stress_blue, recovery_blue, baseline_yellow, stress_yellow, recovery_yellow) - while not reliable with 8 participants - align with general findings about the fluctuation of HRV during the day and reflect the changes resulting from stress. While the baseline-HRV showed on average higher RMSSD in yellow CCT, the recovery-HRV was higher in blue CCT.

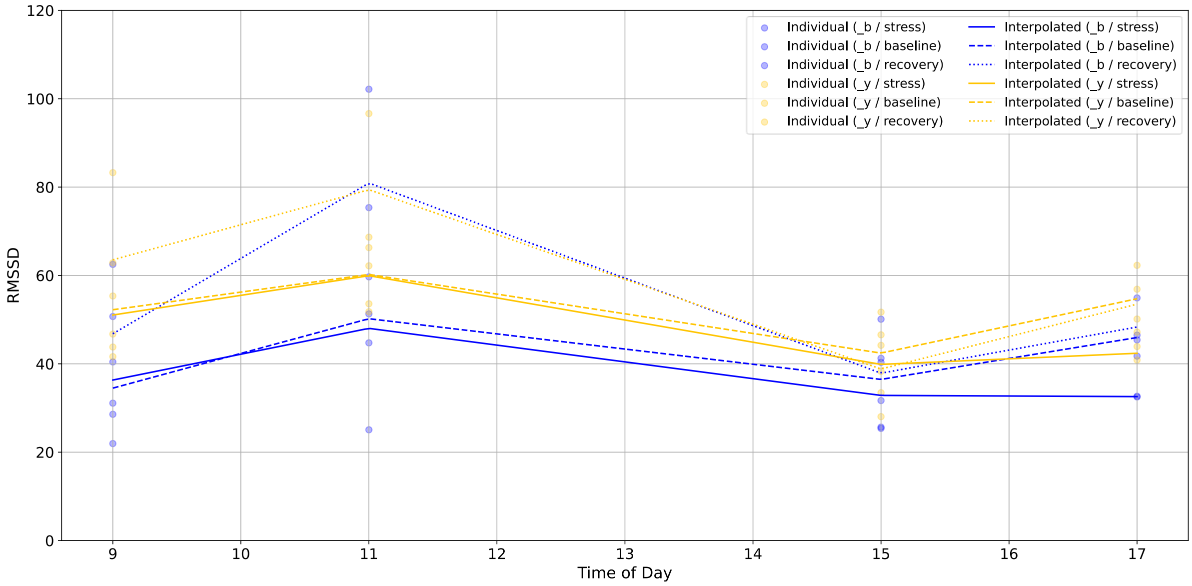

Figure 11 *Graphs showing RMSSD fluctuations depending on the Time of Day and three phases (baseline, stress and recovery) in both CCTs (2700 K and 6000 K)*

II. Overview – Influence of Time of Day and Order

The eight 5-min sequences were analysed regarding changes in direction and magnitude per participant in both CCTs. Across the 16 experimental runs, during 11 experiments the expected decrease in HRV during the stress phase was shown. However, in 4 runs, participants exhibited an increase in HRV during the stress phase. For two of these participants, HRV increased during both of their stress-phase runs. The third participant showed no change in HRV during the first run and an increase during the second.

An iterative subgroup analysis was conducted to explore the effects of three categorical variables - CCT (correlated colour temperature), ToD (Time of Day), and Order—on the physiological and cognitive outcome measures RMSSD, PSW, and CP (**Table 7**). The analysis involved systematically holding two of the three categorical variables constant while comparing the outcome measures across the two levels of the remaining variable. This approach allows for the isolation of individual effects within controlled subgroups, reducing potential confounding and enhancing interpretability. Subsets were created by fixing two categories (e.g., CCT = 6500K and Order = 2), and comparing the third (e.g., morning vs. afternoon). This process was repeated across all combinations to ensure comprehensive coverage of subgroup comparisons. The mean and standard deviation of each outcome variable were calculated within each subgroup to assess variability and potential trends. This provides a granular view of how each factor independently influences RMSSD, PSW, and CP, while accounting for interactions with the other variables.

	Phase	CCT		Time of Day		Order	
		2700 K	**6000 K**	**Morning**	**Afternoon**	**1**	**2**
RMSSD [**ms**]	**baseline**	52.41 ± 11.01	41.79 ± 15.68	49.30 ± 18.51	44.90 ± 8.82	51.90 ± 14.61	42.30 ± 12.86
	stress	48.3 ± 11.34	37.45 ± 11.10	48.84 ± 12.67	36.92 ± 8.81	43.01 ± 9.26	42.75 ± 15.28
	recovery	58.82 ± 21.39	53.48 ± 23.65	67.67 ± 24.79	44.64 ± 10.75	62.34 ± 21.42	49.97 ± 22.06
PSW [-]	**stress**	0.55 ± 0.18	0.54 ± 0.17	0.59 ± 0.17	0.50 ± 0.16	0.60 ± 0.13	0.49 ± 0.19
CP [-]	**stress**	0.36 ± 0.21	0.35 ± 0.27	0.38 ± 0.27	0.33 ± 0.20	0.41 ± 0.25	0.30 ± 0.21

Table 7 *Summary of Iterative Subgroup Analysis for RMSSD, PSW and CP keeping two out of the three categories constant, while comparing the two variables within the remaining category*

The percentages shown in **Table 8** represent the relative change in RMSSD between two experimental phases, from baseline to stress and from stress to recovery. These values were calculated using the standard formula for relative change. This approach allows for a normalized comparison of physiological responses across conditions, highlighting the proportional increase or decrease in RMSSD relative to each participant group's starting point.

Category	RMSSD Change (Baseline to Stress)	RMSSD Change (Stress to Recovery)
2700K	- 7.8 %	+21.8 %
6000K	-10.4 %	+42.7 %
Morning	-1.0 %	+38.6 %
Afternoon	-17.8 %	+21.0 %
Order 1	-17.0 %	+44.9 %
Order 2	+1.1 %	+16.9 %

Table 8 *Relative Changes resulting from the Iterative Subgroup Analysis*

Based on the summarized data, clear patterns emerge across the categorical variables. Order had the most pronounced impact on all outcomes: participants in their first exposure (Order 1) showed the highest improvement in RMSSD from stress to recovery (+44.9%), the highest cognitive performance (CP = 0.41), and the highest perceived stress workload (PSW = 0.60), suggesting greater sensitivity to the experimental conditions. Time of Day also played a significant role—morning sessions led to stronger physiological recovery (RMSSD +38.6%) and better cognitive performance (CP = 0.38), despite participants reporting higher subjective stress (PSW = 0.59). In contrast, afternoon sessions were associated with weaker physiological recovery and lower CP. Differences between CCT conditions were smaller but still notable: 6500K lighting produced the highest RMSSD increase (+42.7%), although cognitive performance and PSW were slightly better under 2700K. Overall, these findings suggest that time of testing and session order are critical modulators of both physiological and cognitive responses, while lighting conditions may subtly influence recovery dynamics.

III. Overview – PSW and CP

Table 9 displays the Perceived Stress and Workload (PSW) and Cognitive Performance CP for each participant (A – H) in the first and second experiment and in which of the two, the score was higher.

	PSW – 1st run	**PSW – 2nd run**	**CP – 1st run**	**CP – 2nd run**	**Higher PSW**	**PSW difference**	**Higher CP**	**CP difference**
A	0.70	0.66	0.58	0.38	1st exp.	0.04	1st exp.	0.2
B	0.44	0.74	0.76	0.72	2nd exp.	0.3	1st exp.	0.04
C	0.47	0.4	0.54	0.26	1st exp.	0.07	1st exp.	0.28
D	0.54	0.39	0.62	0.46	1st exp.	0.15	1st exp.	0.16
E	0.77	0.26	0.08	0.12	1st exp.	0.51	2nd exp.	0.04
F	0.58	0.62	0.36	0.22	2nd exp.	0.04	1st exp.	0.14
G	0.53	0.6	0.22	0.08	2nd exp.	0.07	1st exp.	0.14
H	0.76	0.25	0.12	0.18	1st exp.	0.51	2nd exp.	0.06
Mean	0.60	0.49	0.41	0.30				
SD	0.13	0.19	0.25	0.21				

Table 9 *Overview of Perceived Stress and Workload (PSW) and Cognitive Performance (CP) of the first and second experiment*

The Perceived Stress and Workload (PSW) was on average approximately 10 percent higher during the first experiment (with high standard deviations for both values). This aligns with the theory that familiarity with the procedure might reduce stress. For 5 out of 8 persons, the perceived stress and workload was higher during the first experiment, for the remaining 3 it was higher during the second experiment. The Cognitive Performance (CP) score was on average higher during the first experiment (with high standard deviations for both values). This could imply that the familiarity with the test did not make it easier for participants the second time. The decrease in performance could also be a result of decreased motivation or focus once familiar with the experiment. 6 out of 8 persons performed better at the MAT in the first experiment, the remaining 2 performed better in the second one.

6.1.2. Multi-Criteria Decision Analyses

The Multi-Criteria Decision Analyses (MDCA) focus on the results per person. They were conducted to investigate in which CCT the measured HRV features indicated less stress per person focusing on absolute HRV during each of the three phase and on HRV-change from baseline to stress considering the limited generalizability due to the data size per person.

I. Phase Comparison

The analysis for absolute phase comparison compares the data for each phase in the two CCTs per person. Even though, the fluctuations between different features of HRV correlate, for a detailed analysis it was decided to include each of them individually (not in form of an HRV index). For the difference calculation per feature, the difference between the feature values in blue CCT and in yellow CCT was divided by the sum of absolute values to normalize the score (depending on the optimization direction the score is inverted). The scores of all features are aggregated into a total score to approximate in which CCT participants' HRV was higher for each phase (considering the magnitude of differences). It was defined that positive scores favour yellow and negative scores favour blue. Therefore, for variables that should be high

$$score_{fav\,Y} = \frac{Y - B}{\lceil Y + B \rceil}$$

and such that should be low

$$score_{fav\,B} = \frac{B - Y}{\lceil Y + B \rceil}$$

different formulas were applied. The result is the CCT (blue or yellow) in which the HRV was higher for this specific participant.

II. Change Comparison

The analysis for change comparison uses the differences between baseline and stress for a direction- and magnitude-aware comparison of the features in the two CCTs per person. The HRV features 'RMSSD', 'pNN50', 'HF' and 'HF/(LF+HF)' were included. Other features were excluded because they are not meaningful in short-term investigations. The objectives used to investigate in which CCT stress was lower and recovery was better are seen in Figure 16. If the stress reduces HRV, the drop should be minimal, if it increases HRV, maximize the increase. Similarly for recovery: if HRV improves during recovery, higher values are favoured, if it HRV decreased during recovery, smaller changes are favoured. The feature scores are aggregated into a weighted sum. The result is the CCT (blue or yellow) in which the HRV was higher for this participant.

The two person-specific analyses can be combined to find out in which CCT HRV and CP were overall higher and PSW lower. As mentioned previously, the results of the preferred CCT are not reliable and cannot be generalized due to the small data sample. Further, the influence of confounding variables (especially the order in which participants took part in the MAT and were exposed to the two CCTs) must be investigated (see Chapter 6.1.3).

$$\Delta_{BL-ST} = value_{ST} - \ value_{BL}$$

$$\Delta_{ST-RE} = value_{RE} - \ value_{ST}$$

III. Results

Running both analyses for all 8 participants revealed the following: **8 out of 8 participants** had a higher score in the absolute stress-HRV in yellow CCT. This means that the sum of the chosen HRV features (RMSSD, pNN50, HF and HF/(LF+HF)) and cognitive performance (CP) was higher and PSW (perceived stress and workload) was lower in yellow CCT for each participant and consistent in all 16 experiments. The analysis for HRV changes between baseline and stressed showed that for **4 out of 8** participants the total change-score - considering the change from baseline to stress and change from stress to recovery - was more favourable in the yellow CCT condition. For the remaining **4 out of 8** participants the change-score was more favourable in blue CCT. Figure 18 and Figure 19 show the results for absolute HRV during stress including CP and PSW and HRV changes from baseline to stress on the example of a random participant. The exact scores can be found in the Appendix (Chapter 11).

The two analyses provide an intuitive tool to quantify individual HRV differences across phases and phase changes. Even though the score is magnitude and score contributions are revealed transparently, HRV is complex, and different features and their meaning in the situational context and context of health must be considered. Further, the current stress-HRV analysis includes PSW and CP, which are independent of HRV. Features that should be integrated in the analysis can be changed easily and if needed individual weights can be assigned. For future studies including a higher number of experiment-runs per participant, the two analysis scripts can be used to generate quick overviews of HRV trends considering inter-individuality.

6.1.3. Bayesian Linear Effects Models

The Bayesian linear effects models use aggregated data from all participants to identify factors contributing to the observed results, providing a basis for group analysis as well as individual analysis. A linear effects model investigates the effect of confounding variables, called fixed effects. Due to the complexity of interaction effects and exploratory study design, this was utilized to help find out which factors influence the results (effect shown in HRV) to what degree. Different versions of the model were explored focusing on different types to estimate the probability distributions of model parameters based on both prior beliefs and observed data through Bayes' theorem. This was implemented in Python using the BAyesian Model-Building Interface (BAMBI). Bayesian mixed effects models are a flexible framework for analysing data with hierarchical or grouped structure, such as repeated measures or nested observations. These models estimate both fixed effects (population-level effects) and random effects (group- or subject-specific deviations), while also accounting for uncertainty in all parameters through their posterior distributions. Unlike traditional (frequentist) approaches, Bayesian methods allow the incorporation of prior knowledge and provide credible intervals rather than p-values, giving a more meaningful interpretation of uncertainty. They can be especially powerful in cases with small sample sizes (Song et al., 2017; S. Xu et al., 2023). In categorical predictors, one level is chosen as the reference level, serving as the reference against which all other levels are compared. The models developed estimate the difference in the outcome (here RMSSD) between each non-reference level and this reference, while accounting for uncertainty. The intercept represents the expected outcome value when all predictors are at their reference levels.

All five models intended to use PSS (stress of the last month), ToD (time of day) and Order (number of experiment run – 1 or 2) as fixed effects to investigate their effect on RMSSD. Coincidentally PSS and ToD correlated perfectly. All participants with low PSS scores (< mean PSS) took part in the experiments in the morning timeslots (09:00 and 11:00), while all participants with higher PSS scores took part in the afternoon timeslots (15:00 and 17:00). Since the small dataset challenges the models to distinct between the two overlapping factors, PSS was excluded in the final BLEMs. In the context of this study, the fixed effect "Order" is of particular interest to find out if the familiarity with the stress test, the second time participants took part, influenced the stress reaction. In this model, RMSSD during stress is modelled as a function of CCT, Order, and Time of Day. Using a random intercept for each participant (ID) led to no significant changes in the results, likely due to the small participant number preventing the model from having enough information to estimate subject-level variance. Resultingly, the following linear effects model was used:

$$RMSSD \sim CCT + Order + ToD$$

Priors for the model were derived from the dataset. The intercept prior was set to a Normal distribution centred at the mean RMSSD for participants in the reference condition (2700 K, afternoon, and Order 1). For categorical predictors, the priors were centred on the observed mean-differences between the two categorical groups that are compared. This was done for each model accordingly. For example, the prior for CCT was specified as Normal (-10.87), reflecting the mean RMSSD difference between the 2700K and 6000K CCT. Similarly, ToD and Order priors were centred at the observed differences between afternoon vs. morning sessions and Order 1 vs. Order 2, respectively. Further, a sigma for each prior was defined to reflect prior uncertainty about that fixed effect's coefficient (e.g. how much the effect of CCT might vary around the prior mean). Each prior sigma was defined between 10 and 20 % of the prior value to show moderate to considerable uncertainty. Changes of the values within this range showed to not affect the results significantly. A prior predictive distribution was plotted before running each model to ensure that the defined priors are able to generate plausible data consistent with the scale and variability of the observed measurements.

