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A Bayesian Approach for Modeling Occupants' Use of Window Shades

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ABSTRACT

Despite the significant impact of occupant interactions with window shading systems on visual comfort and building energy consumption, there are still significant gaps in understanding and predicting these complex phenomena. This paper presents a Bayesian modeling approach for the prediction of states of motorized roller shades operated by occupants. It is based on a field study with a large number of human test-subjects, conducted in a high performance building with advanced technology and easy-to-access user interfaces for environmental controls. Unlike the Frequentist methods used in previous studies, the Bayesian approach allows for uncertainty quantification which provides further insight on parameter estimates in models. This information is important when dealing with small-sized datasets which is often the case in real applications of human data collection. In addition, this study contributes to the body of knowledge by: (1) expanding the investigation of human-building interactions to motorized interior roller shades; (2) incorporating human attributes and personal characteristics as important underlying variables in occupant-shading interaction models; (3) enabling the prediction of continuous intermediate states of the shading system.

1. INTRODUCTION

In recent years, there has been a growing interest in studying behaviors of building occupants in regards to their interactions with building systems such as window shades. Following the chronological progress in the literature, one can note the two main motivations for conducting these studies. First, to attain an understanding of the reasoning behind the human-building interactions which can provide useful insights to the development of optimal control algorithms for building systems. Second, to discover a mapping path between human-building interactions and environmental conditions, which can be used to predict the operating status of building systems within the framework of Building Performance Simulation (BPS).

Several indoor variables have been monitored in previous studies to investigate the triggers of occupant interactions with shading systems. These include indoor air temperature (Mahdavi et al., 2008; Inkarojrit, 2005), work plane illuminance (Sutter et al., 2006; Mahdavi et al., 2008; Haldi and Robinson, 2010), vertical illuminance on VDU screens (Sutter et al., 2006), daylight glare index and probability (da Silva et al., 2013), daylight work plane illuminance (Love, 1998), solar penetration length (Inoue et al., 1988), and transmitted solar radiation (Inoue et al., 1988; Sutter et al., 2006; Inkarojrit, 2005). Horizontal and vertical global illuminance and irradiance (Sutter et al., 2006; Mahdavi et al., 2008), outdoor temperature, solar altitude are among the outdoor variables which were investigated. Seasonal effects (Mahdavi et al., 2008), façade orientation Oreszczyn (2001), and sky conditions were considered as well. Rubin (1978) considered sunny, cloudy, and hazy conditions and found that blind position seemed to be independent of those. As a counter example, Rea (1984) noticed that blind occlusion was significantly different between different sky conditions. This study also concluded that occupants have a long term perception of solar irradiances that may affect the use of blinds. Overall, findings (Haldi and Robinson, 2010; O'Brien et al.,

2012) suggest that observed variations can be explained by variables such as solar intensity, daylight levels, and geometry. That is, considering the right triggering variables, human-shading interactions throughout the year can be described regardless of façade orientation.

Personal characteristics and human attributes, i.e. non-physical variables, have also been reported to describe occupant interactions with shading and electric lighting systems. These are variables which are not measurable with typical sensors, such as view and connection to the outside or privacy or daylight-health perception. Inoue et al. (1988) reported that most occupants preferred to have seats close to the windows, although these were known to be the most possible locations to have glare and direct sunlight. This finding implies that occupants may tolerate some discomfort in order to have a better quality of view and connection to the outdoors. Veitch et al. (1993) found that people prefer daylight to artificial lighting due to their beliefs regarding health issues. Inkarojrit (2005) reported visual privacy as second important reason for choosing the blind positions. Moreover, Foster and Oreszczyk (2001) unexpectedly observed higher rate of blind lowering in the north facade than the west facade. They believe this was due to the fact that north facade of the building was facing another office building and occupants deployed their blinds to preserve their privacy. Similarly, Reinhart and Voss (2003) tried to correct the privacy-related bias in their observations and suggested that if blinds were lowered at ambient horizontal illuminance less than 1000 lux, it would have occurred due to occupants' desire to maintain privacy.

