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Predictive analytics in facilities management: A pilot study for predicting environmental comfort using wireless sensors

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Abstract

Purpose: Advancements in wireless sensor technology and building modelling techniques have enabled facilities managers to understand the environmental performance of the workplace in more depth than ever before. However, it is unclear to what extent this data can be used to predict subjective environmental comfort. Thus, the aim of this study was to pilot test a methodological framework for integrating real-time environmental data with subjective ratings of environmental comfort.

Design/Methodology/Approach: An open-plan office was fitted with environmental sensors to measure key indoor environmental quality parameters (carbon dioxide, temperature, humidity, illumination, and sound pressure level). Additionally, building modelling techniques were used to calculate two spatial metrics (‘workspace integration’ and workspace density) for each workspace within the study area. 15 employees were repeatedly sampled across an 11-day study period, providing 78 momentary assessments of environmental comfort. Multilevel models were used to explore the extent to which the objective environmental data predicted subjective environmental comfort.

Findings: Higher carbon dioxide levels were associated with more negative ratings of air quality, higher ‘workspace integration’ was associated with higher levels of distractions, and higher workspace density was associated with lower levels of social interactions.

Originality/Value: To our knowledge, this is the first field study to directly explore the relationship between physical environment data collected using wireless sensors and subjective ratings of environmental comfort. The study provides proof-of-concept for a methodological framework for the integration of building analytics and human analytics.

One of the facilities manager's core responsibilities is to ensure that the workplace environment remains comfortable for its occupants, so that they can work in a healthy and productive manner. The traditional focus on cost reduction is increasingly seen as outdated, and practitioners are now expected to support their clients through value-added services instead (Haynes, 2007). One such way to add value is to optimise indoor environmental quality (IEQ), as this plays a major role in either supporting or impeding the health and productivity of workplace users (Al Horr *et al.*, 2016). For example, practitioners might follow guidelines for IEQ maintenance found in best-practice certifications such as the WELL Building Standard (International WELL Building Institute, 2018).

Evidently, to ensure optimal IEQ is being maintained it is necessary to perform physical measurements of key environmental parameters to determine whether these remain in pre-specified comfort boundaries. Previously, such measurements would have necessitated the use of a mobile cart equipped with numerous on-board meters (e.g., Candido *et al.*, 2016; Parkinson *et al.*, 2015). The inherent limitations of this approach, namely the high material and labour costs and the fact that it is only possible to monitor a certain location within the building for a limited period of time, meant that organisations traditionally performed IEQ measurements rarely or eschewed them entirely.

However, recent developments in the field of wireless sensor technology have introduced an encouraging alternative solution. Sensors are comparatively cheap to install and operate, and are capable of providing continuous measurements of key environmental parameters, bound to specific locations at specific times. The output from hundreds of sensors can be overlaid onto a three-dimensional model of the workplace and visualised in real time, allowing the immediately identification and remediation of sub-optimal environmental conditions. Indeed, technology is being developed to integrated sensor readings into ‘smart’ heating, ventilation, and air-conditioning (HVAC) systems to ensure that the process of remedying poor IEQ occurs automatically, whilst simultaneously improving the energy efficiency of the HVAC system by up to 39% (Foster *et al.*, 2016; Salamone *et al.*, 2017). In this way, wireless sensors can help facilities managers to understand and manage the environmental performance of the workplace in more depth than ever before.

Whilst such developments certainly appear promising, they have somewhat preceded a clear framework for how the building data can be effectively used in the overall workplace strategy. In particular, the prediction that compliance with environmental comfort boundaries will optimise occupant comfort remains to be empirically validated in real workplace environments. To our knowledge, only one previous field study has used sensors to monitor IEQ in offices (MacNaughton *et al.*, 2017). However, the environmental data in that study was provided for largely descriptive purposes to illustrate differences between ‘green’ and ‘non-green’ buildings, and was not directly tested against occupants’ subjective responses. As such, there is still limited information regarding the extent to which the measured environmental parameters predict relevant subjective outcomes.

Thus, the aim of this study was to pilot the use of environmental sensors in a real workplace environment and trial a methodology for testing the extent to which objective IEQ measurements predict momentary subjective environmental comfort. Additionally, a secondary aim was to test whether certain responses could be predicted by other (non-sensor-based) spatial metrics, recognising that the complexity of the workplace environment cannot be captured through sensors alone. Specifically, it is proposed that the combined approach would more accurately capture aspects of both the ‘physical environment’ (i.e., IEQ) and the ‘behavioural environment’ (occupants’ experiences of distraction and interaction).

IEQ Comfort Boundaries

Typical sensor-based measurements of IEQ include carbon dioxide (CO_2; in parts per million [ppm]), temperature (in degrees Celsius [°C]), humidity (in relative humidity, expressed as a percentage [%RH]), sound pressure level (in A-weighted decibels [dBA]), and illuminance (in lux). These metrics generate a detailed approximation of IEQ within the workplace, and can be benchmarked against pre-determined comfort boundaries. In this paper, we will generally refer to the comfort boundaries recommended within the WELL Building Standard (International WELL Building Institute, 2018).