I. BLEM 1 Absolute RMSSD during Stress

In this model, the posterior mean of the intercept was 42.02 ms (SD = 4.218), with a 94% highest density interval (HDI) ranging from 34.34 to 49.98 ms, reflecting the estimated RMSSD for the reference condition (CCT = 2700 K, Order = 1, ToD = afternoon).

	Mean	SD	HDI 3%	HDI 97%
Sigma [ms]	10.01	1.9	**6.87**	**13.65**
Intercept [ms]	42.02	4.18	**34.34**	**49.98**
Order [2] [ms]	-0.24	2.56	**-5.2**	**4.38**
CCT [6000] [ms]	**-10.83**	4.44	**-19.24**	**-2.47**
ToD [morning] [ms]	11.82	4.49	**3.05**	**19.84**

Table 10 *Bayesian Statistics Summary for RMSSD during Stress (using CCT 2700 K, Order 1 and Afternoon as Time of Day as reference)*

The effect of CCT [6000 K] is estimated at - 10.83 ms (SD = 4.44, 94% HDI [-19.24 -2.47]), suggesting higher RMSSD under warm CCT compared to cool CCT, with the HDI excluding zero which indicates a clear effect. The effect of ToD [morning] is +11.82 ms (SD = 4.49, HDI [3.05, 19.84]), indicating higher RMSSD values in the morning than in the afternoon. As mentioned above this could also be related to the PSS scores, which were coincidentally lower (meaning lower stress) for the participants in the morning group. The influence of Order (2) is small and uncertain (mean = -0.24 ms, SD = 2.56, HDI [−5.2, 4.38]), suggesting that the familiarity of the experiment and the stress test the second time participants took part had no relevant influence on absolute RMSSD. The model's posterior estimate of the residual standard deviation (sigma) is estimated at 10.01 ms (SD = 1.90), indicating the average within-group variability (data variability that is not explained by the model). An overview of the results is seen in **Table 10**.

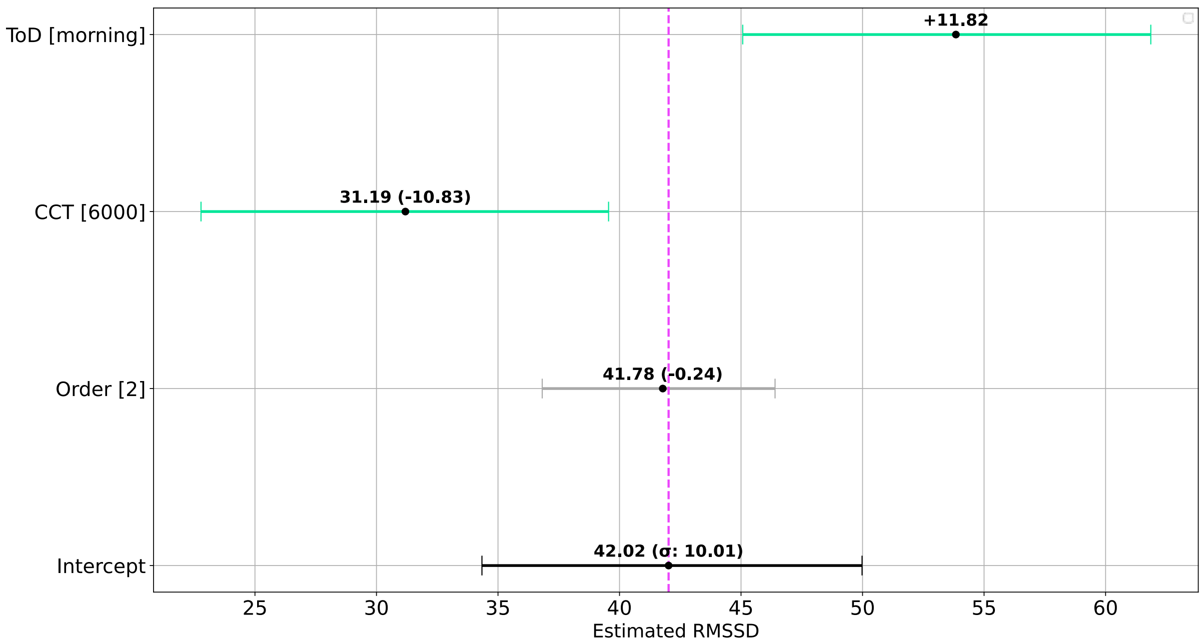

Figure 12 *Posterior Estimate for Absolute RMSSD during Stress (using CCT 2700 K, Order 1 and Afternoon as Time of Day as reference)*

II. BLEM 2 - Absolute RMSSD during Baseline

For BLEM 2, the process from BLEM 1 was repeated and the data and priors adjusted accordingly (using the same logic to define the priors and the same reference level - 2700 K, Order 1 and afternoon - as described for BLEM 1).

The model results suggest that the lighting condition with a CCT of 6000K clearly reduces the outcome RMSSD compared to the reference of 2700 K, with a mean estimate of -6.35 and a 94% HDI that excludes zero. Similarly, Order 2 also shows a negative effect (-8.51). That subjects had lower RMSSD during the second time they participated because it was the second time seems not obvious. This could be the result of anticipatory nervousness due to participants remembering the stress test from the first session, or it may simply be a coincidental, non-meaningful effect. Morning time appears to increase the outcome (+4.36), though the uncertainty is greater, as the HDI includes zero, suggesting this effect is less robust. The intercept is 53.04, with relatively low uncertainty, and the model's residual variation (sigma) is estimated at 12.69 (see **Table 11**).

	Mean	**SD**	**HDI 3%**	**HDI 97%**
Sigma [ms]	12.69	2.24	**8.89**	**16.82**
Intercept [ms]	53.04	4.1	**45.2**	**60.58**
Order [2] [ms]	-8.51	3.88	**-15.74**	**-1.15**
CCT [6000] [ms]	**-6.35**	2.71	**-11.39**	**-1.21**
ToD [morning] [ms]	4.36	2.73	**-0.89**	**9.31**

Table 11 *Bayesian Statistics Summary for RMSSD during Baseline (using CCT 2700 K, Order 1 and Afternoon as Time of Day as reference)*

The Intercept is estimated at 53.4 (SD = 4.1), reflecting the average RMSSD across conditions, while the residual variation (sigma) is moderate (12.69) but slightly higher than during the stress phase. This may reflect the inherently individual nature of HRV, suggesting that the observed differences at baseline were due to inter-individual variability rather than fixed effects.

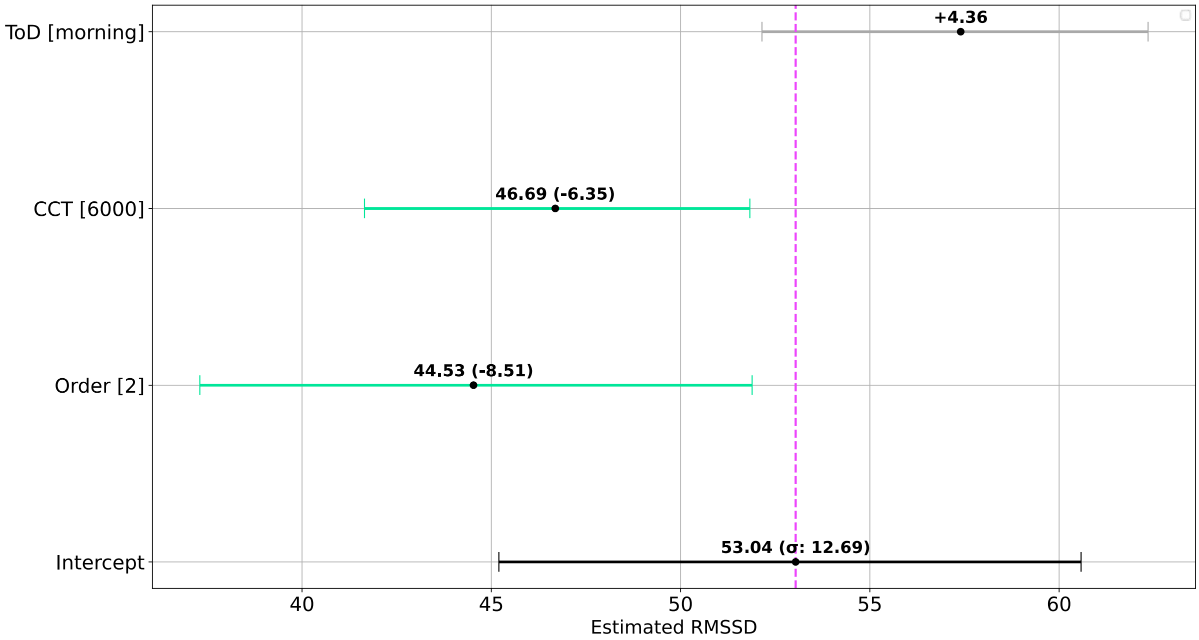

Figure 13 *Posterior Estimate for Absolute RMSSD during Baseline (using CCT 2700 K, Order 1 and Afternoon as Time of Day as reference)*

III. BLEM 3 - Absolute RMSSD during Recovery

BLEM 3 (**Table 12**) is built like the previous models using the RMSSD data during the recovery phase and accordingly adapted priors. The model estimates a residual standard deviation (σ) of 17.82 (SD = 2.88), indicating moderate variability. The intercept is 47.49, suggesting the reference level of the outcome.

	Mean	**SD**	**HDI 3%**	**HDI 97%**
Sigma [ms]	17.82	2.88	**12.66**	**23.02**
Intercept [ms]	47.49	6.26	**35.55**	**59.06**
Order [2] [ms]	-12.36	6.65	**-24.88**	**0.38**
CCT [6000] [ms]	**4.52**	2.46	**-0.22**	**8.95**
ToD [morning] [ms]	23.06	6.49	**10.84**	**35.24**

Table 12 *Bayesian Statistics Summary for RMSSD during Recovery (using CCT 2700 K, Order 1 and Afternoon as Time of Day as reference)*

Order 2 shows to have a negative effect (-12.36), with its HDI crossing zero, indicating uncertainty. Without further analysis it is not clear why RMSSD would be lower the second time subjects participated in the experiment. The "CCT [6000]" condition shows a small positive effect (4.52) (with wide uncertainty) suggesting that RMSSD-values during the recovery phase were higher in blue CCT. The "ToD [morning]" variable has a strong effect (23.06), with its HDI well above zero, indicating a credible, positive influence on RMSSD in the recovery phase.

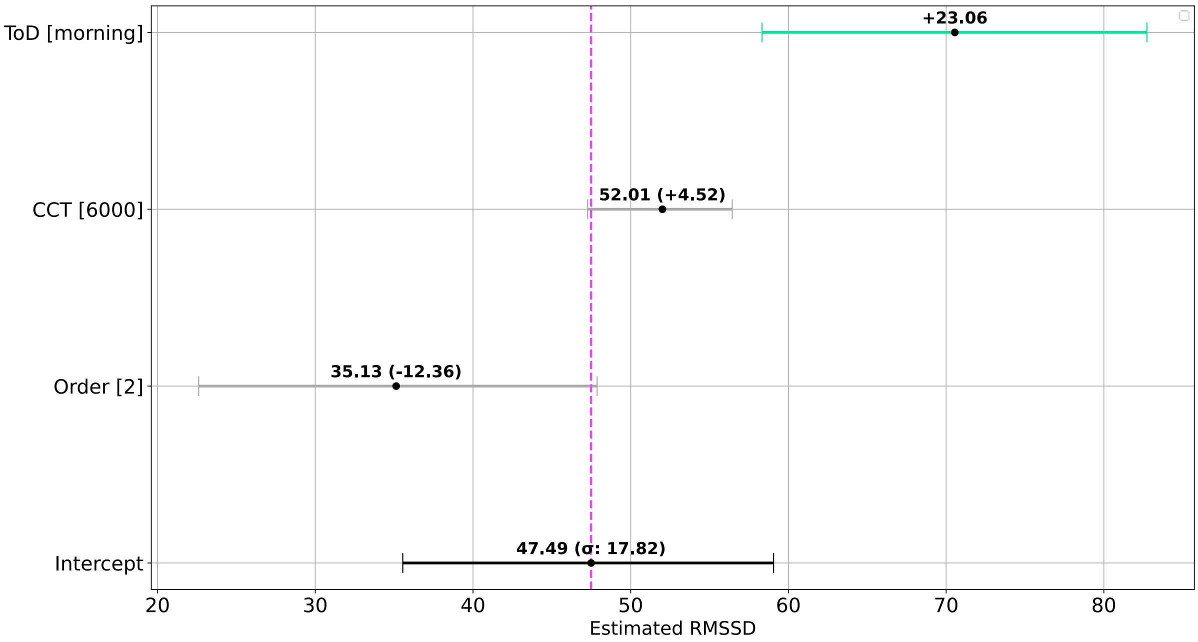

Figure 14 *Posterior Estimate for Absolute RMSSD during Recovery (using CCT 2700 K, Order 1 and Afternoon as Time of Day as reference)*

IV. BLEM 4 – Relative Changes from Baseline to Stress

The model uses the (direction-aware) relative change between baseline-RMSSD and stress-RMSSD. In this model, all fixed effects including Order [2], CCT [6000], and ToD [morning] - have mean estimates that exclude zero. The intercept of -0.20 (mean) suggests that under the reference conditions - CCT 2700 K, Order 1, and ToD afternoon - there is a moderate decrease in RMSSD during stress with a significantly high residual standard error of 0.42. The time of day has a notable effect: participants in the morning group showed a smaller reduction (or even a relative increase), with a positive coefficient of 0.27 (HDI 3% to 97%: [0.11, 0.44]). Order 2 is associated with a further decrease from baseline to stress in RMSSD (mean = -0.13). Regarding CCT, exposure to 6000 K light slightly increased RMSSD compared to 2700 K (mean = 0.05), though the effect is small (HDI: [0.03, 0.07]). Overall, the model indicates that time of day and experiment order have the stronger influence (**Table 13**).

