Testing the relationship between objective indoor environment quality and subjective experiences of comfort

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Abstract:

At present, workplace researchers lack a suitable methodology for combining objective indoor environmental quality (IEQ) data with repeated subjective assessments of comfort in real offices. To address this gap, we conducted a study at two office sites. Four IEQ parameters (carbon dioxide, temperature, humidity, and illuminance) were continuously monitored at each site, and brief environmental comfort surveys were sent to employees' smartphones four times per day across the study period. In total, 45 employees across the two sites completed 536 surveys.

The findings confirm that the repeated sampling approach is a more appropriate method for measuring comfort than a questionnaire delivered at one time only. Adherence to recommended temperatures reduced the risk of thermal discomfort, however this effect was weak and other predicted associations between the physical environment and environmental comfort were not supported. The results also showed a strong association between environmental comfort and self-rated productivity, such that employees rated themselves as most productive when they were satisfied with noise levels, temperature, air quality, and lighting within the office. Overall, the results highlight that it is critically important to consider strategies for optimising occupant comfort, although this is unlikely to be achieved through adherence to environmental comfort boundaries alone.

The workplace industry is in the midst of a paradigmatic shift, whereby the traditional focus on cost reduction is being gradually superseded by a more user-centric approach in which the building occupants are seen as vital assets to which value can be added through the provision of more supportive working environments (Haynes, 2007a). A crucial part of making workplaces healthier and more suitable for their users is by mitigating environmental sources of physical and/or psychological discomfort (Roskams & Haynes, 2019; Vischer, 2007. 2008), enabling the employees to conserve attentional focus and energy for their work, instead of expending it to cope with adverse environmental conditions.

Sub-optimal indoor environmental quality (IEQ; the physical conditions within a building, encompassing air quality, the thermal environment and the luminous environment) can be a major source of discomfort in office buildings, leading to deficits in employee wellbeing and productivity (see Al Horr *et al.*, 2016a, 2016b, for reviews). Hence, a key component of best-practice sustainability and wellbeing certifications such as the WELL Building Standard (International WELL Building Institute, 2018) is the prescription of recommended ranges or limits for key parameters of IEQ. These guidelines are premised on the assumption that occupant comfort, and consequently occupant wellbeing and productivity, will be highest when these ‘comfort boundaries’ are adhered to. However, a major limitation is that the supporting literature is largely derived from experimental studies performed in climate chambers, and so questions remain over whether the guidelines will generalise to real office environments where numerous additional confounds might be present.

Suitable field studies remain very rare. This can be at least partially ascribed to the fact that previous solutions for continuous IEQ measurements in offices required the use of costly and impractical mobile carts equipped with on-board sensors (e.g., Candido, Kim, de

Dear & Thomas, 2016; Parkinson, Parkinson & de Dear, 2015), leading field researchers to instead take spot measurements of IEQ at indicative locations and combine these with questionnaires which ask respondents to report how they feel *in general* whilst in the office. In these types of study, a significant problem is that neither the IEQ measurements nor the employees' perceptions are spatio-temporally specific (i.e., the measurement cannot be assigned to a particular space at a particular time). Hence, there are growing calls for field studies which capture "right-here-right-now" assessments of the workplace environment, conducted multiple times across an extended period and combined with objective IEQ data (Candido *et al.*, 2016; Choi & Lee, 2018; Deuble and de Dear, 2014; Li *et al.*, 2018).

Such studies have now been made possible through recent developments in technology. In particular, "smart building" sensor technology enables IEQ to be measured more easily than before, and with highly precise spatio-temporal specificity. Sensors can be installed and operated at a relatively low cost, enabling the continuous measurement of key IEQ parameters at different locations within a workplace. In terms of subjective data, advancements in computer and smartphone technology have also made it easier for occupants to provide repeated assessments of their workplace environment. As such, there is now a golden opportunity for researchers to conduct research which will enable them to more rigorously evaluate how occupants are affected by environmental factors in the workplace.

Two existing studies have made valuable contributions here, but neither quite demonstrates how specific aspects of IEQ can be tested against momentary assessments of comfort. MacNaughton *et al.* (2017) used sensors to measure IEQ in office buildings with or without sustainability certifications, and confirmed that occupant's environmental satisfaction and cognitive performance was higher in the certified buildings. However, their analyses did not directly associate environmental data with subjective responses, and so the precise effects of different aspects of IEQ cannot be ascertained. Romero Herrera *et al.*, (2018) also used sensors to monitor IEQ within real offices and combined these with repeated subjective comfort ratings, however their analyses focused solely on temperature and thermal comfort, and they did not consider the role of specific comfort criteria.

