INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN, ICED15
27-30 JULY 2015, POLITECNICO DI MILANO, ITALY

QUANTIFICATION OF INDOOR ENVIRONMENTAL QUALITY IN SUSTAINABLE BUILDING DESIGNS USING STRUCTURAL EQUATION MODELING

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Abstract

This paper presents an experimental design framework for quantifying Indoor Environmental Quality in sustainable buildings, by estimating causal relations between design attributes, and both the stated and revealed post occupancy user preferences. In this research, a combination of statistical data and qualitative assumptions are used to formulate a structural equation model (SEM) to determine a subsequent latent construct between variables. The SEM is comprised of fixed attributes, observed variables, and latent variables, and is designed to evaluate postulated significant correlations between each. Results show that quantifying relationships among user preferences and built environment attributes will allow designers to consider and incorporate characteristics in early design that support these correlations.

Keywords: Human behaviour in design, Design engineering, Built environment, Structural equation modeling

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Please cite this paper as:
Surnames, Initials: *Title of paper*. In: Proceedings of the 20th International Conference on Engineering Design (ICED15), Vol. nn: Title of Volume, Milan, Italy, 27.-30.07.2015

1 INTRODUCTION

Sustainable building mandates such as the U.S. Green Building Council's (USGBC) Leadership in Energy and Environmental and Design (LEED) are becoming increasingly prevalent as strategies for resource conservation in commercial buildings (U.S. Green Building Council 2011). With commercial buildings consuming 19% of total energy demand in the United States, sustainable design practices are a creditable consideration for energy reduction (United States Energy Information Administration 2010). Many commercial institutions, such as universities, have declared all future new construction buildings will meet minimum LEED standards in an effort to reduce energy use and limit their overall environmental footprint. While this may be a viable energy conservation strategy for academic institutions with sufficient funding, additional costs above traditional commercial buildings are a primary barrier for many sustainable building design projects (Tatari and Kucukvar 2011).

One approach to mitigate the additional costs associated with sustainable building design is to consider post occupancy user interactions within the built environment. The literature has shown that individuals can respond positively to various characteristics of their indoor environment, citing qualitative preferences for lighting, temperature, and workspace geometry (Jensen et al. 2009, Boyce et al. 2003). In industrial manufacturing environments, these preferences have been linked to motivation, job satisfaction, and technical competence (Day et al. 2012). The USGBC has recognized the value of designing for these preferences by awarding 17 points (out of 100 possible) to a metric described as *Indoor Environmental Quality* (IEQ), toward their LEED certification (U.S. Green Building Council 2009). Currently, LEED's IEQ mandate includes 15 metrics, however, they are primarily focused on material selection and environmental control strategies.

The approach presented in this paper focuses on understanding the impacts of sustainable building design on an individual's stated and revealed preferences for the built environment, and how each of these preferences affect post occupancy behavior. Brownstone et al. (2000) observed the importance of capturing both of these metrics as consumers' stated preferences don't always align with their actual choices. By understanding the sustainable building design characteristics that drive user preferences, and the effect these designs have on their behavior, designers can incorporate building characteristics that support these correlations.

2 BACKGROUND

As building standards such as LEED become more complex, designers must explore a greater breadth of feasible solutions for meeting these requirements. Building users are playing a more prominent role in modern building design as literature has shown measurable effects on individuals' well-being, productivity, and creativity as a result of their indoor environment (Kamarulzaman et al. 2011, Dul and Ceylan 2011, Yi 2011). During the schematic design of the *Oregon Sustainability Center* for example, user preferences and building interactions were considered for quantification of energy consumption (Piacenza et al. 2011, Oregon Sustainability Center 2011).

The literature regarding the effect of indoor environment on a user's behavior has shown various methods attempting to quantify this relationship. Positive behavioral changes such as decreased absenteeism, and increased employee efficiency and productivity have been recognized. Jensen et al. (2009) examine a Bayesian Network approach comparing various effects of thermal environment on the performance of office workers. In addition to temperature, effects of natural lighting in the workplace have also been linked to various performance metrics such as well-being, ability to perform, motivation, job satisfaction, and technical competence. Research by Juslén (2007) has quantified a productivity unit increase based on workplace metrics associated with lighting relationships including visual performance, visual comfort, visual ambience, and job satisfaction.