	Mean	SD	HDI 3%	HDI 97%
Sigma [ms]	0.42	0.08	**0.28**	**0.58**
Intercept [ms]	-0.20	0.11	**-0.44**	**0.01**
Order [2] [ms]	-0.13	0.05	**-0.22**	**-0.04**
CCT [6000] [ms]	0.05	0.01	**0.03**	**0.07**
ToD [morning] [ms]	0.27	0.09	**0.11**	**0.44**

Table 13 *Bayesian Statistics Summary for Relative RMSSD Changes from Baseline to Stress (using CCT 2700 K, Order 1 and Afternoon as Time of Day as reference)*

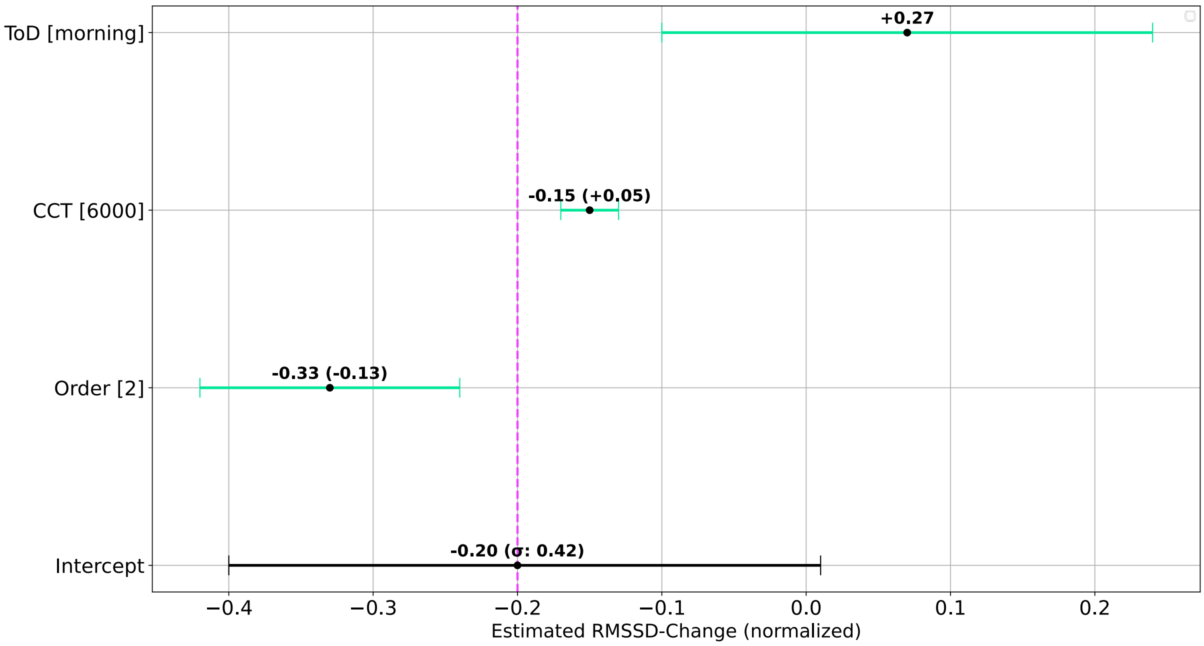

***Figure 15** Posterior Estimate for Relative RMSSD Change from Baseline to Stress (using CCT 2700 K, Order 1 and Afternoon as Time of Day as reference)*

V. BLEM 5 - Relative Changes from Stress to Recovery

In the BLEM for relative changes from stress to recovery a strong order effect is observed: participants in Order 2 show a large decrease (25 %) in RMSSD change (mean = -0.25, HDI: [-0.34, -0.16]). In contrast, exposure to CCT 6000 K light leads to an increase in relative RMSSD change (mean = 0.19, HDI: [0.14, 0.25]). Similarly, participants tested in the morning exhibit an increase in RMSSD-change from stress to recovery (mean = 0.17, HDI: [0.12, 0.23]). The model estimates the intercept at -0.15 (SD = 0.12)., as reference level of the outcome and a very high residual standard deviation (σ) of 0.5 (SD = 0.13) (**Table 14**).

	Mean	SD	HDI 3%	HDI 97%
Sigma [ms]	0.5	0.13	**0.26**	**0.74**
Intercept [ms]	-0.15	0.12	**-0.38**	**0.07**
Order [2] [ms]	-0.25	0.05	**-0.34**	**-0.16**
CCT [6000] [ms]	0.19	0.03	**0.14**	**0.25**
ToD [morning] [ms]	0.17	0.03	**0.12**	**0.23**

***Table 14** Bayesian Statistics Summary for Relative RMSSD Changes from Stress to Recovery (using CCT 2700 K, Order 1 and Afternoon as Time of Day as reference)*

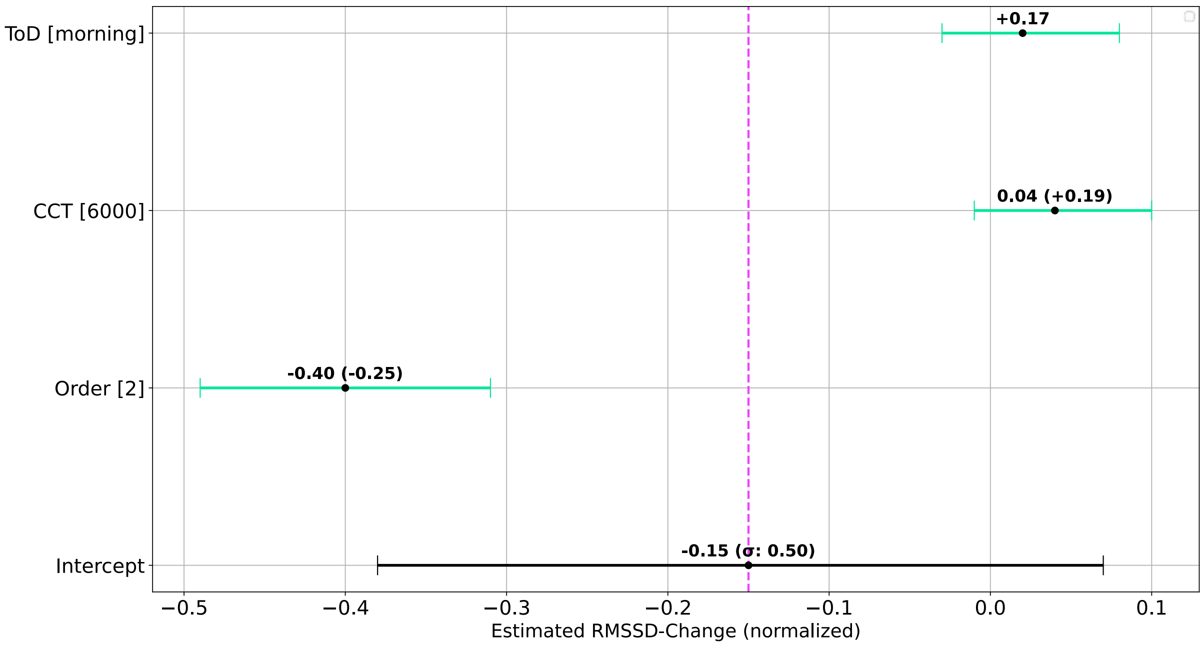

Figure 16 *Posterior Estimate for Relative RMSSD Change from Stress to Recovery (using CCT 2700 K, Order 1 and Afternoon as Time of Day as reference)*

6.1.4. Summary of Analysis Results

This chapter summarizes the results of the analysis, while interpretations of the results are provided in Chapter 7.1. As mentioned before, the small dataset (n = 8) and the fact that HRV is very individual limits the reliability of the results. While the data size and inter-individual variance are specifically addressed through the computational analysis, the model's functionality is also restricted through limited data input. Further, HRV - even on the individual level – is highly dynamic which is why short-term measurements are known to provide limited meaning. The data analysis for the pilot study on CCT as countermeasure to stress shown in HRV revealed the following findings.

I. Results on the Individual Level

As predicted, the different features of HRV showed a high variance between participants underlying the individuality of HRV baseline and the relevance of considering this for data analysis. Similar, stress response (in general and to this particular stress test) is very individual, not just in magnitude but also direction. 5 out of 8 participants responded to the stress phase as expected - with lower HRV compared to the baseline. The HRV of 3 participants increased during the stress phase. For 2 out of those 3, the HRV increased during the stress phase in both experiments. For 1 out the 3, the HRV decreased during the stress phase in the first experiment and increased during stress in the second experiment. The multi-criteria decision analysis (MCDA) showed that the sum of HRV features was higher for all participants in warm CCT. It also suggested that for 50 percent of them, warm CCT was correlated with more favourable stress reactions shown in HRV features (smaller decrease from baseline to stress, higher increase from stress to recovery).

II. Results on the Group Level

The Bayesian linear effects models investigated the data on the group-level to investigate the effects of different confounding variables. The findings are still relevant on the on the individual level to inform result interpretation and future study design. On average, baseline-HRV was generally higher in yellow CCT, and the recovery had a higher magnitude in yellow CCT. In both CCTs, the HRV of all participants followed a certain pattern (higher HRV in the morning, lower HRV in the afternoon). The comparison of baseline-HRV, stress-HRV and recovery-HRV to the absolute and relative changes between the phases shows was conducted to analyse stress response considering starting conditions shown in the baseline. It agrees with the prior expectation that for participant-specific CCT analysis as well as inter-participant analysis, personal baseline-HRV must be considered to draw meaningful conclusions from the changes during the stress test. The theory that yellow CCT could positively contribute to lower stress shown in HRV and the patterns of influences resulting from confounding variables seen in the Iterative Subgroup Analysis were investigated further in the Bayesian linear effects models.

Regarding **absolute differences** between the two CCT, the BLEMs showed an effect of warm CCT (with 94 % certainty) on higher RMSSD during the stress (+ 10.83) and a similar but slightly less certain effect during the baseline phase (+ 6.35). In contrast, the recovery-HRV indicates higher RMSSD in blue CCT (+ 4.52 with nearly 94 % certainty) (**Figure 17**).

Variable	Est. (94% Conf. Int.)
Absolute rmssd (ms) during stress	
Order [2]	-0.24(-5.20 to 4.38)
Cct [6000]	-10.83(-19.24 to -2.47)
Tod [morning]	11.82(3.05 to 19.84)
Absolute rmssd (ms) during baseline	
Order [2]	-8.51(-15.74 to -1.15)
Cct [6000]	-6.35(-11.39 to -1.21)
Tod [morning]	4.36(-0.89 to 9.31)
Absolute rmssd (ms) during recovery	
Order [2]	-12.36(-24.88 to 0.38)
Cct [6000]	4.52(-0.22 to 8.95)
Tod [morning]	23.06(10.84 to 35.24)

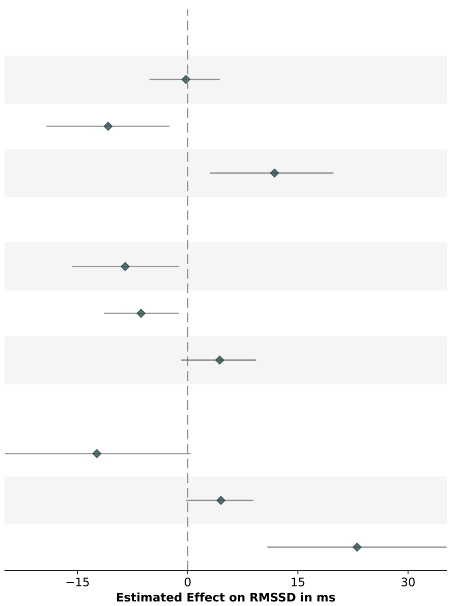

Figure 17 *94 % Confidence Interval for Absolute RMSSD Effect (in ms) during Baseline, Stress and Recovery using CCT 2700 K, Order 1 and Afternoon as Time of Day as Reference*

Relative changes of RMSSD between baseline and stress, and stress recovery showed the following were investigated to consider individual baseline values. The Order influenced both relative changes: the baseline-to-stress change was 13 % smaller during the second experiment, the stress-to-recovery change was 25 % smaller during the second experiment. Warm CCT caused a 5 % less severe baseline-to-stress change, while blue CCT created a 19 % higher stress-to-recovery change. The time of day showed a clear influence on both changes. The baseline-to-stress change was 27 % higher in the morning, the stress-to-recovery change was 17 % higher in the morning (**Figure 18**). The results must be considered with caution due to the very high residual error.

Variable	Est. (94% Conf. Int.)
Rmssd-change (%) baseline to stress	
Order [2]	-13.00(-22.00 to -4.00)
Cct [6000]	5.00(3.00 to 7.00)
Tod [morning]	27.00(10.00 to 44.00)
Rmssd-change (%) stress to recovery	
Order [2]	-25.00(-34.00 to -16.00)
Cct [6000]	19.00(14.00 to 25.00)
Tod [morning]	17.00(12.00 to 23.00)

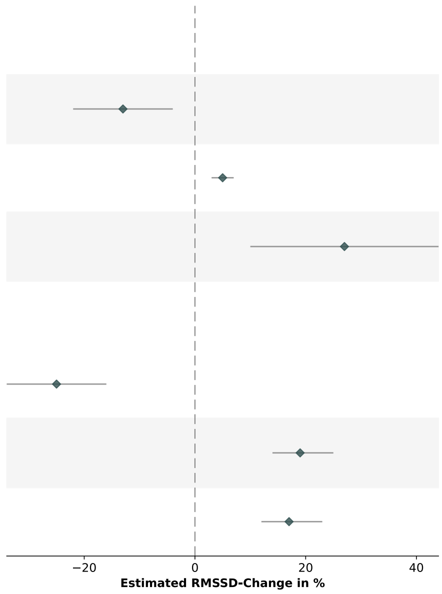

Figure 18 *94 % Confidence Interval for Relative RMSSD Changes from Baseline-to-Stress and Stress-to-Recovery (in %) using CCT 2700 K, Order 1 and Afternoon as Time of Day as Reference*

6.2. Future Data Application

Research in neuroarchitecture examining the impact of architectural design on biomarkers associated with long-term stress response has the potential to inform countermeasure systems and contribute to the development of personalized architecture in extreme environments. The findings can inform the design of adaptive systems in confined environments (such as remote research stations), high-stress settings like hospitals (**Figure 19**) and everyday-environments such as student housing and office building. This chapter focuses on how the data of the pilot study and future larger datasets resulting from similar experiments can be used to field research and real-life applications in extreme environments. The aim was to theorize an application of the research that simultaneously functions as field-based study which – if implemented – would generate new empirical data, drawing inspiration from the research by (Ojha et al., 2019), detailed in Chapter 3.2.2. This system would not only test the practical relevance of the initial findings but also extend the research through iterative, context-specific and longitudinal investigation. Since the system includes real-time biomarker monitoring through wearable sensors, the focus is on allostasis-relevant biomarkers that can be measured in a non-intrusive way (while the integration of hormones and neurotransmitters would need dedicated further research). The system doesn't focus on the specifics of the wearables. It assumes that they could be integrated into clothing or be worn as headband or smartwatch providing reliable monitoring. The concept focuses on four occupants (referred to as ID). A potential configuration is outlined for an application in confined spaces occupied by the same set of individuals over time. This could be a microgravitational space station like the ISS, or a remote research station (in the following referred to as 'station').