Therefore, the purpose of this study was to build upon these existing studies by developing a more comprehensive methodology for combining sensor-based IEQ data and repeated subjective assessments of the workplace environment. We also aimed to evaluate the process for using environmental sensors as part of operational practice. The study can be seen as a second cycle in the development of this methodology, following on from a small pilot study (authors, blinded for review). One major finding from the pilot was a low response rate, so further aims of the present study included testing strategies for improving the response rate whilst rolling out the implementation to a wider group of employees. Additionally, we also demonstrate how hypotheses regarding the nature of the IEQ-comfort relationship can be tested, starting with the baseline assumption (as might a building manager) that adherence to the WELL guidelines will lead to the highest levels of environmental comfort.

Measuring environmental perceptions through experience sampling

First, it will be necessary to verify that the proposed methodology is valid in the first place. To do this, we can assess the extent to which each individual's responses differ every time they complete the survey. If their responses are relatively stable each time, then the use of repeated sampling is unnecessary and a questionnaire distributed once will be sufficient. However, in line with the criticisms of existing methodologies (Candido *et al.*, 2016; Choi & Lee, 2018; Deuble and de Dear, 2014; Li *et al.*, 2018), we predict that there will actually be a high degree of variability in their survey responses, indicating that repeated sampling is the most appropriate method for measuring these experiences.

H_1**:** There will be high variability in each respondent's perceptions of environmental comfort each time they complete the survey.

Exploring the role of air quality

At the time the research was conducted, most commercially-available sensor devices used carbon dioxide (CO_2) as their sole indicator of indoor air quality. CO_2 rises in indoor environments due to the combination of human respiration and insufficient ventilation, and so it is often used as a surrogate measure of the effectiveness of the ventilation system for removing airborne pollutants *in general,* and therefore as a surrogate measure of overall air quality. WELL recommends that indoor carbon dioxide (CO_2) is maintained at 800 parts per million (ppm) or lower (International WELL Building Institute, 2018).

This 800 ppm threshold is in accordance with research that shows the risk of 'sick building syndrome' symptoms increases progressively when CO_2 rises above 800 ppm (Apte, Fisk & Daisey, 2000; Seppänen *et al.,* 1999; Tsai, Lin & Chan, 2012). Furthermore, the 800 ppm threshold is also approximately consistent with research demonstrating that cognitive performance and decision-making abilities are highest when CO_2 concentrations are at 600 ppm, and progressively deteriorate at higher concentrations (Allen *et al.,* 2016; Satish *et al.,* 2012). Therefore, it can be assumed that CO_2 concentration, as measured using the sensors, can be used to predict occupant satisfaction with air quality.

H_2**:** Satisfaction with air quality will be negatively associated with CO_2 concentration.

Exploring the role of temperature

Thermal comfort is not only a function of the ambient air temperature itself, but also depends upon a range of environmental and individual factors. As such, WELL does not prescribe a particular temperature range, but rather recommends that temperatures within mechanically-ventilated offices should adhere to ASHRAE Standard 55-2013 (ASHRAE, 2013), which itself uses Fanger's (1970) Predicted Mean Vote (PMV) equation to develop a suitable range. This method enables practitioners to input three environmental parameters (mean radiant temperature, air velocity, and relative humidity) and two occupant-related parameters (clothing insulation and metabolic rate) in order to generate an ambient air temperature at which a predicted 95% of occupants will be comfortable.

The PMV method is based on decades of experimental research from climate chambers (van Hoof, 2008), although the extent to which it generalises to real offices has been called into question by studies indicating its predictive validity actually tends to be very low in practice (Cheung *et al.*, 2019; Oseland, 1995). However, given the aforementioned methodological limitations of previous field studies, it is important to verify these findings using the "right-here-right-now" data collection procedure. Therefore, we start with the baseline assumption that thermal comfort really will be highest at the recommended temperature, and that employees will increasingly feel "too warm" the more that the recommended temperature is exceeded and "too cold" the more that the actual temperature falls below the recommended temperature.

H_{3A}: Thermal comfort will progressively decrease the more that actual temperature deviates from (PMV-derived) recommended temperature.

H_{3B}: The likelihood of feeling "too warm" will increase the more that temperatures exceed the recommended temperature.

H_{3C}**:** The likelihood of feeling “too cold” will increase the more that temperatures fall below the recommended temperature.

Exploring the role of illumination

Office guidelines for illumination simply seek to ensure that the light level is sufficient for supporting visual acuity during computerised tasks, balanced with sustainability requirements for preserving energy where possible. According to WELL, this is achieved by ensuring that light levels are maintained between 300-500 lux, or by maintaining light levels above 215 lux and additionally providing individualised task lighting at each workstation so that the user can increase the light level above 300 lux if they prefer (International WELL Building Institute). The 300 lux lower limit also corresponds with guidelines issued by the Society for Light and Lighting (2015).

Though research evidence in this area is limited, there is some evidence to suggest that these guidelines match actual employee preferences. For example, in one study where office workers were given control over individual task lighting, approximately 90% chose an illumination of 300 lux or above (Veitch & Newsham, 2000). Hence, it can be assumed that illumination measured through sensors will be useful for predicting employee’s visual comfort, particularly when the illumination falls below 300 lux.