This paper presents a field study that focuses on motorized roller shades as studies on occupant interactions with such systems are rather limited (Bakker et al., 2014; Meerbeek et al., 2014). The contributions of this work include a Bayesian modeling framework that enables: (a) Uncertainty quantification in model parameter estimates which is important when dealing with small-sized datasets; a ubiquitous issue when collecting human data. (b) Incorporation of underlying personal characteristics and human attributes of human-shading interactions. (c) Prediction of continuous intermediate states of the shading system.

2. FIELD STUDY

This section presents a brief overview of the experimental study that provided the basis for the development of human–shading interaction model. For more detailed information on the experimental setup the reader may refer to Sadeghi et al. (2016). Four south-facing private offices (3.3m×3.7m×3.2m high) in the Herrick Laboratories, a high performance building located in West Lafayette, Indiana, was selected for the purpose of this study. Figure 1 shows a general view of the building and monitored offices. A Building Management System (BMS) is available through the installed Tridium JACE controllers and Niagara/AX software framework, which provides the ability to monitor and control all the building systems. Each office has one exterior curtain wall façade with 54% window-to-wall ratio, and a high-performance glazing unit with a selective low-emissivity coating (visible transmittance: 70%, solar transmittance: 33%). The window is equipped with a dark-colored motorized interior roller shade that has a total visible transmittance equal to 2.53% (measured with an integrating sphere) and an openness factor of 2.18%. There are two electric lighting fixtures with two 32-watt T5 fluorescent lamps (total of 128 watts) in the office which can provide a maximum of 500 lx on the work plane. During the field study, the temperature in the office was well kept within ± 0.5 °C of the set point to ensure that there were no thermal effects on occupant interactions with shading.

The field study was conducted in two rounds in order to cover a wide range of sky conditions and solar paths. First, over a period of 40 days between April 1st and June 15th 2015 including 22 sunny days, 10 cloudy days, and 8 mixed sky days. Second, over 38 days between October 19 and December 10 2015 covering 21 sunny days, 11 cloudy days, and 6 mixed sky conditions. Overall, 208 office occupants participated in the study (131 males and 77 females). Participants were students and staff (between 20 and 40 years old) not familiar with this research. Each office was occupied by one participant every day between 9:00 am and 4:00 pm. All participants were asked to perform their usual workload (computer-related work, reading, writing, etc.) during the day and answer four short web-based questionnaires, which were sent by e-mail and combined with phone alarm reminders at specific times during the day. They were free to take breaks or leave the office if they needed to (e.g. attend meetings, classes etc.) to create realistic dynamics of occupation. Participants were advised to interact with electric lights, shading system, and thermostat as they usually would, and to avoid any direct contact with the monitoring instrumentation. The instrumentation was installed so there was no interference with the occupant regular position and task. To eliminate any bias in the results, each person participated in the monitoring campaign only for a single day in one office setup. This sampling method enabled a large number of participants, which is necessary for the purpose of this study, and did not require the installation of experimental equipment in a large number of offices.

Three different control setups were deployed in the offices. In setup 1, participants used commercially available wall switches (Figure 2, right) to control motorized roller shades and electric lights. Participants could open/close roller shades or turn on/off electric lights with a single button push (top and bottom), or they could choose intermediate shade positions or light dimming levels (both in 25% increments) by pressing middle increase/decrease buttons respectively. In setup 2, participants used a modular web-based graphical interface (designed by the authors) to control shade position and electric lighting levels (Figure 2, middle). Participants could use sliders or click on buttons to control roller shade position and electric light levels in 25% increments. Other important features were designed on the graphical interface, including comfort sliders for capturing the level of comfort with the amount of light and visual conditions, as well as a four-scale reasoning slider in the middle to capture non-physical motives of human-shading interactions. In setup 3, roller shades were controlled automatically but occupants could override the shade position using the same interface as in setup 2. The automatic controller followed an algorithm to prevent direct sunlight on the occupant/work plane, but allowed direct light on the floor, up to 1 m from the window. In addition, there were adjustments for low light and high brightness conditions. Once overridden, the automatic controller would remain disabled for one hour. Electric lights were controlled manually using the same graphical interface as in setup 2. Side-by-side comparisons of occupant interactions in different control setups are presented in Sadeghi et al. (2016). For this paper, data collected from all three setups are used to develop occupant-shading interaction models.