For indoor air quality, WELL recommends that CO_2 levels are kept below 800ppm. This in accordance with research indicating that the risk of experiencing 'sick building syndrome' (SBS) symptoms (e.g., concentration difficulties, fatigue, headaches) increases progressively as CO_2 rises above 800ppm (Seppänen *et al.*, 1999). It is also expected that productivity will be higher if this threshold is met, based upon a study indicating that cognitive performance was 101% higher when CO_2 was reduced from 1400ppm to 600ppm (Allen *et al.*, 2016). It is worth noting that deficits are not necessarily directly caused by the presence of CO_2 *per se*, but rather that CO_2 is used as a surrogate measure of other airborne pollutants (e.g., particulate matter, volatile organic compounds). Generally speaking, however, good indoor air quality can be assumed when CO_2 is below 800ppm.

To optimise thermal comfort, WELL prescribes compliance with Standard 55-2013 from the American Society for Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE, 2013), which itself prescribes that acceptable temperature ranges in mechanically-ventilated offices should be determined using the 'predicted mean vote' (PMV) method. The PMV equation uses five input values (radiant temperature, air velocity, humidity, clothing insulation, metabolic rate) to prescribe an ambient air temperature range which will purportedly satisfy 95% of occupants.

For humidity, the comfort boundary is derived from the United States Environmental Protection Agency (US EPA, 2019), which recommends that optimal indoor humidity is achieved at 30-50%RH, although humidity up to 60%RH is acceptable. If these conditions are not maintained, there is increased risk of the development of mould and respiratory irritation.

In terms of illumination, it is suggested that light intensity must simply support visual acuity of office tasks without causing eye strain or discomfort (e.g., through insufficient light exposure or glare). To achieve this, WELL prescribes that ambient lighting should exceed 215 lux and that, if ambient lighting is below 300 lux, task lighting should be made available to provide light of 300-500 lux at individual workstations. This corresponds to recommendations issued by the Society for Light and Lighting (SLL, 2015), indicating that computerised office work is supported by an ambient illumination level of 300-500 lux.

Finally, for noise levels, WELL does not prescribe comfort boundaries for sound pressure level, suggesting instead a behavioural solution in which certain sections of the office are segmented as ‘quiet zones’. This reflects growing consensus amongst workplace practitioners that the objective properties of sound only account for approximately 25% of its propensity for annoyance (Oseland and Hodsman, 2018), and that the same noise source can be viewed by different employees as a useful form of interaction or as an annoying distraction (Haynes, 2008). Accordingly, an effective acoustic design solution focuses on providing functionally different workspaces and providing occupants the ability to choose between them, rather than on trying to control noise levels as such. Having said that, it has previously been suggested that the optimal noise level within open-plan is 45-48 dBA

(Bradley and Gover, 2004), on the basis that measurements which exceed 48 dBA are indicative of excessive and potentially disruptive levels of human speech. Possibly, this could be a useful comfort boundary for facilities managers to consider.

Additional Spatial Metrics

Whilst the use of sensors can provide facilities managers with a useful approximation of IEQ, these parameters are limited to the physical environment and do not capture the complexity of the behavioural environment. As such, we also considered whether two additional spatial metrics might also be used to predict occupants' experiences of interactions and distractions in the workplace.

First, we considered *workspace density*, referring to the ratio between the size of the workplace and the number of occupants it houses. In recent years, workspace density has generally increased as organisations pursue strategies aimed at maximising space efficiency. Whilst this offers a competitive advantage in terms of corporate real estate costs, higher-density offices have been associated with lower overall environmental satisfaction and increased perception of crowding (Hua *et al.*, 2011; May *et al.*, 2005).

Additionally, although it might be logical to assume that more dense workplaces will engender higher levels of interaction between colleagues, research actually indicates that higher workspace density is associated with lower perceived support for collaboration (Hua *et al*., 2011). Possibly, this occurs because occupants in more dense environments need to concentrate harder to block out distractions, thus reducing collaboration (Hua *et al.*, 2011) and/or because they lose the ability to regulate their face-to-face interactions, and so revert to digital forms of communication to preserve their privacy (Bernstein and Turban, 2018).

Second, we also considered the ‘visibility graph analysis’ (VGA) technique, which can be used to calculate objective measurements of *workspace integration* by assigning a numerical score to each individual workspace based upon the extent to which it can be seen from other workspaces. For example, a workspace with low architectural privacy (e.g., located away from dividing walls, no partitioning between desks) will be highly visible from other locations and so receive a high score for integration, whereas workspaces with high architectural privacy are less visible and so receive a low score for integration. This overcomes limitations of previous approaches which differentiated between overall office layouts rather than between desks (Bodin Danielsson and Bodin, 2008), meaning that the variation between different workspaces within an office (e.g., due to architectural characteristics of the desk) could not be captured.

VGAs have been most commonly used in urban design, but researchers have recently considered their potential utility in the context of the workplace. In previous studies the technique has been used to distinguish between ‘sociopetal’ and ‘sociofugal’ workspaces (designed to encourage or prohibit interaction, respectively) (Sailer and Psathiti, 2017), and there is evidence to suggest that employees working from more integrated workspaces tend to engage in a higher number of knowledge-sharing activities (Appel-Meulenbroek, 2014). Thus, in the present study we considered whether workspace integration could be used to effectively predict experienced interaction and distraction levels.

The Present Study

To summarise, the aim of the present study was to investigate the extent to which objective real-time measurements of IEQ and spatial workplace metrics could predict subjective ratings of environmental satisfaction. Based on the research and guidelines discussed earlier, it was hypothesised that:

H_1: CO_2 concentration will be negatively associated with ratings of air quality.

H_2: Compliance with thermal comfort policy will be positively associated with ratings of thermal comfort.

H_3: Compliance with humidity comfort policy will be positively associated with ratings of satisfaction with humidity.

