Understanding the Impact of Environmental Conditions on Students' Emotions in a University Building

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ABSTRACT

This research paper presents a study that investigates the emotional responses and comfort levels of students within an informal learning environment. We created a custom sensor toolkit to monitor the environmental changes in these spaces and integrated the results with data from pre-existing building sensors. Simultaneously, we conducted a survey to understand the emotional states of the occupants, linking these responses to the collected data on ambient conditions such as sound, light, temperature, and occupation rate. Our data analysis revealed that noise negatively affects the comfort levels of occupants in these spaces, while an increase in daylight positively affects their mood. These insights can enhance our understanding of what constitutes an optimal informal learning environment and can be employed to design better adaptable spaces.

KEYWORDS

emotions, comfort, informal learning environments, human building interaction, sensors

1 INTRODUCTION

A growing trend has emerged within higher education institutions to design 'sticky campuses'. These campuses are characterised by multi-purpose spaces, referred to as informal learning spaces, that serve not just for learning, but also for socialization and other activities. The aim is to craft environments that will entice students to spend more time on campus, thereby enhancing their overall university experience [6]. As these spaces are increasingly used by universities, it is important to evaluate how well they fulfil their purpose of supporting students in their learning activities.

Occupant comfort is a commonly used measure for evaluating the effectiveness of a space in providing the intended environment. These comfort levels can be measured for sound, visibility, air quality and temperature and then combined into an Indoor Environmental Quality (IEQ) index [11]. With this approach, a single value is created that can be used to evaluate the comfort provided by a space.

Alongside comfort, emotions play a significant role in influencing a student's ability to learn [27]. As emotions are also partially influenced by the built environment surrounding an occupant [17], can serve as an additional evaluation factor for spaces intended for learning and concentration. Due to solely focusing on comfort, current measuring techniques, like IEQ, fall short of fully capturing an occupant's experience. Instead, we propose a more holistic approach for analysing occupant-specific environment quality, by factoring in emotions and the different needs that arise in multi-purpose environments. Concretely we pose the following research question: *How do alterations in temperature, light, sound, and occupational density affect students' perceived emotions and comfort in informal learning spaces?*

To answer this question, environmental data was collected from various informal learning spaces at the Lab42 building of the University of Amsterdam. This combined built-in sensors of the building with custom sensors placed at informal learning spaces for more location-specific measurements. In addition to this, occupants of these spaces were asked about their emotions and comfort. The connections within this dataset were used to discover how differences in environmental parameters influence the students' experience in the surveyed spaces.

2 RELATED WORK

This chapter explores the relevant literature in the area of learning environments, emotions in built environments, their effects on learning and concentration, and IEQ. It analyses how these components intersect and influence the overall experience within an educational setting.

2.1 Learning environments

Ellis and Goodyear (2016) show that learning environments can be divided based on the three categories seen in Table 1 [6]:

Setting	Formality	Provider
Physical	Informal	University
Hybrid	Formal	Third party
Virtual		Personal

Table 1: Learning environment classifications

In the following, we will only focus on the *physical, informal* and *university-provided* learning environments. This describes environments present on a university campus and used by students without the direct supervision of the teaching staff [3]. Spaces that fit these descriptions include libraries, common areas and atriums of university buildings [6, 18]. These environments were introduced in greater quantity in connection with the before-mentioned 'sticky campus design', which focuses on providing spaces for students to study and interact socially outside of classes. Studies also show that students in higher education spend more time in these informal settings than in the formal settings of a lecture room [6]. This popularity, in combination with the different use cases makes these spaces the focus of this research.

2.2 Emotions in built environments

Research by Nembrini and Lalanne (2017) finds that interaction within a built environment is not only influenced by the occupant's comfort but is also connected to emotions and feelings [17]. This concept is backed up by a detailed study from Bower and colleagues (2019), who argue that as people spend more time indoors, the emotional effect of these spaces is becoming increasingly influential [4]. It is also apparent that certain environmental factors, like temperature, light, and air quality, impact our emotions. In addition to these parameters, it has been found that the number of people in a space, or its 'crowding', can also change how the occupants feel [7].

However, a review study by Bower (2019) also points out that most research focuses on how IEQ and crowding relate to physical comfort, not emotions. The study also mentions limitations with the self-assessment of emotions. The delay between the actual experience of an emotion and a persons awareness of it can lead to discrepancies in the recorded emotional state when compared to the actual emotional response measured through physiological signals [4].

2.3 Emotional effects on learning and concentration

Emotions play a significant role in learning and concentration among students, acting as a double-edged sword that can either facilitate or hinder academic performance. The connection between emotions and cognition is well-established in the literature [27]. Positive emotions, such as interest, enjoyment, and curiosity, promote engagement, enhance motivation, and foster a deeper understanding of the material [20]. Conversely, negative emotions like anxiety, frustration, and boredom can impair attention, working memory, and cognitive processing, leading to decreased performance and learning [30]. Therefore, fostering a positive emotional climate in the learning environment is crucial for maximizing student concentration and learning outcomes.

2.4 Indoor environment quality

Research regarding IEQ focuses mainly on physiological comfort, as previously mentioned. Nevertheless, these studies are useful as they also evaluate built environments based on their environmental parameters. The parameters analysed for the computation of an IEQ index can give a good indication which data sources are needed to describe a built environment. A literature review by Roumi et. al (2022) focuses on different IEQ studies and evaluates the produced data in terms of quality and quantity.[23]. This review shows that specific aspects of computing an IEQ score differ from approach to approach. It also identifies sound, light, temperature and air quality as the parameters that are present in most of the reviewed studies.

There are also studies focusing on IEQ evaluation specifically in educational buildings. A study by Mihai and Iordache (2016) analyses the IEQ of an educational building by using the sensor data provided by the building and attaching weights to the different outputs by interviewing a subset of occupants [15]. This in combination with the before-mentioned work gives a good baseline for our experiment design.

3 METHODOLOGY

3.1 Informal learning space selection

The building selected for this study is the most recent addition to the science campus of the University of Amsterdam. Equipped with various sensor solutions, it already provides a base of environmental data that can be used and extended for further analysis. Lecture halls, learning rooms, and the relevant open learning spaces make up the two lower floors, with the upper four being primarily assigned to the universities academic staff and external offices. The spaces inside of this building were designed with the intend of creating open spaces for collaboration [5]. A characteristic that sets this building apart from the rest on the campus is the centrally located Atrium, which can partially be seen in Figure 1. The Atrium is illuminated by a skylight that spans the entire visible roof of the main hall. This primary open space can be divided into several sub-environments that act as informal learning spaces. Out of the multiple available informal learning spaces a subset of four was chosen to be equipped with further environmental sensors. Pictures of these spaces can be seen in Figure 2. In the following, they will be referred to as places 1 to 4 as indicated by the pictures captions.

The four chosen spaces are spread over the first and second floors of the building. These were selected as they provide differing lighting condition, as well as differing seating arrangements and placements within the atrium. While more informal learning spaces can be identified within the building, the experiment is limited to four spaces by the availability of additional sensors to record all the needed environmental data. The placement of these spaces on the building floorplan are shown in Appendix C as well detailed descriptions in Appendix B.

3.2 Data collection

Both environmental data and occupant feedback are crucial for our comprehensive understanding of the role of built environments in influencing emotions. The following elaborates on the data collection process used throughout our study, focusing on the existing building sensors and additional custom sensors, as well as surveys filled out by the occupants. The data gathered by the sensors provides insights into various parameters such as sound, light, temperature, and occupancy, as outlined in Table 2. The sampling rate referenced in the table describes the time interval in which the data was recorded, while the source describes from which kind of sensor the data originates.

Parameter	Unit	Sampling rate	Source
Sound	Decibels	1 Minute	Custom
Light	Lux	1 Minute	Custom
Temperature	Celsius	1 Minute	Building
Occupation	Occupied Spots	5 Minutes	Building

Table 2: Sensor details

3.2.1 *Existing building sensors.*

As the selected building is new and was only opened for full use by the university in 2022, it was constructed with various sensors that are primarily used for managing amenities like heating, blinds and lighting management, as well as sensors used for mointoring the buildings occupancy.

