Daily peak chilled water consumption is 20.30-22.94 times larger than hourly consumption (Table 1). This scale is approximately close to 24. Figure 5 represents box plots for seasonal analysis between summer and winter at the different temporal resolution levels. Chilled water consumption data are not normally distributed (right skewed).

Table 1. Statistical Summary of Chilled Water Consumption

	Hourly Chilled Water Consumption (BTU/SF)	Daily Chilled Water Consumption (BTU/SF)
Min.	0.00	0.37
Median	9.33	195.67
Mean	13.28	277.18
Maximum	114.92	2556.11

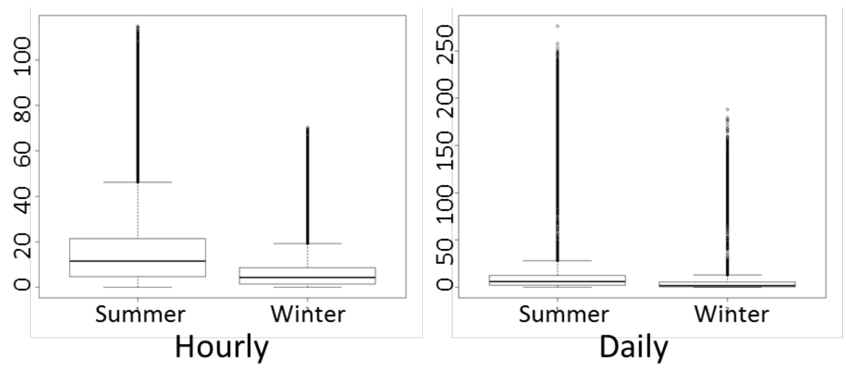

Figure 5. Boxplot for seasonal analysis

REGRESSION MODELS ANALYSIS

To select the best subset regression models, we imputed all 14 variables, which were significant in the simple linear regression. We examined all individual variables through p-value in the regression models and plots with a dependent variable for checking relationship and significance. Besides, three possible interaction terms were examined, which were 1) Bldg.Age*Renov., 2) U_Window*WWR, and 3) U_Wall*WWR. As a result, 22 variables were remained for the full model (equation (4)): six quadratic terms and two interaction terms. Therefore, 22 regression models were checked from the aspect of Mallows's C_p and Root Mean Square Error (RMSE) (Figure.6). As seen in Figure 6, the 20th-22nd models have the lowest Cp, and the 22nd model has the lowest RMSE, BIC, and the highest R-square. Therefore, the full model with 22 variables was satisfied with the lowest Cp, BIC, RMSE, and the highest R-square.

Equation (1) is a simple regression model, which measured only temperature and chilled water consumption, and equation (2) is a quadratic regression model. According to the prediction results from the regression models, a quadratic regression model fit (Adjusted R-squared: 0.37) better than a linear model (Adjusted R-squared: 0.32) (Figure 7). Chilled water consumption increases exponentially as temperature increases due to global warming.

$$Y_{\text{Chilled water consumption}} = -276.84 + 10.34 * X_{\text{Temp.}} \quad (1)$$

$$Y_{\text{Chilled water consumption}} = 293.99 - 14.44 * X_{\text{Temp.}} + 0.24 * X_{\text{Temp.}}{}^{2} \quad (2)$$