H_4: Illumination will be positively associated with ratings of satisfaction with light levels.

H_5: Sound pressure level, workspace density, and workspace integration will be positively associated with distraction levels.

H_6: Sound pressure level and workspace integration will be positively associated with interaction levels, whereas workspace density will be negatively associated with interaction levels.

Method

Participants

The participants for this study were real office workers from one office used by a large private-sector organisation in the United Kingdom. The office had an open-plan design which was divided into different ‘neighbourhoods’ for each business unit. The organisation employed an activity-based working concept, meaning employees did not have assigned desks and generally worked from different workstations within their neighbourhood. One neighbourhood within the office, containing 58 non-assigned workstations, was designated as the study area (see Figure 1 for floorplan).

An e-mail containing information about the study was sent to 47 employees, using the distribution list for the business unit. Additionally, given that employees from other business units also used the study area semi-regularly, flyers with an invitation to participate in the study were placed on each desk, and the primary investigator verbally communicated information about the study whilst in the office. No incentives were offered for participation. In total, 15 employees (9 male, 6 female) volunteered to participate.

INSERT FIGURE 1 HERE

Building Analytics

Prior to the first day of the study period, the study area was equipped with wireless environmental data loggers. The position of the data loggers is shown on Figure 1. On each of the 11 banks of desks within the study area (each containing between four and six individual workstations), a HOBO U12 Data Logger (Onset, 2019a) was placed in the centre of the desks to continuously measure temperature, humidity, and light intensity. Additionally, separate data loggers were also placed on two desks (F1 and I5): Telaire 7001 CO2 sensors (Onset, 2019b) were used to continuously measure CO_2 (ppm) and PCE-322A Sound Level Meters (PCE Instruments, 2019) were used to continuously measure sound pressure level (dBA). The two desks were specifically chosen as they were approximately in the middle of the two zones within the study area.

For the purposes of data analysis, we averaged the environmental data across the half hour preceding the completion of each survey. For CO_2, light intensity, and sound pressure level, raw measurements were used given that it was predicted that occupant comfort would get progressively worse (in the case of CO_2 and sound pressure level) or better (in the case of light intensity) as the measurement increased. For temperature and humidity, it was necessary to calculate the degree to which the readings were within or outside of the 'optimal' comfort zone (i.e., the degree of compliance with the comfort policy), given that both 'too low' and 'too high' readings were predicted to result in lower occupant comfort.

For temperature, the PMV method was used to calculate an optimal value, using an online thermal comfort tool compliant with ASHRAE Standard 55 (Center for the Built Environment, 2019). Inputted values included the average measured humidity during the study period (52.18%RH), a typical office air speed value (0.1 metres per second), a typical metabolic rate for office work (1.1 met), and the clothing insulation value for typical winter indoor clothing (1.0 clo). Based on these values, the online tool indicated that 22.4°C was the optimal temperature. For the purposes of the analysis, 22.4 was subtracted from the raw values and the resultant scores were squared to yield a value to represent the extent of non-compliance, in absolute terms, with the thermal comfort boundary.

For humidity, 30-50%RH was the optimal range indicated by the US EPA (2019). Therefore, for the purposes of analysis, any raw value that was within this range was scored as '0'. As it happened, during the study period the humidity never dropped below 30%RH, and the only measurements which were outside of the comfort policy were those which exceeded 50%RH. As such, to reflect the extent to which these measurements were outside of the comfort boundary, 50 was subtracted from these raw values, and the resultant scores were used in the analyses.

Finally, building modelling techniques were used to calculate the additional building metrics, using the DepthmapX software (DepthmapX development team, 2017). The VGA technique was used to attain an objective value of workspace integration at each of the workspace, where scores range between 1 (highly segregated) to 10 (highly integrated). Workspace density was calculated as the number of additional workspaces within 15 feet of the target workspace.

Human Analytics

Each day during the study period, participants were sent an e-mail with a link to a workplace evaluation survey. On each occasion, the survey was sent at one of four times (10:00 a.m., 11:30 a.m., 1:30 p.m, or 3:00 p.m.), using a random number generator to randomly assign participants to different time-slots each day.

The survey contained items that corresponded approximately to the items found on typical workplace occupant questionnaires, with slight adaptations so that ratings were confined to the preceding half hour, in order to capture momentary rather than general perceptions. The full list of items used, including summary statistics, is shown in Table 1. Specifically, the different sections of the survey included:

Identification code. Participants provided a unique identification code using the first letter of their surname, their birth month, and the first two letters from their birthplace, each time they completed the survey. This enabled their responses to be linked from one time to the next without compromising their right to anonymity.

Work location. Participants viewed the floorplan in Figure 1 and selected their current workspace (or chose 'Other' if they working at a different location). This enabled their responses to be linked with the corresponding set of environmental data from the nearest sensors.

Physical Environment. Four items were included to measure satisfaction with different components of IEQ. Specifically, respondents rated their satisfaction with *air quality, temperature, humidity,* and *light intensity* in the past half hour. As shown in Table 1, ratings for each tended to be slightly higher than the midpoint on the 7-point scale ($4.5 \leq M \leq 4.94$), indicating moderate satisfaction with the physical environment.

