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A data-driven analysis of occupant workspace dissatisfaction

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Abstract

Studies often aim to determine which indoor environmental quality parameters best predict the overall workspace assessment. However, this method overlooks important differences distinguishing satisfied and dissatisfied occupant groups. We used a new analytical approach on 36671 post-occupancy evaluation responses to overcome this problem and better understand workspace satisfaction in office buildings. Principal components analysis reduced satisfaction votes with 15 different IEQ items into two principal components related to: 1) privacy and amount of space, and 2) cleanliness and maintenance. We grouped the data by occupants that were either satisfied or dissatisfied with their workspace. Principal component 1 explained half of the variability in the dataset and reliably distinguished occupants satisfied with their workspace from those that were dissatisfied. We used support vector machine to classify the satisfied and dissatisfied groups based on principal components 1 and 2. Classification of occupant satisfaction with the overall workspace was highly accurate (approximately 90%) and based predominantly on the component related to privacy and amount of space. Further analyses showed that occupants satisfied with their overall workspace were generally satisfied with all other IEQ items. There was greater independence between workspace attributes for those dissatisfied with their overall workspace. Issues of privacy and available space were an overwhelming determinant of occupant dissatisfaction irrespective of the success of other workspace attributes. These findings suggest that efforts to improve occupant satisfaction with workspaces should leverage designs that ensure privacy and provide sufficient space to support occupants in their work.

Keywords: Indoor environmental quality; Workspace satisfaction; Offices; Post-occupancy evaluation; Privacy; Machine learning

1. Introduction

Satisfaction with the conditions inside buildings usually implies that occupants deem several environmental parameters to be within comfortable or acceptable limits. Traditionally, these parameters have included, but are not limited to, thermal comfort, indoor air-quality, (day)lighting, and acoustics, and physical features of the spaces (e.g. furniture and layout) [1]. Collectively, these parameters underlie what is often referred to as indoor environmental quality (IEQ). On the basis that it affects occupants' satisfaction with their workspace [2], the provision of good IEQ in commercial office buildings is considered a core performance target for building operators. Beyond workspace satisfaction, IEQ also serves an integral role supporting the health and wellbeing of occupants [3]. Yet differences in occupant expectations mean that high levels of satisfaction or dissatisfaction with one or more IEQ items does not necessarily influence overall building satisfaction [4]. The total assessment by occupants is greater than the sum of the parts, and "subjective averaging" (i.e., the trade-off between good and bad features) can influence overall satisfaction [5]. Furthermore, the weighting of an IEQ item on the overall evaluation differs depending on whether it was positively or negatively perceived [6]. Moreover, given that most studies are observational, showing causal relationships between individual IEQ items and overall satisfaction is very difficult.

Evaluating IEQ in commercial office buildings often involves collecting feedback on multiple environmental parameters from occupants. The most common method in field studies (e.g. [7–11]) is the use of subjective rating scales to measure occupant satisfaction with different IEQ items. These questions and scales are mostly disseminated through post-occupancy evaluation questionnaires. Sophisticated analytical techniques utilising dimension reduction are often employed to analyse resulting survey data to better understand whether indoor environments meet the expectations of occupants (see Table 1). These techniques include principal components analysis (PCA) or factor analysis, which reduce the number of IEQ variables into a smaller subset of components or factors [12]. Although studies in Table 1 used these analyses to reduce the number of dimensions in their data, the purpose of the analysis is often to evaluate more general or summative parameters like overall workspace satisfaction. In some studies, this involves using principal components as predictors in regression models [5,6,10–13], while others [17,18] used factors derived from several different IEQ items to model latent relationships that underlie the overall construct of IEQ.

It is common for 30-40% of occupants to be dissatisfied with their office [5,19]. This relatively large number demonstrates the challenges and importance of understanding the root cause of occupant dissatisfaction in order to improve workspace designs. Studies in Table 1 displayed promising techniques to relate individual IEQ items with overall workspace satisfaction or dissatisfaction. Often this involves identifying which new constructs (e.g. principal components) explain the most variance and using those to model and predict overall workspace satisfaction. This approach can obscure important information within the newly constructed variables that could help understand why building occupants were satisfied or dissatisfied with their workspace. Other studies have examined this in a more general manner by comparing individual items against an overall item of IEQ. When evaluating individual IEQ items from a database of 52980 responses, Frontczak *et al.* [1] found that amount of space, noise level and visual privacy had the highest influence on workspace satisfaction. Similarly, Humphreys [4] compared overall thermal comfort ratings of 4655 occupants across five European countries with evaluations of different IEQ items. Although the six measured items (i.e. warmth, air movement, humidity, light, noise and air quality) all had significant relationships with ratings of overall thermal comfort, the level of prediction of the resulting model was relatively low (R^2= 0.26). Kim and de Dear [6,20] showed that across different office layouts and configurations, and amount of space were the most important predictors of overall workspace satisfaction. This confirmed the findings of Frontczak *et al.* [1] using the same occupant survey dataset, but with a different analytical technique. Kim and de Dear [20] also found that the purported benefits of open-plan office from greater collegial interactions were significantly outweighed by negative trade-offs from reduced acoustic and visual privacy.

Table 1. List of extant studies using large occupant survey datasets, including study population and methods, analysis (dimension reduction technique) used to analyse the IEQ data, and usage summary.