H_4**:** Visual comfort will be positively associated with illumination.

Exploring the impact on productivity

Finally, it should be acknowledged that the implementation and ongoing use of sensor technology within offices represents an additional cost for building owners and employers, and so it is important to demonstrate their significance not only for subjective comfort *per se*, but also for other organisational outcomes such as productivity. As we have already mentioned, WELL and similar guidelines are premised on the assumption that higher environmental comfort will consequently improve employee wellbeing and productivity. However, this too is yet to be tested using the proposed methodology. As such, in this study we also test the extent to which environmental comfort (including satisfaction with air quality, thermal comfort, visual comfort, and also acoustic comfort) is associated with self-rated productivity.

***H_5*:** Each aspect of environmental comfort (satisfaction with air quality, thermal comfort, visual comfort, and acoustic comfort) will be independently and positively associated with self-rated productivity.

Method

Site Characteristics

The study took place in late summer in the United Kingdom. The research occurred opportunistically, following a request by a large facilities management organisation to help them interpret the practical significance of data they were collecting through (commercial-grade) environmental sensors installed at one of their offices. The research was conducted at this office site and at one additional office site belonging to the same company, who had not installed any sensors permanently but had expressed an interest in trialling temporary data loggers to measure the same parameters. Both sites could be considered as relatively typical examples of office buildings within the United Kingdom, and neither had achieved any sustainability or wellbeing certification.

Both offices featured predominantly open-plan layouts, where banks of permanent workstations without partitions were shared by four, six, or eight employees. Additionally, both sites had enclosed meeting rooms as well as breakout areas within the open-plan areas, so that employees could hold formal and informal meetings. In total, Site A had permanent seating for 142 employees, whereas Site B had seating for 56 employees. Due to differing levels of availability indicated by building managers at each site, there was a 4-week data collection period at Site A and a 2-week data collection period at Site B. The employees at both sites had a similar set of work activities, involving knowledge-based activities such as data analytics, report writing, and managing relationships with clients.

Environmental sensors

At Site A, 17 Elsys ERS CO2 sensors (Elsys, 2019) had been permanently installed on interior and exterior walls around the workplace, at approximately head height. These sensors provided continuous measurements of carbon dioxide (CO_2, in parts per million [ppm]), temperature (°C), relative humidity (%RH), and illumination (lux). At Site B, no permanent sensors were installed, so the lead researcher visited the site to install temporary data loggers to measure the same environmental parameters. Eight HOBO U12 (Onset, 2019a) data-loggers were installed in the office, with one data-logger placed on a central desk within each bank of desks. The HOBO sensors continuously monitored temperature, relative humidity, and illumination. To measure CO_2, three Telaire 7001 CO_2 sensors (Onset, 2019b) were attached to three of the HOBO data-loggers. The location of the sensors at each site is shown in Figure 1.

Although the use of different sensor models with low scientific precision at each site may be construed as a limitation, this was an unavoidable consequence of conducting the research with an industry partner who had already chosen the technology to implement at each site. However, the use of commercial-grade technology can also be seen as a positive in that it mirrors the type of device that is actually used in practice, enabling us to explore their strengths and limitations. Additionally, the technical specifications for each sensor suggest that their measurement accuracy is largely similar (see Table 1). The one possible exception to this is the measurement of illumination using the HOBO U12, for which the manufacturers provide no information regarding measurement accuracy. This limitation is discussed in the interpretation of findings relating to visual comfort and illumination.

Hypotheses relating to CO_2 and illumination assumed linear relationships with environmental comfort, so raw sensor measurements were used. For temperature, the hypothesis concerned the extent to which the actual temperature deviated from the recommended temperature, rather than the actual temperature *per se*. As such, a transformation was applied to the temperature data. The recommended temperature (i.e., the temperature at which PMV = 0) was calculated at each of the two offices, using the online thermal comfort tool developed by the Center of the Built Environment (CBE) at the University of California (CBE, 2019). We inputted the average measured humidity at each site (45.63% RH at Site A, 45.47% at Site B), and assumed constant radiant temperatures (same as dry-bulb temperature), a typical office airspeed value (0.1 m/s), a typical metabolic rate for office work (1.1 met), and a typical clothing insulation matching office dress code guidelines (1.0 clo) between participants. This calculation indicated that the optimal temperature at both sites was 22.55°C. Consequently, to represent “deviation from recommended temperature”, we created a new variable by taking the absolute difference between each measured value and 22.55 (i.e., measurements of 20.55°C and 24.55°C would both be scored “2”).