Behavioural Environment. Originally, satisfaction with the behavioural environment was conceptualised as the extent to which distractions and interactions had been experienced in the preceding half hour, using a 7-point scale. To measure distractions, four items were taken from Lee and Brand's (2005) measure (auditory distractions, too much noise, visual distractions, adequate privacy) and one item was taken from Haynes' (2008) measure (crowding). However, the Cronbach's alpha associated with this scale was poor ($\alpha = 0.58$), but would be significantly improved by dropping the item relating to privacy. As such, the remaining four items were retained as the measure of *distractions* ($\alpha = 0.84$), and the single item measuring *privacy* was also included in the analyses. It was predicted that sound pressure level, workspace density, and workspace integration would be negatively associated with perceived privacy.

To measure interactions, the same 7-point scale was used to rate two items from Haynes' (2008) measure, reflecting interactions for work and for social purposes. However, the correlation between these items was weak ($r = 0.18$), so *work-related interactions* and *social interactions* were analysed separately. It was predicted that sound pressure level and workspace integration would be positively associated with both forms of interaction, whilst workspace density would be negatively associated with both forms of interaction.

The descriptive statistics shown in Table 1 indicate that participants generally had positive perceptions of the behavioural environment, indicating relatively high levels of work-related (M = 5.46) and social interactions (M = 5.55), and low levels of distractions (M = 3.67). However, perceived privacy was low (M = 3.36).

INSERT TABLE 1 HERE

Results

Given that the same participants were repeatedly sampled at different occasions during the study, multilevel linear modelling was used to accommodate the nested structure of the data (repeated measurement occasions within participants). All data analysis was performed using the RStudio software (R Studio Team, 2016), following the procedure outlined by Field, Miles and Field (2012). The *nlme* package (Pinheiro *et al.*, 2017) was used for fitting and comparing multilevel models, and the *MuMIn* package (Barton, 2018) was used for calculating pseudo-R^2 estimates for the final models. All regression models were fitted using the restricted maximum likelihood estimation method.

Descriptive Statistics for Sensor Readings and Spatial Metrics

Table 2 shows average sensor measurements for each component of IEQ. The full dataset contains tens of thousands of individual measurements from different locations around the study area, providing a high degree of spatio-temporal specificity. For the purposes of simplicity, in this table we have combined the measurements from the different sensors on the different days into single hourly averages and overall averages for each environmental parameter.

As shown, the average CO_2 level (*M* = 1424.9ppm) and average sound pressure level (*M* = 53.99dBA) were above the recommended range. Humidity (*M* = 52.18%RH) also tended to be slightly outside the optimal comfort boundary, but was within the wider boundary judged to be acceptable by the US EPA (2019), which extends to 60%RH. Temperature (*M* = 23.59°C) was slightly higher than the ‘optimal’ temperature of 22.4°C, but was still within the wider comfort boundary determined using ASHRAE 55-2013. The average illumination (*M* = 448.91 lux) was within the comfort boundary.

INSERT TABLE 2 HERE

Descriptive statistics were also calculated for the spatial metrics. The scores for workspace integration (*M* = 4.98, *SD* = 0.58, *Min* = 4.55, *Max* = 6.58) indicate that all of the workspaces were in moderately integrated locations, with relatively low variation. Workspace density showed more response variance, and indicated that on average there were 12 employees within 15 feet of the workspace (*M* = 12.3, *SD* = 12.4, *Min* = 4, *Max* = 22).

Main Analyses

Physical environment. To assess the need for a multilevel structure in the regression analyses, intercept-only and random-intercept regression models were compared for satisfaction with air quality, temperature, humidity, and light intensity. The reduction in loglikelihood ratio was significant in the cases of air quality ($p < 0.0001$) and light intensity ($p = 0.05$), so multilevel regression techniques were used for these variables. However, there was no improvement in model fit for the models predicting temperature ($p = 0.49$) or humidity ($p = 0.14$), so ordinary regression techniques were used in these cases.

For each environmental comfort variable, regression models were conducted to predict the subjective response using the appropriate objective environmental variable(s). There was no evidence to support the predictions that compliance with thermal comfort policy would predict satisfaction with temperature ($p = 0.27$), that compliance with humidity comfort policy would predict satisfaction with humidity ($p = 0.07$), or that light intensity would predict satisfaction with light levels ($p = 0.9$).

The only significant effect in the physical environment analyses was for air quality. There was evidence to suggest that higher measured levels of CO_2 were associated with more negative ratings of air quality ($p < 0.0001$). The pseudo-R^2 estimate for this model indicated that approximately 14.8% of the variance in ratings of air quality could be attributed to the CO_2 level ($marginal\_GLMM^2 = 0.148$).

Behavioural Environment. Again, intercept-only and random-intercept regression models for each of the behavioural environment variables were compared to assess the need for a multilevel structure. In this case, there was a significant improvement in model fit for perceived privacy ($p < 0.0001$), social interactions ($p < 0.0001$), and work-related interactions ($p = 0.04$), indicating that multilevel modelling was appropriate. However there was no significant improvement in model fit for distractions ($p = 0.42$), so an ordinary regression was appropriate here.

For each behavioural environment outcome, the effects of three explanatory variables (sound pressure level, workspace integration, and workspace density) were tested. In each case, simple regression models were constructed to assess the bivariate relationship between each predictor and outcome. If more than one predictor was significant at the bivariate levels, multiple regression models were constructed and compared with the earlier model, using the Bayesian Information Criterion to determine the model which best fit the data.

The results showed that none of the explanatory variables were significantly associated with perceived privacy ($p \geq 0.23$) or work-related interactions ($p \geq 0.2$). The model predicting social interactions showed that neither sound pressure level nor workspace integration were significant predictors ($p \geq 0.14$), but that there was a significant negative relationship between social interactions and workspace density ($p = 0.05$).