A temperature sensor, mounted on the first floor of the building's atrium (location marked in Appendix C) is used to adjust the heating inside the main hall and reads the room's temperature in one-minute intervals. Given all observed spaces are within the same climate-controlled area, this sensor provides temperature data representative for all four spaces.

Passive-infrared sensors, mounted under certain tables within the main hall, monitor the number of people using the tables at any given time. A single unit of this sensor is displayed in Figure 3. They register movement between the unit itself and a specified floor area under and in front of the table. This allows the sensor to detect a person sitting at the desk. As movement is required to trigger the sensor, static objects like chairs would not result in a recognition. One table holds multiple sensors facing different directions to monitor each working space at the table. This solution

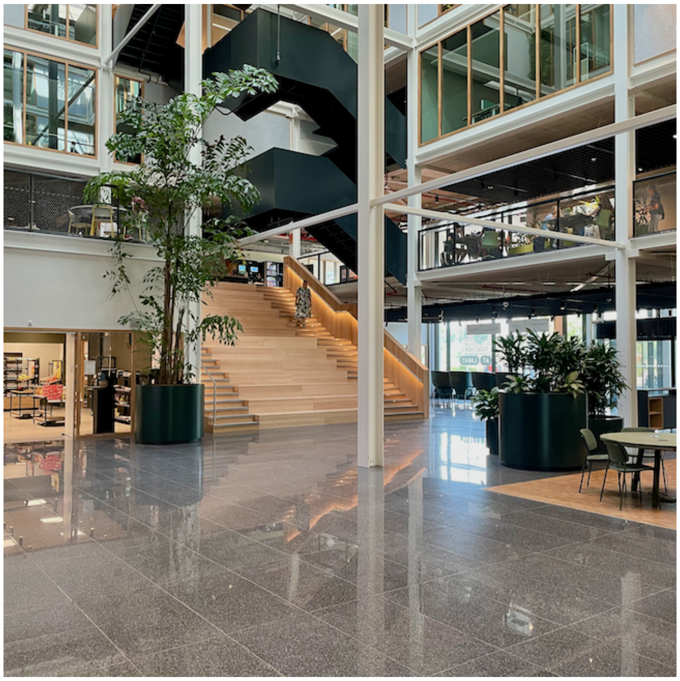
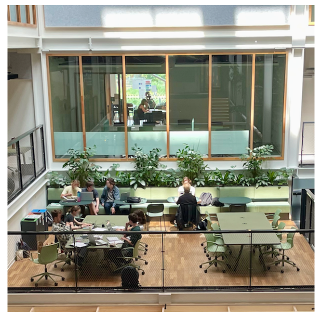


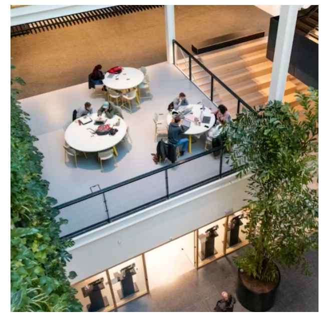
Figure 1: Partial atrium overview

(a) Place 1

(b) Place 2



(c) Place 3



(d) Place 4

Figure 2: Pictures of the selected learning spaces

Figure 3: Passive infrared sensor under the table

Figure 4: Wifi enabled custom sound and light sensor

is not completely accurate, as a more widespread movement could activate multiple sensors per table, but they can be used for an approximation of the occupancy rate. The sensors monitor in five-minute intervals and provide a true or false value about their trigger status. Only certain tables within the main hall are equipped with sensors and have been marked on the floor plan in Appendix C. None of these sensors are present at place 2. Place 3 and 4 are only partially equipped, with some tables having no sensor installed. As a consequence data from place 2 will need to be excluded when analysing on the basis of occupancy. For places 3 and 4 a percentage of places filled will be used as an approximation of the places' actual occupancy.

Even though the building is equipped with sensors to evaluate the air quality within the atrium, the data collected by these sensors was unavailable for the duration of the experiment. Due to this the following evaluations will not be able to take air quality into account.

3.2.2 Additional custom sensors. As noise and light data were not collected by the building's sensors, we developed a custom solution to measure these parameters at each of the defined places. To provide this capability a system on the base of an ESP8266 Microcontroller was designed. The four resulting sensors read the sound level in decibels and the ambient light level in lux in a one-minute interval. One of the sensor units can be seen in Figure 4. As a permanent installation of the sensors was not possible for the timeframe of the experiment, the sensors were installed before 09:00 and collected after 16:00. The sensors were placed as centrally as possible in the chosen areas and always reinstalled at the same position. These positions are marked on the floor plan in Appendix C. To enable time-accurate measurements the sensors were developed to be Wifi capable and pull a current timestamp from a predefined network during every startup sequence. The data itself is stored on a built-in SD card and collected at the end of the day. To ensure reproducibility the full source-code as well as the part-list and connection schema can be found in Appendix A.

With the Wifi capability of the sensors we also attempted another way of approximating the occupation rate of the surveyed places. While installed, the custom sensors were constantly scanning available WiFi channels for probe requests send by devices in their proximity. The sensors attempted a count of surrounding devices by logging those probe requests over a given amount of time and recording the amount of detected devices every minute. The resulting device counts were split into groups based on received signal strength, to make later removal of noise and distance approximation possible. The data collected using this method, unfortunately, could not be employed by us to estimate the building's occupation rate. The device count recorded did not correlate with the far more reliable data produced by the passive infrared sensors installed under the buildings tables. The data also displayed no correlation with other recorded parameters and the overall behaviour of the recorded device count over time can be described as erratic. This suggests a sizeable amount of noise in the data set that could have been influenced by the unreliable signal strength in a environment with multiple transmitting devices and the irregularity with which modern devices send probe requests. The wifi generated occupation data was therefore not included in the following analysis.

3.2.3 Survey. Parallel to environmental data collection, occupant data on comfort and emotions was recorded via a survey. In addition to this, the survey also collected data on the participant's location in the building and their current activity through multiple-choice questions.

Inquiring about comfort and emotions, the survey offered free-form text fields to capture nuanced responses, avoiding the constraints of predetermined scale responses. The free-form questions asked were:

(1) How would you describe your *feelings* and *emotions* in this space, at this moment?
(2) Could you describe how *comfortable* you feel in this space? (Please consider temperature, noise, light, air quality, or any other factors that you feel may be impacting your comfort.)

This open answer approach allows for a subsequent sentiment analysis. It also gives an opportunity to analyse the vocabulary used to answer these questions. The survey was distributed by handing out QR Codes to students present at the observed places. This distribution was done during the active time of the custom sensors to facilitate a later mapping of responses to environmental conditions. A full overview of the provided survey can be seen in Appendix I .

3.3 Preprocessing

3.3.1 Calibration. Calibration was essential to achieve independently comparable values with the custom sensors' off-the-shelf components. For sound level data, calibration involved recording a range of sounds at different noise levels with the custom sensor and a calibrated microphone. A static difference was observed in the decibel values recorded, allowing the creation of a simple calibration function that adjusted all readings by 11.3 decibels (Appendix A). Light level data was calibrated by comparing the custom sensor's readings with those of an ambient light sensor in a smartphone equipped with a light diffuser. The application used to extract the data was pre-calibrated to the equipment of the phone model [8]. While not as accurate as calibration with a specialised tool, the achieved accuracy of this approach was deemed sufficient. The light level data was compared within the context of data collected by the custom sensors, so absolute accuracy was not required. Measurements with both devices were conducted under changing lighting conditions. The difference between measurements could be approximated with a linear function so the corresponding calibration function was implemented.

3.3.2 Cleaning. For the data retrieved from the custom sensors, a removal of outlier values was needed. These outliers could significantly distort the average environmental conditions as recorded by the sensors. For example, outliers in the sound level data appear to primarily stem from people accidentally touching the sensor's microphones. On the other hand, outliers in the light-level data typically resulted from obstructions like fully extended laptops or paper sheets, which shaded the sensor. One distinct instance of an outlier was observed when one of the tables with a mounted sensor, was temporarily moved to a better-illuminated location and then moved back. These outlier producing behaviors were observed while distributing the survey at the observed places.

The survey responses, although conducted in English, occasionally contained responses in Dutch. These responses, typically short, grammatically simple phrases of two to three words, were translated into English.