This research aims to explore both stated and revealed user preferences for design attributes commonly used in LEED buildings. These methods have been refined over several decades by statisticians, and have recently been refined to include specific methods for preference modeling (Louviere et al. 2000, Street and Burgess 2007). Chen et al. (2012) have outlined a method to observe the effect of differing values of a factor, or user-based attributes, on a response variable.

For example, multiple design alternatives can be presented to a customer or product user, and a corresponding rating response can be chosen, ultimately resulting in a single design preference. Individual factor levels and combinations (or interactions) are then identified which will define a design alternative. Hoyle et al. (2008) provide a case study of this method, using human appraisal data for automobile seating ergonomics using both Blocked and Split-Plot statistical analysis to capture significant attributes of customer design preferences (Jones and Nachtsheim 2009).

Since LEED buildings are based on energy efficiency design mandates, typical design qualities include passive energy savings features such as large window-to-wall ratio, passive air ventilation, and an open floor plan. These architectural attributes consequently end up satisfying constraints for energy efficiency, but do not actively contribute to improving the workspace preferences that LEED's *IEQ* metric attempts to capture. However, research by Fisk (2000) corroborates LEED design strategies, suggesting that energy efficiency and *IEQ* are not mutually exclusive, since many sustainable buildings address both considerations.

Existing literature shows a long history of positive effects of lighting on individuals in different workplace environments (Abdou 1997, Edwards and Torcelleni 2002). Romm and Browning (1994) have presented several case studies where increased lighting in an existing workspace resulted in lower absenteeism, lower productions errors, and higher productivity. Research by Day et al. (2012) relate the attributes of building lighting design, in terms of natural lighting, to user satisfaction, health, and occupancy. Hua et al. (2011) examine post-occupancy response to lighting conditions in a LEED Gold certified laboratory building. This research combined illuminance measurements on work plane surfaces with rating surveys of long-term occupants, to determine overall user satisfaction of the building.

3 CONTRIBUTIONS

This paper presents a novel approach to sustainable building design that identifies key relationships between user preferences and building design characteristics (e.g. LEED mandates). A framework is presented for quantifying *IEQ* in sustainable buildings by estimating the causal relations between design attributes and both the stated and revealed user preferences for these designs. The metrics in this framework are based on post-occupancy user preferences for the indoor environment of sustainable buildings (e.g., LEED certified). Structural equation modeling (SEM) is used to evaluate postulated significant correlations between fixed attributes, observed variables, and latent variables. Within this model, latent variables uncovered in the statistical analysis represent emergent preferences resultant of a building's indoor environment. This approach will enable designers to explore trade offs between *IEQ* and other performance metrics (e.g., energy use, cost, environmental impact) when creating optimal building designs.

4 METHODS FOR QUANTIFYING USER PREFERENCES

4.1 Structural Equation Modeling and Latent Variables

In this paper, a structural equation modeling (SEM) approach is explored as a viable strategy for understanding the effects of sustainable building mandates on building users. This approach estimates causal relations by combining different types of performance metrics including empirical measurements, categorical survey evaluations, and causal assumptions. SEM strategies are primarily used in sociology and medicine where a combination of several observed variables are needed to assess the nature of a latent variable construct (Song and Lee 2012). The term *latent variable* refers to a variable that cannot be observed directly, but is a function of other related variables that are more easily quantified. Wheaton et al. (1977) originally formulated this approach based on a need to determine an underlying "true score" variable that measured two or more points in time. A primary function of SEM is the ability to correlate a combination of fixed attributes, observed variables, and latent variables (Fox 2006). This approach is slowly gaining momentum in the design community, specifically when trying to identify driving customer preferences for product design. Hoyle et al. (2008) use utility theory to extract design preferences from individuals by analyzing product attributes, sociodemographic factors, and customer survey responses. The importance of customer feedback is described in previous work by Everitt (1984), Loehlin (1998), identifying the ability to capture an individual's attitude toward a specific design through the use of a psychometric survey. Chen et al. (2012) have further developed this work, outlining a method identifying user preference indicators, based on specific product attributes.