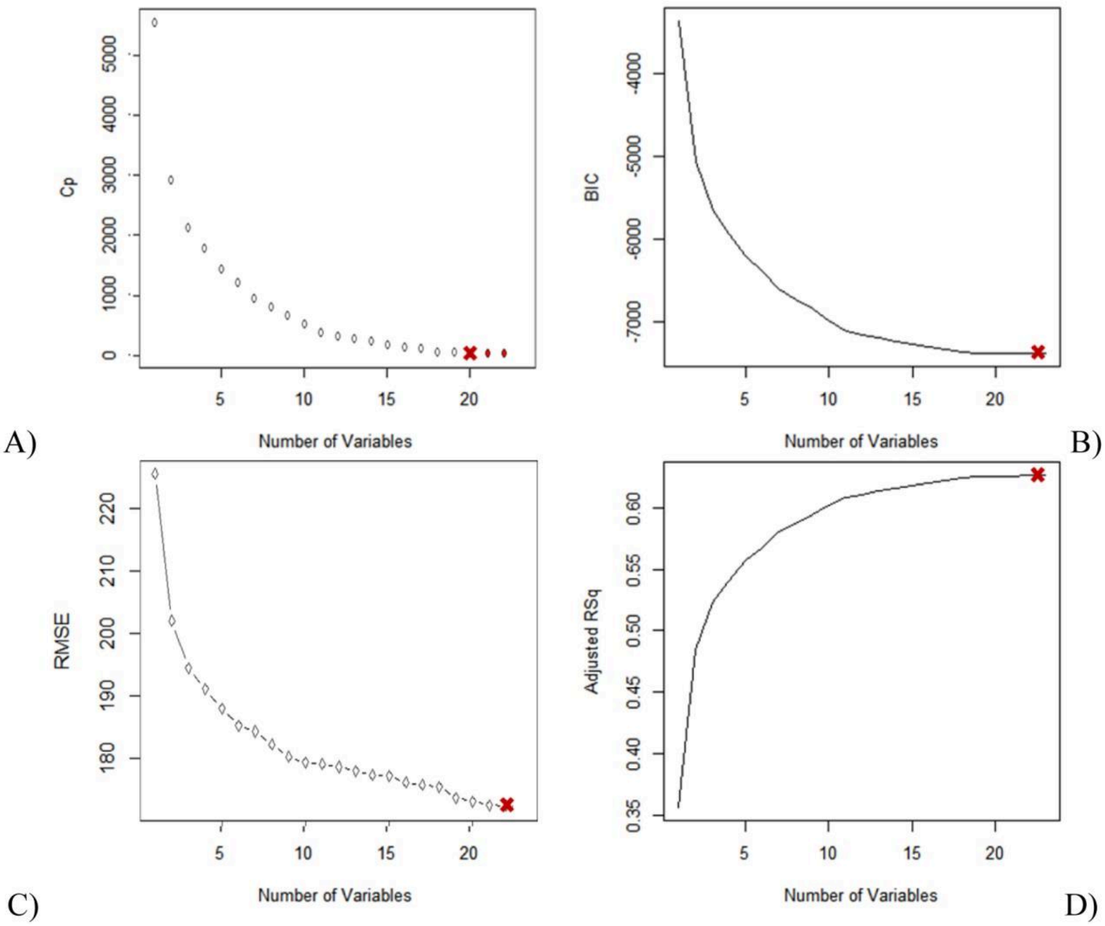

Figure 6. A) Cp, B) BIC, C) RMSE, and D) Adjusted R-square

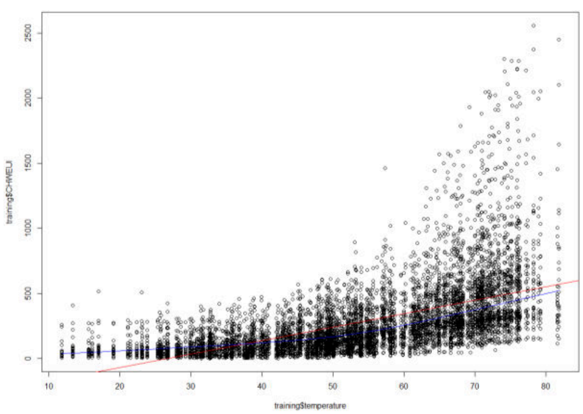

Figure 7. Regression model with temperature and chilled water consumption

To predict chilled water, the polynomial regression model with interaction terms fits (Adjusted R-squared: 0.63) better than a linear model without interaction terms (Adjusted R-squared: 0.55). The quadratic terms improved the regression model 8% to predict chilled water consumption in the equations (3).

$$Y_{\text{Chilled water consumption}} = -114910.52 + 275.67*X_{\text{U\_Roof}} + 1687.90*X_{\text{U\_Wall}} - 342.02*X_{\text{WWR}} - 1442.99*\left(X_{\text{U\_Wall}}\right)^2 - 107.05*X_{\text{U\_Window}} - 20.05*X_{\text{Floor}} + 3.90*X_{\text{Height}} - 0.01*\left(X_{\text{Height}}\right)^2 - 6.49*X_{\text{Bldg.Age}} + 0.03*\left(X_{\text{Bldg.Age}}\right)^2 - 2.82*X_{\text{Renov.}} - 12.09*X_{\text{Equip.}} + 95.44*X_{\text{LPD}} - 14.21*X_{\text{Temp.}} + 0.24*\left(X_{\text{Temp.}}\right)^2 + 85.15*X_{\text{Humidity}} - 31.49*X_{\text{windSpeed}} + 4.35*\left(X_{\text{windSpeed}}\right)^2 + 224.33*X_{\text{pressure}} - 0.11*\left(X_{\text{pressure}}\right)^2 - 429.20*X_{\text{U\_Wall}}*X_{\text{WWR}} + 0.05*X_{\text{BuildingAge}}*X_{\text{Renov}}. \quad (3)$$