3.4 Analysis

This chapter explains the analytical procedures and methods used to analyse the collected data. With Python [28] as the cornerstone of our data analysis framework, we harnessed the power of pandas [14], numpy [9], sklearn [19], and statsmodel [24] libraries to manipulate, analyse, and model our data. Our techniques spanned from Natural Language Processing to correlations studies, with each bringing valuable insights into the dataset. The related code can be found in Appendix A.

3.4.1 Natural language processing. The sentiment of comfort and emotion-related responses was analysed by employing a pre-trained sentiment classifier, based on the BERT Large Language Model (LLM). This classifier was adjusted using labelled data from Twitter [1]. Considering the brevity and simplicity of sentence structures commonly found in tweets, we hypothesised that the model would deliver high performance in analysing survey responses. As the average answer to the emotion question included ten and to the comfort question included 17 words, the survey answers display similar characteristics as the training data tweets.

To evaluate the classifier's analysis, a random subset of 15 responses was selected for manual evaluation preceding the sentiment analysis. The evaluation demonstrated near-flawless classification of the subset with only one instance of misclassification, where the model incorrectly categorised a neutral statement, as determined by the researcher, as positive. This discrepancy may occur as the classifier demarcates distinct categories for statements that could potentially be included in multiple sentiment groups, resulting in ambiguity.

In addition to this approach, we utilised rule-based, aspect-based sentiment analysis, which searches a given text for specific keywords and evaluates the sentiment of the surrounding words or grammatical structures [21]. To generate the required list of keywords for our survey data, we tokenised and stemmed the words in the emotion as well as the comfort aswers. Subsequently, each unique word was manually labelled with one of the four possible categories: sound, air, temperature, or light, as appropriate.

These groups then served as the foundation for aspect-based sentiment analysis. Based on these groups, sub-sentences were extracted from the responses whenever a respective keyword was identified. Finally, these extracted sub-sentences underwent sentiment classification using the previously mentioned BERT model, which had been fine-tuned using Twitter data.

3.4.2 Correlations. We studied the relationship between environmental conditions and survey responses by looking at the average environmental values just before a survey answer was given. We considered three time-frames: a short period (5 Minutes), a medium period (30 Minutes), and a long period (60 Minutes) before each response. To analyse how the environmental parameters relate to the survey answers, the average environmental parameters during these time-frames were taken into account. The following analysis then investigated the correlation between these averaged values and sentiment of the corresponding survey answer.

To check the correlations of categorised sentiment values of the survey answers (positive, neutral, negative) with the continuous environmental data provided by the sensors the Analysis of Variance (ANOVA) approach can be used. This method compares the variances of various means to determine if there are statistically relevant differences between the groups. [16]. ANOVA can also be utilized to establish correlations between the occurrence of specific terms in the vocabulary and changes in environmental parameters. This process involves dividing the data into two categories: one group with the specified term and another without it. Then, ANOVA analysis is used to compare the mean values of the environmental parameters for each of these newly constituted groups.

As ANOVA only gives an indication that a variable is able to influence the analysed groups further tests are needed afterwards. Performing a Tukey Honest Significance Distance (HSD) test [26] reveals the influence the parameter has on a relationship between the groups. Afterwards, the eta score can be calculated for that relationship to asses the strength this relationship has on the data [16].

4 RESULTS

4.1 Environment

Over a period of 12 non-consecutive work-days, between the hours of 09:00 to 16:00, data was collected with the custom-built sensors. All the gathered environmental data can be seen averaged over the collection timeframe in the Figures 5 to 8. These figures show the average value of an environmental parameter and the corresponding variability.

4.1.1 Noise. As can be seen in Figure 5, places 1 and 2 demonstrated higher average noise levels in comparison to places 3 and 4. Both place 1 and place 2 are situated on the ground floor, adjacent to the main hall, which may have contributed to the increased noise levels. Overall the recorded noise levels ranged from 40 db, similar to a whisper, to nearly 70 db, comparable to a nearby vacuum cleaner. The pattern of noise at places 1, 2, and 3 escalated until midday and then reached a plateau. On the other hand, place 4 exhibited regular spikes in noise level throughout the day. The possible correlation between these spikes and the comings and goings of students from nearby lecture halls were also noted. Similar, albeit less pronounced, hourly spikes were observed at the other three places, suggesting that the noise generated near place 4 impacts the overall noise level in the main hall. The high variance at all places indicates daily variations in noise levels. This is further validated by the day-by-day noise data for each place provided in Appendix 4, which also shows that a noise level spike at one place often appears in other places in a weaker form.

4.1.2 Light. In the case of light levels seen in Figure 6, the effect of the main hall's skylight is clearly noticeable. Both places 3 and 4 exhibited a pattern of increasing illumination that dipped in the afternoon. Place 1 showed a similar pattern, albeit less pronounced due to partial coverage by a footbridge. This footbridge crosses the atrium on height of the fourth floor and is located directly over the tables of place 1. In contrast, place 2 maintained a steady illumination level, likely due to artificial lighting. The variance in lighting levels was high, as depicted by the daily illumination plots in Appendix E. This variability can be attributed to changes in weather and cloud cover. The light levels ranged from 200 lux, equivalent to a dimly lit room, to 1000 lux, which equals bright indirect sunlight.

4.1.3 Occupation. Occupation followed a unique trend at each location. Places 1 and 3 saw a rise in occupants until midday, followed by a plateau at approximately half the space's capacity. Place 4 showed an irregular pattern with spikes and drops between 9 and 12 o'clock, potentially related to nearby lecture hall schedules, before settling to a plateau at a lower capacity in the afternoon.

4.1.4 Temperature. Due to the main halls temperature control, the measured value stayed between 20.6 and 21.2 degrees Celsius as can be seen in Figure 8. Within this minor variation, an upward trend was observed until midday, followed by a plateau. Even with this general trend visible the overall temperature change displayed is minor, as the indoor temperature stays nearly the same over the whole day.

4.1.5 Environmental correlations. Figure 9 presents the Pearson Correlation Coefficient (PCC) for each of the collected environmental parameters, enabling a comprehensive comparison. In the shown correlation heatmap a higher number indicates a stronger correlation, with the values ranging between 0 and 1 [22]. Initially, the PCC was calculated for the average values of the main hall. For this computation, the sound and light values from all four recorded spaces were averaged, and all occupation data from the main hall was taken into account. The data demonstrated a strong correlation between the noise level and the occupation of the space. This observation indicates, that the count of occupied areas within a space may reliably predict sound levels.

Appendix F presents the PCC values for each space individually. Places 1 and 3 display a similarly strong correlation between noise level and occupation. As space 2 lacks related occupation data, no correlation could be calculated. Interestingly, place 4 did not show a correlation between these parameters, which could be due to the influence of the nearby lecture halls. It is also worth noting that only half of the tables in place 4 are equipped with a near-infrared