4.2 Structural Equation Model Development

A model was constructed using fundamental SEM principles originally outlined by Wheaton et al. (1977). In this paper, the SEM principles are applied to quantify *IEQ*, a subjective building design performance metric. This approach is unique, specifically due to its applications for sustainable building design. In this research, key latent performance metrics are formulated by identifying relationships between sustainable building design attributes, individual preferences for these designs, and subsequent interactions between the two. First, an initial path diagram was constructed displaying the conceptual ideas behind the actual situation (Figure 1). This diagram includes four primary components relative to the model including *categorical variables* (taken from a psychometric survey), *empirical data* (collected within a LEED certified building), explanatory observed variables (building attributes such as window to wall ratio or LEED certification - i.e., *fixed covariates*), and *latent variables.*

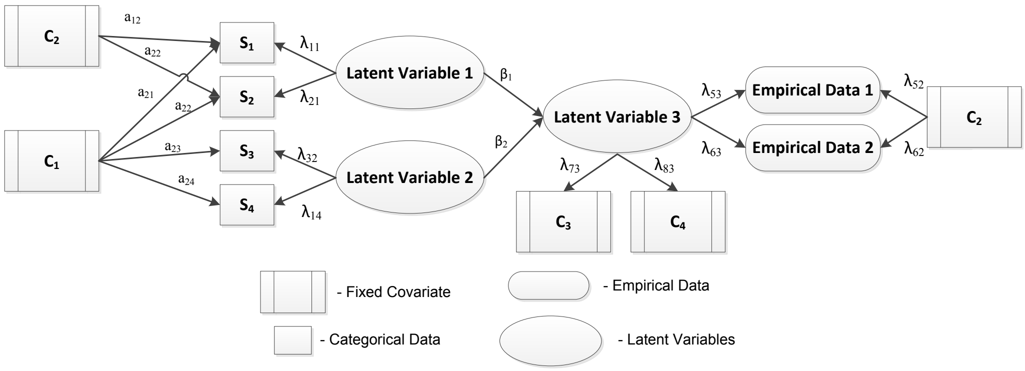

Figure 1. Hypothetical path diagram displaying conceptual model relationships

The one-way arrows between each variable represent a postulated significant correlation between one variable and another. The first component captures the latent building characteristics as identified from the *stated preference survey data.* These characteristics represent user's opinions about post occupancy building attributes. The second component incorporates the *empirical revealed preference data*, which aims to validate the individual's stated preferences. This is done by experimentally identifying which elements of sustainable building design drive occupancy. The third component is the addition of the *explanatory observed variables*, or fixed covariates. These variables provide additional information about the model landscape, reducing the estimation uncertainty for the latent variables (Song and Lee 2012). Finally, *latent variable relationships* are added to the model for both the categorical survey data, as well as the empirical data. For the stated preference survey, these are defined from the factor analysis as outlined in Table 1. For the empirical data, latent variables are incorporated based on results from the ANOVA analysis. This variable represents correlations between building occupancy and the associated independent variables. It is predicted that these latent variables from each data set can then be used to identify a higher-level latent variable that is directly influenced by each. The measurement equation for the predicted path diagram is defined by Equation 1:

$$\begin{bmatrix} s_1 \\ s_2 \\ s_3 \\ s_4 \\ e_1 \\ e_2 \\ c_3 \\ c_4 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & 0 \\ a_{41} & 0 \\ 0 & a_{52} \\ 0 & a_{62} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} \lambda_{11} & 0 & 0 \\ \lambda_{21} & 0 & 0 \\ 0 & \lambda_{32} & 0 \\ 0 & \lambda_{42} & 0 \\ 0 & \lambda_{52} & 0 \\ 0 & \lambda_{62} & 0 \\ 0 & 0 & \lambda_{73} \\ 0 & 0 & \lambda_{83} \end{bmatrix} \begin{bmatrix} LV_1 \\ LV_2 \\ LV_3 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \epsilon_3 \\ \epsilon_4 \\ \epsilon_5 \\ \epsilon_6 \\ \epsilon_7 \\ \epsilon_8 \end{bmatrix} \tag{1}$$

where $s_{1\ldots4}$ are the factored results of the categorical survey questions, $e_{1,2}$ are empirically sampled variables, $c_{1,2}$ are fixed covariates influencing both of these variables. In addition, $c_{3,4}$ are fixed covariates influencing the latent variables LV_1, LV_2, LV_3 directly, a_{11-62} are regression coefficients, β_1

and β_2 are the factor scores relating LV_3 to LV_1 and LV_2, λ_{11-83} relate the latent variables to each of the observed variables, and $\epsilon_{1\ldots8}$ are the error terms.

