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Abstract

Occupant behavior influences office building energy performance. The level of human-building interactions (HBIs) in shared offices strongly influences building energy use and occupant well-being. This study explored the link between occupant personality types and their behaviors of sharing energy and environment control systems and interactions with their colleagues. Inspired by the Five Factor Model (FFM), we classified HBI behaviors into four dimensions: *willingness to share control*, *knowledge of control*, *group decision behavior*, and *adaptive strategies*. These four variables can be mapped to the four personality traits proposed by the FFM: agreeableness, openness, extraversion, and conscientiousness. Our cluster analysis identified six behavioral patterns: average (17.7%), reserved (15.3%), environmentally friendly (16.6%), role model (24.2%), self-centered (17.2%), and mechanist (9.0%). We further applied association rules, a widely utilized machine learning technique, to discover how demographics, building-related contextual factors, and perception-attitudinal factors influence HBI behaviors. Country, control feature accessibility, and group dynamics were found to be the three most influential factors that determine occupants' HBI behaviors. The study provides insights about building design and operation, as well as policy to promote socially and environmentally desirable HBI behaviors in a shared office environment.

Keywords: human building interaction; occupant behavior; Five Factor Model; personality type; machine learning; office buildings

1. Introduction

Reducing energy use in buildings remains a critical strategy for decarburization, considering buildings account for 36% of global final energy consumption and nearly 40% of total direct and indirect carbon dioxide (CO_2) emissions [1]. Because people spend 86.9% of their time in buildings [2], a well-designed built environment is crucial for energy conservation and occupants' well-being.

1.1 Human-building interactions

Occupant behaviors are as important as the technologies that influence building design, operation, and energy consumption [3] [4]. Occupant behaviors influence building operation and performance through human-building interactions (HBIs). The term *human-building interactions* refers to occupants' interactions with the building energy and environment control system (e.g., thermostats, operable windows, shades, lights) to meet their individual needs or thermal comfort in an indoor environment. HBIs have become increasingly important in modern buildings, because research has identified individual thermoregulation differences among humans [5] and because individualized comfort demands are increasingly respected [6]. The tradition of using a predetermined, fixed, and universal thermostat set point listed in building codes and standards for building control was found to conflict with each individual's true comfort needs [7]. Data on HBIs are needed to facilitate the development and use of occupant-responsive controls. Therefore, HBIs play a decisive role in determining not only building energy usage [8], but also occupant comfort and well-being [9]. A well-designed HBI system encourages occupants to control the built environment to reduce energy use while enhancing their comfort [10],[11], productivity [12], and health [13]. Due to their importance in modern buildings, HBIs have become a popular topic [14], new models have been introduced to simulate HBIs [15], and new tools have been developed [16]. However, the majority of the studies that address those issues focus on single-person offices, overlooking the influence of multiple occupants on HBIs.

In recent decades, many office buildings have transitioned from single-person cubicles to an open-plan style [17], [18], [19]. Today, about 70% of U.S. offices are open concept, and they accommodate a significant amount of the working population [20]. Shared offices expose multiple occupants to similar environmental conditions; however, this type of office neglects individual preferences and personal need [21]. For instance, it was found that females are more sensitive to cold exposures than males [22]. In individual offices, female workers and male workers might select a different temperature set point. However, in a shared office, female and male colleagues need to negotiate a common thermostat set point that satisfies their different thermal comfort demands. Some research has found that HBIs in a shared environment are more silent than those in single-person office [23], [24]. Occupants in a shared office generally rely more on psychological coping mechanisms (e.g., tolerating or ignoring discomfort) [25] than on adjusting environmental settings, partly due to a lack of control over the building energy system [26], [27]; therefore, occupants are consistently reported to be less comfortable [28], [29], [30], healthy [26], [27], and satisfied [27] in open spaces than in single-person offices.

1.2 Five-Factor Model

HBIs are influenced by building types, climates [31], [32], and social dynamics such as norms or organizational culture [33]. Occupants' personality traits also drive HBIs and pro-environmental behaviors.

The Five-Factor Model (FFM) is a personality traits model that is widely used to analyze the link between personality traits and workplace behaviors and outcomes, including employee job attitudes, job satisfaction, organizational commitment, and work-related motivation and behaviors [34]. For example, traits such as conscientiousness, extraversion, and emotional stability (the opposite of neuroticism) have been found to have positive and significant relationships with job satisfaction [34]. Another study found that conscientiousness and emotional stability both had a significant relationship with organizational commitments [35]. Similarly, scholars found counterproductive workplace behaviors to be negatively associated with the traits of agreeableness and conscientiousness; whereas, organizational citizenship behaviors are positively associated with the traits of extraversion and conscientiousness, and negatively associated with neuroticism [36]. Wingate, Lee and Bourdage's findings suggest that those with more altruistic motivations (i.e., a desire to help the organization or coworkers) had higher levels of honesty-humility, extraversion, conscientiousness, and agreeableness, and worked in an environment with more motivating leaders and low perceptions of workplace politics [37]. Conversely, those with self-serving motivations had lower levels of honesty-humility, which is more common in workplaces with high perceptions of workplace politics. This study demonstrates that not only personality traits, but also workplace culture, can influence employee behavior.

The literature also suggests that personality traits can influence a wide range of pro-environmental behaviors and investment in household energy efficiency. For example, Hirsh found that greater environmental concern was related to higher levels of agreeableness and openness; whereas, less-positive relationships were related to neuroticism and conscientiousness. Similar research found that agreeableness, conscientiousness, and openness to experience were the main traits associated with pro-environmental engagement, such as electricity conservation, positive environmental concern and attitudes, and harmony values. Further, the desire to reduce greenhouse gas emissions was predicted by openness, conscientiousness, and extraversion, with the effects mediated by attitudes towards the environment. Another study suggested that openness to experience predicts eco-helping, [1] conscientiousness predicts eco-initiatives, and extraversion predicts eco-civic engagement [38].

1.3 Objectives

From the literature review, two research gaps could be identified. First, HBIs in shared offices are different from those in single-person offices; however, previous occupant studies do not distinguish the influence of office type [28], and HBI-related analyses tend to focus on those in single-occupant offices [36]. There is clearly a lack of research on HBIs in shared offices, even though more people are working in shared offices rather than in single-person offices. Second, even though occupants' personality traits are the fundamental drivers influencing HBI behaviors, the link among personality traits, building contextual factors, and HBI behaviors is underexplored.