Study	Population and methods	Analysis	Usage summary
Klitzman and Stellman [15]	Four buildings in United State and Canada, 2074 occupants, 35 questions (18 IEQ items)	Factor analysis	New variables were constructed from IEQ items in each factor, which were then used to predict the impacts of the physical work conditions on psychological well-being.
González *et al.* [17]	One building in Spain, 83 occupants, 10 user perception questions and three user satisfaction questions	Factor analysis and structural equation modelling	Five latent factors (evaluation (aesthetics), temperature, noise, air and space) were used to predict user satisfaction with the building.
Veitch [18]	Nine buildings in United States and Canada, 779 occupants, 18 IEQ questions, two overall environmental questions, and two job satisfaction questions	Exploratory and confirmatory factor analyses, and structural equational modelling	Data was reduced into three factor solution (privacy/acoustics, satisfaction with lighting, and satisfaction with ventilation/temperature). Factor structure used to inform structural equation model for environmental and job satisfaction.
Schakib-Ekbatan *et al.* [16]	Fourteen buildings in Germany, 867 occupants, six IEQ questions	Principal components analysis (PCA), correspondence analysis and factor analysis	New IEQ variable obtained from principal components analysis and used to predict overall workspace satisfaction.
Bluyssen *et al.* [13]	Eight European buildings, 5732 occupants, 18 IEQ questions	Principal components analysis	In each principal component, the mean across the original IEQ items was calculated. The new variables were then used to predict overall comfort.
Candido et al. [8]	Eighteen Australian office buildings, 2903 occupants, 31 IEQ questions		New variables created from principal components were used to predict: work area comfort, building satisfaction, productivity, and health.
Göçer *et al.* [14]	Seventy-seven buildings in Australia, 9794 occupants, 29 IEQ questions	Factor analysis	New variables were created by averaging the individual questionnaire scores in each factor. These were then used to predict perceived productivity.
Cheung *et al.* [9]	Seven buildings in Singapore, 666 occupants, 17 IEQ questions	Principal components analysis	Eigenvectors from principal components used as predictors in a linear mixed-effects model to predict overall workspace satisfaction.
Graham *et al.* [19]	Included 897 buildings, several countries (mainly United States), 51,625 occupants, 16 IEQ questions	Principal components analysis and hierarchical cluster analysis (HCA)	PCA and HCA were used to find the underline structure of the survey.

Minimising the gap between what occupants expect of their buildings and the IEQ conditions they experience is the key to improving workspace environments. It remains unclear whether the emphasis should be on “dissatisfier” or “satisfier” items when determining the strategic management of workspace designs. Analogies can be found in the field of human thermal comfort, where HVAC engineers and building operators typically use the PMV-PPD model [21] to estimate occupant *dis*satisfaction indoors. This approach assumes that an absence of dissatisfaction equates to satisfaction, which overlooks the potential of indoor environments to elicit positive sensations [22]. Similarly, proposed models of human lighting comfort [23,24] aim to remove sources of discomfort (e.g. glare) which result in occupant dissatisfaction. These paradigm shifts signal that satisfaction is not necessarily driven by simply avoiding dissatisfaction.

To expand this discussion into the context of workplace IEQ, it is necessary to investigate how positive and negative IEQ items are perceived by occupants in relation to overall workspace satisfaction. The purpose of this work is to propose a new method to understand why occupants are satisfied or dissatisfied with their workspace. To this agenda, we address the following three research objectives:

1) Determine whether the relationship between reduced IEQ dimensions varies with overall workspace satisfaction: i.e., are the reasons for occupant satisfaction the same as dissatisfaction?

2) Investigate the ability of reduced IEQ dimensions to accurately classify occupant attitudes towards their workspace

3) Discuss whether dissatisfied occupants provide a more insightful summary of both the successful and unsuccessful aspects of the workplace experience.

2. Method

2.1. CBE Occupant Survey

We used 73192 responses (663 office buildings) to the CBE Occupant Survey for our analysis; see Graham *et al.* [19] for a detailed summary of the survey database. The CBE Occupant survey was developed and administered by the Center of Built Environment at the University of California, Berkeley. Respondents were emailed a link to a survey designed to assess the indoor environment of their buildings. The survey included questions about demographics (e.g. age and gender), experience in the space (e.g. years in building and time at workspace), and satisfaction with different aspects of the indoor environment, including: air quality, amount of light, amount of space, building maintenance, cleaning service, cleanliness, colors and textures, comfort of furnishings, ease of interaction, furniture adjustability, noise, overall building, personal workspace, sound privacy, temperature, visual comfort, and visual privacy. The survey was designed to be completed in no more than 10-15 minutes and succinctly capture the occupant experience of key aspects of indoor environmental quality. Completed surveys were archived in the CBE database for later analysis. We included satisfaction items on 15 different indoor environmental parameters assumed to contribute to the summative experience. Satisfaction with personal workspace was considered a proxy measure of overall IEQ experienced at the workstation. All satisfaction items were evaluated using a single 7-point bipolar scale ranging from "very dissatisfied" (-3) to "neither satisfied nor dissatisfied" (0) to "very satisfied" (+3). All questions had a standardised format (e.g. "*How satisfied are you with the […]*") applied to each IEQ item.

Based on the approach of Kim and de Dear [6,20], we grouped occupants into "satisfied" or "dissatisfied" groups based on their response to overall workspace satisfaction. The satisfied group is comprised of respondents who were "satisfied" (+2) or "very satisfied" (+3) with their workspace overall; the dissatisfied group were "dissatisfied" (-2) or "very dissatisfied" (-3) with their workspace overall. The other evaluations given to the 15 IEQ items were then organised according to their overall workspace satisfaction group. Respondents who were "slightly satisfied" (+1), "neutral" (0) or "slightly dissatisfied" (-1) with their overall workspace were removed from the analysis. The decision to exclude occupants who were slightly satisfied and slightly dissatisfied was on the assumption that their general indifference would make it difficult to distinguish other IEQ items according to overall workspace satisfaction. The resulting dataset had 36671 respondents for our analyses.

Summary data in Table 2 shows, as expected, that there were many more occupants who were satisfied with their workspace than dissatisfied. The percentage of satisfied and dissatisfied were relatively similar across subcategories. However, workspace layout had higher percentages of satisfied occupants for enclosed offices (i.e. private and shared) and higher percentages of dissatisfied occupants for open offices (i.e. high and low partitions).

Table 2. Summary of demographic and physical parameters for the satisfied and dissatisfied groups. For each parameter, the total (number of building occupants) and percentage across the sub-categories are given.