For distractions, the bivariate models revealed significant positive associations with both sound pressure level ($p = 0.02$) and workspace integration ($p < 0.001$), but not workspace density ($p = 0.69$). The two significant variables were retained in a multiple regression model which accounted for approximately 19.6% of the variance in levels of distractions ($R^2 = 0.196$), and in which workspace integration remained significant ($p = 0.02$) but sound pressure level rose marginally above significance ($p = 0.056$).

Discussion

The aim of this pilot study was to test the extent to which the data collected via wireless environmental sensors and additional spatial metrics could predict employees' momentary ratings of environmental comfort. The results of the study provided mixed support for the hypotheses, and are discussed with respect to their theoretical and practical implications.

Physical Environment

It had been predicted that measured CO_2 levels would be negatively associated with momentary air quality satisfaction ratings (H_1). Our results supported this hypothesis, indicating that more negative ratings of air quality were more likely at higher concentrations of CO_2. This is in accordance with previous laboratory studies demonstrating an association between CO_2 and subjective ratings of air quality (Park and Yoon, 2011; Zhang *et al.*, 2017). Associations between higher levels of CO_2 and the prevalence of SBS symptoms has also been previously demonstrated (Allen *et al.*, 2016; Seppänen *et al.*, 1999), indicating that the indoor air quality may have contributed to issues such as concentration difficulties and respiratory problems amongst the employees within our office.

The predictions that compliance with thermal comfort policy would be associated with higher ratings of thermal comfort (H_2), that compliance with humidity comfort policy would be associated with higher satisfaction with humidity (H_3), and that higher illuminance would be associated with higher satisfaction with light intensity (H_4) were not supported by the data. We suggest that two factors may have contributed to these non-significant findings, both of which will be discussed in more detail in later sections.

First, it should be noted that temperature, humidity, and illumination were almost entirely within the prescribed comfort boundaries, meaning that we were not able to test the effects of sub-optimal environmental conditions for these parameters. Second, it has also been previously demonstrated that individual difference characteristics can moderate the individual response to a particular component of the physical environment (e.g., the response to temperature is moderated by gender and age; Wang *et al.*, 2018), so it is also possible that the extent to which occupant comfort can be predicted using a single environmental variable will always be significantly restricted.

Behavioural Environment

It had been hypothesised that higher perceived distractions would be predicted by higher sound pressure level, workspace density, and workspace integration (H_5). The data provided partial support for this hypothesis, demonstrating that higher levels of distractions tended to occur at more integrated workspaces. This effect was observed despite the fact that there was relatively low variance in workspace integration, and may have been even more pronounced had the study included a wider range of workspaces. Thus, the suggestion that using VGA to calculate workspace integration can helpfully distinguish sociofugal and sociopetal workspaces (Sailer and Psathiti, 2017) was supported. There was also a trend to suggest that higher levels of distractions were associated with higher average sound pressure level, although this effect rose marginally above the criteria for statistical significance in the multiple regression analysis.

It was also predicted that sound pressure level, workspace density, and workspace integration would be associated with levels of work-related and social interactions (H_6). Only one significant effect was observed for these outcomes, indicating that respondents working from areas with higher workspace density tended to report lower levels of social interaction. This is in accordance with research suggesting that interpersonal communication actually worsens in more dense and open workplaces (Bernstein and Turban, 2018; Hua *et al.*, 2011; Kim and de Dear, 2013), and suggests that workplace alterations designed to increase space efficiency (e.g., transition to open-plan office, increasing desks within existing space) should not be justified in terms of supposed interpersonal benefits.

Finally, we also tested whether sound pressure level, workspace integration, and workspace density were associated with perceived privacy. Privacy had originally been conceptualised as an aspect of distraction, but transpired to be relatively independent of the other items used to measure distractions. It had been anticipated that employees would report lower perceived privacy at more dense and more integrated workspaces, and when the average sound pressure level was higher. However, there was no support for this hypothesis. Again, this might also reflect the fact that there was relative low variation in workspace type and/or that individual difference factors, particularly noise sensitivity, can significantly moderate the individual's experience of the acoustic environment (authors, manuscript accepted for publication; Haapakangas *et al.*, 2014), which in turn could affect their perception of privacy.

Limitations

The main aim of this study was to provide proof-of-concept for a methodological framework for integrating human analytics and building analytics, and so a relatively small-scale study within one zone of a single workplace was conducted. Whilst this enabled us to develop the framework, it also led to various limitations which might explain the lack of support for some of the hypotheses.

Firstly, it should be acknowledged that three IEQ factors (temperature, humidity, and illumination) were almost entirely within the prescribed comfort boundaries during the study period. From the research perspective, this is a limitation because there was insufficient data to test whether poor environmental conditions (i.e., non-compliance with comfort boundaries) results in lower levels of environmental comfort. In future research, it could be useful to adopt a quasi-experimental approach in which the investigators are able to manipulate environmental conditions, or to conduct field studies at a more diverse range of workplaces, including those with poorer IEQ.

Similarly, the types of workspace within the study area were all relatively similar, in that they were all located within a medium-to-large open-plan area. Whilst there was some variance in workspace density, generally reflecting the position of the workspace relative to exterior walls, the scores for workspace integration tended to be quite similar. Whilst some significant effects were observed even at this low level of variation, it would be more beneficial in future research to test a greater diversity of workspaces (particularly enclosed and segregated working areas), to more rigorously test the hypotheses.