This study aimed to address those research gaps by taking a step further to analyze HBIs in shared offices. Investigating occupants' personality traits with the FFM helps researchers analyze occupants' underlying behavioral intentions. Some social scientists attempt to group people into different personality types [39], [40]; similarly, we first clustered the HBI behaviors into different clusters, since clustering analysis can provide a deeper understanding of the problems prior to proposing solutions. Specifically, this study focused on discovering whether there are typical HBI behavioral patterns in shared offices; and if there are, then what the major characteristics of each pattern are (Section 3) and how different behavioral patterns are influenced by demographics and building contextual factors (Section 4).

[1] Eco-helping relates to motivation to encourage and help colleagues to take into account environmental concerns.

This study's findings could help us better understand the role of HBIs in shared offices, such as how and in what way occupants share and use the building control system. As a majority of office workers are located in shared offices, a better understanding of HBI behaviors in shared offices can help us improve the design of HBI interfaces and building controls to facilitate reductions of energy use and carbon emissions, as well as to increase occupant productivity and well-being.

The building control system in this paper refers to building energy and environment controls, including adjustment of HVAC system thermostats, turning lights on and off, switching plug-in equipment on and off, and pulling shades up and down. Hereafter, we will use the terms *building control* or *control* for these types of activities.

2. Methods

2.1 Framework

To answer the research questions proposed in the previous section, we proposed the following workflow, as presented in Fig. 1. This section will introduce the study's computational methods. Section 2.2 will introduce the data collected, and sections 2.3 and 2.4, respectively, will introduce the data preprocessing and the selection of the optimal cluster number.

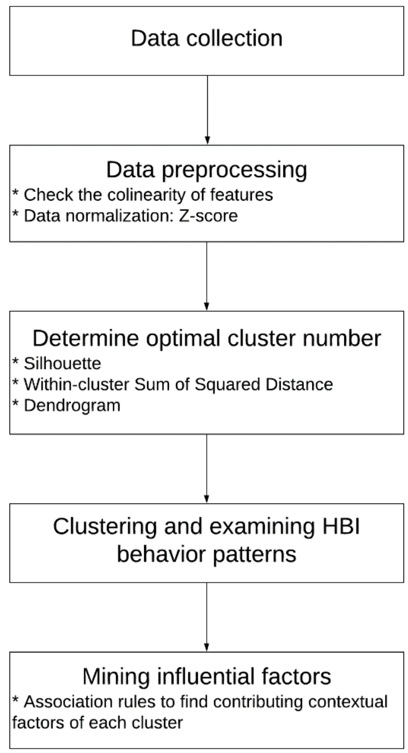

Fig. 1 Workflow of data analysis

2.2 Data collection

2.2.1 Variables collected

In this study, the survey collected two types of variables, as shown in Fig. 2. To answer the first research question (whether there are typical HBI behavioral patterns in shared offices; and if there are, what the major characteristics of each pattern are), we collected *HBI behavior variables* to measure occupants' HBI behaviors. To answer the second question (how different HBI behavioral patterns are influenced by demographics and building contextual factors), we collected *contextual variables*, including personal and building contextual variables, that could influence occupants' HBI behaviors.

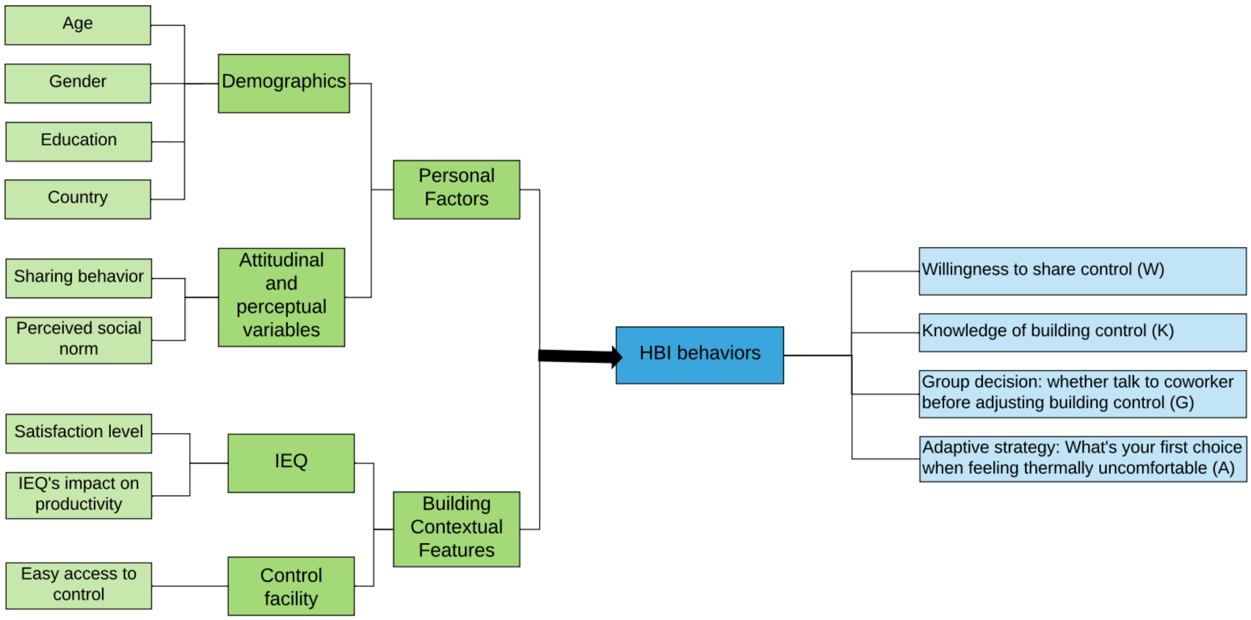

Fig. 2. Conceptual framework: Key HBI variables mapped with the FFM. The variables in the blue boxes are *HBI behavior variables*, and the variables in the green boxes are *contextual variables.*

(a) HBI behavior variables

Inspired by the FFM, we propose a framework linking HBI behaviors and personality traits in shared offices. The FFM contains five trait domains: (1) neuroticism versus emotional stability, (2) extraversion versus introversion, (3) openness versus closeness to experience, (4) agreeableness versus antagonism, and (5) conscientiousness versus disinhibition [41]. We classified the HBI behaviors by considering four dimensions: (1) willingness to share control, (2) knowledge of control, (3) group decision behavior, and (4) adaptive strategies. Again, the *control* here refers to the energy and environment control in buildings, such as adjusting thermostat settings, dimming or switching lights, opening/closing windows, pulling up/down blinds, changing clothing, and turning plug-in equipment on and off. Fig. 3 presents how the collected HBI behavior variables are mapped to the five personality traits proposed by the FFM.