Figure 1: Simplified floorplans showing the location of the sensors at each site

Table 1: Measurement accuracy of the sensors used in the study

Sensor	IEQ Parameter	Measurement range / (accuracy)
Elsys ERS CO_2 (Site A)	Carbon dioxide	0 - 2,000 ppm / (± 50 ppm + 3% of reading)
	Temperature	0 - 40°C / (± 0.2°C)
	Relative Humidity	0 - 100% / (± 2%)
	Lux	4 - 2000 lux / (± 10 lux)
Telaire 7001 CO_2 (Site B)	Carbon Dioxide	0 – 10,000 ppm / (± 50 ppm + 5% of reading)
HOBO U12 Temp/RH/Light (Site B)	Temperature	-20 - 70°C / (± 0.35°C)
	Relative Humidity	5 - 95% / (±2.5%)
	Lux	10-30,000 / (*exact accuracy not stated*)

Questionnaire

Subjective data was captured using the experience sampling methodology, in which the participants provided repeated assessments of momentary environmental comfort during the study. As with the pilot study (authors, blinded for review), the questionnaire was designed to cover the same broad topic areas as a traditional occupant survey, allowing occupants to report their moment-by-moment assessments of core aspects of IEQ. However, in a bid to improve response rate, two major alterations were made to the way in which the survey was designed and distributed.

First, several participants in the pilot study suggested that the daily e-mail reminders to complete the workplace assessment were ineffective, as they had fallen into the habit of ignoring non-urgent e-mails. Second, even though the pilot survey had only taken five minutes to complete, it was reasoned that this may still have been too long for employees with busy workloads. As such, in the present study we used smartphone notifications to deliver a shorter one-minute survey (retaining only the core questions on subjective environmental comfort).

The survey was designed within LifeData (LifeData, 2019), a commercially-available smartphone application (app) for experience sampling research studies. The app was programmed to alert participants (using push notifications) to complete the survey at four random intervals each working day. Hence, participants at Site A each received 80 notifications across the 4-week study period, whilst participants at Site B received 40 notifications across the 2-week study period. Participants were encouraged to respond to as many notifications as they could, without disrupting their ordinary working activities. If the participant chose not to respond within 10 minutes of the notification, the notification disappeared.

On the first page of the survey, participants viewed simplified floorplans of their office divided into different zones (shown in Figure 1), and were asked to select the zone that they were currently seated in. Next, single-item measures were used for each of the five IEQ comfort criteria. The same 7-point Likert scale (1=Very dissatisfied, 7=Very satisfied) was used to assess *satisfaction with air quality, thermal comfort, visual comfort,* and *acoustic comfort.* Importantly, questions were worded so that they referred to the participant's experience 'right-here-right-now', rather than in general (e.g. "How satisfied are you with the noise levels right now?").

If the participant indicated dissatisfaction (i.e., a rating of 1-3) for any component of environmental comfort, then they were prompted with a follow-up question which invited them to list the source(s) of their dissatisfaction. For the purposes of this research, we recorded whether or not a respondent had recorded a vote of "Too warm" and "Too cold" following a response of thermal discomfort.

Finally, *self-rated productivity* was measured using an item asking "What impact has the workplace had upon your productivity in the past half hour?", where participants used a slider scale to indicate their response on a 100-point scale (1=Very negative impact, 100=Very positive impact). This item was intentionally limited to the impact of the workplace environment upon productivity, so that results were not confounded by any non-environmental influences on productivity.

After the data collection period had elapsed, spatial and temporal identifiers were used to combine questionnaire responses with objective IEQ data. The participant's response for "current working location" was used to identify the closest sensor(s) on each occasion, and the relevant timepoint was identified through data automatically collected by LifeData on the exact time each survey was completed. Specifically, we combined each survey response with the data from the nearest sensor, taking the average of each IEQ parameter in the half hour preceding the completion of the survey.

Participants

Participation in the study simply entailed downloading the LifeData app and relevant survey package, and then completing workplace assessments when a smartphone notification was received. At Site A, the 121 permanent employees at the site were contacted by e-mail with information about the study and an invitation to participate. In total, 13 individuals from this site participated in the study, and together provided 119 momentary assessments of the workplace environment across a 4-week data collection period. At Site B, 56 employees were contacted and 32 agreed to participate, together providing 417 momentary assessments across a 2-week data collection period. As such, the combined dataset contained 536 observations from a total sample size of 45 employees (24 female, 21 male). Participants' age ranged between 22 and 63 (M = 32.8).

Results

Procedure

The experience sampling method yields a “nested” data structure, whereby individual survey responses (Level 1) are nested within participants (Level 2). Using ordinary regression techniques for nested data increases the likelihood of producing spuriously significant effects (Hox, 1997), so multilevel modelling methods were used instead, following the procedure outlined by Field *et al.* (2012). Specifically, the intraclass correlation coefficient (*ICC*), which partitions the proportion of total outcome variance attributable to Level 1 and Level 2 factors, was calculated to assess the extent to which subjective responses fluctuated on each measurement occasion (H_1). Then, multilevel linear modelling was used to test the extent to which the subjective responses could be predicted by the objective IEQ data (H_2-H_5).