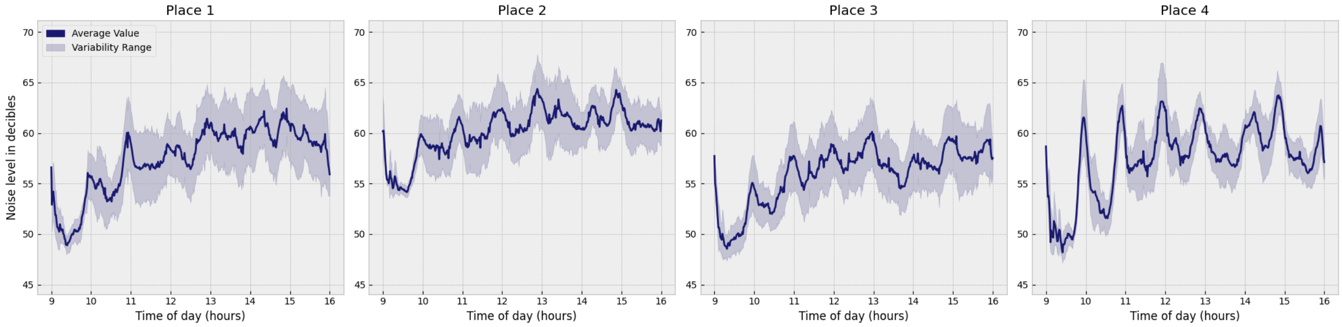


Figure 5: Average noise with variance

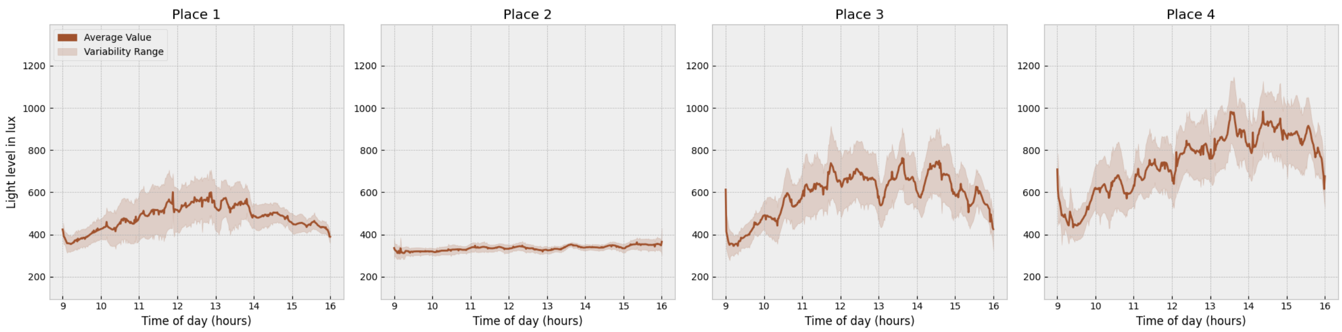


Figure 6: Average light level with variance

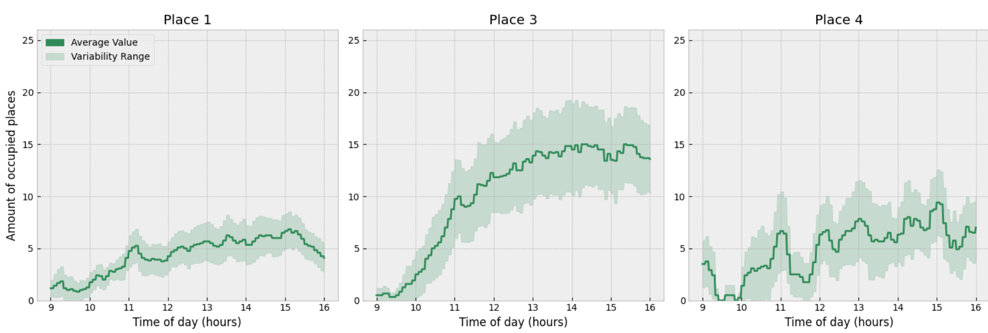


Figure 7: Average occupation in spots used with variance

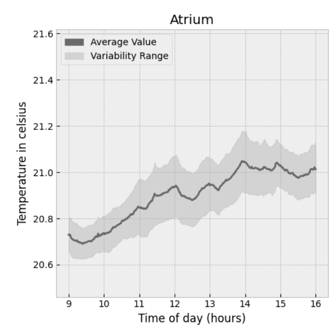


Figure 8: Average temperature

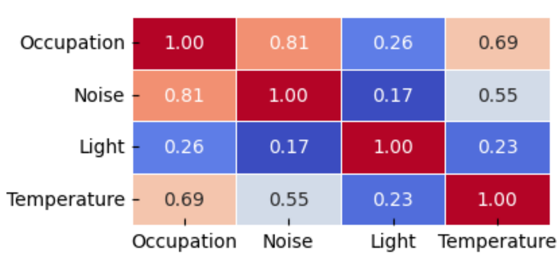


Figure 9: Pearson-coefficients of the Environment values

sensor; therefore, the correlation might be observable if the whole space were monitored. If the effects of the nearby lecture halls are indeed the cause of this discrepancy, this suggests that local factors, such as lecture halls, can have a more substantial influence on the ambient noise level than the occupancy rate of the space itself.

A weaker, yet notable, correlation was found between the temperature and the occupation of the spaces. This relationship was present in all spaces equipped with occupation sensors. This implies that the small changes in the temperature of the main hall may be partially attributed to the number of individuals present.

In contrast, light demonstrated no correlation with other environmental parameters. While this may not be surprising, it does highlight that light is the only parameter not connected to the human presence inside the building, thereby following an independent pattern.

4.2 Survey

During the course of the experiment, a total of 95 survey responses were recorded. Out of these, 85 were fully completed while 10 were partially completed, with some questions skipped. The relative distribution of responses, as visualized in Figure 10, approximately corresponds to the quantity of seating available in each area as can be referenced in Appendix B.

Each activity recorded by the survey was represented at all spaces. The activity with the fewest responses was "taking a break," while "working in a group" received the most responses. It should be noted that the surveys were administered at irregular intervals, and completion was entirely voluntary. Therefore, the data can only provide limited insights into the actual amount of activities taking place at each location.

The sentiment analysis of the survey results indicates that approximately 50% of the emotional feedback was positive, and about 70% of the comfort feedback was positive, as can be seen in Figure 11. It was observed that positive emotions were typically accompanied by positive comfort feedback. Out of 41 responses that conveyed positive emotions, only two were associated with negative comfort feedback, and four were linked to neutral comfort feedback.

Responses with neutral emotional feedback were predominantly paired with positive comfort responses. Out of 30 neutral emotion responses, only six corresponded with neutral comfort feedback, and three were associated with negative comfort feedback.

In contrast, negative emotional feedback was distributed uniformly across positive, negative, and neutral comfort feedbacks. Out of 14 negative emotion responses, five were followed by negative comfort feedback, five by positive comfort feedback, and four by neutral comfort feedback. These findings illustrate the existing understanding that comfort positively influences an individual's emotional state. However, such a relationship is not apparent in

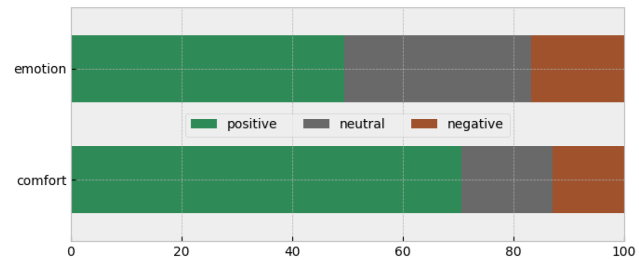


Figure 11: Distribution of overall sentiments

the case of negative emotional feedback, which is spread across different categories of comfort sentiment.

It is noteworthy that when positive comfort feedback co-occurred with negative emotional feedback, respondents often attributed their negative emotions to factors unrelated to the spatial environment. For instance, one respondent expressed, "I feel like I'm under pressure because of my deadlines," a sentiment of negative emotion, yet stated, "I feel very comfortable, it's a perfect temperature. Noise could be a little bit lower and air quality smells fine," reflecting a positive comfort level. This exemplifies how external factors can influence emotional responses independent of spatial comfort.

The findings of the aspect-based sentiment analysis on the comfort answers are depicted in Figure 12. Feedback on sound, temperature, and light were nearly equally represented, with sound being the most commonly mentioned environmental aspect. The sound aspect also accumulated the most negative sentiment statements out of the four parameters. A minor portion of feedback on temperature was classified as negative, with all such statements describing the room temperature as "cold" or "chilly".