Daily chilled water consumption had a predicted average of 807.70 (EUI) in 2054 with the nonlinear regression model, which is three times higher than in 2015-2016 (Table 2). This result from the full model (equation 3) lined up with the prediction from the quadratic regression model (equation 2) with only temperature variable due to global warming. As seen in Table 2, accuracy tests for equation (3) were conducted for training data as well as testing data. For training, MBE was zero, Mean Absolute Error (MAE) was 116.67, and RMSE was 171.92.

Table 2. Nonlinear Regression Models Summary for Chilled Water Consumption

Variable		Training	Testing	Prediction
Mean of the observed value in 2015-2016	MO	277.18	582.96	807.70
Mean of the predicted value in 2016	MM	277.18	574.35	
Mean Bias Error	MBE	0.0	-8.61	
Mean Absolute Error	MAE	116.67	206.51	
Root Mean Square Error	RMSE	171.92	300.77	
R2 (Training)	R^2	0.63	0.66	

Mean Bias Error (MBE, %) mainly reflects the deviation status of estimation results. Since MBE of testing is -8.61, this negative value means the estimation result (574.35 EUI) is lower than the actual result (582.96 EUI). Based on the above error analysis, a conclusion can be made that the smaller the RMSE of the comparison result, the higher the precision. Accuracy decreased in the testing data set in terms of MBE, MAE, and RMSE, but the mean of the observed value was still close to the mean of the predicted value in testing data set.

To calculate the chilled water consumption in 2054, the future climate scenario of climate zone 5 was used, and other values were derived from historical data. Additionally, building age and building age after renovation were updated to reflect their age in 2054.

We applied the mean of the other variables and the future weather data to examine the range of chilled water consumption for the individual variables. The average of daily chilled water consumption projected in 2054 was in the range of 544.11 and 1374.98 in Table 6. The range of chilled water consumption was derived by using the minimum and maximum value of each variable while the rest of the variables remained as the mean values. In addition, possible improvement rates (%) were calculated from these ranges.

Based on the final regression model, we can determine the impact of each variable on the chilled water consumption. The temperature has the most influence on chilled water consumption. Less important in terms of their impact on chilled water consumption are building height, construction year, and U-factor of the wall in this order. The range of the chilled water consumption varies by variables. The difference between lowest and highest temperature was

769.85 EUI, which raised from 605.00 to 1374.98. The second most critical factor is the building age, and building height is the next. We cannot control the building age, but we can consider building height for designing phase because lower building consumes less energy. Also, WWR and the U-factor of the wall were less critical than previous variables. By changing WWR, we can reduce the chilled water consumption up to 44.09%.

Table 3. Variables in the Final Model

	Variables	Min.	Mean	Max.	Range of chilled water consumption
Spatial variables	X_{U_Wall}	0.03	0.25	0.65	544.11~905.08 (39.88%)
	X_{U_Window}	0.25	0.73	1.16	753.15~850.57 (11.45%)
	$X_{U\text{-}Roof}$	0.03	0.14	0.70	768.86~953.55 (19.36%)
	X_{WWR}	0.05	0.29	0.94	507.12~ 907.02 (44.09%)
	$X_{\#Floor}$	3.00	6.91	15.00	636.97~ 877.58 (27.41%)
	X_{Height}	36	76	227	665.05~1164.19 (42.87%)
	$X_{Bldg.Age}$	22+39	74.48+39	148+39	696.84~1199.15 (41.89%)
	$X_{Renov.}$	14+39	33.67+39	94+39	743.66~969.45 (23.29%)
	$X_{Equip.}$	0.40	3.59	10.38	717.07~837.75 (14.41%)
	$X_{Light.}$	0.49	1.25	2.74	726.64~941.39 (22.82%)
Environ mental	$X_{Temp.}$	29.82	58	86.18	605.03~1374.98 (56.00%)
	$X_{Humid.}$	0.67	0.76	0.89	800.03~818.77 (2.29%)
	$X_{Pressure}$	1013	1017	1043	794.66~807.50 (1.59%)
	$X_{WindSpeed}$	0.00	1.06	8.10	836.28~866.49 (3.48%)