The following variables were monitored every five minutes during the field study: window shade position, electric light level, room temperature set point, occupancy state, work plane illuminance, vertical illuminance near eye level (30 cm from occupant's head), transmitted global solar radiation, transmitted illuminance through window, indoor air temperature, black-globe temperature and relative humidity. Figure 2 (left) depicts the office layout, seating position, and locations of sensors and control devices. Two web-based survey questionnaires were designed. Survey type-A included questions about motives of human-building interactions and was completed four times a day. Survey type-B referred to personal characteristics and attributes and was completed once at the end of the day. Survey questionnaires were sent to participants at specific times during the day along with reminders by phone alarms.



Figure 1: The four monitored offices: exterior view (left); Interior view (right)

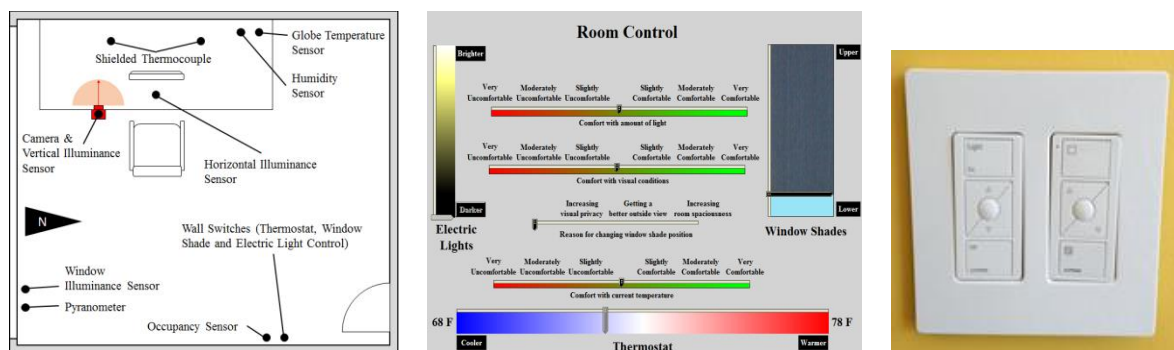


Figure 2: Office layout (left); Graphical interface in setup 2 and 3 (middle); Wall switches in setup 1 (right)

3. EXPERIMENTAL RESULTS

Important observations from the experimental data are presented in this section as they are relevant to the

development of human-shading interaction models. On average, 1.57 shading actions were observed in control setup 1 while the occupants' daily average shade movement rate was 2.12 and 2.75 respectively in setups 2 and 3. These values are higher than what is observed in different studies with non-motorized manual shading devices, operated by turning a rod, pulling a chain or cord (Inoue et al., 1988; 1993; Inkarojrit, 2005; da Silva et al., 2013) proving that easy-to-control shading devices reduce the effort required to control/improve indoor environmental conditions and result in more human-shading interactions. It was observed that 53.2% of times, the selected position of motorized window roller shade was different from extreme positions of 0% and 100% (0% being fully lowered and 100% being fully raised). This finding indicates that a good behavioral model for occupant interactions with window shades should predict the intermediate operating states of the system as well as the fully lowered/raised positions.