It's noteworthy that there were no negative remarks about lighting conditions. Although air quality was less frequently mentioned

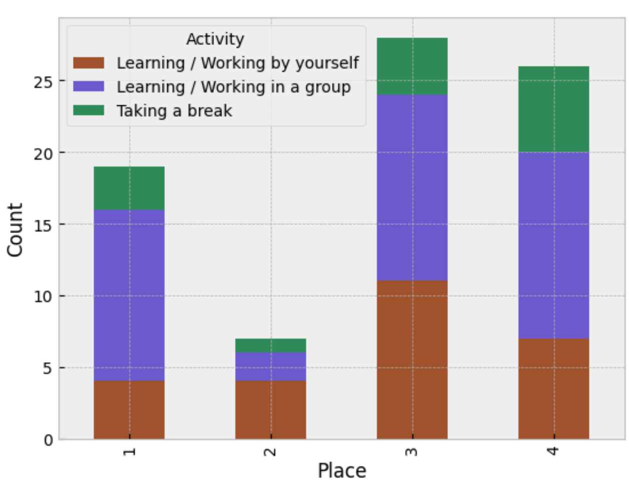


Figure 10: Survey Answers by Place and Activity

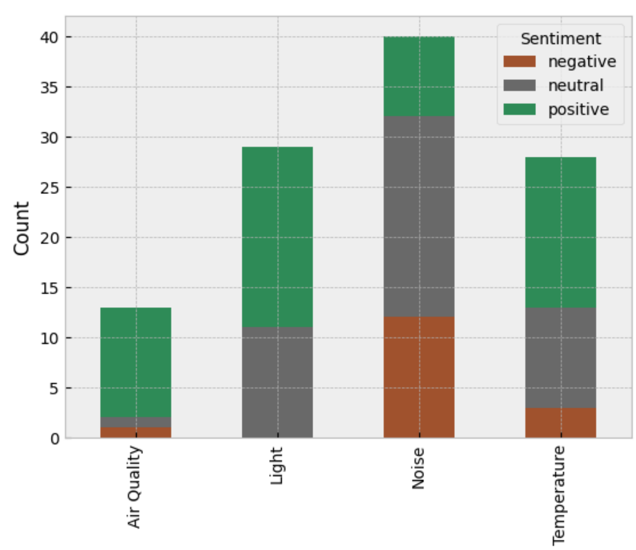


Figure 12: Sentiments of environmental aspects

compared to the other aspects, the majority of the mentions were positive. Only one neutral and one negative sentiment were identified related to air quality. Positive sentiments often associated the perceived air quality with the presence of plants in the main hall.

Approximately half of the respondents who completed the survey specifically mentioned sound, totaling 40 mentions. However, this observation needs to be contextualized, as the survey included a prompt suggesting sound and other parameters as possible topics of feedback. Hence, the frequency of mentions can only be evaluated relative to other parameters. This places sound as the most recognized parameter, with air quality receiving the smallest amount of attention.

The analysis of survey responses revealed that while the comfort question mostly elicited responses connected to the prompted environmental parameters, the interpretation of the emotion question was left open for respondents. A breakdown of the most frequently used words, both overall and split by activity, is presented in Table 3.

Overall	Group	Alone	Break
calm:19	stress:7	stress:7	calm:4
relax:16	calm:7	calm:7	relax:4
stress:16	like:6	relax:4	neutral:2
study:10	happy:6	space:4	
nice:9	nice:5	give:3	

Table 3: Most used words (Emotion)

The tabulation was carried out after eliminating structural words like 'bit' and 'very.' Standard stop words like 'a' and 'I' were already removed during the initial data processing stage. The word 'feel' was excluded from the analysis since the majority of responses began with the phrase 'I feel,' which would disproportionately inflate its count without adding substantive value.

The analysis revealed that the words 'stress,' 'relax,' and 'calm' frequently occurred in the responses. Predictably, 'stress' was not mentioned by respondents who were taking a break. However, 'stress' was the most commonly cited word among respondents who were working alone. Both 'stress' and 'calm' were frequently mentioned across the responses. Interestingly, a typical emotional classification like 'happy' appeared only six times, exclusively within the context of group learning activities. This observation indicates that 'calm/relax' and 'stress' are the prominent emotional states expressed by the surveyed student population.

4.3 Correlation analysis

When preparing for the ANOVA analysis, certain fundamental assumptions were made. First, it was assumed that the data drawn from each group in the population would follow a normal distribution, reflecting the natural variability of real-world data. Second, the homogeneity of variance was assumed, which means that the standard deviations of the different groups are statistically equivalent, ensuring a fair comparison between groups. To check the normality and homogeneity of the data Levene's test and Quantile-Quantile plots [16] were used. Both tests were run for all analysed subgroups before conducting an ANOVA test and groups that did not have the required distributions were not analysed any further.

4.3.1 Emotion and comfort sentiment. Initially, all survey responses were analyzed without grouping. This preliminary analysis did not reveal any statistically significant relationships among the environmental variables. This means that none of the tested options was able to push the probability of the null hypothesis under 5%.

In the next stage of the analysis, survey responses were grouped based on the activity described by the respondents. This grouping method revealed one statistically significant relationship when only students working in a group were analysed, with a p-value of 0.029. This indicated a statistically relevant correlation between the emotion sentiment of this group and the recorded ambient light level. This correlation was found for the medium and long time-periods with the 30 minute time-period having the higher statistical significance.

Given that the ANOVA test only identifies the presence of a significant relationship within a grouping and does not provide detailed information, additional tests were required. A subsequent Tukey HSD analysis [26] revealed that the significant relationship was between neutral and positive emotion sentiments within this group. The results are displayed in Table 4.

Group 1	Group 2	Mean difference	p-adjusted
negative	neutral	-97.9486	0.1172
negative	positive	3.9014	0.9956
neutral	positive	101.85	0.0291

Table 4: Tukey HSD results for emotion sentiment and the average light level for students conducting group work

This analysis demonstrates a correlation between the light level and a shift from neutral to positive emotional sentiment. The mean values for these two groups differed by 101 lux. It's important to note, however, that the same relationship does not apply for shifts from negative to neutral or from negative to positive sentiment as the respective p-values indicate.

4.3.2 Calm and stress. The research proceeded with a second step, which involved analysing the occurrences of the most common words in the emotional responses given by participants. These being the phrases "calm / relax" and "stress" the responses were labelled based on the occurrence of the phrases. When again looking at the complete response body no correlations were found. However, upon further splitting of the group by activities as before, a correlation emerged within the group of answers belonging to the activity "taking a break".

Group 1	Group 2	Mean difference	p-adjusted
-	Calm	151.5705	0.0188

Table 5: Tukey HSD results for the occurrence of calm and the average light level when taking a break

The Tukey HSD results shown in Table 5 show that the occurrence of the word calm within this group can also be correlated to the recorded light levels. Here the difference in means was 151 lux and also present for the 30 as well as the 60 minute timeframe.

5 DISCUSSION

5.1 Key findings

Our results revealed that individuals engaged in group activities and subjected to higher levels of light exhibited more positive sentiments compared to those experiencing lower light levels. This finding suggests that improved lighting conditions, characterized by greater brightness, might have the potential to enhance the emotional states of people learning or working in groups. This interpretation is consistent with existing research that establishes a link between exposure to daylight and emotional well-being [10, 29].

However, these observations raise two significant questions: First, why does the influence of light only appear to affect students working in groups. And second, why does the effect only appear to shift sentiments from neutral to positive? A plausible explanation for the second question may lie in the observed behavior that negative emotional states are heavily influenced by external factors. It is possible, that the impact of these external influences might be so profound that it overshadows the positive effects of improved lighting. Consequently, those with neutral or positive responses might be more susceptible to the influence of better lighting.

Addressing the first question involves conjecturing on the effect of lighting on the social interactions of occupants, which are more pronounced when working in a group. Several studies have shown that lighting conditions can influence our social interactions, although the nature and extent of this influence varies across different research [2, 13]. These findings suggest that improved lighting conditions might specifically aid social interactions in an educational environment. Another possibility is that the influence of light level exists across all activities, but it may be more pronounced during group work.

A similar analysis can be made from the increased usage of the word 'calm' in responses from occupants taking a break. It suggests that occupants feel calmer under better lighting conditions during their break times, which can again be associated with the positive impact of daylight on people's mood. The observed relationship raises the question of why it is only evident among individuals taking a break. It is conceivable that the calming influence of better lighting may have an higher impact when occupants are not engaged in learning-related tasks and therefor have a better chance of actively noticing their surroundings.

Interestingly, sound emerged as the most frequently mentioned aspect of comfort, as well as the most often negatively referred one. This trend may indicate the importance of sound for tasks requiring concentration, a relationship that is already well-studied [25]. Moreover, it may reflect the greater ease of noticing noise disturbances compared to other factors like air quality.

5.2 Limitations

The dataset employed in this analysis, while robust, is not without certain limitations, primarily due to its temporal and spatial boundaries. Specifically, potential bias could arise from the composition of the student body, given that cultural differences have the potential to shape how individuals perceive environmental influences [12]. This is further complicated by the fact that the data was collected exclusively during the spring season in the Netherlands, which could further skew the occupants' perception of various environmental parameters. Shifting seasons could affect not only the indoor conditions of the building, but also the students' perceptions and interactions with these parameters, given the changing environment around the building.