Figure 19 *Examples of Applications: Left: Halley VI British Antarctic Research Station (Architects, n.d.), Middle: Hospital Operation Room (*The "Golden Supporting Actor" in The Operating Room*, n.d.), Right: International Space Station (*Home Sweet Home in Orbit - The New York Times*, n.d.)*

Although such an environment offers limited architectural variability due to spatial constraints, it is particularly well-suited for this demonstration, as the occupants are likely already accustomed to frequenting health monitoring and are receptive to the use of wearable sensors. Further, the crew rarely leaves the facilities which allows continuous data collection for all times of day and activities. Additionally, this use case is highly relevant for the development of support strategies targeting circadian rhythm regulation. The strict spatial limitations in such environments amplify the challenges that can potentially be addressed through adaptive-neuroarchitecture.

6.2.1. System Overview

The proposed system considers individual acute and long-term health, architectural functionality (including task-specific lighting requirements, accessibility and circadian rhythm) and balances inter-individual needs within the group with spatial limitations. Three main aims are proposed: 1) counteracting acute stress, 2) lowering the risk for mal-functional allostasis by preventing chronic stress and 3) supporting physiological changes resulting from stressor exposure. This is enabled by different functions that adapt the visual quality of the surroundings to react to biomarkers indicating acute stress, track and detect trends and consider those in the adaption.

I. System Design

The system acts as a closed feedback loop where visual quality (VQ) adjustments based on current biomarkers and contextual data continuously inform future decisions. It includes four main sub-systems; the Activity Detection System (ADS), Database (DB), Decision System (DS) and Adaption System (AS) (see **Figure 20**). Data inputs can be categorized into three types of data: Environmental Data (ED), Realtime Biomarker Data (RBD) and Training Data (TD). The Activity Detection System recognizes the position of the four IDs, the task each ID is working on and current VQ settings (illuminance, CCT and light distribution). This data is used to choose the appropriate settings from the functionality requirements (circadian requirements, task-specific requirements and accessibility requirements). The location of IDs is inserted into the Prioritization System to inform decisions on compromises between ID-specific needs. The ED and RBD is processed through Multi-Sensor Data Fusion (MSDF) and stored in the database. Current RBD and past RBD are fed into the Long-Short-term Memory (LSTM). The LSTM is used to analyse temporal patterns in biomarker data, producing either trend embeddings or trend labels that reflect changes in stress or physiological states over time. These outputs feed into the State Estimator to help assess chronic stress levels and guide personalized lighting adaptations. The Bayesian Reinforcement Learning Module (BRLM) is initially trained on the pre-application data (that could result from a cross-sectional study) to establish personal profiles, but it continues to learn by incorporating new biomarker data in real time. It uses the past and current RBD for two main objectives. For one, the Effect Analysis (EA) which isolates the effects of VQ features and other influences (e.g. time of day, task) on the different biomarkers and considers potential changes resulting from VQ adaption during acute stress-response through Bayesian methods resulting in probability distributions for actions. The Effect Analysis is implemented using Bayesian causal inference techniques, to estimate the magnitude, direction, and probability of VQ and contextual influences on biomarkers. This allows the system to disentangle overlapping effects and make informed, probabilistic decisions even under uncertainty. The other analysis resulting from the BRLM is the Trend Analysis (TA) which uses temporal patterns in past RBD and ED to detect evolving physiological trends. These trends inform the Prioritization System PS about which IDs to prioritize and the BRLM's probabilistic decision-making, The results of the BRLM are used to detect similarities in preferences for different IDs which are fed into the Prioritization System. Similarly, the results of the Trend Analysis which are fed into the same system through the State Estimator which defines Chronic Stress Levels (CSL). The State Estimator uses a probabilistic classification model, supported by regression-based trend analysis, to define Chronic Stress Levels (CSL) for each occupant. It outputs both a categorical stress level (e.g., low, moderate, high) and a confidence score, enabling the system to prioritize individuals based on both current state and long-term physiological trends. All data streams and partial results come together in the Decision System, which computes a command that balances the different functional and health needs of the individual and the group. This command is forwarded into the Adaption System which controls the different actuators and leads them to change the illuminance, CCT and light distribution in the different areas accordingly. This creates a closed feedback loop where lighting adaptations influence future biomarker responses, which are then re-evaluated by the system to refine future decisions. General System Requirements are explained below, while the Multi-Sensor Signal Fusion and Bayesian Reinforcement Learning are detailed in Chapter 6.2.2 and 6.2.3.

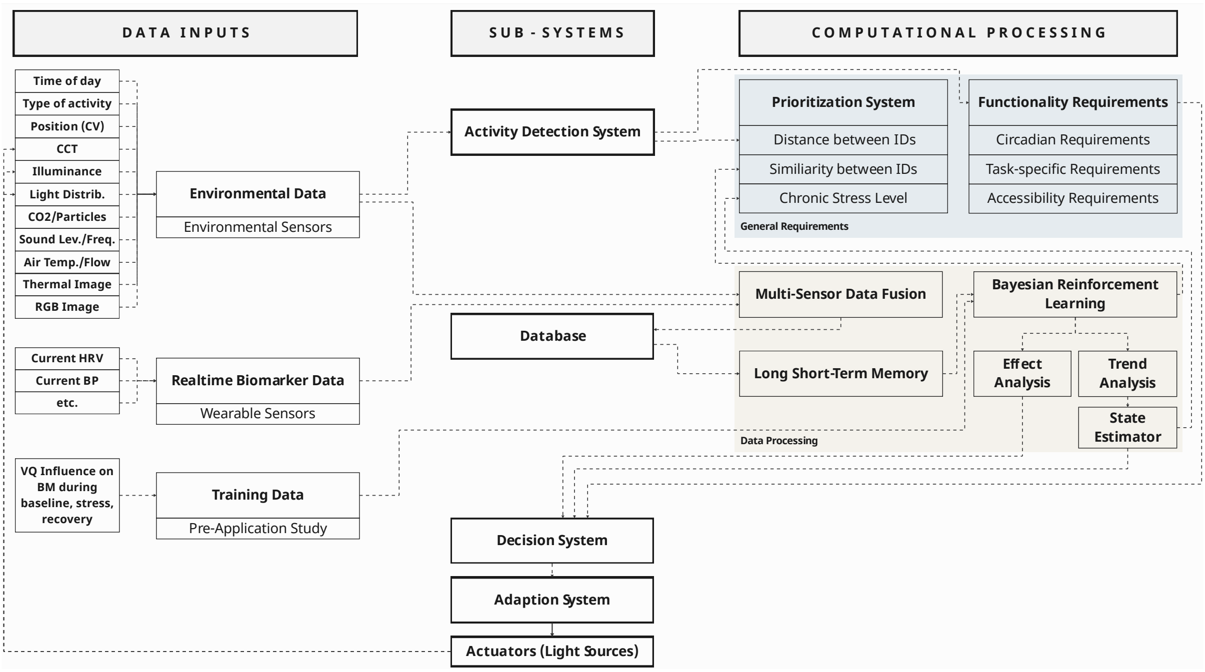

Figure 20 *System Architecture showing the Data input, Subsystems and Computational Processing: The system uses multi-sensor data fusion to integrate environmental, biomarker, and positional data, which is analysed through a Bayesian Reinforcement Learning Module using Effect Analysis and Trend Analysis to estimate optimal VQ strategies tailored to individual needs and considering Functionality Requirements, while the Prioritization System balances these with group-level requirements.*

II. General System Requirements

Due to the strong influence of visual quality on human circadian rhythm, functionality of spaces and health, especially in the context of extreme environments (e.g. with the absence of a natural circadian rhythm and specific architectural requirements for critical tasks), two areas of system requirements were defined: Functionality Rules (including task-specific requirements, accessibility requirements and circadian requirements) and a Prioritization System (including rules depending on occupant's health condition, similarity of needs and spatial distance between them).

Functionality Requirements determine light settings supporting the current work considering individual needs and accessibility. Depending on the area in the module and the corresponding activity that takes place in this area, standard recommendations for illuminance and CCT can be followed (e.g. 750 lx for regular work, 1000 lx for high-precision work and 500 lx for free time). Depending on the Time of Day (ToD), pre-settings for gradual CCT changes from morning (e.g. CCT of 5000 K), to noon (e.g. CCT of 4000 K) to evening (e.g. CCT of 3000 K) can be used, which aligns with current systems as explained in Chapter 2.1.3. For specific conditions like reduced near vision clarity or reduced depth additional features can be integrated e.g. directional light cones or angled lighting. The **Prioritization System** builds on the functionality rules and balances individual and group-level lighting needs through a multi-objective optimization framework. As mentioned above, the position of the IDs during certain tasks is logged into the system and the distance between them and personal preferences are considered. Another driver for the Prioritization System is the Chronic Stress Level (CSL) which is derived from past data and detailed in Chapter 6.2.3. For all inputs, the system uses a weighted utility function that integrates the circadian, task-specific, and accessibility requirements for each occupant (ID), assigning dynamic weights based on factors such as chronic stress levels, task urgency, and group overlap. In cases of conflicting needs, Pareto optimization (Mahapatra & Rajan, 2020) could be applied to identify solutions that offer the best trade-offs.

6.2.2. Data Architecture

The following chapter explains the different types of data, collection methods and processing for the downstream modules.

I. Types of Data

The system processes three core categories of data: Environmental Data (ED), Realtime Biomarker Data (RBD), and Training Data (TD). Environmental Data includes measurements of light intensity (lux), colour correlated temperature (CCT), spatial light distribution, and other IEQ factors. Realtime Biomarker Data refers to physiological indicators captured from wearables and biosensors, such as heart rate variability, electrodermal activity, or blood pressure. Training Data is composed of pre-collected datasets from the occupants that provide generalizable biomarker responses to environmental stimuli, and it is used for pretraining the Bayesian RL models. These data types form the foundation for both immediate decision-making and long-term personalization.

II. Data Acquisition

Data acquisition is conducted through a combination of environmental sensors and wearable biosensors. Environmental sensors are installed throughout the modules and continuously monitor parameters such as lighting conditions, ambient temperature, humidity, and sound levels. These provide contextual awareness of the environment's impact on users. In parallel, users wear biometric monitoring devices - such as wristbands, smartwatches, chest straps, or EEG headbands - which capture real-time physiological signals. These signals are timestamped and synchronized with environmental data. All data streams are logged in a centralized database for use in both real-time processing and analysis of past data. This dual-channel acquisition ensures both the external and internal states of the user are represented accurately.

Lux meters and spectrometers provide precise measurements of ambient illuminance and CCT. RGB and thermal cameras, together with depth sensors, could reconstruct the spatial distribution of light sources and identify both direct (e.g. screens) and indirect (e.g. reflected walls) illumination (T. Zhang et al., 2022). Through computer vision the orientation of occupants can be detected (Lan et al., 2023). This information can be used to reconstruct their field of view and identify which light sources are within their perceptual cone.

III. Data Fusion

The Multi-Sensor Data Fusion (MSDF) module is responsible for aggregating incoming data from all sources (Muzammal et al., 2020) (visualized in **Figure 21**). Temporal synchronization could be achieved by aligning timestamps across modalities and frequency unification can be used to align different sampling rates. Depending on the type of biomarker, different steps in signal processing (e.g. bandpass filters and outlier removal) can be conducted to reduce noise (e.g. resulting from sensor error or motion artifacts) and ensure smooth signals. Through classification events in the biomarker data could be labelled (e.g. stress vs. recovery). After normalization, sensor values are merged into fused state vectors - high-dimensional representations of the current user-environment system state. These vectors are fed into the Bayesian Reinforcement Learning module for real-time action planning.

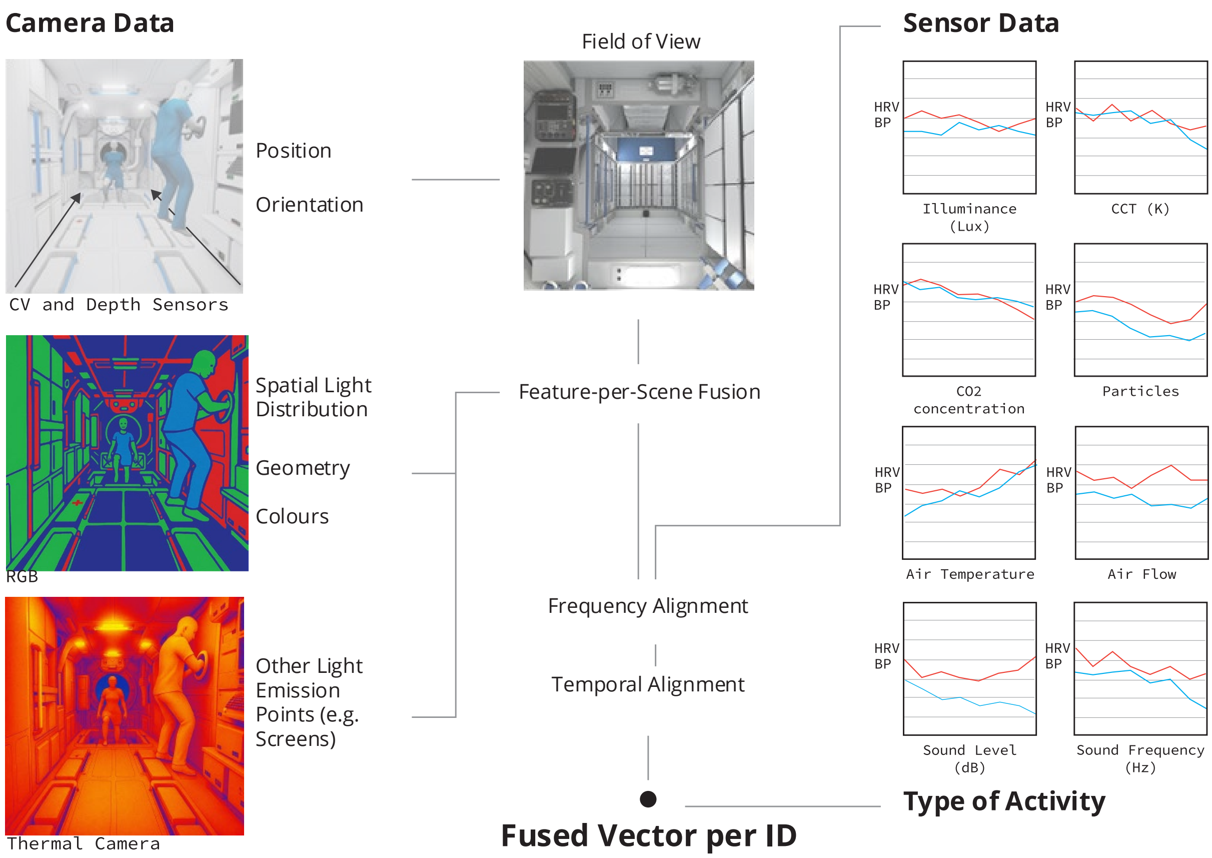

***Figure 21** Overview of Multi-Sensor Data Fusion (MSDF) module: It aggregates and temporally synchronizes data from multiple sources (camera data, sensor data, situational data), applying signal processing techniques to combine datapoints into fused state vectors (using images credited to* (GATEWAY | SpaceArchitect.Org, *2020) and (Norman, 2024)).*

IV. Long-Short-term Memory

The Long Short-Term Memory (LSTM) network functions as the system's temporal memory (Van Houdt et al., 2020), processing sequences of fused state vectors to learn patterns in physiological and environmental data over time. It captures temporal dependencies such as circadian fluctuations, stress recovery dynamics, and gradual biomarker shifts. These insights could be encoded into trend context vectors for a compact, time-aware representations of each user's physiological trajectory. These vectors are needed for downstream modules: they inform the Trend Analysis (module in identifying long-term changes in stress and recovery patterns; they support the State Estimator in computing Chronic Stress Levels (CSL); and they enhance the Bayesian Reinforcement Learning Module by providing historical context for more informed and personalized decision-making.