		Workspace			
Parameter	**Sub-category**	***Satisfied***		***Dissatisfied***	
		Total	*%*	*Total*	*%*
Age (years)	30 or under	4264	14	469	8
	31 – 50	9160	30	1528	26
	Over 50	5088	17	854	14
	Not available	12322	40	2986	51
Gender	Female	14292	46	2787	48
	Male	12365	40	2357	40
	Not available	4177	14	693	12
Years in building	< 1 year	6426	21	855	15
	1-2 years	6560	21	1256	21
	3-5 years	5508	18	1209	20
	>5 years	9798	32	2192	38
	Not available	2542	8	325	6
Time at personal workspace	<3 months	3177	10	511	9
	4-6 months	3044	10	515	9
	7-12 months	5120	17	875	15
	>1 year	17246	56	3612	62
	Not available	2307	7	324	5
Workspace layout	Private	10028	33	662	11
	Shared	1775	6	371	7
	High partition	7152	23	1950	33
	Low partition	7635	25	1871	32
	No partition	3200	10	683	12
	Other	1044	3	300	5
Total	-	30834	84	5837	16

2.2. Principal components analysis

We reduced the 15 IEQ satisfaction items into a smaller number of composite variables based on their linear relationships using PCA [12] to aid the interpretation of a large number of variables [25]. There were 550065 individual responses in our dataset (i.e. 15 IEQ items and 36671 occupants) with 44227 missing values (i.e. 8 % of the total). In order to run PCA with missing data [26], we used the 'missMDA' package [27] to impute missing entries based on the relationships between the IEQ items and similarities between occupants. We determined the number of principal components to retain using a scree-plot [28] and kept those with eigenvalues (i.e., the variability along the principal component) above one [29]. To provide a robust evaluation, the parallel analysis [30] was used to adjust the eigenvalues based on randomly generated data with uncorrelated variables [31,32].

We checked several important assumptions of the dataset before performing the PCA. We used the Kaiser-Meyer-Olkin test [33] to verify the measure of sampling adequacy, where higher values closer to one suggest the proportions of variability in the data might reveal distinct patterns. To interpret the outcome, we used the benchmarks proposed by Kaiser [34]. The Bartlett's test of sphericity [35] was used to ensure that there was multicollinearity within the data (i.e., IEQ items) had linear relationships with each other). This compared the correlation matrix using the measured items against an identity matrix, which contain zero correlations across its variables. The overall measure of sampling adequacy from the Kaiser-Meyer-Olkin was 0.91 (meritorious), and individual survey items ranged from 0.87 to 0.98. The Barlett's test of Sphericity confirmed the correlation matrix of the 15 IEQ items was statistically different from an identity matrix that contained zero correlations: $\chi^2(105)= 890$, $p<0.000$. The dataset was therefore suitable for PCA as it met the assumptions of these tests.

Correlation coefficient loadings from the PCA describing how well an IEQ item correlated with all other parameters in a principal component [36] were extracted using an orthogonal rotation technique [37]. We supressed Pearson's, r correlation coefficients less than ± 0.80 to help interpret the PCA loadings. This threshold describes "larger" relationships between variables [38]. Any IEQ items with correlations $\geq \pm 0.8$ were retained and used in further analyses. To understand what each principal component represented, we used the original satisfaction votes and organised the IEQ items based on the PCA results. We plot a correlation matrix of Spearman's, ρ coefficients [39] to demonstrate the strength of association between an IEQ item and all other parameters. This allowed us to highlight the strongest relationships between the IEQ items constituting different principal components.

We applied 95 % confidence ellipses [40] to determine if there were any differences between the satisfied and dissatisfied occupants. This compared principal components against each other by plotting the eigenvectors (i.e., direction in which the variability that can explained across each principal component [12]) to determine which combination of the 15 IEQ items had the highest influence on overall workspace satisfaction.

2.3. Data classification

We wanted to know how well the reduced dimensions could represent (i.e. classify) overall workspace satisfaction and dissatisfaction. Assuming that any one of the principal components is a reliable indicator, this would show what group of IEQ items have the largest relation to overall workspace satisfaction. Supervised machine-learning algorithms were used to determine how well principal components could correctly classify workspace satisfaction (i.e. satisfied and dissatisfied). Three different supervised machine-learning algorithms were tested: linear support vector machine (SVM) [41,42], radial SVM (SVMr), and random forest [43]. Linear SVM was the simplest [44,45] and produced similar results to the SVMr and random forest algorithms (Table B.1. – Appendix B). We therefore used linear SVM to classify the satisfied and dissatisfied groups by creating a margin of separation, commonly referred to as the hyperplane [46]. Prior parameter reduction techniques using PCA are often applied before SVM for data containing several measured outcomes [44].

The classifier model was trained [47] from partitioned data using a 70 % to 30 % allocation ratio [48] for training and test datasets, respectively. We used a grid-search approach [49] to find the optimal parameter settings for each model (Table A.1. – Appendix A). The performance of the SVM model was evaluated using measures of precision, recall, *F*-measure [50], and the area under a receiving operating characteristic (ROC) curve [51,52]. Precision and recall range from zero to one, with higher values indicating better accuracy (i.e. no false positives or negatives). The *F*-measure is a weighted average of precision and recall [50]. AUC values range from zero to one, with better-performing models closer to one and poor-performing models near 0.5 [53].

3. Results

3.1. Data reduction

The scree-plot in Figure 1a shows the adjusted eigenvalues from the parallel analysis and the cumulative variance explained for each principal component. We retained two principal components that explained 60 % of the variability in the dataset. Also shown are a comparison of the eigenvectors across principal component 1 and 2 (Figure 1b) as well as principal components 3 and 4 (Figure 1c) for reference. The satisfied and dissatisfied groups in Figure 1b are separated more along principal component 1 and less along principal component 2. Principal components 3 and 4 (Figure 1c) did not separate satisfied and dissatisfied occupants, confirming the decision to retain two principal components.