The fact that this was a pilot study also means that there were a relatively low number of observations used in the analysis, which raises the possibility that there may have been insufficient statistical power for detecting significant effects. Thus, the present findings should be viewed tentatively until further research has been conducted. As the methodological framework for integrating building analytics and human analytics continues to develop, it will be necessary to conduct similar investigations but with significantly larger samples and across a large and diverse group of different workplaces, to test the hypotheses more definitively. With the core infrastructure in place (i.e., sensors installed within workplaces, technological solution to repeatedly sample employee experiences), very large datasets can be compiled relatively easily and analysed for valuable insights.

Finally, there is a small risk that a Hawthorne effect may have occurred (i.e., that changes in the employees' responses were a result of being observed rather than fluctuations in environmental conditions). To mitigate this risk, we took several steps to ensure that participants' working environment and practices during the study period closely replicated normal conditions. The sensors used were small and unobtrusive, and the daily questionnaires were designed to be completed relatively quickly. All communications about the study clearly outlined the purpose of the study, and encouraged participants to answer completely honestly so that their responses could be used to help researchers to learn more about the environmental conditions which best support occupant comfort and productivity. As such, we believe there is only low probability that a Hawthorne effect occurred, and it can be reasonably concluded that the findings truly reflect individuals' responses to different environmental conditions.

Practical Implications

Overall, the results of the study provide moderate support for the utility of using wireless sensors to effectively support occupant comfort. When viewed together with the fact that sensors are comparatively cheaper than traditional solutions for measuring IEQ, particularly in the long term and with a high degree of spatio-temporal specificity, the results here suggest that the installation of sensors will be useful for helping facilities managers to monitor and improve IEQ in workplaces.

For example, our results indicated that lower ratings of air quality were more likely when CO_2 concentrations were higher. A sensor-based approach could be used to continuously monitor CO_2 that it stays below the 800ppm threshold, where remedial action is prompted whenever the measurements rise above this threshold. As smart building technology continues to develop, this could be done completely automatically as part of a demand-controlled ventilation system which automatically triggers increased ventilation when the sensors detect CO_2 levels have risen above 800ppm. In this way, adherence to best-practice certifications can be balanced with a sustainable energy strategy using a sensor-based climate control system (Foster *et al*., 2016).

We previously noted that for certain environmental parameters, particularly temperature and noise, the employee's response can be moderated by various individual difference factors, limiting the extent to which comfort policy adherence can adequately predict subjective comfort. However, sensors may also form part of the solution here. Researchers are working on the development of office desks with integrated systems for personal control over the local environment, where machine-learning algorithms use both environmental sensor data and occupants' behaviours to generate individual 'comfort profiles' that can be automatically loaded for individual users (Aryal *et al.,* 2018). Similarly, a recent trial of office desk chairs which allowed the user to customise local temperatures found that thermal satisfaction votes increased to 96% across a range of ambient air temperatures (Kim *et al.,* 2019). Whilst such technology is still in early stages of development, it is certainly feasible that the offices of the future will combine wireless sensors and controllable comfort systems in this manner, to ensure high occupant comfort even when individual users have markedly different preferences.

The results also supported the utility of the spatial metric analyses, particularly the use of VGAs to distinguish between sociopetal and sociofugal working areas (Sailer and Psathiti, 2017), on the basis that less integrated spaces appear to be more suitable for shielding occupants from distractions. It is becoming increasingly common for workplaces to employ activity-based working concepts, in which employees do not have assigned desks but are encouraged to use different functional workspaces on an ad-hoc basis to support different types of task (Wohlers and Hertel, 2017). In particular, 'spaces for concentration' and 'spaces for collaboration' are two functional zones which are frequently highlighted as important aspects of the modern workplace. Possibly, the use of VGAs could assist workplace practitioners to ensure that these spaces are appropriately designed. Additionally, it might be useful for different functional zones to have different acoustic comfort policies (e.g., strict in spaces for concentration, relaxed in spaces for collaboration), and environmental sensors could be used to ensure that the spaces are being used in the intended manner.

Conclusion

In conclusion, we have provided proof-of-concept for a methodological framework to integrate building analytics and human analytics, towards the goal of optimising environmental comfort in the workplace. The findings of our study provide a tentative indication that the data from sensors can help to ensure occupant satisfaction with air quality, and that the visibility graph analysis technique can help to support the provision of different types of functional workspace. In future research, significantly larger sample sizes and greater diversity in the types of workplaces under investigation will be necessary so that hypotheses regarding the effects of different elements of the workplace environment can be more rigorously tested.

Reference List

Al Horr, Y., Arif, M., Kaushik, A., Mazroei, A., Katafygiotou, M., and Elsarrag, E. (2016). “Occupant productivity and office indoor environment quality: A review of the literature”, *Building and Environment,* Vol. 105, pp. 369-389.

Allen, J. G., MacNaughton, P., Satish, U., Santanam, S., Vallarino, J., and Spengler, J. (2016). “Associations of cognitive function scores with carbon dioxide, ventilation, and volatile organic compound exposures in office workers: A controlled exposure study of green and conventional office environments”, *Environmental Health Perspectives,* Vol. 124 No. 6, pp. 805-812.

American Society of Heating, Refrigerating and Air-Conditioning Engineers (2013). *Standard 55 – Thermal environmental conditions for human occupancy.*

Appel-Meulenbroek, R. (2014). *How to measure added value of CRE and building design: Knowledge sharing in research buildings* (Doctoral dissertation). Technische Universiteit Eindhoven.