*0 represents that it is a significant variable
**X represents that it is an insignificant variable
*** (A/ B) A is in Summer and B is in Winter season

U-factor is used to express the insulation value of windows (Efficient windows collaborative, 2018). Lower the U-factor, better the window is at keeping heat inside. The U-factor of windows ranged between 0.20 to 1.20 and the mean of sample data was in this range. Assuming the university replaced all windows with triple-pane windows with 0.15 U-factor, chilled water consumption can decrease 13.25%. Exterior walls typically have U-factor between 0.5 – 2.5 W/m^2C and the mean of sample data is in the range. In cold climates, the area covered by windows might be as low as 15 percent of the wall, but this can increase to 50 percent if the windows are installed on the south side of the house, which receives the most sun.

CONCLUSION AND LIMITATIONS

This paper introduced the statistical analysis approaches and methodologies used to estimate chilled water consumption in the university setting to represent the urban energy modeling. It focused on regression analysis in the bottom-up approach. The regression model in energy prediction is still a robust model approach. The process of developing statistical regression models enables us to understand the relationship and impact between each variable and chilled water consumptions. Even though the regression approach is not accurate as much as machine learning approaches for prediction, regression analysis can provide better interpretation.

Temperature was the most critical variable influencing chilled water consumption. Construction year was more critical in regression prediction model compared to the renovation year of the building. For chilled water consumption, building height has a greater impact compared to the number of floors.

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Impact of Design on Human Experience: Evaluating Space Preferences in Interior Design Alternates Presented in a Crowdsourcing Platform

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ABSTRACT

Built environments are influential in shaping human experiences, such as motivation to work, stress/anxiety, and pleasure. Subtle differences in architectural design feature configurations (e.g., texture of surfaces, symmetry of building components) influence the resulting human experiences. This paper is part of a larger study that aims to quantify human experience in designed spaces, and evaluates how these subtle differences are perceived by people with different demographic backgrounds (e.g., age group and occupation). Through a data-driven approach, this paper examines how different configurations of design features related to stress and anxiety can result in people's decision of preferring one space over another. A crowdsourcing study was designed and administered on a platform with 296 participants without informing the participants about the differences in these spaces. During the study, the subjects were asked to select a preferred space out of two options, presented as dual-images rendered from 3D models of real buildings. Each image for a space presented a design feature configured differently, while keeping other features constant, to give alternate experiences (i.e., positive or negative), depending on the aspect attributed to that feature in the literature (e.g., poor lighting being attributed to negative feelings and vice versa). A total of six architectural design features, resulting in twelve paired spaces, were evaluated. This paper analyzes the collected data to identify configurations of preferences across design features using unsupervised learning algorithms. The results showed four clusters of preferred configurations of the design features. When the demographics of participants across clusters are analyzed, it is apparent that age and education level have little influence on the preferences of design features, while occupation is impactful for people's selection of desired spaces. The outcome can be used as a design guidance for architects, given the demographics of the prospective occupants.

INTRODUCTION

Built environments impact people in various aspects, such as productivity and well-being. Previous studies showed that well-designed buildings can reduce stress while increasing satisfaction and engagement, and improve the productivity for occupants (Morton and Ramos 2014). Given that people spend about 87% of their time in buildings (Klepeis et. al., 2001), it is essential to identify the relationship between the interior built environments and human experience. Human experience in spaces (e.g., stress anxiety, sense of restorativeness) is defined as the impact of the space on people's mood, level of comfort, and interactions with surroundings (Eberhard 2009). Such impact can change with architectural design features (e.g., openness of space, presence of windows, and luminance levels), which are the elements that constitute a space and gives it its unique characteristics.