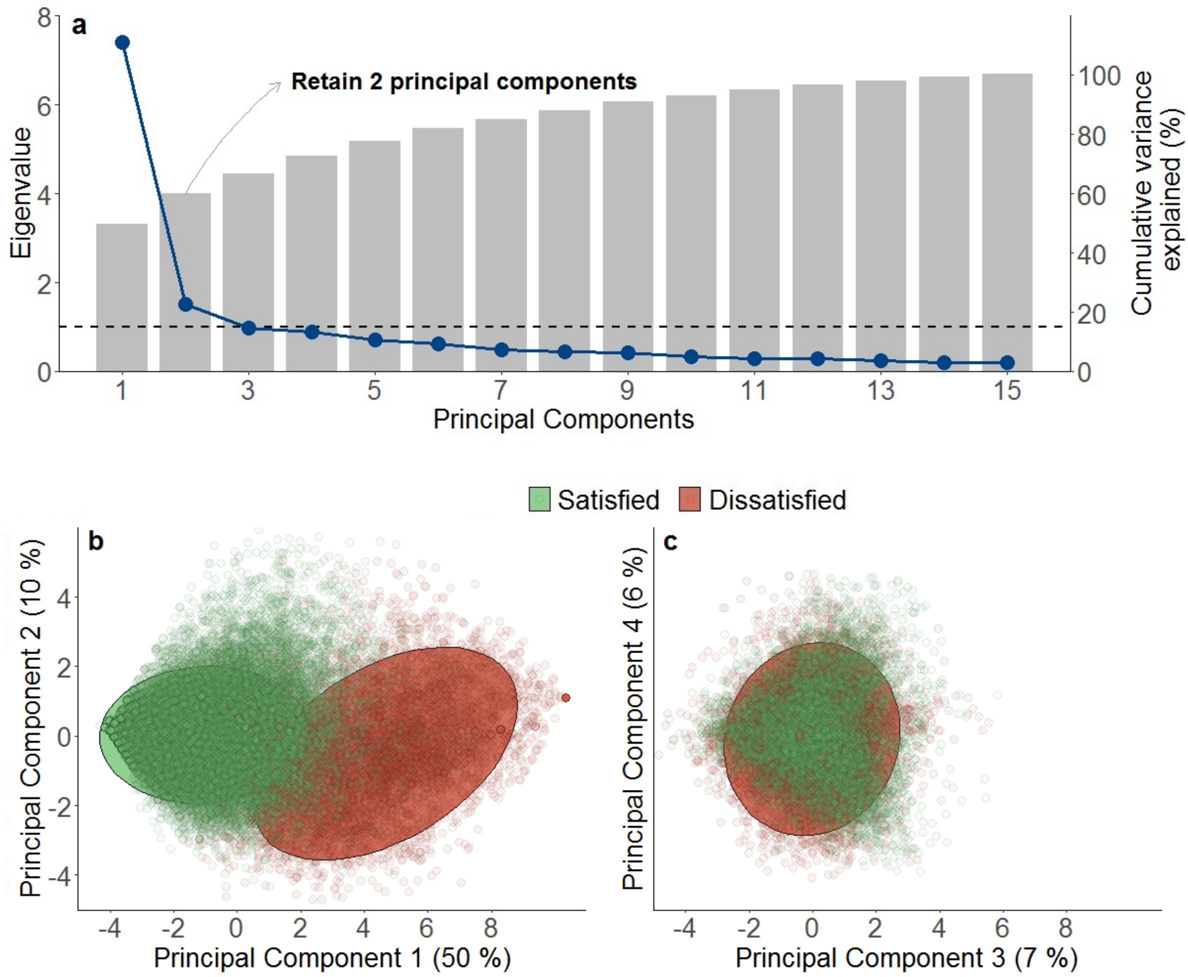

Figure 1. Plot (a) shows the scree-plot and number of principal components to retain based on adjusted eigenvalues from the parallel analysis. The variance that can be cumulatively explained by each principal component is shown on the secondary axis. Note: the horizontal guide corresponds to the Kaiser criterion of one [29]. Below are the eigenvectors that are coloured according to occupants that were satisfied or dissatisfied with their workspace when comparing: (b) principal components 1 and 2 and (c) principal components 3 and 4. The 95 % confidence ellipses show the position of the eigenvectors for satisfied or dissatisfied occupants.

We used correlation matrices (Figure 2a, b, c) and dendrograms (Figure 2d) to identify which of the 15 IEQ items constitute principal components 1 and 2. We labelled the principal components based on the relationships seen in the correlation plots (Figure 2) to help interpret the results. Principal component 1 is labelled "privacy and space" as it comprises of visual privacy, sound privacy, noise, and amount of space. While noise is a distinctly different attribute than the amount space, they both encompass the spatial dimensions of an office and coalesce to influence sound and visual privacy. Considering that noise and sound privacy may share some similar characteristics, they both may also share a similar relationship with amount of space and for this reason, we refer to the four IEQ items in principal component 1 as privacy and space. Principal component 2 is labelled "cleanliness and maintenance" and comprises of cleaniness, maintenance, and cleaning service.