The occupation dynamics was found to have an impact on the way participants would interact with roller shades. The first ten minutes after arrival in the morning and the last ten minutes before the departure (at the end of the day) were selected as threshold limits for arrival and departure time intervals. The same threshold was used for determining events before and after absences during the intermediate time interval. As shown in Table 1, a considerable portion of shading interactions (55.3%) occurs outside the intermediate time interval with continuous occupation. A high frequency of shading interactions is observed during the arrival time, which is in agreement with findings of previous studies (Inoue et al., 1988; Reinhart and Voss, 2003; Haldi and Robinson, 2010; da Silva et al., 2013). Compared to actions throughout the day, the number of shading actions per unit time is significantly higher upon arrival. Therefore, only shading actions in arrival time has been considered for modeling in this study. A similar approach has been undertaken elsewhere (Reinhart and Voss, 2003; Inkarojrit, 2005).

Table 1: Summary of survey questionnaires

	Arrival	Departure	Intermediate, before absence	Intermediate after absence	Intermediate, continuous occupation
Shading interactions	36.6%	1.7%	0%	17%	44.7%

Among the reasons for human-shading interactions reported in survey type-A, reducing the overall brightness of workspace and glare in workspace were found to be the main motives for lowering the motorized roller shade (respectively reported with frequency of 27% and 45%). Increasing the amount of daylight was also reported to be the main reason for raising the roller shade (with frequency of 47%). Actions governed by these motives can be described by physical variables (e.g. work plane illuminance, vertical illuminance etc.). Figure 3 presents the boxplots of environmental variables during the whole course of the experiment as well as the moments right before raising and lowering actions took place during the arrival time. As shown in the figure, variables such as indoor illuminances, window un-shaded fraction, solar penetration length, transmitted global solar radiation and ratio of diffuse over total solar radiation explain lowering actions to some extent as at lowering moments, they have quite different distribution than the distribution over the course of the experiment. The same can be stated about work plane and vertical illuminance, window un-shaded fraction, work plane daylight illuminance, solar penetration length, solar azimuth and altitude for describing shade raising actions.

Based on the survey questionnaires, achieving a better outside view was a significant motive for raising/opening the window roller shade (with frequency of 37%). The desire to increase visual privacy was also reported by participants as an important reason for window shade lowering/closing actions (with frequency of 26%). Figure 4 illustrates boxplots of the selected shade position versus occupants' self-reported level of importance for having a clear outside view and visual privacy (importance level of one is excluded for visual privacy since there was no vote on it). Higher un-shaded portions are selected by participants to whom having a clear view is more important; and lower shade positions correspond to participants who reported visual privacy to be of high level of importance. Figure 5 illustrates the distribution of all human variables collected from survey type-B in overall and at the moments when actions occurred. The significance of human variables on shade raising and lowering actions is clear from the figure and therefore, need to be considered, when developing models for human-shading interactions.

4. MODELING METHODOLOGY

Four sub-models have been considered to construct a probabilistic model for human-shading interactions while allowing for predictions of intermediate shade positions (Figure 6). Model S1 predicts binary actions of shade raising (raising events versus non-raising events) and model S2 predicts binary actions of shade lowering (lowering

events versus non-lowering events). The states of the shade between each two consecutive time steps (five-minute intervals) are compared and if a change is detected, the observed event is coded as “1” and “0” (existence and non-existence of event respectively) for the first time step among the two, corresponding to the row of all explanatory variables (human and environmental state variables) for which occupants decided to undertake the action. Models S3 and S4 respectively predict the magnitude of shade raising and lowering. Figure 6 indicates the hierarchy within which models S1, S2, S3, and S4 work together to predict human-shading interactions given all the explanatory variables.