Aryal, A., Anselmo, F., and Becerik-Gerber, B. (2018). *Smart IoT desk for personalizing indoor environmental conditions.* In Proceedings of 8th International Conference on the Internet of Things, Santa Barbara, CA.

Barton, K. (2018). Package “MuMIn”. *Multi-Model Inference, Version 1.42.1.*

Belojevic, G., Slepcevic, V., and Jakovljevic, B. (2001). “Mental performance in noise: The role of introversion”, *Journal of Environmental Psychology,* Vol. 21 No. 2, pp. 209-213.

Bernstein, E. and Turban, S. (2018). "The impact of the 'open' workspace on human collaboration", *Philosophical Transactions of the Royal Society B*, Vol. 373 No. 1753, pp. 20170239.

Bodin Danielsson, C., and Bodin, L. (2008). "Office type in relation to health, well-being, and job satisfaction among employees", *Environment and Behavior,* Vol. 40 No. 5, pp. 636-668.

Bradley, J., and Gover, B. (2004). *Criteria for acoustic comfort in open-plan offices*. In Proceedings of Inter-Noise, the 33rd International Congress and Exposition on Noise Control Engineering, Prague, Czech Republic.

Candido, C., Kim, J., de Dear, R. and Thomas, L. (2016). "BOSSA: A multidimensional post-occupancy evaluation tool", *Building Research & Information*, Vol. 44 No. 2, pp. 214-228.

Center for the Built Environment (2019). *CBE Thermal Comfort Tool.* Retrieved from http://comfort.cbe.berkeley.edu/

DepthmapX development team (2017). DepthmapX (Version 0.6.0) [Computer software]. Retrieved from https://github.com/SpaceGroupUCL/depthmapX/

Edwards, L., and Torcellini, P. (2002). *A literature review of the effects of natural light on building occupants*. Report NREL/TP-550-30769, National Renewable Energy Laboratory: Golden, CO.

Field, A., Miles, J. and Field, Z. (2012). "Multilevel linear models", In *Discovering Statistics Using R*, London: Sage, pp. 855-910.

Foster, T., Bhatt, D., Hancke, G., and Silva, B. (2016). “A web-based office climate control system using wireless sensors”, *IEEE Sensors Journal,* Vol. 16 No. 15, pp. 6104-6113

Geen, R. G. (1984). “Preferred stimulation levels in introverts and extraverts: Effect on arousal and performance”, *Journal of Personality and Social Psychology,* Vol. 46 No. 6, pp. 1303-1312.

Haapakangas, A., Hongisto, V., Hyöna, J., Kokko, J., & Keränen, J. (2014). “Effects of unattended speech on performance and subjective distraction: The role of acoustic design in open-plan offices”, *Applied Acoustics,* Vol. 86, pp. 1-16.

Haynes, B. (2007). “Office productivity: A theoretical framework”, *Journal of Corporate Real Estate,* Vol. 9 No. 2, pp. 97-110.

Haynes, B. (2008). “Impact of workplace connectivity on office productivity”, *Journal of Corporate Real Estate,* Vol. 10 No. 4, pp. 286-302.

Hua, Y., Loftness, V., Heerwagen, J., and Powell, K. (2011). “Relationship between workplace spatial settings and occupant-perceived support for collaboration”, *Environment and Behavior,* Vol. 43 No. 6, pp. 807-826.

International WELL Building Institute (2018). *The WELL Building Standard, v1 with Q1 2018 addenda.*

Kim, J., and de Dear, R. (2013). “Workspace satisfaction: The privacy-communication trade-off in open-plan offices”, *Journal of Environmental Psychology,* Vol. 36, pp. 18-26.

Kim, J., Bauman, F., Raftery, P., Arens, A., Zhang, H., Fierro, G., Andersen, M., and Culler, D. (2019). “Occupant comfort and behavior: High-resolution data from a 6-month field study of personal comfort systems with 37 real office workers", *Building and Environment,* Vol. 148, pp. 348-360.

Lee, S. and Brand, J. (2005). "Effects of control over office workspace on perceptions of the work environment and work outcomes", *Journal of Environmental Psychology,* Vol. 25 No. 3, pp. 323-333.

MacNaughton, P., Satish, U., Laurent, J., Flanigan, S., Vallarino, J., Coull, B., Spengler, J. D., & Allen, J. (2017). "The impact of working in a green certified building on cognitive function and health", *Building and Environment,* Vol. 114, pp. 178-186.

May, D., Oldham, G., & Rathert, C. (2005). "Employee affective and behavioral reactions to the spatial density of physical work environments", *Human Resource Management,* Vol. 44 No. 1, pp. 21-33.

Onset (2019a). *HOBO U12 Data Loggers.* Retrieved from https://www.onsetcomp.com/products/data-loggers/U12-data-loggers

Onset (2019b). *Telaire 7001 CO2 Sensor.* Retrieved from https://www.onsetcomp.com/products/sensors/tel-7001

Oseland, N. and Hodsman, P. (2018). "A psychoacoustical approach to resolving office noise distraction", *Journal of Corporate Real Estate,* Vol. 20 No. 4, pp. 260-280.

Park, J., & Yoon, C. (2011). "The effects of outdoor air supply rate on work performance during 8-h work period", *Indoor Air,* Vol. 21 No. 4, pp. 284-290.

Parkinson, T., Parkinson, A., and de Dear, R. (2015). Introducing the environmental quality monitoring system. In R. Crawford & A. Stephan (Eds.), *Living and Learning:*

Research for a Better Built Environment: 49th International Conference of the Architectural Science Association, pp. 1139-1148.