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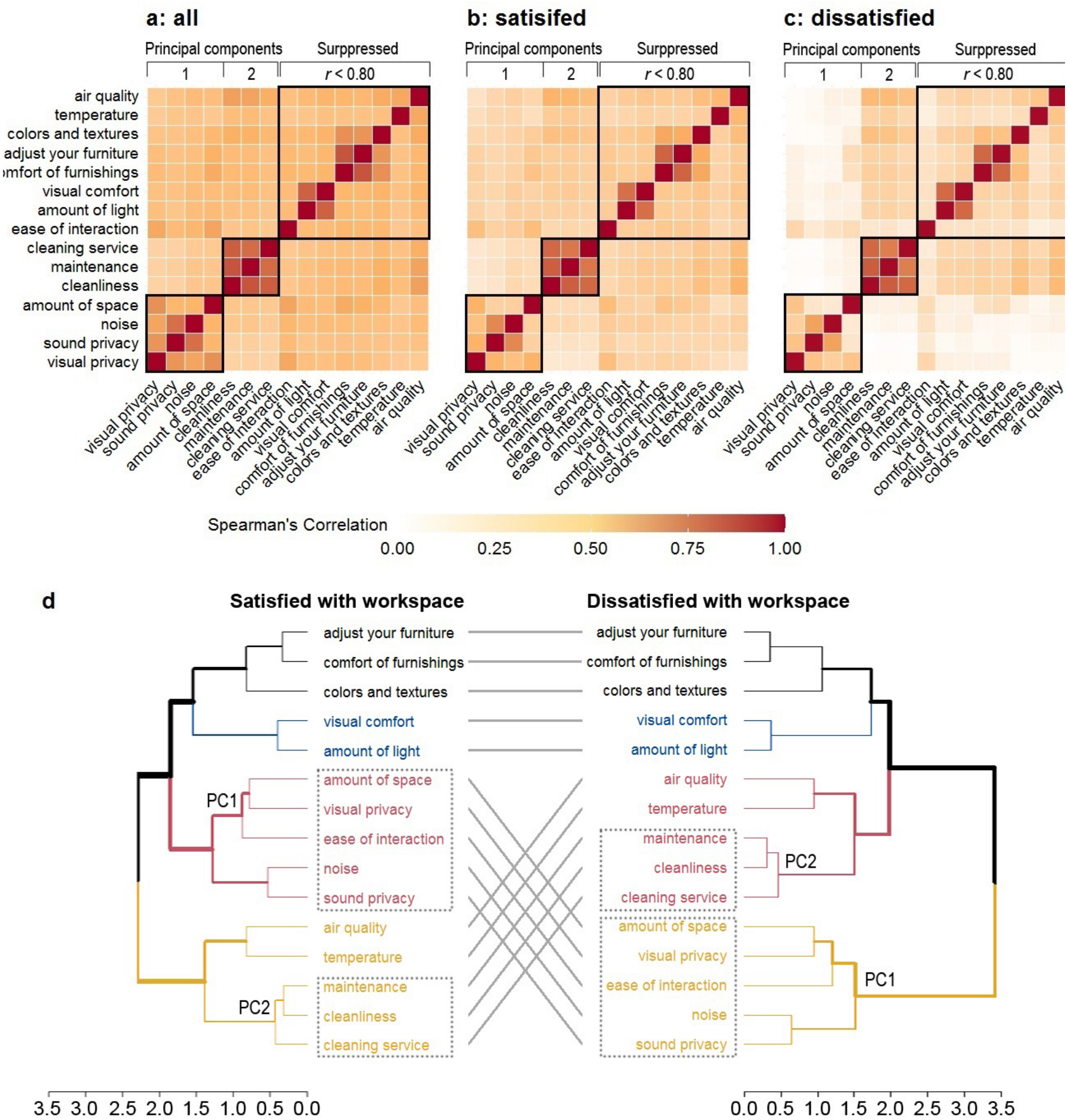

Figure 2. Correlation matrices containing the Spearman's, ρ correlation coefficients between the 15 IEQ items that loaded into principal components 1 and 2. The plots show: (a) all data, and data when occupants rated that they were either (b) satisfied or (c) dissatisfied with their workspace. The IEQ items in principal components 1 and 2 and the variables that that were suppressed are highlighted. The hierarchical dendrograms (d) connected by a tanglegram analysis show the relationship between the correlation coefficients (in plots, (b) and (c)) for the two principal components for the satisfied and dissatisfied groups. The x-axis is the distance i.e. level of similarity or congruence. Note: PC (principal component).

We compared the relationships between IEQ items across principal components 1 and 2 for three cases: (a) the full dataset, (b) only satisfied occupants, and (c) only dissatisfied occupants. The strength of the relationship between IEQ items reveal clearer principal components for the dissatisfied occupants (Figure 2c) than for satisfied occupants (Figure 2b). Related IEQ items in each principal component are also more independent from IEQ items in the other principal component as well as those that were suppressed. It is unclear why this occurs, but suggests that it is easier to identify the IEQ items underlying

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dissatisfication than satisfaction. Conversely, the source of satisfication becomes less apparent for occupants that are generally satisfied with most IEQ items.

The tanglegram in Figure 2d compares the relationship between the 15 IEQ items across the dendrograms for satisfied occupants (left) and dissatisfied occupants (right). Connecting lines show which item shares the closest relationship in the adjacent dendrogram. The items were grouped and colour coded based on their correlation coefficients. While the relationships are generally the same, the distances between IEQ items are different for satisfied and disatsfied occupants. The first branch separating principal components 1 and 2 at the highest point has a larger distance for dissatisfied occupants. This indicates principal component 1 is more dissimilar than all other IEQ items, including principal component 2. For satisfied occupants, principal component 2 is more independent than all other IEQ items. Entanglement is caused by different relationships between the two principal components between the satisfied and dissatisfied groups. These findings support earlier obervations drawn from Figure 2 that the relationship between all IEQ items are stronger for satisfied occupants (Figure 2b) compared to dissatisied occupants (Figure 2c). Both dendrograms suggest that ease of interaction may belong in principal component 1. While it is thematically similar to the other IEQ items in ‘privacy and space’, they were suppressed in the correlation matrices (Figure 2a, b, c) by the relatively high threshold (r<0.80) in the PCA.

The forgiveness score [5] was also used to estimate the leniency of occupants to forgive less-successful workspace attributes. Forgiveness scores greater than one suggest that occupants may be more lenient toward attributes due to the success of other attributes considered more desirable by the occupant. We calculated the forgiveness score using the mean satisfaction vote of all 15 IEQ items, as well as the four items in principal components 1 (amount of space, noise, sound privacy, visual privacy) and the three items in principal component 2 (cleanliness, maintenance, cleaning service) for the satisfied and dissatisfied groups. Finally, these values are divided by the average vote for overall workspace satisfaction (1.58) to obtain the final score.