4.3 Psychometric Stated Preference Survey

Based on relationships identified from the hypothetical path diagram, a psychometric survey was developed to elicit a preference for various sustainable building design attributes by frequent users. This survey is based on a seven point Likert scale, commonly used for quantitatively evaluating social attitudes (Guy and Morvell 1977). The Likert scale is a bipolar scale, containing a neutral preference option, indicating the respondent does not have an opinion on (or is unfamiliar with) the content of the questions (DeVellis 2003).

The overall goal of this survey is to determine which architectural attributes of LEED certified buildings are preferred by frequent users. The buildings were chosen based on several characteristics such as departmental usage, age, presence of public workspace, and geometry. The primary common feature among the buildings is a public atrium, sharing similar stylistic construction features including use of natural lighting and high ceilings. To obtain a point of reference on which buildings are being evaluated, respondents are asked to identify which building they are the most familiar with at the beginning of the survey.

This survey was distributed to university students during a course in which they were enrolled, and the questions were tailored around an individual's potential preference for certain building attributes. These attributes included features such as lighting, temperature, presence of windows, amenities, and workspace features. The questions were further divided to investigate an individual's specific attitude toward how they interact within the common workspace of the building, and which attributes contribute to this usage. The first question asks how often the respondent uses the building they selected, and is the only question not using the seven point Likert scale. This gives the researchers a baseline for occupant frequency. The survey contains 21 questions, and was administered to 213 students to obtain a quality data set (DeVellis 2003). Extra credit course points were not issued to students agreeing the participate (Church 1993). The finalized questions submitted to the Institutional Review Board (2012) can be obtained by contacting the corresponding author.

To interpret the results of the preference survey, a factor analysis was performed. The purpose of factor analysis is to describe the covariance relationships among many random variables in terms of a few underlying, but unobservable, random quantities called factors (Johnson and Wichern 2002). The factor analysis model is shown in Equation 2:

$$\begin{aligned} X_1 - \mu_1 &= l_{11}F_1 + l_{12}F_2 + \ldots l_{1m}F_m + \varepsilon_1 \\ X_2 - \mu_2 &= l_{21}F_1 + l_{22}F_2 + \ldots l_{2m}F_m + \varepsilon_2 \\ X_p - \mu_p &= l_{p1}F_1 + l_{p2}F_2 + \ldots l_{pm}F_m + \varepsilon_p \end{aligned} \tag{2}$$

where:
X_i = latent factor (i.e., unobservable latent random variable)
μ_i = mean of latent factor
l_{ij} = loading of the *i*th variable on the *j*th factor
F_j = *j*th common factor
ε = *i*th specific factor (error)

While there are different methods of factor analysis estimation, the Maximum Likelihood Method for parameter estimation is used since the log-likelihood is additive as opposed to multiplicative (Johnson and Wichern 2002). This method assumes factors $\mathbf{F}$ and specific factors $\boldsymbol{\varepsilon}$ are normally distributed. To determine an accurate number of latent variables, the factored correlation matrix is examined, and the convention of selecting factors based on eigenvalues greater than one is used (Loehlin 1998). In order to assist with the interpretation of factor loading, a factor rotation is performed to position the orthogonal axis where variables load highly (Everitt 1984). This oblique rotation is nonrigid, leading to a new axis that passes through the most prominent loading clusters (Johnson and Wichern 2002). The Varimax rotation, developed by Kaiser (1958), is used based on its ease of loading interpretation (Lewis-Beck et al. 2003).

4.4 Experimental Design for Revealed Preference

As a way to observe an individual's actual, or revealed preferences for sustainable building indoor environments, an experiment was designed to correlate workspace occupancy as a function of available lighting, or illuminance. This hypothesis is based on the assumption that a user will choose to occupy a publicly accessible workspace based on specific design attributes, such as increased lighting levels due to large window-to-wall ratios (WWR), often present in LEED architectures (Tzempelikos and Athienitis 2007). While workspace occupancy cannot directly infer causation between a building design and a user's preference for this design, it can be used as an indicator to learn more about the relationship.