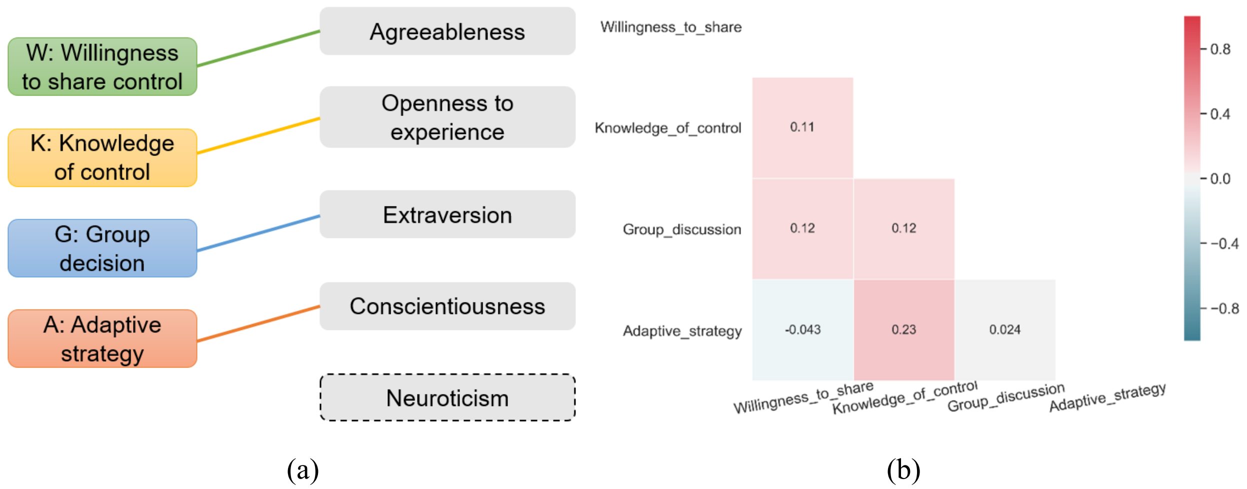

Fig. 3. HBI behavior variables. (a) Mapping of HBI behavior features to the FFM personality traits:[42] willingness to share control (W) to agreeableness; knowledge of control (K) to openness; group decision behavior (G) to extraversion; and adaptive strategy (A) to conscientiousness. **(b)** A correlation matrix of the four features selected: the features selected have a low Pearson correlation coefficient (PCC) with each other.

As shown in Fig. 3, the four HBI behavior variables could be mapped to four of the five personality traits proposed by FFM [42]. Specifically, *willingness to share (W)* is mapped to *agreeableness* because *agreeableness* indicates the degree an individual exhibits characteristics such as friendliness, cooperativeness, altruism, and trust in others [43]. Therefore, this study hypothesizes that people who score higher in *agreeableness* are more likely to share building control features. Additionally, *knowledge of control (K)* is mapped to *openness to experience*. O*penness to experience* measures one's willingness to try new activities [43]. In the public building context, people with higher *openness* scores are considered more likely to learn new ideas or concepts, and thus be more knowledgeable about the building control system. *Group decision strategy (G)* is mapped to *extraversion*. Extraverts are considered more likely to consult their coworkers before adjusting the building control systems, while introverts may be likely to avoid any social interactions [43]. Lastly, *adaptive strategy (A)* is mapped to *conscientiousness*. *Conscientiousness* suggests that if people are aware of the consequences of their behaviors, they have a sense of responsibility [43]. People with higher levels of conscientiousness may be more aware of the consequences their actions have on the environment and/or the comfort of other people; therefore, they may prefer personal, non-mechanical approaches (e.g., putting on clothes, having a hot drink) over mechanical ones such as raising thermostat settings or using a personal heater, which would potentially affect other occupants. This study did not propose an HBI behavior feature corresponding to *neuroticism*, which measures the emotional stability of occupants, because the effects of *neuroticism* on organizational behaviors are not consistent and also depend on other individual and organizational factors such as self-esteem and organizational friendliness [44],[45].

(b) Contextual variables

The second type of HBI variables, including personal and building contextual variables, are the predictive factors that could influence occupants' HBI behaviors. Personal variables include demographic factors and attitudinal-perceptual factors. Attitude has been proven as a strong predictor of multiple pro-environmental behaviors, including energy-saving behaviors at work [46], [47], [48]. Previous studies also suggest group norms have a profound influence on individuals' pro-environmental and HBI behaviors [24], [49], [50], [51]; therefore, we measured perceived group norms: the perceived expectations or approval from coworkers in sharing the building control system. Building contextual variables include two measures of indoor environmental quality (IEQ)—perceived IEQ satisfaction level and the impacts of IEQ on productivity—as well as accessibility to building controls.

2.2.2 The Survey

An Internet-based questionnaire was designed with Qualtrics survey software and administered through the Qualtrics Paid Panel Service, a popular online data collection platform used by researchers. The participants, age 18 and older, were recruited from the university staff, faculty, researchers, and graduate students regularly occupying office buildings from nine universities and research centers across six countries, including Brazil, Italy, Poland, Switzerland, the United States, and Taiwan, to present various cultural backgrounds. The final sample size was 4285 (Brazil = 252, Italy = 1127, Poland = 512, Switzerland = 191, USA = 1920, China = 283). Ethics protocols and privacy issues for handling human subject data were approved in all the participating institutions.