Table 3. Forgiveness scores calculated when considering occupants that were either satisfied or dissatisfied with their workspace for all IEQ items, and principal components 1 and 2.

Workspace satisifaction	**Forgiveness scores**		
	All IEQ items	*Principal component 1*	*Principal component 2*
Satisified	1.03	0.83	1.18
Dissatisified	-0.44	-1.05	0.07

The forgiveness scores for the three different satisfied groups were near or greater than 1, suggesting that occupants were generally satisfied with all other IEQ items and may therefore overlook some dissatisfactory workplace attributes. This is aligned with findings from analyses using an earlier version of this dataset [1]. As expected, forgiveness scores for the dissatisfied group were much lower compared to the satisfied group, particularly for principal component 1. Principal component 1 appears to have a much larger influence on dissatisfied occupants, but this same effect was not apparent for satisfied occupants. Therefore, although principal component 1 is an obvious source of general dissatisfaction, it does not necessarily contribute to overall satisfaction. The independence of principal component 1 from other IEQ items makes it possible to identify which attributes perform well, despite occupants expressing overall dissatisfaction. In fact, principal component 2's forgiveness score was comparatively larger to all IEQ items in the dissatisfied group, indicating that cleanliness and maintenance generally performed well.

3.2. Data classification

The performance of the SVM linear model in classifying workspace satisfaction and dissatisfaction based on principal components 1 and 2 for the test dataset (30%) is shown in Figure 3. The model was able to correctly classify the overall workspace satisfaction of most respondents (precision and *F*-measure = 0.97, recall = 0.98 AUC = 0.90, 95% CI [90, 90]). Performance measures of the more complex algorithms (i.e. SVMr and random forest) were similar (see Appendix B). The intercept of the hyperplane passes across principal component 1 (privacy and space) and suggests that this single dimension largely separates occupants who are satisfied with their overall workspace from those that are dissatisfied.

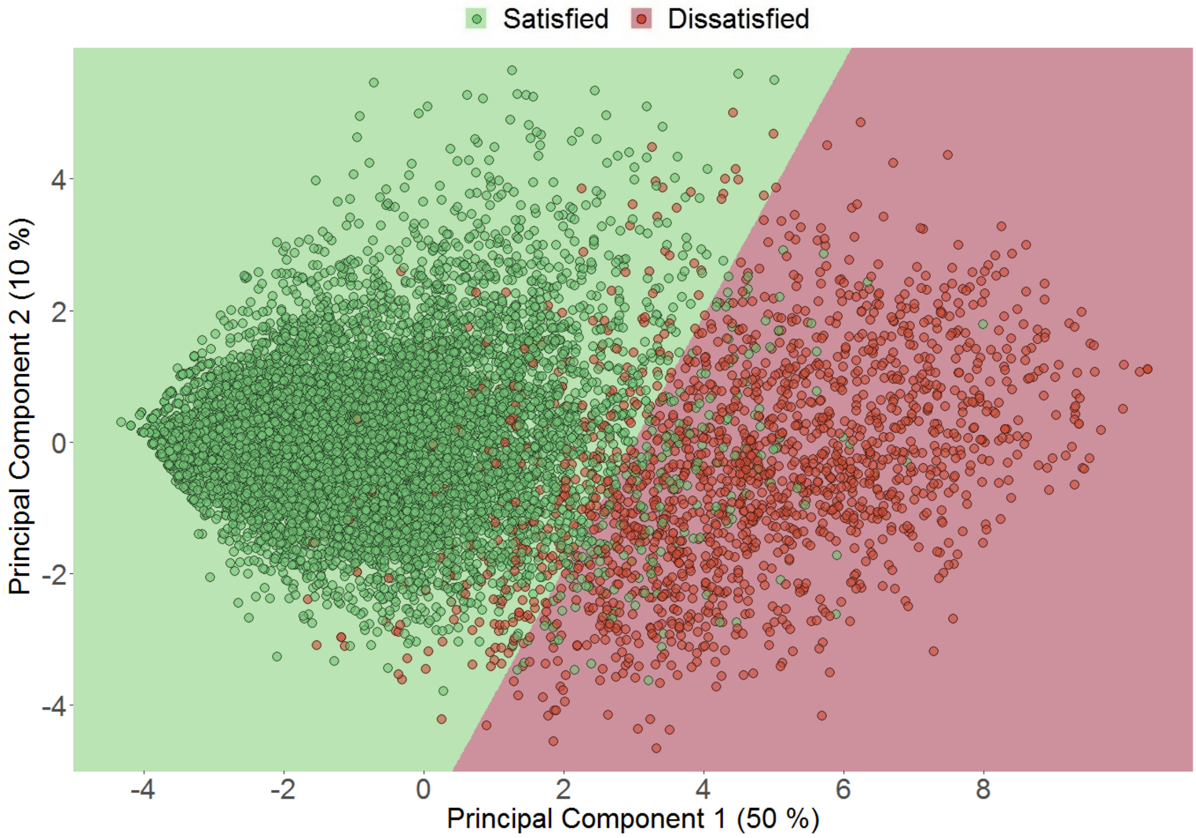

Figure 3. The results of the linear support vector machine (SVM) when classifying overall workspace satisfaction in the test dataset using principal component 1 (privacy and space) and principal component 2 (cleanliness and maintenance).

4. Discussion

Two components from the PCA explained 60% of the variance in the dataset, with 50% originating from principal component 1 alone. Principal component 1 was comprised mostly of items related to visual privacy, sound privacy, noise, and amount of space. We labelled this component "privacy and space" and the other "cleanliness and maintenance". Using only these two principal components, we were able to accurately classify whether occupants were

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satisfied or dissatisfied with their workspace. The distinction between these two groups depended heavily on principal component 1. While this finding should not discourage the investigation of other IEQ items (e.g. temperature and lighting), we believe it points to privacy and space as the most significant causes of dissatisfaction within office buildings.