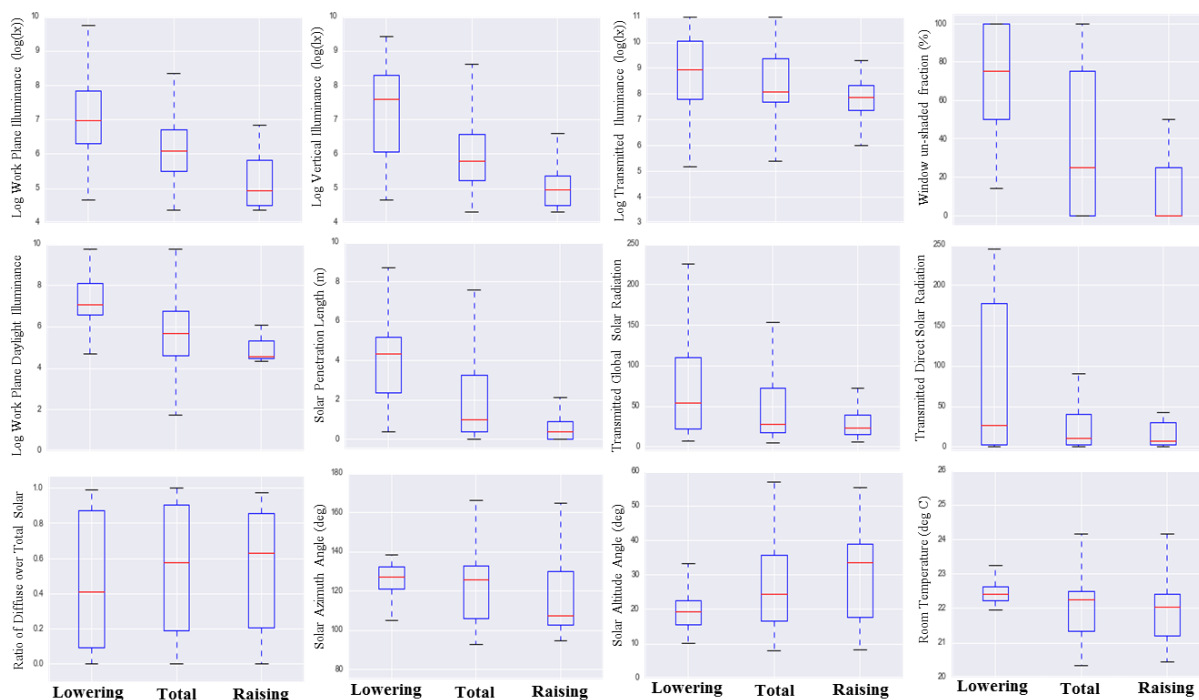


Figure 3: Distribution of environmental variables

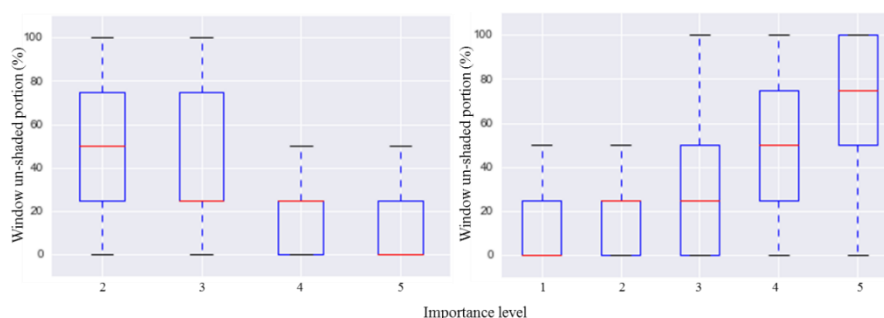


Figure 4: Impact of visual privacy (left) and window view (right) on selected shade positions

The multivariate binary-choice logit model along Bayesian parameter estimation has been used for the set of models in higher level of hierarchy (S1, S2). In addition, Bayesian linear regression has been used for magnitude models, or the models in lower level of hierarchy (S3, S4). Bayesian inference is a method of statistical inference in which the Bayes’ theorem is used to update the probability of a hypothesis (beliefs) as more and more evidence or information (data) becomes available. Bayesian inference differs from the traditional Frequentist approach in the sense that it preserves the uncertainty in predictions.