All data analysis was performed using R Studio (R Studio Team, 2016), using the *nlme* package (Pinheiro *et al.*, 2017) for fitting and comparing the multilevel models and the *MuMIn* package (Barton, 2018) for calculating pseudo-R^2 estimates for the models. Models were fitted using the restricted maximum likelihood procedure.

Descriptive Statistics

Table 2 shows the mean measurements for each IEQ parameter across the working day at each site. As shown, the 800 ppm upper bound for CO_2 concentration was rarely exceeded at either office, and the overall average was within the comfort boundary (M = 753 ppm at Site A, M = 785 ppm at Site B). Temperature was very close to the 22.55°C recommendation at Site A and was maintained within a relatively narrow range, but at Site B temperatures were significantly warmer and the average measurement (*M* = 25.33°C) was almost three degrees higher than the recommendation. Humidity at both sites was entirely within the 30-50% boundary specified by WELL (*M* = 45.6% RH at Site A, *M* = 45.5% at Site B). Finally, both sites failed to achieve the recommended lower bound for light intensity (*M* = 233 lux at Site A, *M* = 171 lux at Site B), indicating that both offices were relatively dark throughout the working day.

Table 3 shows the corresponding descriptive statistics from the subjective questionnaire responses. All responses were approximately normally distributed, and averages tended towards the midpoint of the scale. Interestingly, despite the closer adherence to recommended temperatures at Site A than Site B, subjective thermal comfort was lower at this site (*M* = 3.49 at Site A vs *M* = 3.71 at Site B). The most positively-rated aspects of each office were the acoustics, which were slightly higher than satisfactory at both sites (*M* = 4.97 at Site A, *M* = 4.39 at Site B).

Table 3 also shows the *ICC* for each of the outcome measures. *ICC* ranges between 0 and 1, with values closer to 1 indicating a lower proportion of within-participant variance. As such, the *ICC* is commonly used as a measure of reliability, where *ICC* > 0.6 is viewed as the minimum criteria for “good” test-retest reliability (Cicchetti, 1994). As shown, the only outcome which met this cut-off point was perceived visual comfort (*ICC* = 0.61), whilst self-rated productivity (*ICC* = 0.59) and perceived acoustic comfort (*ICC* = 0.56) were marginally below the cut-off point. The weakest test-retest reliability was observed for perceived thermal comfort (*ICC* = 0.26). Together, these results demonstrate relatively high fluctuation each time each respondent completed the survey, and so H_1 was supported.

Table 2: Mean measurements of the environmental parameters at the two sites.

	Carbon Dioxide (in ppm; <800ppm recommendation)		**Temperature (in °C; 22.55°C recommendation)**		**Humidity (in %RH; 40-60%RH recommendation)**		**Illumination (in lux; 300-500 lux recommendation)**	
Time of Day	**Site A**	**Site B**	**Site A**	**Site B**	**Site A**	**Site B**	**Site A**	**Site B**
09:00-10:00	748.33	847.76	22.64	24.71	46.32	48.32	247.25	157.62
10:00-11:00	794.43	872.02	22.73	25.10	45.94	47.58	244.07	166.85
11:00-12:00	788.15	854.75	22.70	25.36	45.82	46.61	242.07	174.30
12:00-13:00	774.78	812.78	22.71	25.52	45.52	45.50	252.09	177.18
13:00-14:00	794.66	784.56	22.75	25.62	45.41	44.69	253.66	173.14
14:00-15:00	779.87	749.59	22.79	25.61	45.57	44.00	234.43	183.45
15:00-16:00	733.76	724.86	22.76	25.59	45.57	43.48	213.21	188.39
16:00-17:00	641.98	675.74	22.62	25.50	45.01	43.34	187.29	165.00
Overall	**753.19**	**785.05**	**22.71**	**25.33**	**45.63**	**45.53**	**233.16**	**171.13**

Table 3: Descriptive statistics for each of the survey items.

	Site A		Site B		Combined		
Item	***M***	***SD***	***M***	***SD***	***M***	***SD***	***ICC***
[PERCEIVD AIR QUALITY] “How satisfied are you with air quality right now?” (1=Very dissatisfied, 7=Very satisfied)	4.55	1.45	3.76	1.24	3.93	1.33	0.51
[PERCEIVED THERMAL COMFORT] “How satisfied are you with temperature right now?” (1=Very dissatisfied, 7=Very satisfied)	3.49	1.7	3.71	1.39	3.66	1.46	0.26
[PERCEIVED ACOUSTIC COMFORT] “How satisfied are you with noise levels right now?” (1=Very dissatisfied, 7=Very satisfied)	4.97	1.46	4.23	1.28	4.39	1.35	0.56
[PERCEIVED VISUAL COMFORT] “How satisfied are you with the overall lighting right now?” (1=Very dissatisfied, 7=Very satisfied)	4.18	1.33	4.37	1.17	4.35	1.18	0.61
[SELF-RATED PRODUCTIVITY] “What impact has the workplace had upon your productivity in the past half hour?” (1=Very negative impact, 100=Very positive impact)	51.05	19.36	48.71	17.83	48.93	17.95	0.59