To measure illuminance, a light meter equipped with a data logger was placed at work plane level, in the atrium seating area. To measure occupancy, a time-lapse digital camera was placed at one end of the atrium, with the ability to capture an image of all users occupying the workspace. Both the light meter and the camera concurrently collected measurements every 15 minutes from 6:00am to 6:00pm, Monday through Friday. The total number of occupants present in the images collected were recorded with the corresponding time of day and illuminance measurements.

Data measurements are taken in different buildings, and randomization restrictions are incorporated in the analysis. Since the goal of this experiment is not to compare buildings against one another, blocking is utilized to address effects on individual building occupancy. In addition, the experiment is conducted during the academic school year, so there is a concern that student schedules could drive occupancy changes. To mitigate these issues, a nested split-plot design is used to analyze the data. This concept is helpful when there are two levels of randomization restrictions within a block (Montgomery 1991). In this design, the experiment is identically performed, Monday through Friday, in each of the buildings. The time-lapse camera captured *occupancy*, and the *illuminance* levels are recorded simultaneously during the same time period. The resulting data is then organized in groups of six categorical time ranges. Based on initial illuminance testing in each of the buildings, lighting values range from 20 – 4000 *lux*, depending on local weather conditions. Time ranges are grouped as 6:00 am – 8:00 am, 8:00 am – 10:00 am, 10:00 am – 12:00 pm, 12:00 pm – 2:00 pm, 2:00 pm – 4:00 pm, and 4:00 pm – 6:00 pm.

To analyze the data, the statistical program StatGraphics is used (StatPoint Technologies Inc. 2012). The primary relationship of interest is occupancy as a function of illuminance, however confounding factors from each building, day of the week, and time of day are also examined.

5 LEED CERTIFIED BUILDING CASE STUDY

To illustrate an application of the methodology described above, a LEED certified building case study is presented. The initial data acquisition and subsequent analysis is included for both the stated and revealed user preferences.

5.1 Stated User Preferences

Incorporating the analysis from the psychometric survey is the next step for creating the SEM. The survey results were manually entered in STATA, where factor analysis estimation was performed. Based on the eigenvalues of the factored correlation matrix, three factors were determined to be significant. Table 1 displays the variable indicator descriptions, resulting factors (latent variables), and corresponding factor loadings (> 0.3).

Beginning with *Factor 1*, the positively loaded variables are associated with frequency of use, studying preference, socializing preference, availability of amenities, work speed, use for homework, perceived popularity, and "green" construction. From this data it can be suggested that this factor reflects a latent variable of Personal Building Preference, where an individual prefers attributes associated with a familiar workspace where they can work productively, while still interacting socially and having access to amenities.

Factor 2 contains all positive loadings including lighting quality, temperature quality, seating quality, architecture quality, use of windows and color preference. This latent variable can be described as Building Design. Factor loadings infer general positive building preferences for specific architectural features, indicating the user recognizes their importance. The loadings also indicate users prefer comfortable seating, presence of natural light, and a comfortable temperature.

Factor 3 was positively loaded for preferences pertaining to importance of lighting, importance of temperature, traditional workspace (desk instead of couch), quiet environment, fresh air importance, and color preference. This factor can be associated with Building Usability. For this factor, stated user preferences described a practical workspace with specific requirements. These individuals indicate a preference to work in a practical, productive environment, free from distractions.
These three factors are imported into the SEM, representing empirical input variables for the model.