The survey instrument, originally developed in English, was translated into several languages, including Chinese, French, German, Italian, Polish, and Portuguese. A translation guideline protocol was developed and followed to ensure equivalence across languages. Semantic, conceptual, and normative equivalence of the survey questions was guaranteed by retranslating survey questions back into English before finalizing the translated versions, as outlined in the double translation process (DTP), one of the most adopted translation processes for survey questionnaires [52]. University listservs were used to distribute the survey. An individual survey link for each university was thus created and sent to participants. The survey was anonymous, and no personal identifiers were collected. The structured questionnaire consisted of five parts. The first part asked about current thermal comfort, IEQ satisfaction, belief in the impact of IEQ on work productivity, and reasons of thermal discomfort. The second part asked about control system options and the behaviors used to exercise control. The third part consisted of the measure of conformity intention and social-psychological variables that potentially predict conformity intention (a dependent variable). Five-point Likert-type scales were used in the measures. The fourth part included two questions regarding the first and second actions taken when the participant feels too cold or too hot in the office. The final part of the survey contained questions about building contextual factors (e.g., office type, access to building control features, occupancy hours) and demographic information. Multiple response methods, such as checking a box or clicking and dragging a statement were used to ease participant choices and reduce boredom.

2.3 Data preprocessing

After the data were collected, the first step was to use the correlation matrix to check the collinearity of the four features used to describe the occupants' HBI behaviors (W, K, G and A) using the correlation matrix (Equation 1). The relative low Pearson correlation coefficients (PCC), as shown in Fig. 3b, indicated that the four HBI behavior features have low multi-linearity, and therefore do not overlap with each other. Each feature demonstrated one unique aspect of HBI behaviors.

$$\mathrm{R} = \begin{bmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ r_{ij} & \cdots & 0 \end{bmatrix} \qquad (1)$$

Where $r_{ij} = 0$ if $i \leq j$;

$$r_{ij} = \frac{\sum_{k=1}^{n}(x_{ik}-\mu_{xi})(x_{jk}-\mu_{xj})}{\sqrt{\sum_{k=1}^{n}(x_{ik}-\mu_{xi})^2}\sqrt{\sum_{k=1}^{n}(x_{jk}-\mu_{xj})^2}} \; (PCC\ between\ x_i\ and\ x_j) \text{ if } i > j;$$

We then used Z-score (Equation 2) to normalize the value of each feature. Otherwise, features with a higher variation would have higher impacts on the clustering results.

$$Z_i = \frac{x_i-\mu_x}{\sigma_x} \qquad (2)$$

Where μ_x is the mean of vector *x,* and σ_x is the standard deviation of vector *x*.

Z-score was used in this study to ensure each feature had similar weights when assigning samples to different clusters.

2.4 Determine the optimal number of clusters

As a non-supervised machine learning approach, the optimal number of clusters needs to be found through a manual iteration process. We used three references—a higher Silhouette score, a lower Within-cluster Sum of Squared Distances (WSSD), and the Dendrogram[2]—to determine the optimal number of clusters and validate the robustness of the clustering results, as shown in Fig. 4.

Silhouette score measures how similar an object is to its own cluster (cohesion) compared to other clusters (separation). The Silhouette score is a commonly used metric to evaluate and validate the clustering configuration [53]. As shown in Equation (3), the Silhouette score compares separation with cohesion, ranging from -1 to 1. A higher Silhouette score indicates that the sample is closer to its own cluster, while farther away from other clusters. A higher average Silhouette score indicates that the clustering configuration is more appropriate. As shown in Fig. 4a, we plotted the average Silhouette score of all members with different numbers of clusters, which helped to determine that the optimal number of clusters should be either 3 or 6 to achieve a higher average Silhouette score.

$$s(i) = \frac{b(i)-a(i)}{\max\{a(i),b(i)\}} \qquad (3)$$

[2] The Dendrogram is a diagram that shows the hierarchical relationship between objects, based on the distance of each object.

Where $a(i) = \frac{1}{\#(C_i)-1} \sum_{j \in C_i, i \neq j} d(i,j)$ is measuring how similar a member is to other members in the same cluster (cohesion), and $b(i) = \min_{i \neq j} \frac{1}{\#(C_j)} \sum_{j \in C_j} d(i,j)$ is measuring how similar a member is to members in other clusters (separation). The distance function $d(i,j)$ could use Euclidean or Manhattan or Chebyshev distance. In this study, we used Euclidean distance, which is most widely used in clustering analysis.