Main Analyses

For each outcome (perceived air quality, thermal comfort, visual comfort, and productivity), a random-intercept model fit the data better than an intercept-only model (*p*-values < 0.0001), indicating that multilevel modelling procedures were appropriate for testing the hypotheses. A binary variable representing site (1 = Site A, 2 = Site B) was added to all of the models to control for any contextual variance between the two sites. Linear models were used in all cases except for H_{3B} and H_{3C}, where logit models were used to model the binary response variables. The number of observations that each analysis was performed upon ranged from 460 to 536 due to missingness. Summary statistics for each of the multilevel linear models are presented in Table 4.

The results of the analyses provided mixed support for the study's hypotheses. In terms of the effects of the physical environment, the only significant effects arose with respect to the thermal environment. As expected, deviation from recommended temperatures was negatively associated with thermal comfort (p = 0.031), although the pseudo-r^2 estimate indicated that this was a very small effect, with only 1.1% of the outcome variance explained ($marginal\_GLMM^2$ = 0.011). The results of the logit models also confirmed that higher temperatures increased the likelihood of a "Too warm" vote (p < 0.001), but there was no evidence that the likelihood of a "Too cold" vote increased at lower temperatures (p = 0.84). Overall, H_{3B} was supported and H_{3A} was partially supported.

Contrary to expectations, there was no evidence to support a negative association between CO_2 concentration and satisfaction with air quality (p = 0.21). Thus, H_2 was not supported. However, a second model was tested *post-hoc* in which deviation from recommended temperature was added in as an explanatory variable. The results confirmed a significant effect whereby satisfaction with air quality decreased the more that temperature deviated from the thermal comfort policy (p < 0.0001). Approximately 6.3% of the variance in satisfaction with air quality was accounted for by the predictors ($marginal\_GLMM^2$ = 0.063).

There was also no evidence to support the predicted positive association between illuminance and visual comfort (p = 0.74). Indeed, the very small coefficient for illumination indicates that illuminance and subjective visual comfort were almost entirely independent of one another in the sample. Therefore, H_4 was not supported.

Finally, a multivariable multilevel regression model was used to test the hypothesised relationship between environmental comfort and self-rated productivity. As expected, the results of the model confirmed that self-rated productivity was independently and positively associated with acoustic comfort ($p < 0.0001$), thermal comfort ($p < 0.0001$), perceived air quality ($p < 0.0001$), and visual comfort ($p = 0.0001$). The pseudo-r^2 calculation revealed that these four components of environmental comfort together accounted for 50.8% of the variance in ratings of productivity ($marginal\_GLMM^2 = 0.508$). Acoustic comfort had the strongest impact upon ratings of productivity. As such, H_5 was supported.

Table 4: Summary statistics for each of the multilevel linear regression models.

	Model for predicting perceived air quality (*n* = 536 observations, from 39 participants)		
Explanatory Variable	**Estimate**	**t-value**	**p-value**
Organisation	-0.26	-0.75	0.46
CO_2 concentration (ppm)	0.0001	0.89	0.37
Temperature (deviation from comfort policy; °C)	-0.18	-4.24	<0.0001
Marginal $r^2 = 0.063$			
	Model for predicting perceived thermal comfort (*n* = 535 observations, from 39 participants)		
Explanatory Variable	**Estimate**	**t-value**	**p-value**
Organisation	0.45	1.34	0.19
Temperature (deviation from comfort policy; °C)	-0.12	-2.17	0.031
Marginal $r^2 = 0.011$			
	Model for predicting perceived visual comfort (*n* = 460 observations, from 31 participants)		
Explanatory Variable	**Estimate**	**t-value**	**p-value**
Organisation	-0.93	-1.73	0.1
Illumination (lux)	0.00004	0.33	0.74
Marginal $r^2 = 0.054$			
	Model for predicting self-rated productivity (*n* = 460 observations, from 31 participants)		
Explanatory Variable	**Estimate**	**t-value**	**p-value**
Organisation	-0.78	0.19	0.85
Visual comfort	2.41	4	0.0001
Satisfaction with air quality	2.23	4.34	<0.0001
Thermal comfort	3.46	7.68	<0.0001
Acoustic comfort	4.2	8.21	<0.0001
Marginal $r^2 = 0.52$			

Discussion

The development of environmental sensor technology opens up a golden opportunity for research combining spatially- and temporally-bound measurements of IEQ with "right-here-right-now" assessments of environmental comfort in real offices. Accordingly, the aim of this study was to develop a methodology for integrating building and human analytics in this way, and to evaluate the process by which it could be used in real offices to measure and improve employee's comfort and productivity. The findings and their implications are discussed in the following sections, along with the limitations of the study and suggestions for future research.