A notable effort in the current design practice to improve human experience in buildings is evidence-based design (EBD) (Pati 2011). EBD is a performance-based design practice aiming to provide suggestions for design decisions based on past evidence collected from research, expert opinions, and occupant feedbacks. Typically, post-occupancy surveys are administered to collect self-reports of people about their level of satisfaction in the spaces. However, post-occupancy surveys are after-the-fact, and they cannot detect specific architectural design features that are contributing to the variations in the reported satisfaction levels. Other standardizing efforts aiming to advance health and well-being of occupants in buildings also exist. For example, the WELL standard (WELL 2014) focuses on generalized features of built environments (e.g., air quality, water quality, nourishment, lighting) to identify whether a specific building design meets the criteria of enhancing wellness of people living in buildings. However, none of the current efforts advance the understanding of the impact of architectural design features when they are presented to people with diverse demographic backgrounds (e.g., age group, occupation).

This paper provides the findings of a crowdsourcing experiment conducted through an online platform to identify the preferred configurations of architectural design features for people with diverse demographic backgrounds. During the experiments, subjects were presented with a series of dual-image sets. Each dual-image set represented a space where a unique architectural design feature was modified on the two extreme ends of a bipolar scale. For example, if the luminance level was the architectural design feature being evaluated, one image would show the space with poor lighting and the other one with adequate luminance level. These features to be evaluated were identified through a rigorous literature review in an earlier study (Ergan et. al., 2018). The subjects were asked to select the preferred designed spaces out of the dual-image sets. This paper focuses on the architectural design features that are identified as influential to the stress and anxiety of occupants (e.g., density of space, luminance levels, and openness of space). Their choices of preferred designs, completed by around 300 participants, were recorded and used as inputs for a clustering analysis using unsupervised learning algorithms (i.e., k means, Gaussian mixture models, and spectral clustering). The output of the clustering analysis are groups of preferred architectural design feature configurations selected by the subjects. The goal of the clustering analysis is to find correlations between people’s choice of design features and their demographic information, hence helping the architects to tailor design spaces that can enhance human experience given the demographics about the prospective occupants.

ARCHITECUTURAL DESIGN FEATURES RELATED TO STRESS AND ANXIETY

Previous studies on the cognitive influence of architectural features showed that people feel stressed and experience anxiety when certain architectural design features are configured at odd values as compared to what is suggested by expert architects and researchers in the design domain for better experiences in spaces. To synthesize the findings, we show these features and the corresponding studies in Table 1 (Ergan et. al., 2018).

As shown in Table 1, crowding, level of luminance, and presence/absence of visual cues (e.g., interior/exterior landmarks) were identified as impactful regarding occupants’ stress and anxiety level in buildings (Ulrich et al. 2008; Sternberg and Wilson 2006, Farbstein and Farling 2007). Density of spaces (i.e., square footage and aspect ratio), height of ceilings, openness of spaces, and flexibility in isolation vs. socialization in spaces are the main factors affecting the sense of crowding in built environments (De Croon et al. 2005; Vartanian et al. 2015). Studies showed that high density of spaces causes stress for occupants, while larger areas are perceived as more spacious and relaxing (Stamps 2010). Studies also showed that rooms with higher ceilings are perceived as less stressful (Franz and Wiener 2005, Vartanian et al. 2015). Furthermore, the flexibility of being isolated in spaces was identified as a factor for reducing stress, especially in healthcare facilities (e.g., Haynes 2008; Shumaker and Czajkowski 1994). Previous research efforts found that poor lighting levels can trigger stress in people (e.g., Sternberg and Wilson 2006), and cause lower work productivity (Beauchemin and Hays 1996). Finally, landmarks in built environments provide a sense of familiarity for people for wayfinding and spatial recognition (Ulrich et al. 2008). Lack of such landmark objects triggers stress and anxiety (Sternberg and Wilson 2006; Beukeboom et al. 2012).

Table 1. Architectural Design Features Influencing Stress and Anxiety

Crowding	Density of spaces	e.g., De Croon et al. 2005; Winchip et al. 1989; Stamp 2011.
	Height of ceilings	e.g., Franz and Wiener 2005; Vartanian et al. 2015.
	Flexibility in isolation and socialization in spaces	e.g., Haynes 2008; Shumaker and Czajkowski 1994; Ulrich 2000; Evans 2003.
	Openness of spaces	e.g., Farbstein and Farling 2007; Sadalla and Oxley 1984; Vartanian et al. 2015.
Level of luminance		e.g., Stone and English 1998; Frasca-Beaulieu 1999; Kwallek et al. 1988.
Presence/absence of visual cues (e.g., interior/exterior landmarks)		e.g., Ulrich et al. 2008; Beukeboom et al. 2012; Sternberg and Wilson 2006.