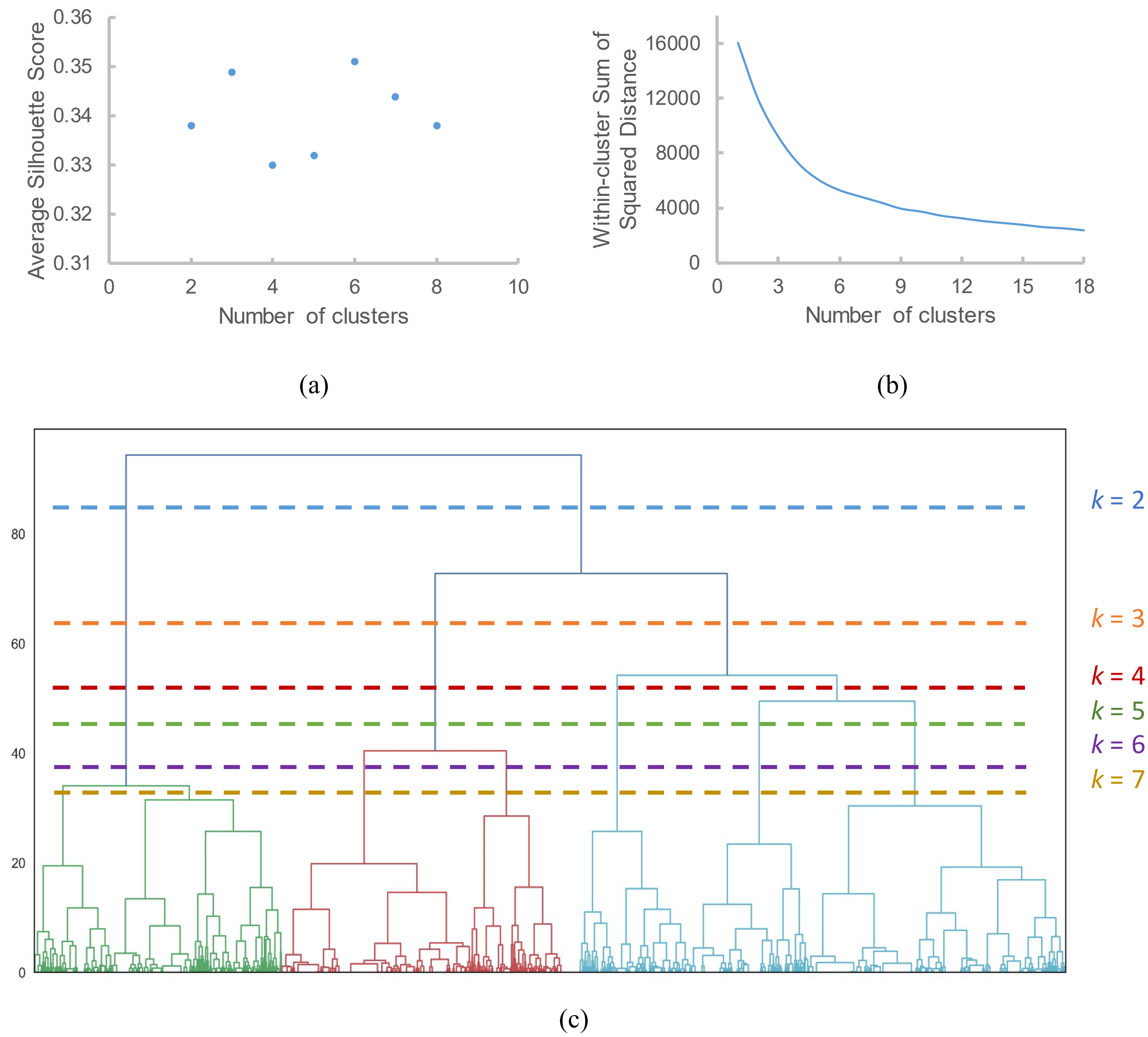

Fig. 4. Determining the optimal number of clusters. (a) The Average Silhouette Score peaks when the number of clusters is equal to 3 or 6. (**b)** The elbow region of WSSD value can be identified when the number of clusters is between 3 and 9. (**c)** The Dendrogram in hierarchical clustering.

Within-cluster Sum of Squared Distance (WSSD) measures the distance between the sample and its cluster centroid. A smaller WSSD indicates the cluster member is closer to its cluster centroid, signaling a better clustering. Unlike Silhouette score, WSSD only measures cohesion, and accordingly is monotonically decreasing with the increasing number of clusters. WSSD can be calculated with Equation (4). As increasing number of clusters would naturally result in a smaller WSSD; the goal is to choose a small value of number of clusters that still has a low WSSD. In practice, we attempted to identify the elbow region to select the optimal number of clusters, because the elbow region usually represents where diminishing returns start with the increasing number of clusters. As shown in Fig. 4b, the elbow region of the WSSD value can be identified when the number of clusters is between 3 and 9.

$$WSSD = \sum_{k=1}^{K} \sum_{i \in C_k} \sum_{j=1}^{p} (x_{ij} - \mu_i)^2 \quad (4)$$

Where x_{ij} is the coordinate of *j-th* instance of *cluster i,* and μ_i is the coordinate of cluster centroid of *cluster i.*

A dendrogram is a diagram that shows the hierarchical relationship between objects, based on the distance of each object. In this study, we used an agglomerative hierarchical approach, which considers each sample in its own cluster, and merged them while moving up the hierarchy. Again, the Euclidean distance was used to measure the similarity of different samples. The dendrogram of the collected data is presented in Fig. 4c.

3. Identified HBI behavioral clusters

Inspecting the analytic results using the three metrics, we selected the optimal number of clusters to be six. Fig. 5 and Table 1 present the final clustering results and the position of each cluster in the space spanned by the four HBI behavior features (W, K, G and A).