Relationship between IEQ and subjective comfort

Mixed support was found for the study's hypotheses about the role of IEQ. It was confirmed that adherence to the recommended temperature reduce the risk of thermal discomfort, and that exceeding the recommended temperature increased the likelihood that the occupants would report feeling "too warm", however these effects were relatively weak. In contrast to the pilot study (authors, blinded for review) there was no association between CO_2 and satisfaction with air quality, and neither was there an association between visual comfort and illumination.

At first glance, these findings seem to imply that environmental sensors are of limited utility for predicting subjective comfort. However, this should be interpreted with caution, given that the IEQ at both sites was generally within recommended ranges. Probably, environmental sensors are most useful for predicting (dis)comfort when physical conditions deviate most strongly from comfort policies. Indeed, the one IEQ issue that was detected in the study (frequent exceedance of temperature at Site B in particular) likely contributed to the statistically significant effects of temperature. In the pilot study, temperature remained almost entirely within the comfort boundary and no significant effect on thermal comfort was found, however CO_2 significantly exceeded the recommended upper bound (M = 1,425ppm) and a significant effect on satisfaction with air quality *was* found (authors, blinded for review). As such, the failure to detect significant effects here does not necessarily imply that the use of environmental sensors would not be valuable at sites which have worse IEQ conditions.

Having said that, it is also important to consider the possible limitations of the sensor technology and the assumptions underlying their use. In particular, the assumption that CO_2 is an accurate measure of overall air quality may not be completely valid. For example, the study by Ramalho and colleagues (2015) showed that whilst CO_2 is significantly correlated with most indoor air pollutants, the associations tend to be weak and can be affected by numerous seasonal, building-related, and occupant-related factors. Moreover, we also unexpectedly found that temperature was a significant predictor of satisfaction with air quality, indicating that air quality judgements may involve complex and multi-faceted determinants. To provide building managers with more useful information, therefore, it will be valuable to extend the range of IEQ parameters that are continually monitored. Indeed, more recent commercially-available sensor devices also monitor five additional types of airborne pollutant as well as CO_2 (e.g., uHoo, 2020).

The failure to find a significant effect of illumination was surprising, given that illuminance at both sites was consistently below the recommended lower bound. Possibly, this may also relate to a limitation of the sensor devices (especially for the data loggers, which did not specify measurement accuracy). However, the observed association in this case was so weak that it is more likely that moderate levels of visual comfort were achieved despite relatively dark conditions simply because the backlit computer screens enabled users to complete their tasks effectively, regardless of ambient illumination. It remains to be seen whether increasing the ambient lighting would be sufficient for achieving even higher ratings of visual comfort, or whether it will be necessary to use additional strategies such as supporting occupants' circadian rhythms through increased daylighting (Edwards & Torcellini, 2002).

Indeed, subjective environmental comfort was relatively modest for all aspects of IEQ, despite relatively high adherence to comfort boundaries. Possibly, the most effective way of optimising environmental comfort will be to allow employees to adjust local conditions to their own preferences, instead of attempting to satisfy all occupants with the same configuration of IEQ. For example, in thermal comfort research it is now recognised that there is significant inter-individual variability in thermal comfort preferences (Wang *et al.,* 2018), which may explain why the PMV method tends to be a relatively poor predictor of actual thermal comfort in practice (Cheung *et al.*, 2019; Oseland, 1995). One study which trialled individual temperature control (through heaters and fans embedded in the desk chair) succeeded in greatly improving thermal comfort amongst a small sample of participants (Kim *et al.,* 2019), and similar strategies have also been suggested to improve visual comfort (Veitch, 2013).

Relationship between subjective comfort and productivity

Interestingly, whilst the relationship between IEQ and subjective comfort was complex and unclear, there was a very clear and strong association between subjective comfort and self-rated productivity. As expected, employees reported the highest levels of productivity when they were satisfied with the air quality, temperature, illumination, and noise levels within the office. This is in line with theoretical expectations that environmental comfort is a crucial factor which mediates the relationship between the physical environment and employee job performance (Roskams & Haynes, 2019; Vischer, 2007, 2008), in that *dis*comfort contributes to stress, and draws attentional and energetic resources away from the completion of work-related activities. Hence, however it might be achieved, the provision of subjective comfort amongst employees should be a crucial consideration for employers.

The strong effect size associated with acoustic comfort in particular is in accordance with previous research highlighting that distraction by irrelevant speech has an especially pernicious impact on employee productivity in open-plan offices (e.g., Haapakangas *et al.*, 2008; Mak & Lui, 2012). Environmental sensors used to measure sound pressure level could ostensibly help to detect conditions which are more likely to result in distraction, however it should be noted that distraction does not result from loudness *per se,* but rather from the intelligibility of the irrelevant noise source and the extent to which it captures the employee's attention (Oseland & Hodsman, 2018). Therefore, it would be most effective to combine their use with psychoacoustic design strategies, such as the provision of silent working areas within the office and/or the use of more absorbent building materials to limit sound transmission.