The reliance on the perceived emotions and comfort levels of participants also introduces potential shortcomings. There is a noteworthy caveat that perceived emotions and comfort do not always perfectly align with the actual emotions a person experiences due to the previsouly mentioned stimulus lag [4]. This mismatch between reported and actual feelings may inject a degree of uncertainty, potentially impacting the accuracy of our analysis and final results.

Adding an additional layer of complexity to the analysis is the utilization of Natural Language Processing (NLP). Although it is an advanced tool, it has its limitations when it comes to interpreting human emotions, which can be intricate and multi-faceted. With the use of predefined categories, NLP simplifies a highly complex spectrum of emotions and comfort into just three categories. This level of generalisation may inadvertently result in the exclusion of valuable information from the collected data, creating a potential gap in the comprehensive understanding of the dataset.

It also needs to be considered that multiple of the sensors employed in the data collection of this study were self build and might therefore have introduced unknown biases into the data even though they were calibrated beforehand.

Thus, while the insights derived from this study are instructive, these limitations must be factored into their interpretation and subsequent application.

5.3 Future work & Ethical considerations

For future iterations of this study, several improvements could be considered. One could encompass the inclusion of additional geographic locations and diverse timeframes throughout the year, thereby augmenting the size and diversity of the dataset.

Further, a focused study on the influence of lighting conditions as a potentially impact-full influence on students emotional states, could be instituted in a more controlled environment to either validate or refute the implicated effect observed in this study.

Moreover, the granularity of data can be further improved. While this research confined itself to defining spaces as the smallest learning units, which may comprise multiple tables and seating arrangements, it's important to note that within these spaces, there are variations that can influence the occupants. However, this increase in granularity also introduces ethical considerations. The ideal analysis of spaces could be facilitated by data granularity at an individual level, paving the way for the development of smart buildings that adapt to the personal needs of each individual occupant. While such structures might initially appear desirable, the data collection required to enable them presents concerns. Therefore, to genuinely advance building design based on these findings, it is critical that data be collected in a manner that avoids tracking individual occupants .

6 CONCLUSION

In our research, we sought to apply a holistic approach to the evaluation of informal learning spaces, integrating both emotional feedback and environmental variables. By doing so, we uncovered relationships in the data that suggest measurable connections between light and the occupants' emotional sentiments. We also found that these relationships vary depending on the activity undertaken by the occupant, introducing another layer of complexity and specificity to our understanding.

This shows that the inclusion of emotions could improve future evaluations of informal learning environments, aiding tin the design of improved educational spaces. By moving towards a more precise evaluation of IEQ, we can better optimize these environments for their intended purpose.

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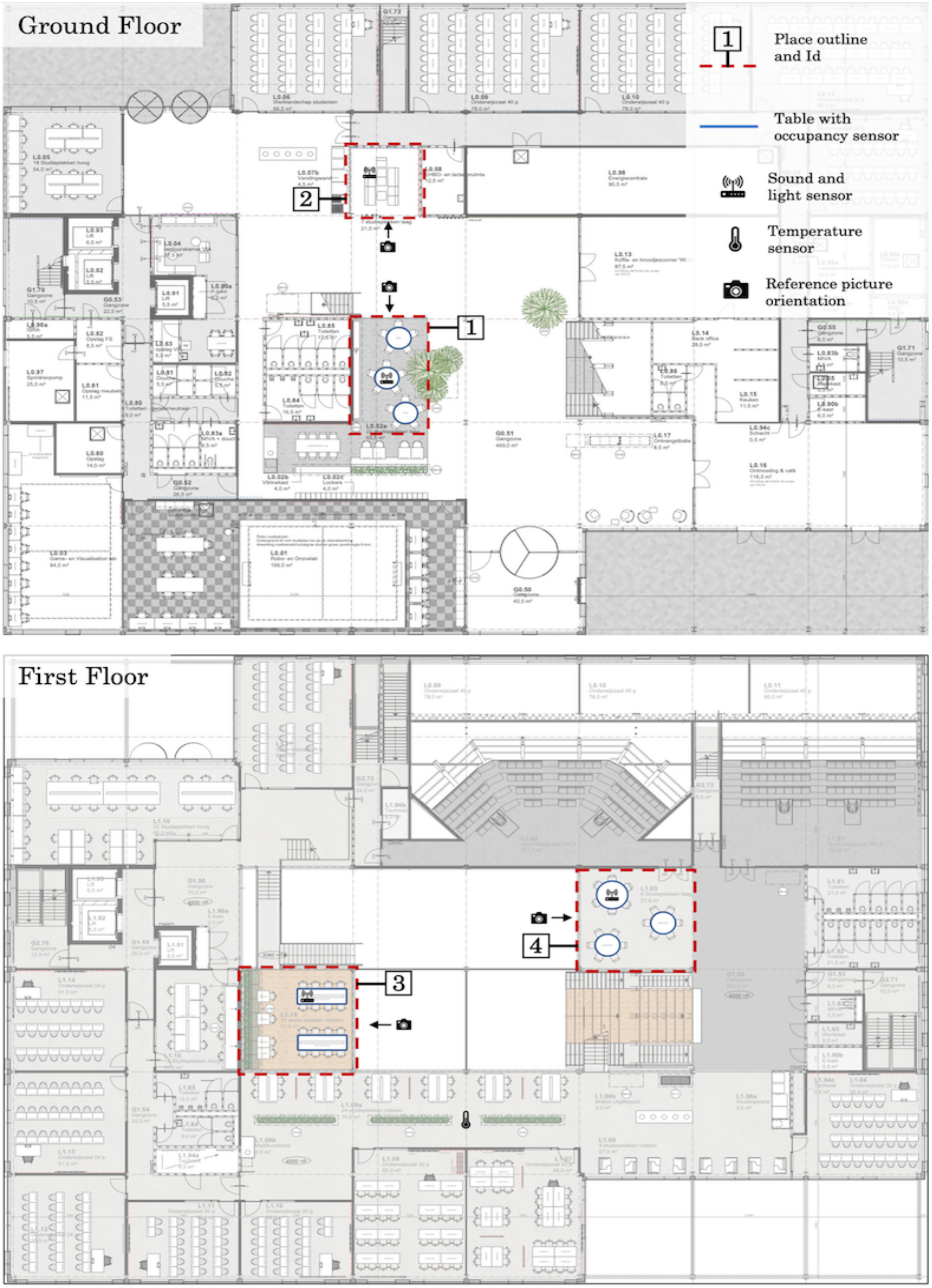
Appendix A RELATED CODE REPOSITORIES

Data Analysis and preparation: Github repository
Custom sensor code: Github repository.