PCE Instruments (2019). *Data Logging Sound Level Meter PCE-322A.* Retrieved from https://www.pce-instruments.com/english/measuring-instruments/test-meters/sound-level-meter-noise-level-meter-pce-instruments-data-logging-sound-level-meter-pce-322a-det_60903.htm

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., Heisterkamp, S., van Willigen, B., and Maintainer, R. (2017). Package "nlme". *Linear and Nonlinear Mixed Effects Models, Version 3-1.*

R Studio Team (2016). *RStudio: Integrated Development for R.* RStudio, Inc., Boston, MA. URL: http://www.rstudio.com

Sailer, K., and Psathiti, C. (2017). *A prospect-refuge approach to seat preference: Environmental psychology and spatial layout.* In Proceedings of 11th International Space Syntax Symposium, Lisbon, Portugal.

Salamone, F., Belussi, L., Danza, L., Galanos, T., Ghellere, M. and Meroni, I. (2017). "Design and development of a nearable wireless system to control indoor air quality and indoor lighting quality", *Sensors,* Vol. 17 No. 5, pp. E1021.

Seddigh, A., Berntson, E., Bodin Danielsson, C., and Westerlund, H. (2014). "Concentration requirements modify the effect of office type on indicators of health and performance", *Journal of Environmental Psychology,* Vol. 38, pp. 167-174.

Seppänen, O., Fisk, W., and Mendell, M. (1999). "Association of ventilation rates and CO_2 concentrations with health and other responses in commercial and institutional buildings", *Indoor Air,* Vol. 9 No. 4, pp. 225-252.

Society for Light and Lighting. (2015). *LG07/15 Lighting Guide 07: Offices – LG7.*

Unites States Environmental Protection Agency (2019). *A brief guide to mold, moisture and your home.* Retrieved from https://www.epa.gov/mold/brief-guide-mold-moisture-and-your-home

Wang, Z., de Dear, R., Luo, M., Lin, B., He, Y., Ghahramani, A., and Zhu, Y. (2018). “Individual differences in thermal comfort: A literature review”, *Building and Environment,* Vol. 138, pp. 181-193.

Wohlers, C., and Hertel, G. (2017). “Choosing where to work at work – Towards a theoretical model of benefits and risks of activity-based flexible offices”, *Ergonomics,* Vol. 60 No. 4, pp. 467-486.

Zhang, X., Wargocki, P. and Lian, Z. (2017). “Physiological responses during exposure to carbon dioxide and bioeffluents at levels typically occurring indoors”, *Indoor Air,* Vol. 27 No. 1, pp. 65-77.

Table 1: List of questionnaire items used in the analyses, including the means and standard deviations for all items and scales, and the Cronbach's alpha values for the Distraction scale.

Scale and item(s) used	M	SD
PHYSICAL ENVIRONMENT		
"Over the past half hour, how satisfied are you with the following elements of the indoor environment?" [1=Very dissatisfied, 7=Very satisfied]		
[SATISFACTION WITH AIR QUALITY] "Air quality (i.e. stuffy/stale air, cleanliness, odours)"	**4.69**	**1.21**
[SATISFACTION WITH TEMPERATURE] "Temperature"	**4.5**	**1.47**
[SATISFACTION WITH HUMIDITY] "Humidity"	**4.72**	**1.17**
[SATISFACTION WITH LIGHT INTENSITY] "Amount of light"	**4.94**	**1.27**
[SATISFACTION WITH DAYLIGHT] "Amount of natural daylight"	**4.88**	**1.55**
BEHAVIOURAL ENVIRONMENT		
"Over the past half hour, how accurately do the following statements describe your experience?" [1=No, never, 7=Yes, all the time]		
[DISTRACTIONS, $\alpha = 0.84$]	**3.67**	**1.26**
"I have experienced auditory distractions in my work area"	4.08	1.6
"I have experienced visual distractions in my work area"	3.36	1.49
"My work environment is too noisy"	3.74	1.49
"My working area feels crowded"	3.51	1.53
[PRIVACY] "I have adequate privacy in my primary, individual work area"	**3.36**	**1.63**
[WORK-RELATED INTERACTIONS] "I am able to easily contact all of the colleagues I need to interact with"	**5.46**	**1.04**
[SOCIAL INTERACTIONS] "My work environment is socially isolating"*	**5.55**	**1.34**

* Item was reverse-scored prior to analysis

Table 2: Average sensor readings for each of the physical environment parameters throughout the working day.

Time of Day	**CO_2 (PPM)**	**Temperature (°C)**	**Humidity (%RH)**	**Illumination (lux)**	**Sound pressure level (dBA)**
08:30 to 09:00	816.8	22.9	51.04	372.57	53.19
09:00 to 10:00	1048.31	23.2	51.69	386.77	54.63
10:00 to 11:00	1286.94	23.43	51.96	406.33	54.5
11:00 to 12:00	1438.51	23.58	52.14	436.82	54.55
12:00 to 13:00	1506.97	23.65	52.13	455.01	54.66
13:00 to 14:00	1515.88	23.64	52.37	462.09	53.12
14:00 to 15:00	1594.72	23.76	52.61	513.12	53.6
15:00 to 16:00	1650.45	23.89	52.56	538.04	54.1
16:00 to 17:00	1623.43	23.85	52.47	492.87	53.11
17:00 to 18:00	1464.74	23.68	52.24	389.84	n/a
Overall	1424.9	23.59	52.18	448.91	53.99