6.2.3. Biomarker-based Machine Learning

Reinforcement Learning is a type of machine learning. Similar to supervised learning it iteratively processes data optimising a reward function in order to improve a task. In RL the feedback is received in the form of rewards rather than labelled examples. The goal is to discover the optimal strategy, called policy, that maximizes cumulative rewards over time. (Baduge et al., 2022). At the core of RL is the Q-function, denoted as *(Q (s, a) = E [future reward | state s, action a])* which represents the expected cumulative reward the agent can achieve by taking action in state s and following the optimal policy thereafter. This function allows the agent to evaluate the quality of different actions in different situations and improve its behaviour over time through trial, feedback, and learning. Bayesian reinforcement learning (BRL) uses Bayesian methods to explicitly represent uncertainty through prior and posterior distributions over model parameters, value functions, or policies (Wiering & Van Otterlo, 2012). BRL can be particularly useful in the implementation of a neuro-adaptive visual quality system as it is one potential solution to handle complex, uncertain, and interdependent influences on physiological biomarkers. Instead of learning a fixed mapping from state to reward, BRL maintains a distribution over possible models of how visual quality affects biomarker responses. As new data is observed, these distributions are updated to reflect what the system has learned, including confidence and uncertainty. This can help to disentangle overlapping effects of different influences and respond more reliably during stress events. To support this, the system could integrate Bayesian Additive Regression Trees into the Effect Analysis module. Bayesian Additive Regression Trees is a non-parametric Bayesian method that estimates treatment effects with uncertainty (Hill et al., 2020), making it well-suited for modelling non-linear and heterogeneous effects such as how different individuals respond to changes in VQ. It outputs posterior distributions over effect sizes, allowing the system to quantify not only the magnitude and direction of VQ (and other) influences on biomarkers but also the confidence in those estimates. This enables the system to make more informed and individualized decisions, especially when multiple influences act simultaneously.

During acute stress situations - identified by sharp changes in HRV or other biomarkers - the BRLM evaluates the causal impact of recent lighting changes using its embedded Effect Analysis. This module isolates the contribution of VQ features from confounding factors like time of day or physical activity. If the lighting intervention leads to measurable stress reduction (e.g., HRV stabilizes after a warm light shift), the BRLM updates its internal model to assign a higher reward to that lighting configuration in similar contexts. Conversely, if stress is not alleviated, or worsens, the corresponding reward is decreased. Over time, this enables the system to personalize lighting strategies per ID, learning both general rules and individual-specific sensitivities. The reward can be based on direct deltas from baseline values, normalized improvements, or contrasts between lighting conditions (e.g., 2700K vs. 6000K during stress). Furthermore, the BRLM outputs user-to-user similarity scores in lighting response, which feed into the Prioritization System, helping the DS resolve group lighting trade-offs in a health-aware manner.

I. Training Process

The model for the final application can be trained on study data of the users before the start of the field research. This could provide the Q-learning agent with informed initial estimates and reduce the need for random or ineffective exploration. The Q-vectors derived from regression models can serve as informative priors where they are updated over time as new data is observed, allowing the system to balance prior knowledge with real-world learning., enabling the policy to evolve and adapt based on user-specific responses (Clifton & Laber, 2020). While random forests are used in the current implementation due to data constraints, the architecture would use Bayesian models for uncertainty-aware Q-estimation as more data becomes available. A Q-estimator was programmed in Python using the Scikit-Learn library and the study data of both experiments of all eight participants. To extend the dataset, both 5-minute baseline and stress phases per participant per experiment were included and the data were grouped per time of day (9, 11, 15, 17) representing four hypothetical users.

Q-values represent the expected cumulative reward of taking action a in state s, and then following a certain policy. Q-vectors represent what the model believes will happen: they are the outputs of a trained regressor that predicts physiological features like RMSSD and HF for a given combination of settings. These predictions reflect the system's expected response, not its desirability. In contrast, the reward function captures what is wanted (Clifton & Laber, 2020; Reiter et al., 2025): it evaluates real physiological measurements to assign a scalar reward based on specific goals, such as promoting high RMSSD during baseline and minimizing deviations during stress. A simple reward function was applied to the study data that favours high baseline and low deviation under stress.

As mentioned, due to the limited size of the dataset, random forest regression with multiple outputs was used instead of Bayesian models (e.g., Gaussian Processes or Bayesian Neural Networks). The predicted Q-vectors, which represent expected physiological responses (e.g., RMSSD, HF) across conditions could still serve as informative priors for the Bayesian Q-values and could be updated over time. For the Q-vectors based on the study data, multi-output regression was used to predict physiological features (RMSSD and HF) based on CCT and state (baseline or stress) per time of day and to evaluate these predictions using feature-specific reward functions as seen in **Table 15**.

Reward Function	R = baseline – abs(stress-baseline)
Reward Results	CCT 2700K → Reward RMSSD: 44.0, HF: 826.85 CCT 6000K → Reward RMSSD: 36.41, HF: 596.41 Reward for Switching to 2700 K: RMSSD 7.59, HF: 230.44

Table 15 *Reward Function and Results using the Data resulting from the Pilot Study as Demonstration*

For each time of day (ToD), the script fitted a random forest model to predict RMSSD and HF from CCT and state labels. Q-vectors were computed for each CCT and phase (see **Table 16**) and saved in a dictionary which can be used further in a future training process.

Q – Vectors	Q(ToD, Phase, CCT) ≈ Predicted RMSSD + HF	
Time of Day 9	baseline	2700K → RMSSD: 41.65, HF: 445.5, 6000K → RMSSD: 31.01, HF: 227.84
	stress	2700K → RMSSD: 54.73, HF: 490.79, 6000K → RMSSD: 38.2, HF: 399.9
Time of Day 11	baseline	2700K → RMSSD: 60.0, HF: 1703.88, 6000K → RMSSD: 50.57, HF: 1587.11
	stress	2700K → RMSSD: 60.78, HF: 1409.76, 6000K → RMSSD: 49.32, HF: 1156.67
Time of Day 15	baseline	2700K → RMSSD: 41.84, HF: 856.57, 6000K → RMSSD: 32.95, HF: 441.1
	stress	2700K → RMSSD: 42.6, HF: 775.7, 6000K → RMSSD: 33.4, HF: 431.75
Time of Day 17	baseline	2700K → RMSSD: 53.3, HF: 1262.18, 6000K → RMSSD: 46.72, HF: 1120.67
	stress	2700K → RMSSD: 44.12, HF: 836.45, 6000K → RMSSD: 36.01, HF: 597.35

Table 16 *Q-Vectors using the Data resulting from the Pilot Study as Demonstration*

Considering the future application (that needs to align large amount of data in very different scales), local normalization per category (using the minimum and maximum values per time of day) was applied. This makes the comparison of Q-vectors more meaningful and reliable for different features but doesn't mix data that is not comparable due to diurnal changes of HRV or stress response. As shown in **Figure 22**, the divergence between normalized Q-vectors and real values is high. This is expected as the more data would be needed for more reliable predictions and to avoid the need to merge data inter-individually.

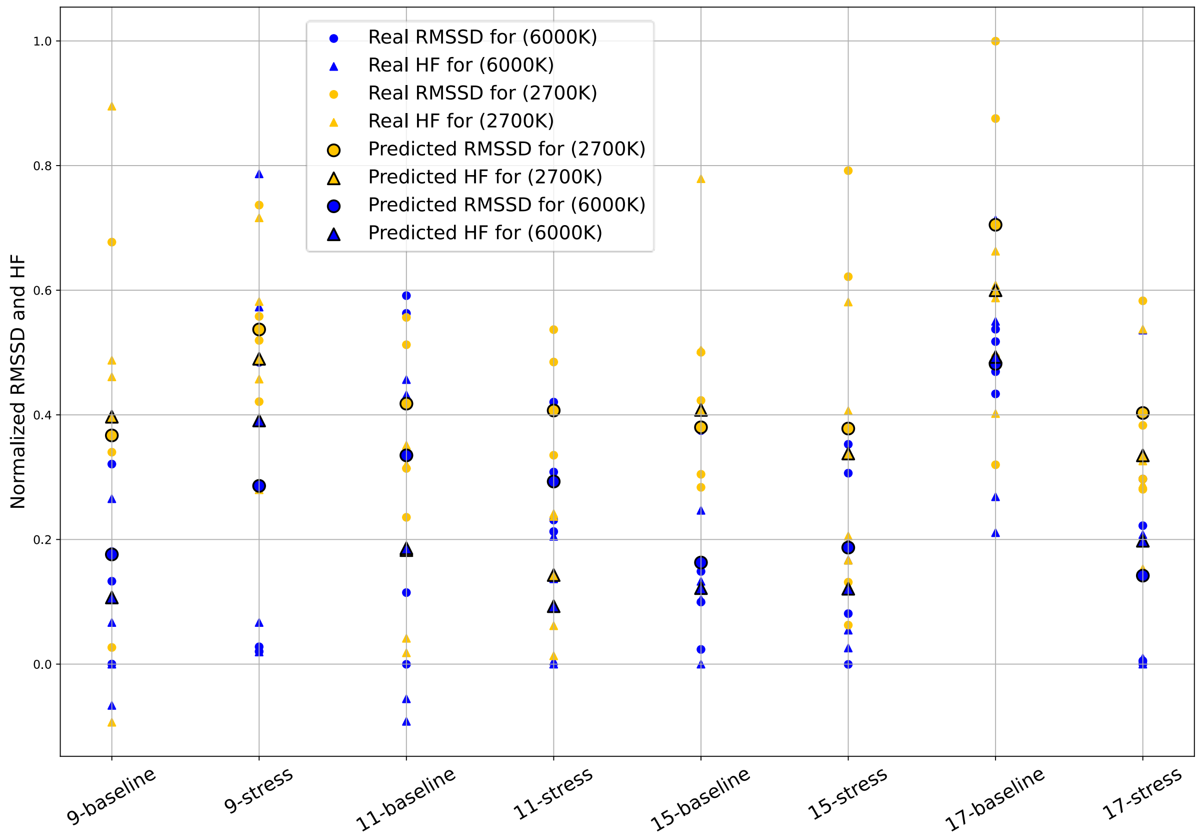

Figure 22 *Locally-normalized Q-Vectors (Predicted Values) and Real Values (Baseline and Stress for each Time of Day)*

The visualization aligns with the findings of the data analysis (Chapter 6.1) showing that HRV was higher in warm CCT. This also did not change by doubling the data through the inclusion of the additional 5-min sequences of each experiment. In contrast to the findings presented in Chapter 6.1, HRV values during the stress condition at ToD 9 were higher than those observed at baseline.

II. Effect Analysis

The Effect Analysis would act as the process within the Bayesian Reinforcement Learning Module (BRLM) that estimates the individual contribution of various influences such as colour correlated temperature (CCT), time of day, and task state on biomarkers like HRV. The analysis uses the fused state vectors from the MSDF as input, which combine real-time biomarker data (e.g., RMSSD, EDA), environmental data (e.g., CCT, illuminance), and contextual data (e.g., task, user ID). The Effect Analysis could use the probabilistic structure of Bayesian models to isolate the marginal effect of each input factor. It can do this by computing the posterior distribution over expected biomarker outcomes when varying one influence (e.g. CCT) while holding others constant (Lorch et al., 2021). The resulting output includes, for each influence, a reward distribution that represents the likelihood of stress reduction or biomarker improvement, along with associated uncertainty (mean ± standard deviation) (direction, magnitude, probability). This allows the system to infer not only the expected effect but also the confidence level in that conclusion. These probabilistic estimates are logged per ID and used to refine future lighting decisions, influence prioritization strategies, and adapt lighting policies under uncertainty. In this system, the Effect Analysis module can account for both independent and dependent influences on biomarker responses. When influences like CCT and time of day are independent, their effects can be estimated separately and combined additively; but when they are interdependent, the Bayesian model captures their joint effect through multivariate inference or interaction terms, allowing the system to adapt lighting decisions based on how specific combinations of factors uniquely affect each user's physiological state.

III. Trend Analysis

The Trend Analysis uses the trend context vectors from the LSTM and longer biomarker histories to identify chronic patterns such as: Persistent changes in HRV-baseline (and other biomarkers), changes in acute stress reaction and changes in recovery effectiveness. This is shown on an augmented dataset resulting from the study on HRV and CCT, seen in **Figure 23**. These trends are used to compute a Chronic Stress Level (CSL) per ID via the State Estimator, which contextualizes acute decisions with a long-term health perspective. For example, if one user is showing chronic stress deterioration despite neutral immediate responses, the DS may prioritize their needs more heavily. The CSLs and trend vectors are also used to update the BRLM's priors, improving its ability to forecast outcomes in more nuanced ways. Similar to the data analysis (Chapter 6.1.3), the data can be categorized into baseline (normal state), stress (triggered by distinct reactions in biomarkers and detected by the system) and recovery (automatically marked by the system following stress), as well as the relative changes between the three states.