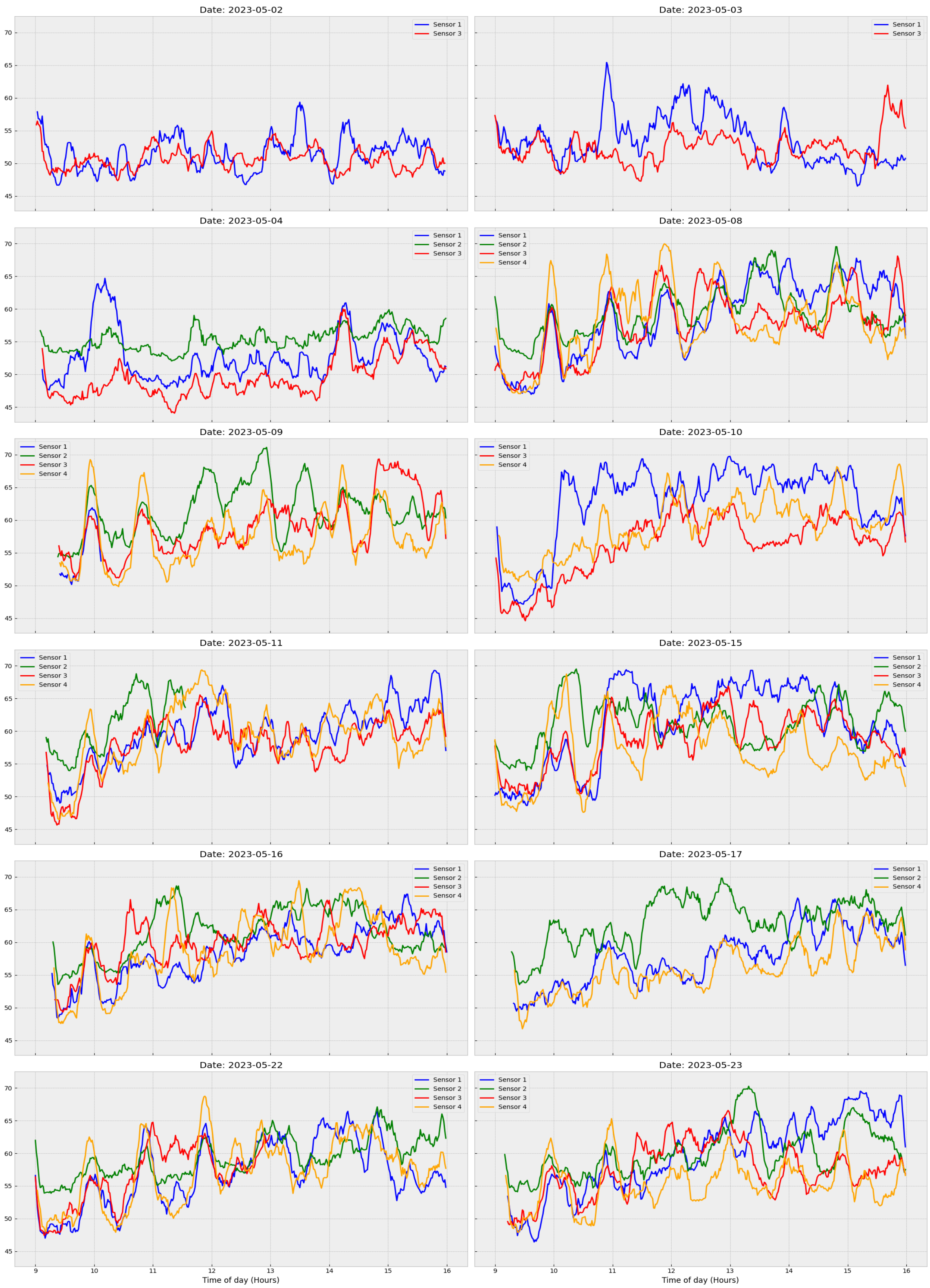
Appendix B PLACE DESCRIPTIONS

Place	Seating Capacity	Skylight	Surroundings
1	15	Partial	Separated from the main floor by 3 large planters. Adjacent to the printing corner and opposite the main stairwell of the building
2	5	No	Walls on 3 sides, with one of them carrying a big whiteboard. Fourth face opens up into the main hall.
3	26	Yes	Open on 3 sides with a metal fence. Separated by tall windows from an adjacent quiet learning room. Can only be accessed through a connecting staircase at one point.
4	18	Yes	Overlooks the main staircase and places 1 and 3. Directly adjacent lie the main lecture halls and their entrances