METHODOLOGY

The objective of this study is to find clusters of preferred configurations of a set of architectural design features for participants with diverse demographics. To achieve this goal, a crowdsourcing study was conducted with 296 participants. The collected results of subjects' preferences over different spaces (i.e., user selections of the preferred spaces) were clustered using unsupervised learning algorithms (e.g., k means, Gaussian mixture models, spectral clustering), and the results are groups of distinct configurations of preferred architectural design features. The details of the crowdsourcing experiment design and the algorithms used in analyzing the data are provided in the following sections.

Crowdsourcing Experiment Design and Demographics of Participants

The authors first identified the architectural design features related to stress and anxiety through a rigorous literature review (as shown in Table 1). For each identified design feature (e.g., height of ceilings, luminance levels), a pair of images representing a bipolar configuration of that feature (e.g., high vs. low ceiling heights, high vs. low luminance levels) were generated. As shown in Figure 1, each pair of images only modified one architectural design feature and the rest of the settings were kept constant.

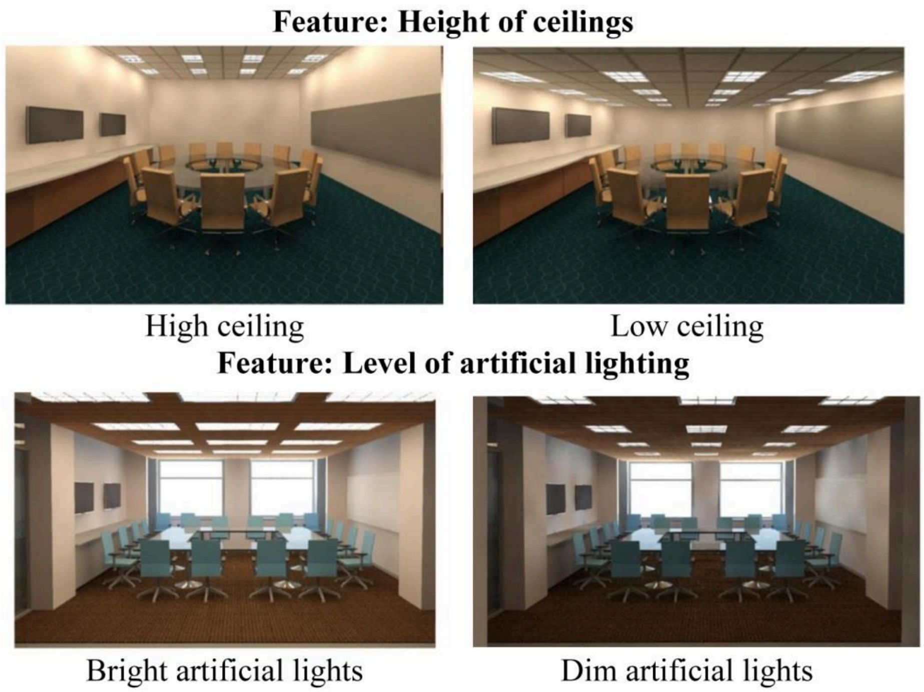
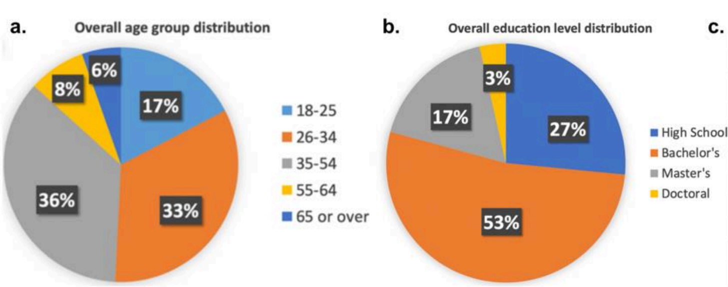


Figure 1. Two example architectural design features represented on bipolar scales