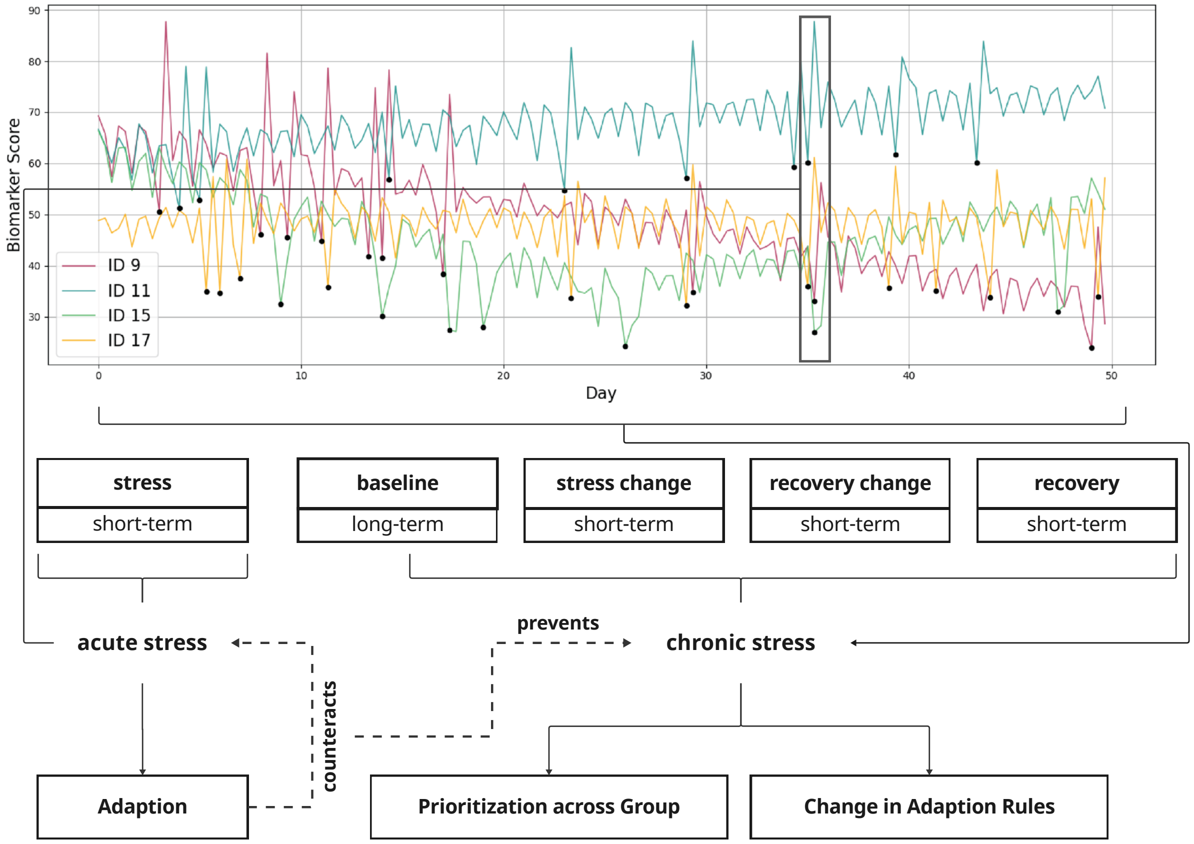

Figure 23 *Trend Analysis Rules shown on the Augmented Data resulting from the Study*

IV. System Output

The system uses real-time biomarker data, real-time environmental data and past biomarker trends to recommend CCT, illuminance and light distribution per actuator considering functional requirements, priority of users and accessibility. Fused state vectors from the MSDF, representing the current state, along with priority estimations derived from trend analysis of the database inform the learning of the state-value and action-value functions. The reward function, fed by new environmental data and changes in biomarkers resulting from architectural adaptation, generates rewards used to update the Q-vectors including direction, magnitude, probability resulting from the effect analysis. These Q-values guide the optimization of the policy, enabling the system to learn adaptive responses that improve physiological outcomes over time.

6.2.4. Summary of Future Application

The chapter shows how future systems could use the data of cross-sectional studies and collect longitudinal data by combining application and field research and mentions examples of computational techniques to achieve the objectives of the system. For this, the four main systems use environmental data derived from a range of cameras and sensors, and biomarker data to derive health trends per person and results on the effect of isolated features. The probability distributions are used to further improve the model which informs the adaption of the visual quality. For this system, the following aspects - that were identified as short-comings of cross-sectionals studies in this area - were applied.

A **high-resolution sensor architecture** captures real-time data from the user's field of vision, enabling a more precise understanding of environmental exposure over a long duration of time. **Biomarker data is aligned with individual experiences** through the integration of environmental embedding (fused state vectors) and situational context (trend context vectors), ensuring a personalized and context-aware analysis that is considering the range of potential influences (which is not possibly in lab experiments). The system also accounts for the **functional requirements of tasks**, making the integration of the research into real applications more feasible and simultaneously exploring how stress-counteracting can be aligned with functional requirements which tests how easily neuroarchitecture and limitations (especially in extreme environments) can be aligned. Furthermore, **accessibility considerations** are taken into account. This is pivotal for any research in order to produce results relevant for a large group of users. Depending on vision impairments or temporary injuries (which gain even more relevance in extreme environments where an increased risk for injuries might be combined with limited options for treatment) visual quality is perceived differently or non-visual effects of light act differently. Finally, it addresses the inherent **ambiguity in environmental effects by applying probabilistic modelling**, allowing for more nuanced and adaptive responses to complex conditions.

7. Discussion and Outlook

The following chapter summarizes the work and specifically the user study conducted as part of this thesis and details the conclusions drawn from this for future research and its application.

The objective of this thesis was the development of a proof-of-concept methodology for the investigation of visual quality of architecture as countermeasure to physiological stress response in extreme environments resulting in the proposed research framework. The small-scale study on CCT and HRV does not deliver general conclusions on the influence of CCT on HRV due to the short experiment duration and small number of participants (further limitations are listed in Chapter 1.5). Instead, the study explored the application of the methods developed as part of the framework. The results provide a basis for future studies exploring how individual architectural needs could be investigated with a higher number of participants, control groups, a higher number of experiment runs per person, and a more advanced, reliable stressor simulation. An overview of the objectives and the most relevant methods that were explored are seen in **Table 17**.

Objective	**Countermeasure Investigation**	**Inter-Individuality**	**Functionality Alignment**	**Isolation of Effects**
Purpose	Prevent chronic stress by reducing acute relative stress reaction through VQ	Individual baseline/reaction to stressors as well as environment	Relevant for application especially in extreme environments	Reliability, application of results, estimates for individual analysis
Method in Cross-sectional Study	Transient stressor simulation (psychological stress test like MAT)	Multi-criteria-decision-analysis, Two experiments per person at the same time of day	Investigated feature combined with functionality e.g. high illuminance in combination with different CCTs in experiment design	Bayesian linear effects models
Potential Method in Field Study	Repetitive experiments or real-life stressors	Trend analysis, state estimator	Functionality requirements	Bayesian RL, Effect analysis

Table 17 *Overview of Objectives resulting from the Research Questions and used Methods to address them*

7.1. Interpretation of Analysis Results

As explained in previous chapters, HRV is complex and different features and their meaning in the situational context and context of health must be considered carefully. Baseline-HRV as well as acute stress reaction (in general as well as reaction to the chosen stress test) is very individual. Further, the residual standard errors (especially of the BLEMs for relative change) very unusually high. Therefore, more data is needed for generalizable results. The analysis of the collected data showed the following.

I. Influence of Order

As stated in Chapter 6.1.1, not all participants showed a decrease in HRV during the stress phase. On average, participants that showed stress-related HRV decrease during the first experiment run, still showed clear stress-related decrease in HRV the second time. Nevertheless, the linear effects models for relative changes showed an effect of experiment order on the results indicating reduced stress reaction during the second time. This aligns with the research indicating an influence of the familiarity with the stress test, rather than studies suggesting its irrelevance (Barthel et al., 2025; Boesch et al., 2014; Jönsson et al., 2010; Pulopulos et al., 2018). Participants still showed a stress-reaction the second time, just a less significant one. For both, the baseline-to-stress change and stress-to-recovery change, the order was more influential than the choice of CCT, which is a relevant methodological finding for future neuroarchitectural studies using individual-level data evaluation.

II. Influence of Time of Day

The time of day during which the experiments took part showed a clear influence on HRV. In both CCTs, the HRV of all participants followed a certain pattern (higher in the morning, lower in the afternoon) which could related to diurnal HRV fluctuations (Sammito et al., 2016). Alternatively, it could be connected to the coincidental correlation between high PSS scores (level of stress experienced in the last month) and experiments in the afternoon, and low PSS scores and experiments in the morning, since constant levels of high stress can contribute to lower HRV (Immanuel et al., 2023b).

III. Influence of CCT

HRV features for all three phases were higher in warm CCT. This doesn't align with findings from previous studies on blue light increasing HRV (Litscher et al., 2013; Petrowski et al., 2023; Schäfer & Kratky, 2006). This could be attributed to individual reaction that is not providing reliable results due to the small number of participants, or it could be a result of interaction effects with the high illuminance. Even though, this was kept constant in both CCTs, different combinations of illuminance and CCT can yield different effects as shown by the study by (Luo et al., 2022), summarized in Chapter 5. In this research, warm CCT caused a 5% less severe baseline-to-stress change, while blue CCT created a 19 % higher stress-to-recovery change. While it is not feasible to provide a definitive explanation for the increased HRV under warm CCT or the enhanced stress recovery under blue CCT - particularly given the limited sample size and lack of replication, which constrain the generalizability of these findings - several plausible mechanisms may underlie these results: Warm CCT aligns more closely with natural light during sunrise and sunset, supporting circadian rhythm regulation and melatonin production both of which are associated with improved autonomic balance (Blume et al., 2019). Additionally, warm lighting tends to reduce psychological stress and arousal compared to blue CCT (which has shown to increase alertness), thereby lowering sympathetic nervous system activity (Westerink et al., 2011). The ambiance which could be considered “cozy” created by warm CCT that is often used in relaxing environments like homes could by contextual association contribute to better mood and emotional regulation, which has shown to further support higher HRV (Grol & De Raedt, 2020). The higher HRV-recovery in blue CCT aligns with previous research that suggests accelerated relaxation may be enhanced under blue-enriched CCT. This effect has been attributed to blue light’s ability to modulate autonomic nervous system activity and reduce physiological arousal (Minguillon et al., 2017).

The main findings include:

1. Participants exhibited higher absolute HRV values - including baseline, stress, and recovery phases - under warm CCT, suggesting a generally more relaxed physiological state.
2. However, warm CCT failed to clearly act as a countermeasure to stress, with only a modest 5% reduction in the stress reaction.
3. Despite lower absolute HRV, in blue CCT a more pronounced relative increase in HRV from stress to recovery was observed, indicating a potentially sharper rebound effect.
4. As expected, HRV responses to the stress test varied strongly between individuals and time of day which substantiates the original assumption that comparing results per-person - on the individual level - yields more meaningful results on the influence of the VQ feature on HRV during stress.
5. Repeated exposure to the same stress test reduced its effectiveness in eliciting a consistent HRV-change and was more influential on the results than the change of CCT which is a relevant finding for future neuroarchitectural studies focusing on individual-level data evaluation.
6. As more data becomes available, the probability distributions of the direction and magnitude of variables influencing the results - derived from the group-level effects analysis - can be used to inform the interpretation of data on the individual level.

An overview of the main findings is shown in **Figure 24**.

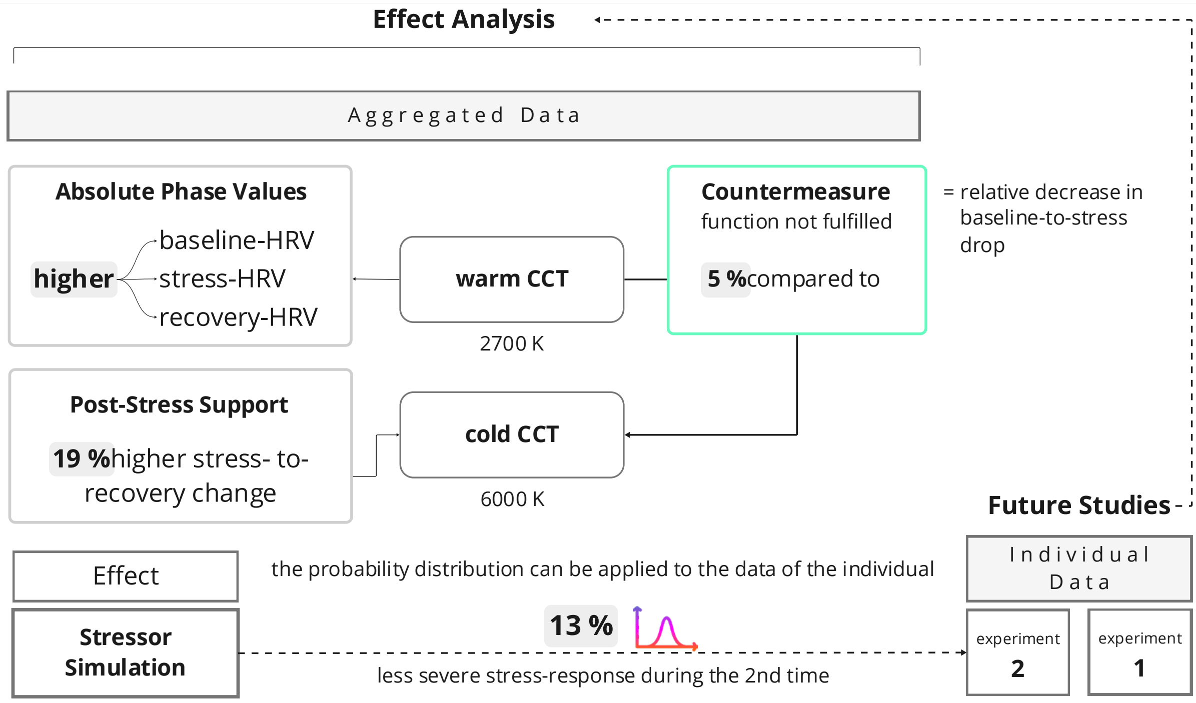

***Figure 24** Summary of the Results from the Pilot Study on CCT and HRV including: higher HRV in warm CCT, a slightly reduced stress of only 5 % in warm CCT compared to cold CCT - not fulfilling the objective of a countermeasure -, a stronger HRV rebound from stress to recovery in cold CCT, repeated stress test exposure reduced test effectiveness, HRV responses varied strongly by individual and time of day, supporting the need for person-specific analysis and the potential usefulness of group-level data to interpret individual-level results as more data becomes available in the future.*

Further Remarks: The large variations shown in the high standard deviations across RMSSD and HF between participants in both CCTs agrees with prior assumption that a per-participant comparison is more meaningful than across-participants comparison. Not only baseline-HRV but also stress reaction to that chosen test is individual and varies for each participant. Further, it must be mentioned that the HRV for one participant was unusually high and for another participant unusually low. For each, this was stable during both experiments (suggesting it was not a technical problem with the ECG) and it was decided not to exclude them.

Further Analysis: Future analyses of the data collected in this study could involve comparing first-time experiments with second-time experiments, rather than merging the two datasets in one computational model. It may also be beneficial to apply linear effects models separately for each CCT to examine how the magnitude or direction of effects varies across them. Likewise, incorporating phase transitions as fixed effects could yield more insightful results than the current linear effects model for relative analysis. Additionally, further exploration of perceived stress and workload (PSW) and cognitive performance (CP), and how they align with the current findings, could provide valuable insights. Each of these methods would profit form a larger data sample including a higher number of experiment runs per person.

7.2. Future Research and Application

The thesis could only provide a limited exploration of the topic due to constraints in scope/resources, time, and participant number. While it offers initial insights into the relationship between stress responses, visual quality features, and adaptive environmental systems, further research is necessary to validate and expand upon these findings. The developed concept for future field research provides relevant considerations and technical requirements but will require further exploration in the future.

7.2.1. Identified Challenges

This sub-chapter summarizes identified challenges in cross-sectional studies on this topic and details theoretical challenges in a future application.

I. Cross-sectional Research

Further research is needed to determine **which is the best method to compare different stress tests for this type of research**, particularly when conducting multiple experiments with the same individual at various times of day. It remains unclear whether variations of the same test or entirely different stress paradigms yield more reliable insights into diurnal stress responses. Increasing the number of experiments per participant could enhance the robustness of findings, but it also raises questions about test fatigue, adaptation, and the comparability of results. A more advanced experimental setup would involve a **broader range of VQ features** and investigate their interplay. While the pilot study of this thesis used static CCT settings, in the context of acute countermeasures, studies including **immediate adaption of VQ** to stress reaction are needed as well as more spatially versatile environmental adaptations. In the current study, participants had corrected vision but exhibited varying degrees of visual impairment. For future work in neuroarchitecture, it is essential to include a **wide spectrum of visual impairments** to better understand their influence on both the visual and non-visual effects of light. This would help ensure that adaptive systems are inclusive and accurately reflect the sensory diversity of real-world users.