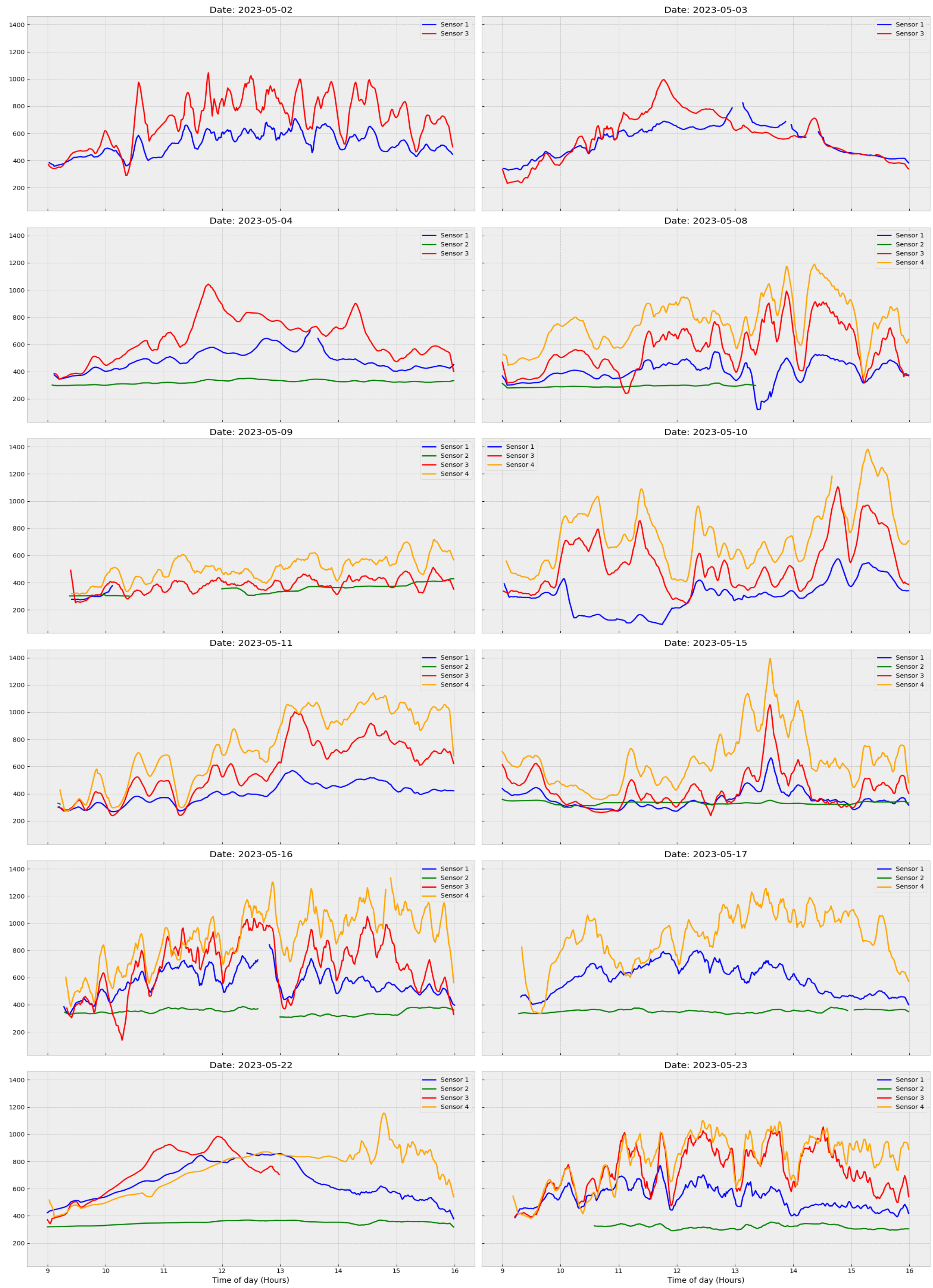
Appendix C ANNOTATED FLOORPLAN



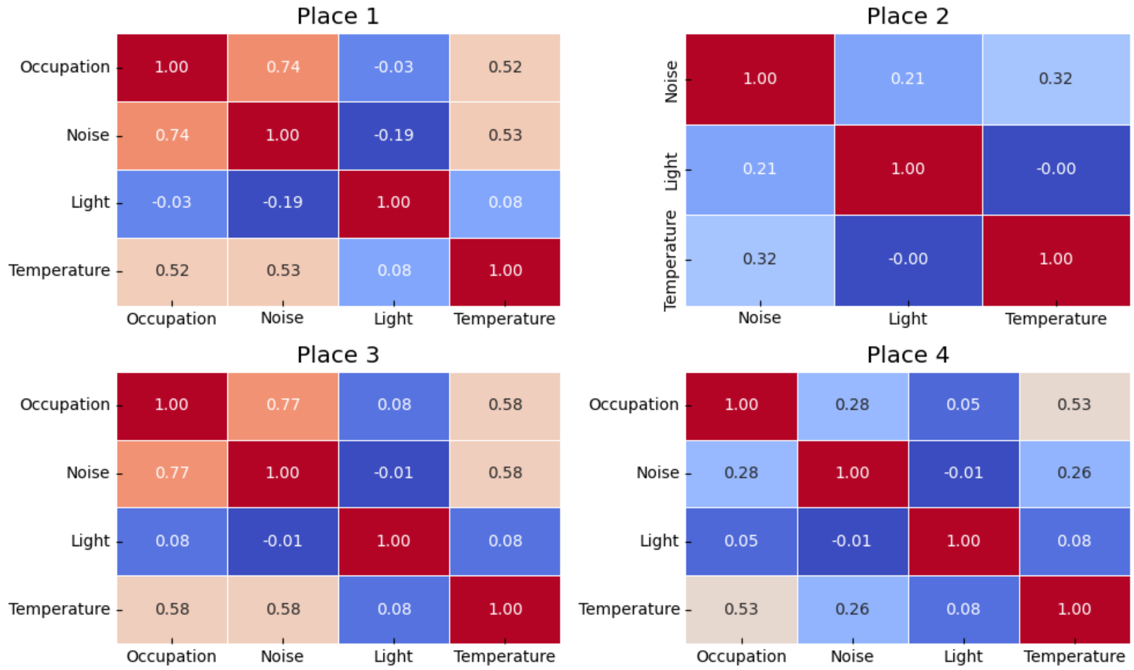
Appendix D DAILY SOUND DATA



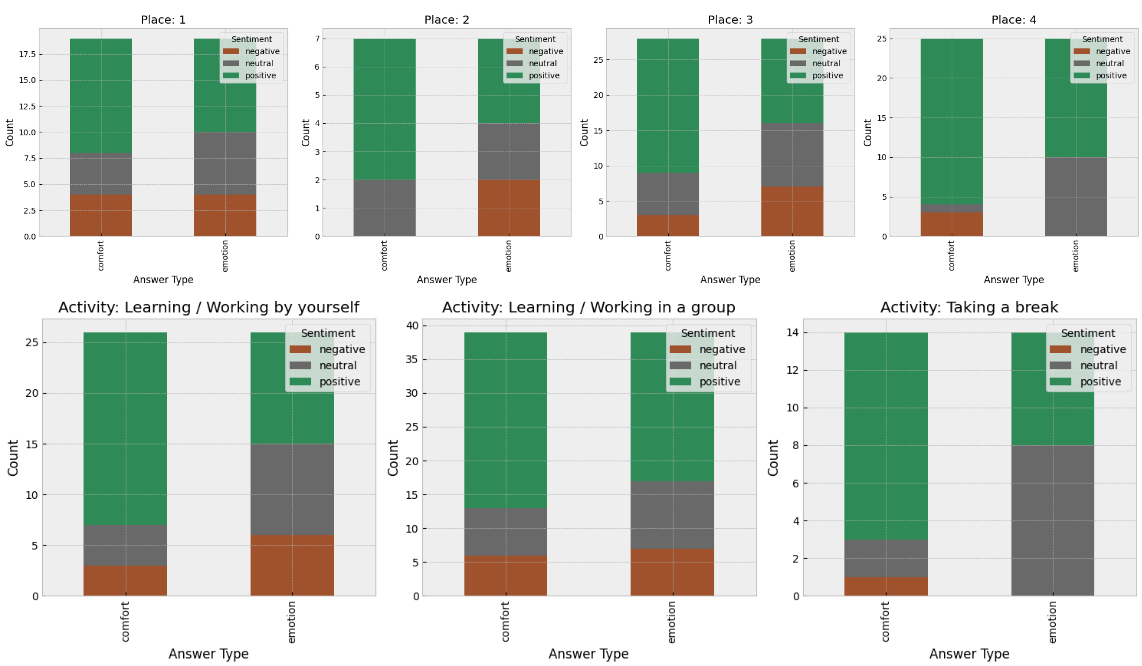
Appendix E DAILY LIGHT DATA



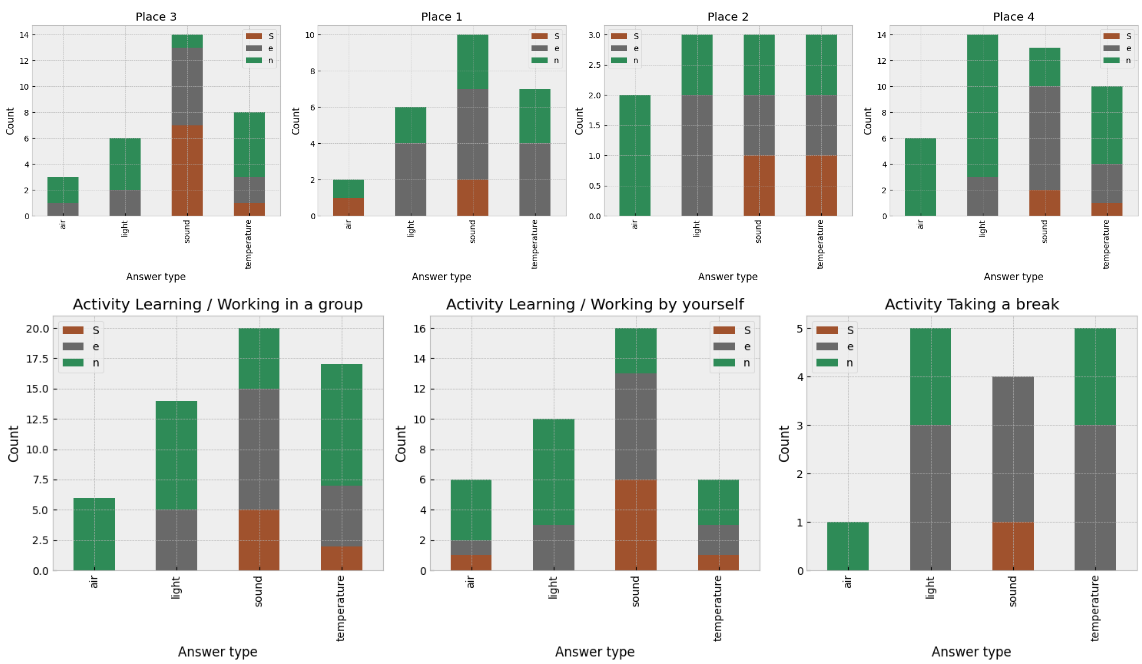
Appendix F PEARSON-COEFFICENTS BY PLACE



Appendix G SENTIMENT ANALYSIS BY PLACES AND ACTIVITIES



Appendix H ASPECT BASED SENTIMENT ANALYSIS BY PLACES AND ACTIVITIES



Appendix I SURVEY

Thank you for participating in our survey!

About us

We at the **Digital Interactions (DI) Lab** are interested in designing human-centric buildings and wish to understand your personal experiences of emotion and comfort within smart buildings such as **LAB42**.

About the Survey

This survey takes around 1 minute and comprises questions about your emotions and comfort at **LAB42**.

Your Informed Consent

The survey will not ask you for any identifiable information; therefore, your data will be anonymous. This anonymous data may be used for future research and shared in scientific publications. Your participation is voluntary, and you may quit the survey at any time. If you decide that you do not want to participate in this survey after you have completed it, you may contact us and ask that your data be withdrawn.

- I understand, and I agree to participate in the survey
- I do not wish to participate in the survey

Could you tell us which floor you are on?

- Ground floor
- 1st Floor
- 2nd Floor
- 3rd Floor
- 4th Floor
- 5th Floor
- 6th Floor

Where on the ground floor are you located? (Ground floor)

- Green chairs by the entrance
- Next to the lockers
- Round tables by the three plants (across wooden staircase)
- Study corner next to the plant wall
- Library learning room
- Unsure

Where on the ground floor are you located? (First Floor)

- Tables on the landing (with wooden floor) accessible by the black staircase
- Partly covered green chairs (along glass wall)
- Green group study tables (between a row of plants and railing)
- Library learning room
- Yellow/white chairs & tables (besides the wooden staircase)
- Unsure

Where on the ground floor are you located? (Second Floor)

- Library learning room
- Group tables by the stairs
- Unsure

Where on the ground floor are you located? (Third Floor)

- Round tables by the coffee machine
- Open lounge area
- Near the printer
- Unsure

How would you describe your feelings and emotions in this space, at this moment?

[Freetext input]

Could you describe how comfortable you feel in this space?

Please consider temperature, noise, light, air quality, or any other factors that you feel may be impacting your comfort.
[Freetext input]

How are you using this space at the moment?

- Learning / Working in a group
- Learning / Working by yourself
- Taking a break

Are you a student or PhD Candidate?

- Yes
- No

Do you use Lab42 at least once per week for various activities?

- Yes
- No