Table 1. Factor loadings for stated user preferences

Indicator Description	Factor 1	Factor 2	Factor 3
	Personal Building Preference	Building Design	Building Usability
Frequency of Use	0.5364		
Studying Preference	0.8009		
Socialize Preference	0.5012		
Lighting Quality		0.6976	
Temperature Quality		0.4129	
Seating Quality		0.3892	
Architecture Quality		0.4064	
Availability of Amenities	0.3565		
Use of Windows		0.4868	
Work Speed	0.6642		
Use for Homework	0.7771		
Perceived Popularity	0.5573		
Importance of Lighting			0.5689
How Others Use Space			
Environment Familiarity			
Importance of Temperature			0.3562
Traditional Workplace			0.4689
Quiet Environment			0.3783
Fresh Air Importance			0.3411
"Green" Construction	0.3167		
Color Preference		0.3978	0.3125

5.2 Empirical Evidence for Revealed User Preferences

The last step in creating the SEM is the incorporation of the empirical data. For research consistency, both the psychometric survey and data collection referenced the same buildings. Occupancy was captured using time-lapse images, and extracting by counting the current number of occupants during a designated time frame. Figures 2a and 2b respectively display images from Buildings 1 and 2.

Figure 2a, b. LEED certified Building 1 and 2 workspace

First, a cursory linear regression analysis of the raw *occupancy* and *illuminance* data was performed to gain an understanding of the relationship between these two variables. Based on these results, a logarithmic transformation was applied to the *illuminance* values, and a square root transformation was performed to *occupancy* values to stabilize the variance (Montgomery 1991). Figure 3 displays the results of the linear regression analysis of these elements, for both Building 1 and 2. The ranges of *occupancy* values are different because the total occupancy for Building 1 is greater than Building 2.

Next, a generalized linear model was created in StatGraphics to determine the statistical significance between *illuminance* and *occupancy*. This model incorporates the categorical effects of *time range* and *day of week* to address randomization restrictions. To capture potential external effects due to scheduling, interactions between each variable were also considered during the analysis. Based on the results shown in Table 2, statistically significant effects (based on a *p-value* ≤ 0.05) on *occupancy* are *time range,* the *building,* and *illuminance*. Significant interactions include every two and three factor interactions between each variable with the exception of the interaction between *illuminance* and *building*. This reinforces the hypothesis that occupancy is truly a function of sustainable building design characteristics, and not a specific building itself.

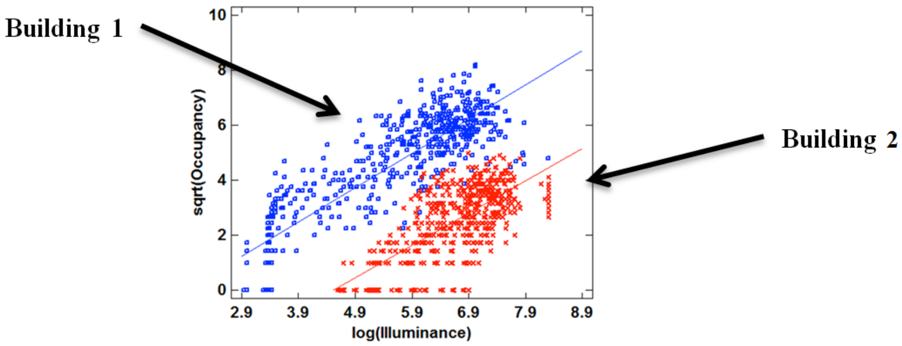

Figure 3. Square-root of occupancy versus log transformed illuminance (lux)

Based on this analysis, user occupancy in each LEED certified building varies significantly as a function of lighting level. This relationship occurs in both buildings, independently of potential confounding factors such as student class schedules or day of the week. From these results, design variables for *illuminance* and *time of day* are incorporated into the SEM.

Table 2. ANOVA results for revealed preferences

Source	Sum of Squares	DF	Mean Square	F-Ratio	P-Value
Time Range	7238.37	5	1447.6700	41.6100	0.0000
Day of Week	161.988	4	40.4969	1.1600	0.3252
Building	3218.81	1	3218.8100	92.5100	0.0000
Illuminance	169.938	1	169.9380	4.8800	0.0271
Time Range*Day of Week	1220.92	20	61.0459	1.7500	0.0212
Time Range*Building	1548.63	5	309.7270	8.9000	0.0000
Time Range*Illuminance	2817.29	5	563.4590	16.1900	0.0000
Day of Week*Building	354.939	4	88.7347	2.5500	0.0378
Day of Week*Illuminance	388.742	4	97.1855	2.7900	0.0252
Illuminance*Building	129.708	1	129.7080	3.7300	0.0535
Time Range*Day of Week*Building	2027.81	20	101.3900	2.9100	0.0000
Time Range*Day of Week*Illuminance	1644.99	20	82.2494	2.3600	0.0007
Day of Week*Building*Illuminance	741.099	4	185.2750	5.3200	0.0003
Time Range*Building*Illuminance	1095.01	5	219.0010	6.2900	0.0000
Residual	35071.8	1008	34.7935		
Total (corrected)	233777	1107			