Descriptor variables in the CBE Occupant Survey summarised in Table 2 do not sufficiently characterise the diversity of occupants, nor the myriad office environments included in the database. In lieu of detailed and specific data for each survey, we can only investigate the more systemic challenges of workspace designs. On this basis, it seems reasonable to connect the disproportionately high representation of dissatisfied occupants working in open-plan offices (77%) with the importance of principal component 1 (privacy and space) in distinguishing them from satisfied occupants (58%) in the same open office layout. Common issues in open-plan offices, such as privacy and amount of space, are less prevalent in dedicated workspaces where occupants have greater control and ownership (e.g. enclosed offices). This was confirmed in analyses of previous versions of the CBE Occupant Survey database [1,6,20].

Using a novel analytical method, our results support past findings while also identifying the source of dissatisfaction and describing its relationship with other IEQ items. Failing to provide adequate privacy and space to support occupants in their work tasks led to unsuccessful office designs and operations that do not deliver their core service. This is most evident in the correlation matrix for dissatisfied occupants (Figure 2c) showing weak correlations between principal component 1 and the remaining IEQ items. Interestingly, the unique characteristics of principal component 1 made it is easier to distinguish the performance of other IEQ items. The correlation matix in Figure 2b shows that satisfied occupants may overlook or ignore their indifference or dissatisfaction with individual IEQ items. In contrast, responses from dissatisfied occupants provided a clearer indication of which elements did and did not perform well. Occupants may be satisfied with certain elements and dissatisfied with their overall workspace (or vice-versa), but our results show it is very difficult to mask or offset any failings in privacy and space with other exemplary design features. This finding underscores the importance of adequate privacy and amount of space, and if these are not provided, occupants will be dissatisfied regardless of other successful attributes.

The notion that workspace evaluations may be skewed towards the least-successful design aspects has been reported elsewhere. Kim and de Dear [6] found that the negative impacts of noise and visual privacy on overall occupant satisifaction are evident, and can outweigh the potential benefits of open office layouts. Given the range of possible reasons contributing to the success or failure of an office, it is difficult to identify why specific workspaces do or do not meet the expections of occupants. Nevertheless, our findings point toward a common shortcoming in contemporary office designs in providing suitable levels of privacy and space for occupants to work. Unsurprisingly, this comes as a negative consequence from trends in workspace design that remove physical barriers and reduce individual working areas. However, it is quite remarkable that our dataset shows the bearing that issues of privacy and space have on occupants' overall satisfaction with their workspace. The accuracy of the SVM model in classifying overall workspace satisfaction almost entirely on one principal component demonstrates the overwhelming influence of privacy and space. We believe that privacy and space in the context of open offices relates directly to the need for offices to support focussed work. For the model to reliably classify overall satisfaction without knowing specific details of either the occupant or the office environment reflects the prevalence of the design problem and the common experience of occupants. While open-plan offices can provide satisfactory environments, often they are not successful in realising their intended benefits [54].

Differences in the perception of IEQ and the experience of office features leads us to question whether workspace satisfaction and dissatisfaction are antonyms. In the context of ergonomics, Zhang *et al.* [55] showed that "comfort" descriptors given by office workers contained items referring to psychological contentment (e.g. relaxation and well-being) while "discomfort" referred to physical pain (e.g. aches and hurting). This could have implications on how the semantics at the extreme ends of the scales are interpreted given satisfaction and comfort are considered – by the building science community – to be relatively synonymous. This idea that "very satisfied" is not the opposite of "very dissatisfied" [56] may have some bearing on our findings. For example, dissatisfaction with items in principal component 1 may not be equivalent to dissatisfaction with those in principal component 2 because some survey items are psychophysical (e.g. privacy and noise), while others evaluate the physical environment (e.g. cleanliness and maintenance). Because dissatisfaction with privacy may also imply that the workspace does not adequately manage noise and other distractors [57], occupants may feel less productive and have difficulties concentrating. Therefore, occupants may have many other reasons to be dissatisfied with their workspace beyond the dissatisfaction felt with privacy alone.

Using post-occupancy evaluations to collect subjective feedback from building occupants is a "basic" level of IEQ performance evaluation in commercial buildings [58]. However, they are unable to fully characterise every facet of the workspace experience. There are some limitations to the POE method and the dataset used for our study; specifically that some building attributes (e.g. window view) were not included in the survey. We believe that including additional satisfaction questions would not have significantly influenced our main findings. Yet, the inclusion of other IEQ items may change the number of principal components to retain since additional dimensions could emerge in the data. Future work could test our method on an independent POE dataset to determine if similar themes appear from a different set of questions.

5. Conclusions

We used PCA to reduce 15 items from 36671 workspace evaluations into two principal components. Principal component 1, comprised of items related to privacy and space, explained half of the total variability of the dataset. After organising occupants into a satisfied or dissatisfied group based on their overall workspace satisfaction, we used SVM to show that principal component 1 largely distinguished these two groups. The main conclusions of our findings are:

- There are contrasting reasons underlying workspace satisfaction and dissatisfaction. Satisfied assessments may reflect occupant satisfaction with all environmental parameters, or the ability to overlook dissatisfaction with some parameters when others perform well. When occupants were dissatisfied with privacy and space, they tend to be dissatisfied with their workspace.

- A linear SVM model was able to correctly classify overall satisfaction with workspace in 90% of cases using just the two principal components based on privacy and space, and cleanliness and maintenance.
- Responses from dissatisfied occupants can be used to pinpoint problem areas and may be better indicators of successful workspace attributes than occupants satisfied with every item.