II. Field-based Research and Application

Despite the potential, a range of challenges that need further consideration and research must be taken into account. One of the key challenges lies in the **translation and reliability of the training model based on the available study data**, as there is a notable discrepancy between the controlled study conditions and the intended real-world use cases. More representative data to enhance model robustness is needed if pre-training of the system is desired. Additionally, the **practicality of wearing sensors throughout the whole day** depends on user acceptance and poses risks regarding signal quality and resultingly reliability (if sensors move throughout the day etc.). This emphasizes the difference between the application in field research (as detailed above) and broader, generalized use e.g. in hospitals where constant real-time monitoring is not possible and results from lab and field studies must be drawn upon. Another complication involves the **negative association between VQ settings and specific situations such as stressful events**. If certain settings have proven to reduce stress but are applied every time stress occurs it is possible that the user will subconsciously associate the visual quality settings with stress thereby diminishing the stress-reducing effect over time. This potential "wear-down' effect must be investigated further. Also, the question **whether compromises between individual preferences still positively contribute to biomarkers remains unclear** till clear usage patterns and preferences and resulting compromises have been tested long-term. Attention must also be paid to understanding how continuous or interrupted exposures to customized **CCT settings affect natural circadian regulation**. This is especially relevant in the context of microgravity or Antarctica, where the circadian rhythm is not supported by natural light and the artificial support of it is already challenged. Furthermore, **data privacy** remains a critical concern and must be addressed to ensure user trust and regulatory compliance. General factors like financial and other expenses needed for the implementation, overall user acceptance and - in the context of extreme environments – transport of components, of course play a crucial role in determining the feasibility of widespread adoption and must be investigated further. The proposed system set-up must be further detailed, tested and adapted.

Accounting not only for **temporal but also for physiological adaptations**, such as those associated with Spaceflight-Associated Neuro-ocular Syndrome (SANS) and general accessibility is needed for reliable, inclusive systems that account for usability with (temporary) impairments and thereby provide higher safety. In addition, **minimizing changes to existing system set-ups**, such as adapting it for use in hospitals or the International Space Station, is essential. Strategies must be developed **to accommodate different spatial layouts** and operational requirements, such as those found in surgical rooms, and effect analysis should be conducted to inform future design improvements. More **research is also needed on baseline groups** to ensure that findings are generalizable to a broader user population. In the future, a **larger set of VQ features** (e.g. including colour chromaticity of light, material colour/reflectivity, colour contrasts, geometric shapes, or light source position) can be considered as adaptive elements. If sufficient longitudinal field research is conducted using a system like the one described - capable of real-time biomarker monitoring and environmental analysis - and the resulting data proves to be reproducible, it could be applied to other settings such as hospitals. These environments may share similar stressor levels but lack the infrastructure for such detailed analysis, making the transfer of validated insights especially valuable once transferability or generalizability is validated through reproducibility of results.

7.2.2. Future Directions

While short-term stressor simulation in the specific context of architectural countermeasure investigation poses the potential to test counteracting effects, the results and their reliability should be explored in next steps with a long-term (repetitive or continuous) stressor simulation. As mentioned, HRV is a very dynamic biomarker and influenced by a wide range of physiological and environmental factors which causes fluctuations over short and long timescales. Though the countermeasure effect can be approximated through the methodology used in the pilot study, overall autonomic function must be investigated over a longer duration. The thesis study is a fragment of the roadmap on which future research can build shown in **Figure 25.**

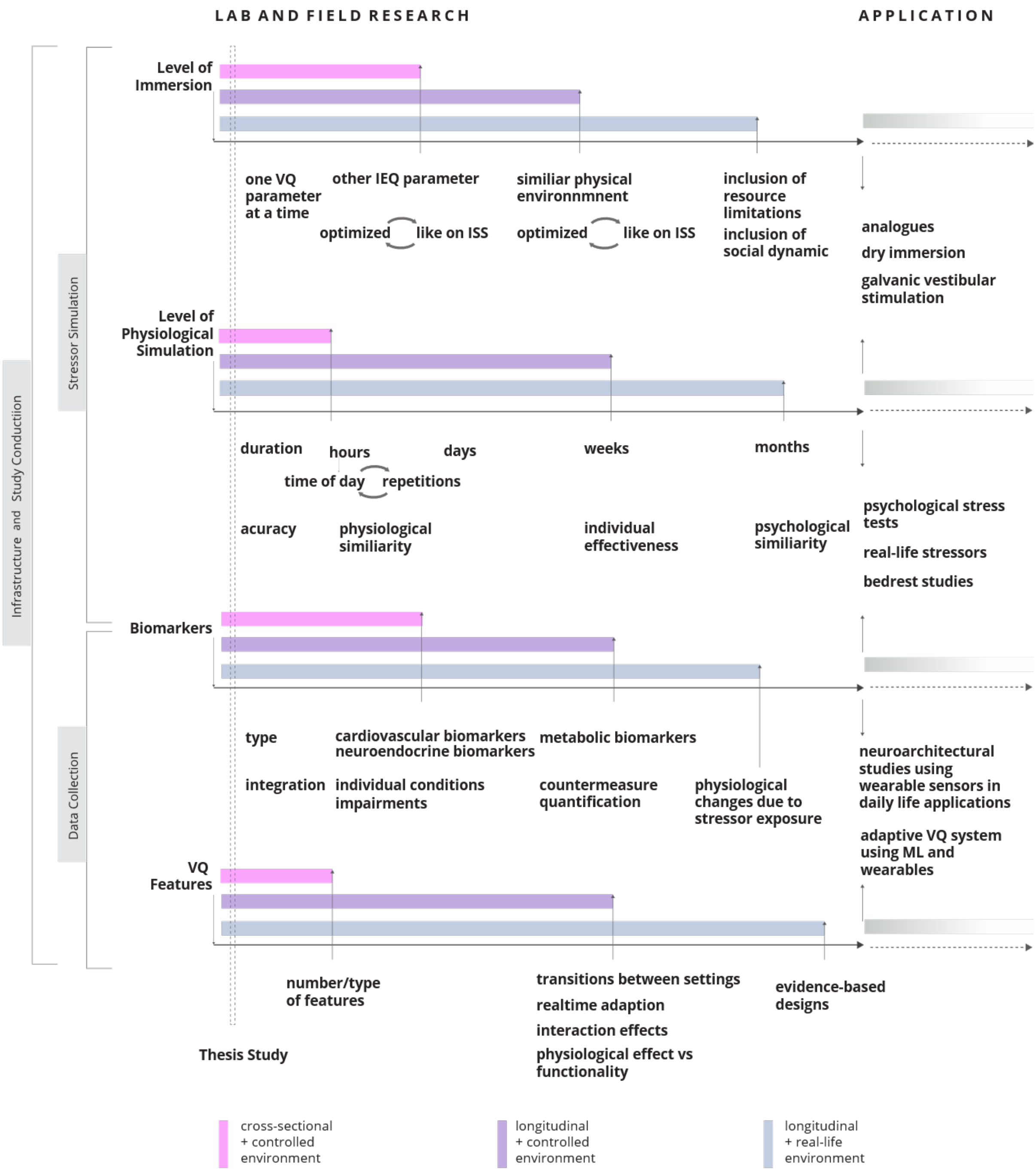

***Figure 25** Future Research Roadmap showing a potential progression from controlled lab and field research to real-world applications of the results with four core dimensions: level of immersion, level of physiological simulation, biomarkers, and visual quality features across a timeline.*

The roadmap illustrates a potential progression from controlled lab and field research to real-world applications of the results. It shows four core dimensions: level of immersion, level of physiological simulation, biomarkers, and visual quality features across a timeline. These research efforts are categorized into three primary study designs: cross-sectional studies in controlled environments, longitudinal studies in controlled settings, and longitudinal studies in real-life environments. As studies advance, the level of immersion can be increased through multiple environmental parameters to simulate conditions similar to the real-life environment (e.g. those on the ISS), ultimately incorporating resource limitations and social dynamics. Parallel to this, the level of physiological simulation progresses from short-duration experiments that aim for physiological similarity, to longer-term exposures that achieve higher similarity across different systems through more complex and realistic stressor simulations. These simulations extend across various timescales allowing for repeated measures and improved accuracy in mimicking individual effectiveness and adaptive responses. The number, type and combination of biomarkers can evolve over time to include metabolic biomarkers and the quantification of countermeasures, tracking physiological changes that result from sustained stressor exposure (e.g. repeated use of stress tests) and general accessibility. The investigation of VQ features should not only be extended through different types of features but consider interaction effects, real-time adaptation, and the relationship between physiological effect and required functionality in the context of use. Different methods serving objectives of the different dimensions are shown at the intersection of research and applications including analogues, novel methods to create a feeling of weightlessness like galvanic vestibular stimulation and dry immersion studies; the use of different and more suitable stress tests, daily-life stressors in the context of field studies and bedrest studies; and neuroarchitectural research using wearable sensors in real-life settings, as well as adaptive VQ systems that apply machine learning and physiological data for smart adaption systems.

8. Conclusion

The thesis investigated the topic of visual quality of architecture and its potential effectiveness as countermeasure to stressor exposure in extreme environments. This was achieved by 1) an extensive literature review analysing the state of the art, extracting the ways in which physical architecture and indoor environmental quality have been investigated in relationship to stress, 2) the development of a research framework focusing on the most relevant challenges in this type of research, 3) the conduction of a pilot study applying the framework focusing on study design (infrastructure, stressor simulation, study conduction, data collection) and study outcomes (data analysis and future data application).

Specifically, the focus was on colour correlated temperature and heart rate variability during stress investigated through cross-sectional research taking into account inter-individuality, diurnal fluctuations of HRV and feasible stressor simulation. As part of the pilot study, each person participated twice (at the same time of day) in the experiment lasting 40 minutes each. The participants HRV was recorded through an ECG during the baseline phase, stress phase (using a mental arithmetic test) and recovery phase. In addition to the HRV and basic physical data, the participant's stress over the last month, chronotype, perceived stress/workload during the experiment and performance in the test was collected.

The most relevant observations include: Participants exhibited higher absolute HRV values - including baseline, stress, and recovery phases - under warm CCT, suggesting a generally more relaxed physiological state. However, warm CCT failed to clearly act as a countermeasure to stress, with only a modest 5% reduction in the stress reaction. Despite lower absolute HRV, in blue CCT a more pronounced relative increase in HRV from stress to recovery was observed, indicating a potentially sharper rebound effect. As expected, HRV responses to the stress test varied strongly between individuals and time of day which substantiates the original assumption that comparing results per-person - on the individual level - yields more meaningful results on the influence of the VQ feature on HRV during stress. Repeated exposure to the same stress test reduced its effectiveness in eliciting a consistent HRV-change and was more influential on the results than the change of CCT which is a relevant finding for future neuroarchitectural studies focusing on individual-level data evaluation. As more data becomes available, the probability distributions of the direction and magnitude of variables influencing the results - derived from the group-level effects analysis - can be used to inform the interpretation of data on the individual level.

The thesis could only provide a limited exploration of the topic due to constraints in scope, time, and participant number and diversity. It does not provide generalizable results. Instead, it offers initial insights into the relationship between stress responses, visual quality features, and adaptive environmental systems, further research is necessary to validate and expand upon these findings. Future studies should include a broader range of stress test types, more diverse participant profiles

- particularly with varying visual impairments - and more advanced adaptive systems to fully understand the complex interplay between environmental stimuli and physiological stress regulation.

The following section summarizes the answers to the research questions found as result of this thesis. To **address inter-individual differences and capture dynamic biomarker changes in combination with stress during a cross-sectional design study,** each participant was assessed twice under standardized conditions, improving reliability despite a limited sample size. Data collection was scheduled at the same time of day to control for diurnal variation in heart rate variability. Both baseline and recovery phases were recorded, enabling relative comparisons in response to stress. The chosen stressor simulation (MAT) was selected based on its documented effects on HRV and its practicality in repeated measures, demonstrating effectiveness even when applied twice to the same participant. Cross-sectional design studies investigating architecture as countermeasure to stress can focus on recreating not the architectural environment but the physiological situation in combination with the isolated design feature that is investigated considering reliability of short-term biomarker measurements, individual response and the effect of confounding variables. Future studies should include more experimental repetitions to ensure reliable data. However, this increase leads to greater familiarity with the stress test for the participant, likely affecting results.

To manage cause-effect ambiguity resulting from the dynamic nature of biomarkers for an increasement of result reliability a computational analysis using different models was developed in Python. The scripts for the models (correlation analyses, multi-criteria decision analyses and Bayesian linear effects models) provide an efficient tool to analyse patterns on the participant and inter-participant level. Individual feature-wise comparisons for HRV during the three phases and changes between them including data on their perceived stress/workload during the experiment and performance in the test can be extracted per person. Different Bayesian linear effect models can be used to estimate the effect of different variables on HRV. This way the influence of the time of day for the experiment, order (if it was the first or second time) and most importantly CCT can be quantified and visualized. Of course, the models still hinge on certain data sizes to be meaningful which was limited as a result of the small number of participants. Nevertheless, their use helps increase reliability and understandability of data resulting from cross-sectional experiments. The relative effect of different confounding variables (especially the use of the same stress test twice) found by the analysis of the data from all participants (assuming the number of participants is significantly higher in future studies) can be applied to the interpretation of individual results. This will be particularly important for future studies that conduct a higher number of experimental repetitions to collect reliable data on individual response to the potential countermeasure, as suggested in the previous paragraph.

The findings of this and similar lab experiments can be further developed in longitudinal research and applied in extreme environments by considering the following aspects: High-resolution sensor architecture that captures continuous data from the user's field of vision to monitor long-term environmental exposure, biomarker alignment to environmental embeddings and situational context vectors to personalize analysis based on individual physiological responses, task functionality that considers the functional requirements of tasks to ensure practical integration into real-world applications, accessibility considerations that account for diverse user needs, including vision impairments and temporary injuries, to ensure inclusive design and probabilistic modelling to manage ambiguity and support adaptive, context-sensitive responses. Further, the training data used to pre-train the model before the beginning of its application should be larger than the one provided by the pilot study of this thesis. This increases the prediction precision for different times of day considering individual baselines.

The answers to the three sub-questions (above) provided by the pilot study and computational analysis in combination with the developed research framework yield the answer to the main research question, **neuroarchitecture can be used in the investigation and application of visual quality as countermeasure to stressors in alignment with functional requirements of architecture in extreme environments.** The methods used in neuroarchitecture can be applied for research concerning visual quality to find potential meaningful relationships between architectural element and biomarker changes during stressor exposure. Thereby, inter-individuality, circadian rhythm and fluctuations related to other confounding circumstances, transient effects of stress introduction and effects of the study design on the dynamic data must be considered. By focusing on results per-participant instead of trying to find patterns across groups with potentially with different baselines, reliability for the results for the individual can be increased. When combined with common clinimetric approaches, the biomarker data can offer more meaningful insights when interpretated together with the perceived stress. The use of different computational models can help further reduce the noise and uncertainty of the data. By automizing the individual-level analysis offering different features for data comparison and by applying statistical models to find insights on the effects influencing the results, research on high-uncertainty independent variables (like visual quality features) and very dynamic dependent variables (like biomarkers) can receive more value. As mentioned before, longitudinal data collection extending the range of different dimensions relevant (level of immersion, stressor simulation, chosen biomarkers and visual quality features) is pivotal for the potential future application of architectural elements aligning with functional requirements in extreme environments and being strategically applied as part of a countermeasure system. This way, neuro-adaptive architecture could help prevent long-term health consequences arising from continuous stressor exposure by acting as acute countermeasure to help prevent the progression towards malfunctional allostasis.