6 STRUCTURAL EQUATION MODEL RESULTS

Based on the results of each independent data analysis from the psychometric survey and the empirical data, a SEM was constructed within the R computing environment (Team 2011). After many iterations stemming from the initial path diagram hypothesis, the resulting diagram is shown in Figure 4. In this model, the three factors resulting from the *categorical variable* (survey) analysis are represented as indicators corresponding directly to a top-level latent variable which can be represented explicitly as *Indoor Environmental Quality (IEQ)*. In addition, *IEQ* is also predicted by an independent latent variable characterized as *User Behavior*. The most appropriate metric to validate this case is the Root Mean Squared Error Approximation (RMSEA) index, which is significantly below the acceptance value of 0.10 (Hooper et al. 2008). This measure indicates how accurately the model describes the correlations within the data using optimal model parameters. Both Goodness-of-Fit and Adjusted Goodness-of-Fit indices are well above the acceptance level of 0.90, describing the model's ability to recreate observed variances between observations. The Non-Normed-Fit index, which has an acceptable value above 0.90, suggests that further refinements could be used to improve model fit, specifically the inclusion of additional latent variable indicators (Hooper et al. 2008).

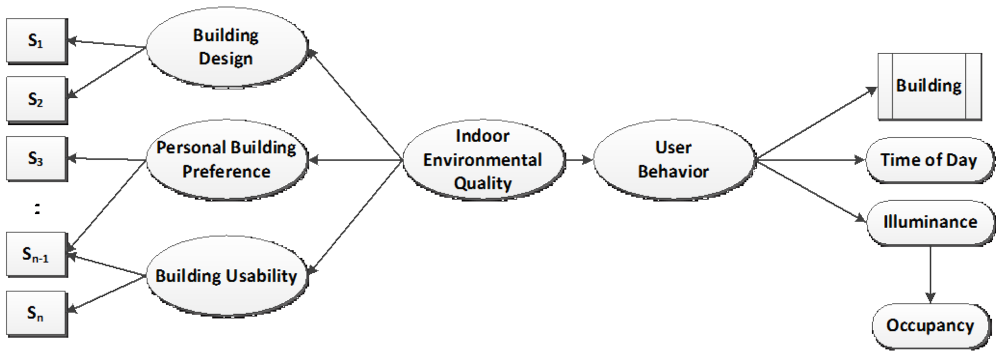

Figure 4. Evaluated Structural Equation Model

Table 3. Structural Equation Model Fit Comparison

SEM Performance Metric	Experimental Value	Acceptance Value
Goodness-of-Fit	0.99236	> 0.90
Adjusted Goodness-of-Fit	0.98568	> 0.90
RMSEA	0.02688	< 0.10
Non-Normed Fit	0.92672	> 0.90

7 CONCLUSIONS AND FUTURE WORK

It is demonstrated in this case study that illuminance affects post occupancy building usage, however additional work is needed to validate the use of IEQ as a performance metric. For example, IEQ could now be incorporated into a building optimization objective function, and could be traded off with other environmental considerations (e.g., heat loss, energy use).

A key benefit of this approach is flexibility, allowing it to be applied to design problems across multiple disciplines where user and product interaction, and subsequent behavior are influenced heavily by the design characteristics. For example, a designer could use this methodology in the automotive domain to estimate the relationships between various vehicle attributes (e.g., body color, fuel economy) and historical purchasing trends of different customer demographics (e.g., age, socioeconomic).

While the approach developed for this paper shows merit, additional research is needed to increase accuracy. In the LEED building case study presented, additional empirical measurements could be included such as indoor temperature, humidity, and air quality. In addition, the input data size should be increased by including measurements from additional LEED buildings to verify consistency. Finally, LEED buildings and users outside of a university campus could be analyzed to address any biases present in an academic institution.

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