Our work shows that if designers and building operators do not provide sufficient privacy and amount of space, occupants will be dissatisfied with their workspace. Since this dissatisfaction cannot be counterbalanced by positive building attributes, priority should be to providing privacy and amount of space to better support occupants in their work.

Declaration of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A: List of supervised machine-learning algorithms

Table A.1. List of supervised machine-learning algorithms used to classify data, parameters that were tuned, search-grid range and interval changes for each parameter, the optimal value calculated from the search-grid, and a description of each parameter.

Algorithm	Parameter	Search-grid *Range*	Search-grid *Interval*	Optimal	Description
SVM (linear)	Cost	2^{-5} to 2^{15}	2^1	0.5	Controls the complexity of classified prediction given by the hyperplane on the training data points (Hastie et al., 2004).
SVM (radial)	Cost	2^{-5} to 2^{15}	2^1	128	Controls the complexity of classified prediction given by the hyperplane on the training data points (Hastie et al., 2004).
SVM (radial)	Gamma	2^{-15} to 2^3	2^1	0.25	Defines how many local data points are considered when the hyperplane margins are created (Ben-Hur and Weston, 2010).
Random Forrest	ntree	250 to 2500	250	750	Determines the number of trees to grow. The larger the number of trees, the more stable a model may become [45].
Random Forrest	mtry	1 to 15	1	1	Number of randomly selected variables available for splitting at each tree node [59].

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Appendix B: Results of the SVM (radial) and random forest models

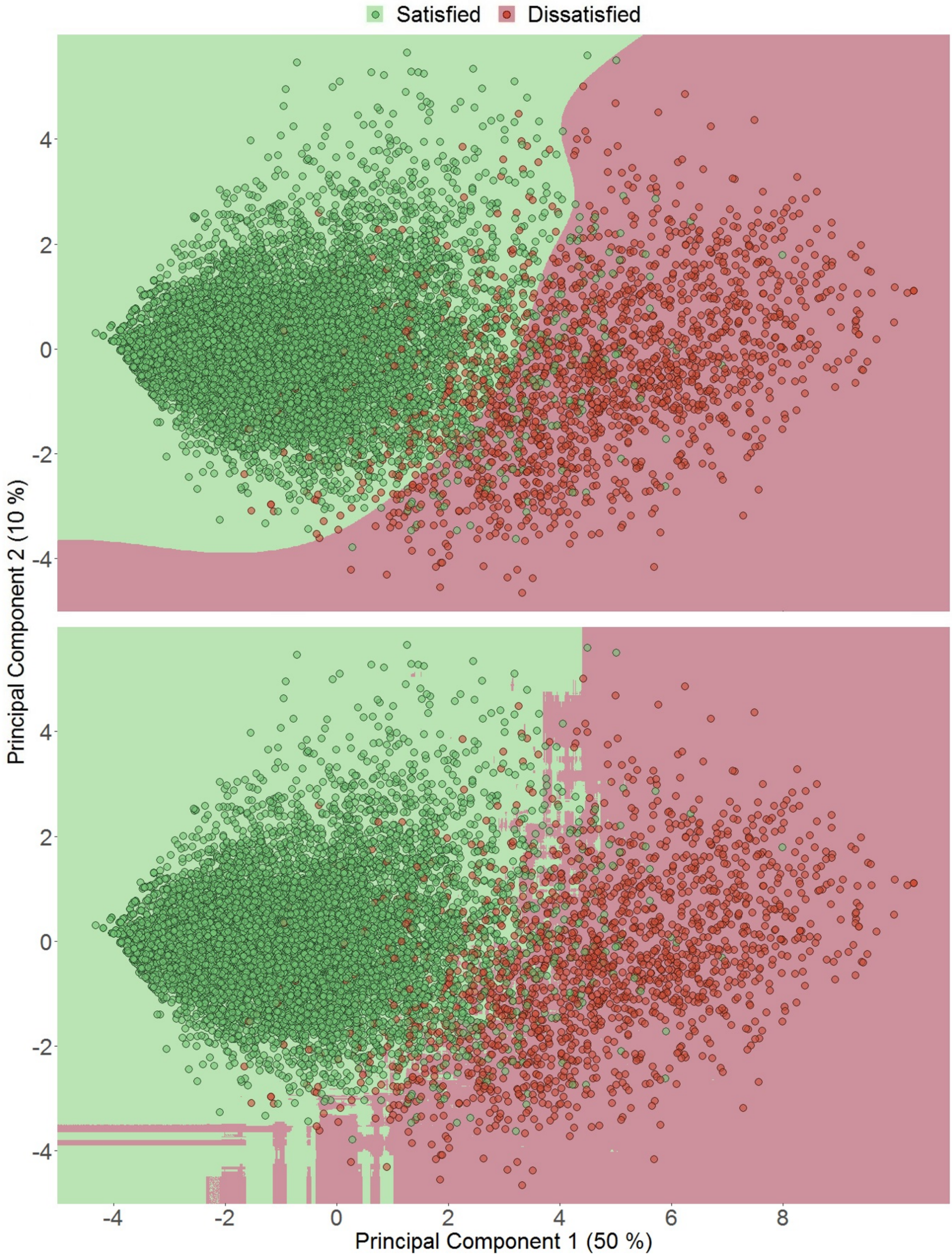

Figure B.1. Plots showing the results of the supervised machine-learning algorithms when classifying the ratings of satisfied and dissatisfied with the workspace using principal component 1 and principal component 2. The plots show the SVM radial model for the (a) training dataset and (b) test (validation) dataset, and the random forest model for the (c) training dataset and (d) test dataset.

Table B.1. AUC values with the bootstrapped 95 % upper and lower confidence intervals for both the training and validation datasets for the SVM kernel and Random Forest classifiers.

Classifier	AUC	95 % confidence interval		Precision	Recall	*F*-Measure
		Upper	*Lower*			
SVM (kernel)	0.90	0.91	0.90	0.97	0.98	0.97
Random Forest	0.90	0.90	0.89	0.97	0.97	0.97