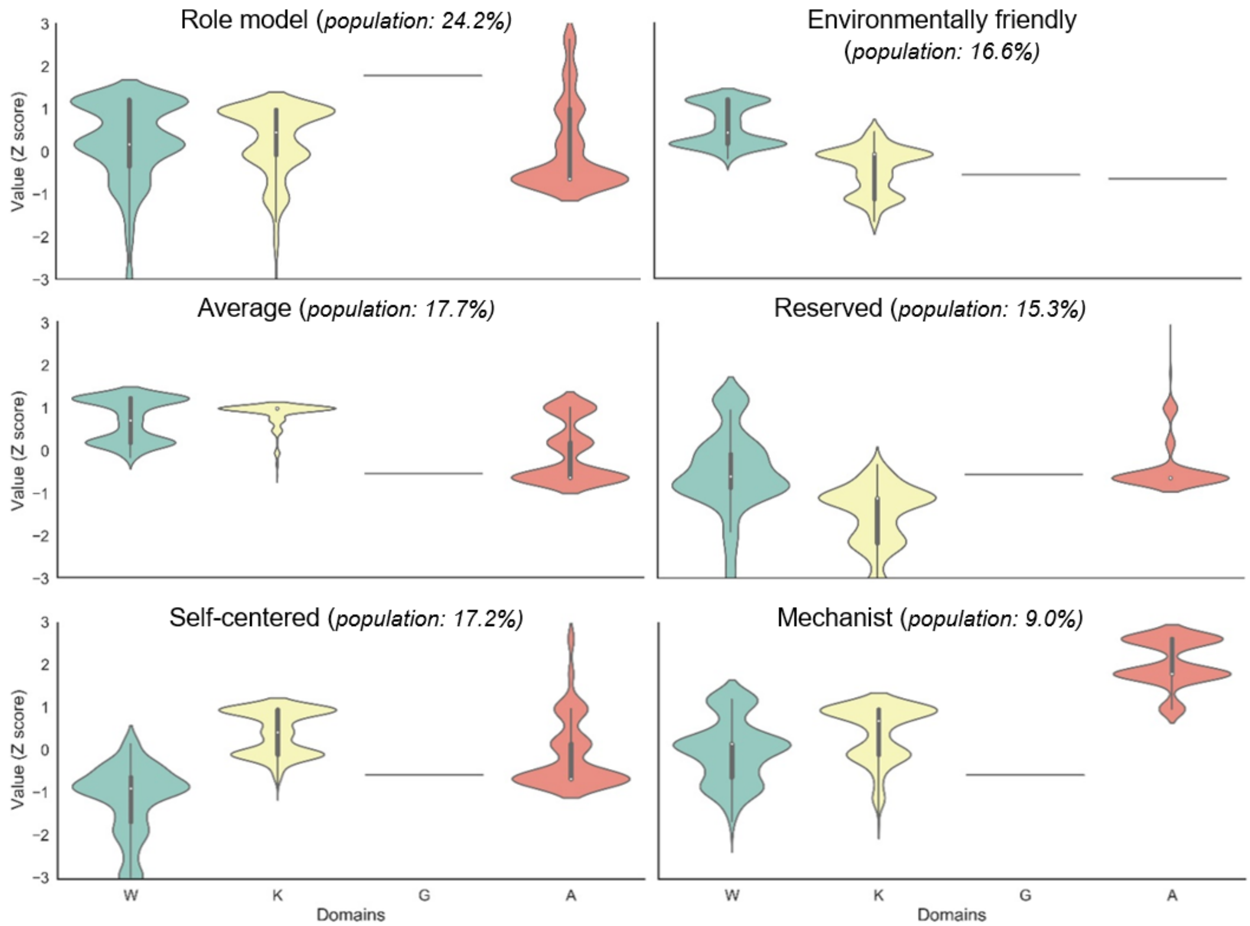

Fig. 5. Clustering results. Six HBI behavior clusters were identified: (1) average, (2) reserved, (3) environmentally friendly, (4) role model, (5) self-centered, and (6) mechanist.

Table 1. Clustering results

Cluster	Percent of sample	Willingness to share (Agreeableness)	Knowledge of control (Openness)	Group decision (Extraversion)	Adaptive strategy (Conscientiousness)
Role model	24.2%	High	High	Yes	Pro-natural
Average	17.7%	High	High	No	Middle
Self-centered	17.2%	Low	High	No	Pro-natural
Environmentally friendly	16.6%	High	Middle	No	Pro-natural
Reserved	15.3%	Middle	Low	No	Pro-natural
Mechanist	9.0%	Middle	High	No	Pro-mechanical

The first cluster we identified is characterized by the occupants' high level of willingness to share building controls with coworkers, knowing building controls well, discussing with coworkers before adjusting building controls, and preferring non-mechanical approaches (e.g., adjusting clothes levels) over mechanical approaches (e.g., adjusting the thermostat) when feeling too hot or too cold. We denoted this cluster as "role model" because it displays socially and environmentally desirable HBI behaviors in shared offices. Among the six clusters we identified, only the "role model" occupants would communicate with their coworkers before adjusting indoor temperature settings. Approximately 24.2% of participants belonged to the "role model" type, accounting for the largest percentage of our sample.

The cluster with the second largest population was the "average" cluster. Individuals in this type were characterized by their level of willingness to share building controls, but an unwillingness to discuss changes with coworkers before making any adjustment; further, this cluster might choose either non-mechanical or mechanical approaches when they feel too hot or too cold. This "mixed" type of behavior was demonstrated by 17.7% of the participants. The third cluster, consisting of 17.2% of the participants, was identified as the "self-centered" type, who demonstrated the lowest level of willingness to share controls. They were likely to be knowledgeable about building controls, but less likely to discuss changes with coworkers before adjusting the controls. They also preferred non-mechanical approaches when feeling thermally uncomfortable.

The fourth cluster, the "environmentally friendly" group, was equally willing to share building controls and preferred non-mechanical adaptive approaches as the "role models" did. However, the "environmentally friendly" people were less knowledgeable about controls, and were less likely to discuss with coworkers before adjusting the building controls; 16.6% of participants belonged to this category.

The fifth cluster was the "reserved" group. These individuals preferred traditional, non-mechanical approaches to achieve a higher comfort level and were not knowledgeable about building controls. The "mechanist" type represented the sixth cluster, and they demonstrated opposite behaviors: they were very knowledgeable about the building controls in office buildings and preferred the mechanical approach (e.g., adjusting the thermostat) when feeling uncomfortable. Approximately 15.3% of participants were "reserved" and 9.0% were "mechanist."

4. Factors influencing HBI behavioral patterns

4.1 Association rules

In this study, we cared about not only the human-building interaction behaviors, but also which factors would influence those behaviors. To analyze whether and which demographic or contextual factors influence HBI behavioral patterns, we applied association rules to discover the meaningful associations between the contextual factors and the HBI behavior patterns. Association rule is a widely used data mining technique to identify the co-occurrence between the antecedent and the consequent, which refer to the predictive factors and HBI behavior patterns, respectively, in this case. In association rules, there are three key concepts: *support*, *confidence*, and *lift*. *Support* (Equation 5) measures the prevalence of observing the antecedent (contextual factors) and the consequent (HBI patterns) in the dataset. *Confidence* (Equation 6) quantifies the percentage of the consequent that occurs given the antecedent observed. *Lift* (Equation 7) measures how much more frequent the antecedent occurs given that the consequent is observed.

$$Support(A) = \frac{\#(\{t \in T; A \subseteq t\})}{\#(T)} \quad (5)$$

$$Confidence(A \Rightarrow C) = \frac{Support(A \cup C)}{Support(A)} \quad (6)$$

$$Lift(A \Rightarrow C) = \frac{Support(A \cup C)}{Support(A) \times Support(C)} \quad (7)$$

Typical threshold values of lift, support, and confidence were selected in this study. Specifically, we mined and filtered those association rules with a higher than 110% *lift* (the observation of the antecedent would at least indicate a 10% more frequent occurrence of the consequent), a higher than 0.2% *support* (the antecedent/consequent pair are not too uncommon), and a higher than 10% *confidence* (the observation of the antecedent should be indicative enough for the prediction of the consequent).

4.2 Results

The mined association rules, which pass the threshold values of lift, support, and confidence defined in the previous section, are presented in Fig. 6.