Process evaluation

In addition to developing a methodology for integrating building analytics and human analytics, we also wanted to evaluate whether this process was justified and to identify the factors which affected its implementation at real office sites. Turning first to the justification for the methodology, the results confirmed that individual experiences of environmental comfort and productivity tended to fluctuate each time the survey was completed, casting aspersions on the assumption that these phenomena can be reliably measured using a one-time-only questionnaire asking employees how they feel *in general.* As critics have noted (e.g., Deuble & de Dear, 2014), this methodology appears to yield responses which are far too general to be practically useful. For example, an average response of "moderately comfortable" could refer equally to an employee who is moderately comfortable at all times and an employee who spends half the time highly uncomfortable and the other half highly comfortable. Hence, our results support the contention that the experience sampling methodology is a more appropriate for measuring employees' experiences in the workplace.

Secondly, recognising that the use of the sensor devices will be most useful when a high proportion of office users agree to provide repeated measures of subjective experience, we also wanted to explore whether response rate could be improved by reducing the length of the survey and distributing it via smartphone rather than e-mail. The effectiveness of this strategy was mixed. At Site A, both the initial uptake (~10.7%) and the subsequent completion rate of the distributed surveys (~11.4%) was notably lower than that of the pilot study. However, at Site B there was significantly higher uptake (~57.1%) and also a relatively good completion rate of the distributed surveys (~32.6%).

This suggests that response rate is not simply a function of the way in which the survey was designed and distributed, but is also strongly affected by organisational-contextual factors. Indeed, it has been previously demonstrated that the degree to which employees within an organisation feel autonomous or externally-controlled affects the way in which they respond to survey reminders (Romero Herrera *et al.*, 2018). On a similar note, in the present study we observed that the building managers at Site B were considerably more enthusiastic about the research, and took it upon themselves to repeatedly encourage employees at the site to participate in the research. These findings imply that organisational leadership and company culture may play a significant role in influencing engagement with the technology. This prediction could be verified in future by also capturing qualitative and/or quantitative data about the organisation itself, and considering which factors differentiate the most and least engaged groups of respondents.

Limitations

The present study demonstrates a sound methodology for interrogating the relationship between IEQ and subjective comfort in real offices, making use of the latest technological developments and overcoming the limitations of previous research. Nonetheless, our current findings are restricted to two office sites with relatively good IEQ, and may not generalise to other environments. Similarly, the relatively small dataset in the present study also limited our ability to add additional important variables to the models (e.g., age, gender), in order to preserve statistical power. By way of contrast, the database of the most popular traditional occupant survey currently has more than 550,000 responses from almost 4,000 different buildings (Oldman, Finch, Percival & Rothe, 2019). Accordingly, we believe an important next step is to grow the overall dataset and increasingly incorporate measurements from a more diverse range of offices with more varied environmental conditions

As the size of the overall dataset grows, so too does the statistical power for analysing the associations between the variables of interest. The methodology we have developed can be easily replicated within any workplace, using commercially-available sensor and mobile smartphone technology. By compiling a large dataset in this manner, and potentially by developing it even further through the inclusion of individual variables and organisational variables, researchers can test increasingly complex models for predicting employee environmental comfort. This will provide valuable new insights into the nature of the IEQ-comfort relationship.

Secondly, it should also be noted that our research is passive, in that we made no active intervention to the workplace environment (other than installing the temporary data loggers at Site B). In practice, facilities managers will increasingly use live environmental sensor data as part of their everyday operational practice, and may also incorporate repeated subjective assessments of occupant experience as this study recommends. However, there is limited understanding at present of how this type of feedback loop between building users and managers can be most effectively used within real organisations to proactively support occupant comfort, wellbeing, and productivity. This would be a useful focus of investigation in future research.

Conclusion

With smart building technology predicted to exponentially increase in popularity in coming years, it is crucial to understand how new technology can be effectively used to enhance occupant experience in the workplace. Our research is the first to develop the methodology for directly combining environmental sensor data with repeated assessments of subjective experience, in order to test the extent to which compliance with IEQ comfort criteria effectively improves occupant comfort.

The results showed that there was a weak relationship between temperature and thermal comfort, but no relationship between CO_2 and satisfaction with air quality, nor between illumination and visual comfort. However, there was a strong effect to suggest that employees felt most productive when they were satisfied with the air quality, temperature, illumination, and noise levels within the office. Therefore, the optimisation of environmental comfort is highly important but also very complex, and may necessitate strategies beyond mere compliance with comfort criteria. In the next stage of the research, it will be necessary to apply the methodology more widely, and to investigate the implementation of a proactive facilities management service which combines both environmental sensor data and subjective human data.

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