Six architectural design features were represented in the form of dual-image sets for the experiment. The dual-image sets were incorporated into an online crowdsourcing surveying platform (i.e., Amazon Mechanical Turk) that was distributed publicly. The subjects participated in this experiment voluntarily. The survey was approved by the New York University Institutional Review Board (No. IRB-FY2016-1264). The survey had two main modules. The first module was designed to collect demographic information of the participants (e.g., age group, occupation, education level). The second module contained the dual-image sets for recording the preferences of design features of participants. Finally, only participants from the United States and Canada who could pass the Ishihara's color-blindness test were allowed to participate in the study to eliminate cultural influences. As an overview of the demographics of the participants (Figure 2), we show the distribution of age groups, education levels, and occupations of the participants. As seen in Figure 2a, most (69%) of the participants were between the age of 26 and 64. More than 70% of the participants had a bachelor's degree or higher (Figure 2b). Finally, the distribution of occupations, which follows the occupation categories provided by the Department of Labor (DOL 2018), shows that education and health services, professional and business services, and trade transportation and utilities were the most common professions in this subject pool (Figure 2c).



c.

Occupation	Percentage
construction	2%
education and health services	26%
finantial activities	9%
information	8%
leisure nad hospitality	7%
manufacturing	1%
natural resources and mining	0%
other services	10%
professional and business services	20%
trade transportation and utilities	17%

Figure 2. Distribution of age group, education level and occupation

Unsupervised Learning Methods and Metrics

Unsupervised learning (i.e., clustering) algorithms can be categorized into two types, (1) ones that calculate the compactness (e.g., Euclidian distance) of data points (e.g., k means, Gaussian mixture models), and (2) ones that calculate the connectivity (e.g., Gaussian similarity) of data points (e.g., spectral clustering). We implemented both types of clustering algorithms to find the optimal separation of our data.

In a nutshell, k means assumes the number of clusters k (as a user input), and assigns data points to clusters based on the Euclidian distance between each data point and the center of each cluster (i.e., centroid). While k means is one of the fastest clustering algorithms, it assumes no covariance among k clusters, which results in spherical clusters. On the other hand, Gaussian mixture models (GMM) assume k Gaussian distributions (i.e., k clusters), each with distinct mean and variance values. Mean values of the Gaussian distributions are similar to the centroids from k means. The difference is that GMM considers the membership of a data point to a cluster to be a probabilistic distribution that can be represented by certain percentages of multiple Gaussian distributions (e.g., point p can be 30% cluster one and 70% cluster two). This approach inherently considers the covariance among clusters, hence is able to cluster data points into complex shapes comparing to only spherical ones from k means.

Alternatively, spectral clustering uses Gaussian similarity (e.g., similarity between point $x_i \text{ and } x_j$, or $c\left(x_i, x_j\right)$, which can be calculated using Equation 1, where $x_i \text{ and } x_j$ are coordinates of data points, and σ is the standard deviation) as a measurement of connectivity among data points. A graph representation (i.e., similarity graph) of data points is created to calculate Gaussian similarities (i.e., only points that have large Gaussian similarities are connected). Finally, data points' membership to clusters is determined by applying the k means algorithm on the similarity graph, where nodes (i.e., data points) closer in the graph are clustered together.

$$c\left(x_i, x_j\right) = \exp\left(-\left\|x_i - x_j\right\|^2 \big/ 2\sigma^2\right) \tag{1}$$

The metric used to compare the goodness of clustering is the Silhouette score. Intuitively, the Silhouette score measures how similar a data point is to its own cluster compared to other clusters (i.e., how well a cluster represents that data point given other points in the same cluster). Therefore, a larger Silhouette score means a better clustering result.

RESULTS

To ensure stability (since k-means randomly assigns centroids initially) of the clustering results, we ran each clustering algorithm 100 times, and calculated the average Silhouette score while changing the number of cluster k from 2 to 64 (the largest number of different configurations of six architectural design features, $2^6 = 64$). All three clustering algorithms pointed to four clusters as the optimal number of clusters. Among three clustering algorithms, GMM achieved the best result (highest Silhouette score), because it allows more complex cluster shapes by considering covariances among clusters. As a result, we selected GMM as the final clustering algorithm and used four as the number of clusters.

The resulting clusters of the participants' preferred configurations of architectural design features are shown in Figure 3a (horizontal axis showing design features, vertical axis showing