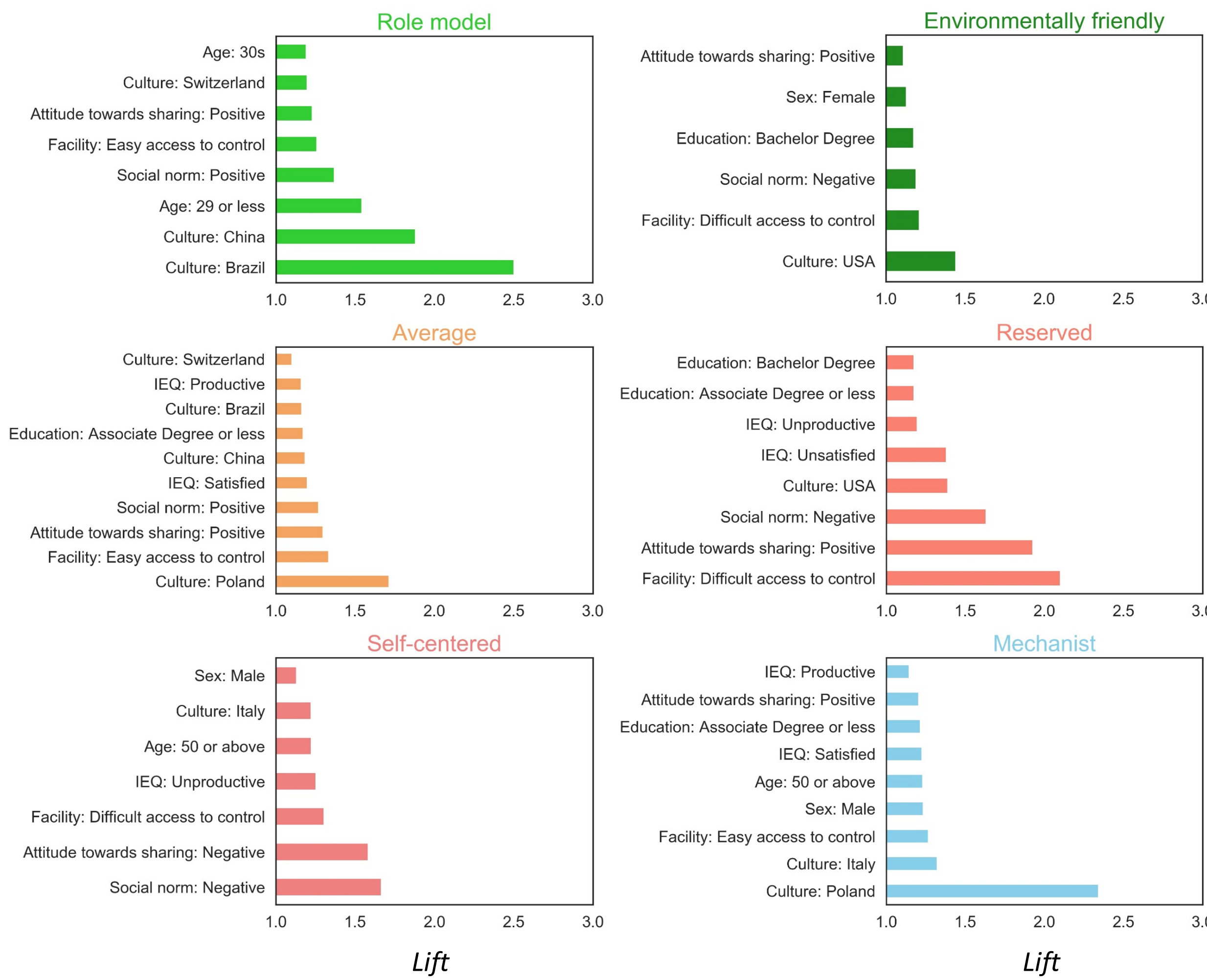

Fig. 6. Influential individual and contextual factors for different HBI behavior patterns. We filtered the identified rules with a higher than 110% *lift*, higher than 0.2% *support*, and higher than 10% *confidence*. Then we ranked the antecedents (contextual factors) based on *lift*.

According to Fig. 6, the strongest predictor of being a “role model” is culture, in particular for this study, being from Brazil or China. Younger age is also associated with a higher likelihood of being a “role model.” In addition, having positive attitudes towards sharing control, positive social norms, and easy-to-access control features all contribute to the higher likelihood of being a “role model.” Conversely, the “reserved” group seems to be shaped by the most aversive conditions, such as having difficulty accessing the control system, negative social norms of sharing controls, and unsatisfactory IEQ.

Among the four demographic factors, the country location was found to be the most influential in determining HBI. Regarding country differences, Brazilians were 150% more likely to be a “role model” in comparison with occupants from other countries (Lift = 2.5). Polish respondents were 134% more likely to be “mechanist” and 72% more likely to be “average.” Americans were 44% more likely to be “environmentally friendly,” and 39% more likely to be “reserved.” Chinese respondents were 88% more likely to be a “role model” and 18% more likely to be “average.” The Swiss were 20% more likely to be a “role model” and 10% more likely to be “average.” Italians were 32% more likely to be “mechanist” and 22% more likely to be “self-centered.”

Evidence shows that FFM traits are linked to workplace behaviors; for example, in collectivist cultures, narcissism is less likely to predict negative workplace behaviors than in more individualistic cultures [54]. This means that negative FFM characteristics are less predictive of negative workplace behaviors in societies with stronger group cohesion. Brazil is widely considered to be a collectivist country [55], [56]; therefore, they would more likely be “role models” in a workplace context, and facilitate overall group harmony and satisfaction. We see the same trend among the data from China, another widely known collectivist culture. Conversely, Americans were considered to be more environmentally friendly but less willing to discuss control options. This could be due in part because America's individualistic culture makes Americans less likely to discuss building control options with their co-workers. Other variations among countries could be due to differences in building type, office layout, or building control options. For example, countries with a more open or shared office layout may be more likely to encourage the behavior of sharing building controls; or perhaps, buildings in countries with more mechanical adjustment options might have more "mechanist" employees. Factors of cultural norms, building design, and personality traits that potentially influence the differences among countries are also essential in determining HBI behaviors.

Age is the second important demographic factor. Younger occupants were more likely to be a "role model," while the senior group (age above 50) were more likely to fall into the "mechanist" (23%) or "self-centered" (22%) categories. As for education, participants with an associate degree or less were more likely to be "reserved," "average," and "mechanist." Occupants with a graduate degree or more were more likely to be "reserved" and "environmentally friendly." In terms of gender, males were 23% more likely to be "mechanist" and 13% more likely to be "self-centered" than females, while females were 13% more likely to be "environmentally friendly" than males.