9. Reflection

The goal of this thesis was to explore the effectiveness of visual quality as countermeasure to stressor exposure. For that, a research framework was developed identifying research gaps and challenges relevant for the topic, a pilot study was conducted and the resulting data analysed according to the framework. Further, a potential application was detailed.

Graduation process: The thesis is on the topic of adaptive visual quality of architecture as countermeasure to stressor exposure in microgravity or other extreme environments. Therefore, it aligns well with the research in the Design Informatics group and the Lunar Architecture and Infrastructure graduation studio at TU Delft. By employing computational techniques to evaluate experimental studies in the context of human spaceflight, this thesis is consistent with the typical methodologies and objectives of both studios. The relation to the track Building Technology and the master programme AUBS is shown in the work by uniting different, relevant research areas (like architecture in extreme environments, neuroarchitecture and adaptive architecture), thereby demonstrating the relevance of interdisciplinarity for solving complex architectural problems which is at the core of this track.

The thesis started out with a broad focus considering many different aspects of architecture/indoor environmental quality and a large range of biomarkers and their role for human allostasis. While in the early stages of the thesis, the focus was centred around human spaceflight, the deeper engagement with the topic revealed increasingly more commonalities between different potential application cases. For the feasible implementation of a user study, the focus was narrowed down to one VQ feature and one biomarker. From the beginning it was clear that the study's objective is to demonstrate/test the methodology but that it cannot deliver results on the relationship of stress, CCT and HRV. This was achieved successfully. The data were used for the computational analysis focusing on inter-individuality, the influence of confounding and independent variables and the repeated use of the same stress test. The results show a potential relationship between higher HRV during stress and warm CCT but most importantly they successfully tested the methodology and revealed relevant follow-up questions and potentials for future work. They also reinforce that more extensive, longitudinal data collection is needed for defining individual VQ settings that can potentially counteract stress. The computational models have proven valuable in analysing complex, cross-sectional data and provided certainty on needed next steps.

The study followed a bottom-up approach by demonstrating feasible neuroarchitectural research set-up that focuses on the most relevant aspects/challenges in a practical way. The methods selected for this thesis proved effective in achieving the research goals, despite known limitations. Although the short timeframe was taken into account at the beginning of the project, the planning, organization, and execution of the user study required more time than initially anticipated and required an additional reduction of the study scope throughout the course of the thesis. Finding a specialized lab, as well an ECG, which is not a standard-device in architectural research, showed to require more time and planning as expected. Nevertheless, the integration of data collection on HRV and CCT combined with the computational analysis enabled an in-depth exploration of the subject matter. The resulting findings would not have emerged from a combination of theoretical framework development and adaptive system design based solely on existing or synthetic data. Further, the search for a lab and ECG led to engaging with many researchers, different universities and projects. This technical exchange –explaining the planned research of this thesis to experts in lighting research or psychology and learning about a range of other related work - was very enriching. Being able to get the feedback from researchers at TU Eindhoven and the German Space Agency was very valuable in steering this very interdisciplinary work. This exchange, as well as extensive literature research throughout the course of the last seven months shaped the final direction of the work. In the beginning the thesis was very focused on architecture in microgravity. The final work focuses on the similarities of different architectural settings that can cause extreme stress for the individual and on the strengths that can result from examining them collectively.

In **Table 18**, a SWOT analysis is shown that summarizes strengths, weaknesses, opportunities and threats of this work.

Strengths	• Reusable framework considering complex challenges • Method can be applied to other VQ features and other non-invasive biomarkers that can be measured in real-time • Collection of new data using exploratory methods (bottom-up-approach) • Per-person comparison increases meaningfulness
Weaknesses	• Small number of participants • Challenges in data comparison due to different times of day for different participants and number of experiments (two) per person
Opportunities	• Several potential use cases • Can contribute to the emerging field of neuroarchitecture • Stronger focus on accessibility focussing on vision impairments
Threats	• Level of inter-individuality could be too high to find generalizable/reproduceable results in the future • Potential high resource-demand for longitudinal, high-level research extending the pilot study of this thesis

Table 18 *SWOT Analysis of the Thesis Research showing the Strengths, Weaknesses, Opportunities and Threats of this work*

The thesis achieved its planned level of innovation by combining state of the art research from a range of different disciplines - architecture and indoor environmental quality, extreme environments (specifically human space flight), physiology and stress research, psychology, statistics, and machine learning. Especially in the context of human space flight, neuroarchitecture is not an established tool even though it aligns particularly well with the demand and limited resources. Considering the strong foundation of research showing the negative influence of architecture can have on human wellbeing, the combination of that knowledge with research about the influence of extreme environments yielded the novel idea to investigate architecture as countermeasure. The potential of using the means of architecture, which inevitably surround us as tool to mitigate the stress pandemic would be of high societal value.

Concerning the ethical aspects of this work, the following factors should be considered. All participants provided informed consent after receiving clear, accessible information about the study's aims, procedures, and potential risks. Given the sensitivity of biomarker data, strict measures were implemented to ensure confidentiality, including pseudonymization and secure data storage. Ethical approval was obtained from TU Delft's Human Research Ethics Committee.

Societal Impact: The study findings and the research framework are applicable for future research that can be useful for many applications that relate to extreme environments and other situations entailing unavoidable stressors for occupants. Findings in this field can inform the design of adaptive architecture in confined environments (such as remote research stations), high-stress settings (like hospitals), and everyday environments such as student housing and office buildings. Although the research does not directly address sustainability measures in the built environment, data on human stress response related to architecture can inform decisions about which comfort measures are essential, and which are expendable. These insights can support resource-efficient design strategies.

Extensive further research is essential before practical application, particularly to address the challenges of inter-individual variability, the complex interplay of environmental and psychological factors, the isolation of specific architectural effects, and the reliability and generalizability of results across diverse populations, abilities, and impairments. Future field research like the concept detailed in Chapter 6.2, must consider ethical and save data protection measures before going any further. While it focuses on a small number of persons at a time, the inclusion of a diverse range of needs and abilities is pivotal for results meaningful to society.

The potential of using the means of architecture - which inevitably shape and surround our daily experiences - as a tool to mitigate the ongoing stress pandemic holds immense societal value. If architecture, a non-intrusive, side-effect-free resource can mitigate chronic stress, which if left unaddressed can lead to a wide range of long-term health consequences, it should be explored further. By intentionally designing built environments that reduce sensory overload, promote restorative experiences, and support emotional regulation, architecture can serve as a preventative health intervention. This approach not only enhances individual well-being but also contributes to reducing the societal challenge of stress-related illnesses, making it a consideration in public health.

The derived findings relating to the methodology, study results and computational analysis can be used as foundation for further investigations. The project can contribute to future research and architecture by bringing attention to and contributing to findings about the potential effectiveness of architectural elements as countermeasure to stress to avoid long-term health effects. Ultimately, this research underscores the importance of integrating neuroarchitecture into everyday spaces as well as architecture in extreme environments, while focusing on the challenges ahead for future research that can inform the design of environments that not only serve functional needs but also actively support human resilience.

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11. Appendix

A	Feature	Preferred	Score
	RMSSD	Yellow	0.044
	pNN50	Yellow	0.117
	HF	Yellow	0.078
	HF/(LF+HF)	Yellow	0.136
	CP	Blue	-0.208
	PSW	Blue	-0.029
			Yellow
A	**Feature**	**Preferred**	**Score**
	RMSSD_Δ_BL_STRESS	Blue	-0.234
	RMSSD_Δ_STRESS_RECOVERY	Blue	-1
	PNN50_Δ_BL_STRESS	Blue	-0.184
	PNN50_Δ_STRESS_RECOVERY	Blue	-1
	HF_Δ_BL_STRESS	Blue	-0.384
	HF_Δ_STRESS_RECOVERY	Blue	-1
	HF/(LF+HF)_Δ_STRESS_RECOVERY	Blue	-0.565
	HF/(LF+HF)_Δ_BL_STRESS	Blue	-1
			Blue
B	**Feature**	**Preferred**	**Score**
	RMSSD	Yellow	0.128
	pNN50	Yellow	0.247
	HF	Yellow	0.154
	HF/(LF+HF)	Blue	-0.103
	CP	Blue	-0.027
	PSW	Yellow	0.254
			Yellow
B	**Feature**	**Preferred**	**Score**
	RMSSD_Δ_STRESS_RECOVERY	Blue	-0.252
	PNN50_Δ_STRESS_RECOVERY	Blue	-0.377
	HF_Δ_STRESS_RECOVERY	Blue	-0.278
	HF/(LF+HF)_Δ_STRESS_RECOVERY	Blue	-0.284
	RMSSD_Δ_BL_STRESS	Yellow	0.821
	PNN50_Δ_BL_STRESS	Yellow	0.395
	HF_Δ_BL_STRESS	Yellow	0.587
	HF/(LF+HF)_Δ_BL_STRESS	Blue	-0.308
			Yellow
C	**Feature**	**Preferred**	**Score**
	RMSSD	Yellow	0.112
	pNN50	Yellow	0.311
	HF	Yellow	0.439
	HF/(LF+HF)	Yellow	0.184
	CP	Yellow	0.35
	PSW	Yellow	0.08
			Yellow

C	Feature	Preferred	Score
	RMSSD_Δ_STRESS_RECOVERY	Yellow	0.011
	PNN50_Δ_STRESS_RECOVERY	Blue	-0.038
	HF_Δ_STRESS_RECOVERY	Blue	-0.579
	HF/(LF+HF)_Δ_STRESS_RECOVERY	Blue	-0.486
	RMSSD_Δ_BL_STRESS	Blue	-0.254
	PNN50_Δ_BL_STRESS	Blue	-0.256
	HF_Δ_BL_STRESS	Blue	-0.3
	HF/(LF+HF)_Δ_BL_STRESS	Yellow	0.367
			Blue
D	**Feature**	**Preferred**	**Score**
	RMSSD	Yellow	0.124
	pNN50	Yellow	0.157
	HF	Yellow	0.22
	HF/(LF+HF)	Yellow	0.2
	CP	Blue	-0.148
	PSW	Blue	-0.161
			Yellow
D	**Feature**	**Preferred**	**Score**
	RMSSD_Δ_BL_STRESS	Yellow	1
	RMSSD_Δ_STRESS_RECOVERY	Blue	-1
	PNN50_Δ_BL_STRESS	Yellow	0.214
	PNN50_Δ_STRESS_RECOVERY	Blue	-1
	HF_Δ_BL_STRESS	Yellow	0.586
	HF_Δ_STRESS_RECOVERY	Blue	-1
	HF/(LF+HF)_Δ_STRESS_RECOVERY	Yellow	1
	HF/(LF+HF)_Δ_BL_STRESS	Blue	-0.636
			Blue
E	**Feature**	**Preferred**	**Score**
	RMSSD	Yellow	0.149
	pNN50	Yellow	0.409
	HF	Yellow	0.136
	HF/(LF+HF)	Yellow	0.094
	CP	Yellow	0.2
	PSW	Blue	-0.495
			Yellow
E	**Y**	**Preferred**	**Score**
	RMSSD_Δ_STRESS_RECOVERY	Blue	-0.267
	PNN50_Δ_STRESS_RECOVERY	Blue	-0.479
	HF_Δ_STRESS_RECOVERY	Blue	-0.06
	HF/(LF+HF)_Δ_STRESS_RECOVERY	Blue	-0.396
	RMSSD_Δ_BL_STRESS	Yellow	0.622
	PNN50_Δ_BL_STRESS	Yellow	0.667
	HF_Δ_BL_STRESS	Yellow	0.283
	HF/(LF+HF)_Δ_BL_STRESS	Blue	-0.143
			Yellow

F	Feature	Preferred	Score
	RMSSD	Yellow	0.05
	pNN50	Yellow	0.327
	HF	Yellow	0.254
	HF/(LF+HF)	Yellow	0.093
	CP	Yellow	0.241
	PSW	Blue	-0.033
			Yellow
F	**Feature**	**Preferred**	**Score**
	RMSSD_Δ_STRESS_RECOVERY	Yellow	0.898
	PNN50_Δ_STRESS_RECOVERY	Yellow	0.99
	HF_Δ_STRESS_RECOVERY	Yellow	0.585
	RMSSD_Δ_BL_STRESS	Blue	-0.492
	PNN50_Δ_BL_STRESS	Blue	-0.64
	HF_Δ_BL_STRESS	Blue	-0.47
	HF/(LF+HF)_Δ_BL_STRESS	Yellow	0.412
	HF/(LF+HF)_Δ_STRESS_RECOVERY	Blue	-0.778
			Yellow
G	**Feature**	**Preferred**	**Score**
	RMSSD	Yellow	0.361
	pNN50	Yellow	0.755
	HF	Yellow	0.31
	HF/(LF+HF)	Yellow	0.094
	CP	Yellow	0.467
	PSW	Blue	-0.062
			Yellow
G	**Feature**	**Preferred**	**Score**
	RMSSD_Δ_STRESS_RECOVERY	Yellow	0.599
	HF_Δ_STRESS_RECOVERY	Yellow	0.198
	HF/(LF+HF)_Δ_STRESS_RECOVERY	Yellow	1
	RMSSD_Δ_BL_STRESS	Yellow	0.068
	PNN50_Δ_BL_STRESS	Blue	-0.089
	PNN50_Δ_STRESS_RECOVERY	Yellow	0.128
	HF_Δ_BL_STRESS	Blue	-0.429
	HF/(LF+HF)_Δ_BL_STRESS	Blue	-0.122
			Yellow
H	**Feature**	**Preferred**	**Score**
	RMSSD	Yellow	0.09
	pNN50	Yellow	0.185
	HF	Yellow	0.166
	HF/(LF+HF)	Yellow	0.174
	CP	Blue	-0.2
	PSW	Yellow	0.505
			Yellow

H	Feature	Preferred	Score
	RMSSD_Δ_BL_STRESS	Blue	-0.832
	RMSSD_Δ_STRESS_RECOVERY	Blue	-0.269
	PNN50_Δ_BL_STRESS	Blue	-0.45
	PNN50_Δ_STRESS_RECOVERY	Blue	-0.787
	HF_Δ_BL_STRESS	Blue	-0.655
	HF_Δ_STRESS_RECOVERY	Blue	-0.128
	HF/(LF+HF)_Δ_BL_STRESS	Yellow	1
	HF/(LF+HF)_Δ_STRESS_RECOVERY	Blue	-0.455
			Blue

Table A1: *Overview of MCDA Results for each Participant*