We found that attitude and group norms play an important role in determining occupants' HBI behaviors, suggesting that if the occupants hold a positive attitude, they were 23% more likely to be a "role model." This idea is also prevalent in the literature [57], [58]: those with higher levels of agreeableness, openness, and conscientiousness are linked with positive attitudes towards the environment. Those who exhibit these positive personality traits tend to be less selfish, more cooperative, more open-minded, and more willing to compromise with others [58]; thus, their "role model" classification fits these positive personality characteristics, as they are more likely to share building controls, know about control options, and discuss adjusting controls with their co-workers. Further, if occupants perceived that their coworkers expected them to share controls, they were 37% more likely to be the "role model." Research [59] suggests that those with higher levels of openness to experience and conscientiousness are more likely to have a stronger reaction to their peers' opinions on purchasing more environmentally friendly technologies. This finding helps link together FFM characteristics with peer-influence on pro-environmental behaviors. Those occupants who are open and conscientious express a higher susceptibility to social norms; and thus, would be more likely to exhibit "role model" characteristics based on how they view their peers' sharing expectations.

Regarding building contextual factors, when IEQ was perceived to be satisfactory and had a positive impact on productivity, participants were more likely to be "average" and "mechanist" by 15%–23%. On the other hand, if the IEQ was perceived as unsatisfactory and a negative impact on work productivity, participants were 20%–38% more likely to be "reserved" or 25% more likely to be "self-centered." In terms of the accessibility to building controls, occupants from offices with easy-to-access to controls were more likely to be "average" (33%), "mechanist" (27%), and "role model" (26%) than occupants from offices with less easy-to-access building controls. By contrast, occupants from a less accessible office were more likely to be "reserved" (110%), "self-centered" (30%), and "environmentally friendly" (21%) than their counterparts.

5. Discussion

5.1 Findings and implications

Our study highlights the importance of occupants' personality traits in interacting with building technology and office design in a shared environment. This is a critical linkage with HBI behaviors, which are fundamental, yet often neglected in occupant behavior research. We clustered the HBI behaviors with four dimensions—willingness to share, knowledge of control, group decision behavior, and indoor adaptive strategy—and these corresponded to the four personality traits of agreeableness, openness to experience, extraversion, and conscientiousness. Based on the results, we identified the following perspectives: (1) six HBI patterns (average, reserved, environmentally friendly, role model, self-centered, and mechanist) were identified among the six countries studied (Brazil, United States, China, Switzerland, Italy, and Poland); (2) attitudinal-perceptional factors such as attitudes, group norms, and the perceived impacts of IEQ on productivity play an important role in determining HBI behaviors; (3) the accessibility level of the control system influences personality traits; and (4) gender, education level, and age all influence HBI behaviors.

Our findings could help researchers more deeply understand HBI behaviors in shared office. In an early stage of job training and team building, personality test results may help inform the most effective way to share building technology in a particular organization. More important, the personal, attitudinal-perceptional, and building contextual factors that influence the HBI behaviors have been explored, and these provide important insights for the design of office interfaces. They also can help building managers take measures that promote more socially and environmentally desirable HBI behaviors in a shared environment. The methodology used to cluster the HBI patterns can be applied to future datasets with a larger sample size or more variables.

Our study also alerts building designers and organizational policymakers to the importance of creating positive norms and attitudes for sharing building controls—as well as encouraging ready access to those controls—in helping to save energy within an organization. Additionally, the role of employees' perceived impact of IEQ on productivity could serve as a possible mediator in influencing employees' energy use. This provides an important insight for an organization's policymakers to consider employee work expectations and well-being beyond the physical factors such as the design criteria of IEQ. Building designers should consider particular needs based on different genders, ages, and education levels by choosing flexible and user-friendly energy or environment control features.

Most important, building design and the analysis of occupant behaviors in relation to personality traits should consider cultural differences. A better understanding of personality traits, the HBI behaviors, and their interactions with building control systems is much needed to improve the design of new buildings and operation of existing buildings to reduce energy use and carbon emissions, as well as to increase occupant productivity and well-being.

5.2 Limitations and future work

The strength and credibility of the results rely on the sample size and quality of the data. Our conclusion is built upon a survey dataset with 4285 samples collected from six countries (Brazil, Italy, Poland, Switzerland, United States, and China). Even though this is the biggest sample size in this field, as far as the authors know, in future it would be great to look at a larger dataset, when available, that can fully represent billions of people from these countries. Additionally, the samples are not proportionally sized. Half the samples were from Italy and United States, while only 5% were from China.

Another constraint is this dataset is mainly collected from university buildings. Therefore, compiling and sharing a larger database with higher data quality that records HBI behavior data could significantly promote HBI studies. A good example that we could learn from is the ASHRAE global thermal comfort database, which collected and open-sourced 81,846 complete sets of objective indoor climatic observations with accompanying “right-here-right-now” subjective evaluations by the building occupants who were exposed to them in Database II [60], in addition to the 22,000 data points published in Database I [61] 20 years ago.

6. Conclusions

In this study, we applied machine learning techniques such as clustering and association rules to analyze HBIs in shared offices. Specifically, we focused on two research questions that had not been answered in previous studies: first, whether there are typical HBI behavioral patterns in shared offices; and if there are, what the major characteristics of each pattern are. Second, how different HBI behavioral patterns are influenced by demographics and building contextual factors.

To answer the first research question, we classified HBI behaviors into four dimensions: willingness to share control, knowledge of control, group decision behavior, and adaptive strategies. These four variables were mapped to the four personality traits proposed by the FFM: agreeableness, openness, extraversion, and conscientiousness. Our cluster analysis identified six HBI behavioral patterns: average (17.7%), reserved (15.3%), environmentally friendly (16.6%), role model (24.2%), self-centered (17.2%), and mechanist (9.0%).

To answer the second research question, we applied association rules to discover how demographics, building-related contextual, and perception-attitudinal factors influence HBI behaviors. Country, control feature accessibility, and group dynamics were found to be the three most influential factors that determine occupants’ HBI behaviors.

To the best of authors’ knowledge, this is the first study on human building interaction in shared offices. The findings of this study provide insights about building design and operation, as well as policy to promote socially and environmentally desirable HBI behaviors in a shared office environment.

Declaration of competing interest

All co-authors declare there is no conflict of interest in the reported work.

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