In what follows, $\mathbf{x} = (1, x_1, \dots, x_d)$ denotes the vector of the d features (explanatory variables) that define the state of the environment as well as any human attributes. Notice that we have prepended a constant unit feature to \mathbf{x} . The purpose of this constant feature is to simplify the notation of the regression models presented below. We will be referring to \mathbf{x} as the *feature vector*.

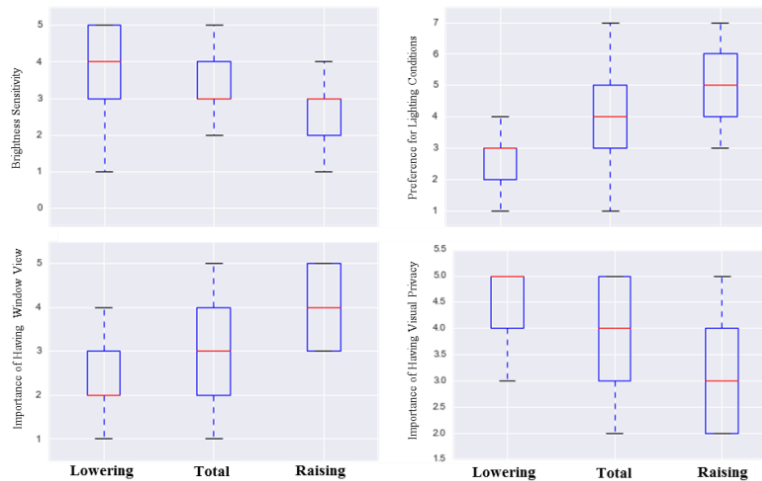


Figure 5: Distribution of human variables

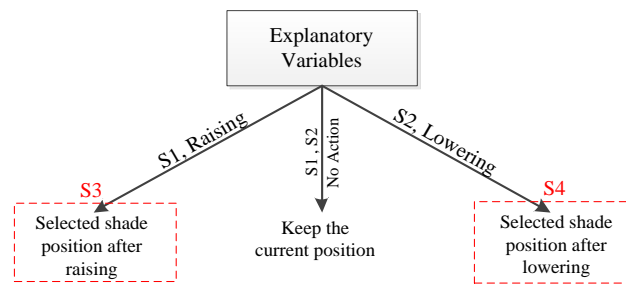


Figure 6: Structure of human-shading interaction model

4.1 Bayesian Hierarchical Modeling – Multivariate Logistic Regression (S1 and S2)

In the higher level models of hierarchy (S1 and S2), we are interested in addressing the following question:

“Given the environment inside the private office, what is the probability that the occupant will lower or raise the shades?”

The model form we develop is identical for S1 and S2. Let z be a binary random variable such that $z = 1$ corresponds to “action” and $z = 0$ to “non-action”. The probability of “non-action” conditioned on the observed features is modeled by:

$$p(z = 0|\mathbf{x}, \mathbf{b}) = \text{sigm}(\mathbf{b}^T \mathbf{x}), \quad (1)$$

Where $\text{sigm}(x) = \frac{1}{1+e^{-x}}$ denotes the sigmoid function, $\mathbf{b} = (b_0, b_1, \dots, b_d)$ is a vector of regression coefficients to be inferred from the data, and $\mathbf{b}^T \mathbf{x}$ is the dot product between \mathbf{b} and \mathbf{x} . Using the standard rules of probability, the probability of “action” conditioned on the observed features is:

$$p(z = 1|\mathbf{x}, \mathbf{b}) = 1 - p(z = 0|\mathbf{x}, \mathbf{b}) \quad (2)$$

We will be calling z the *action target*.

Now, let $\mathbf{x}_{1:N} = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$ and $\mathbf{z}_{1:N} = \{z_1, \dots, z_N\}$ be the observed features and action targets, respectively. Assuming that the measurements are conditionally independent given the features, the *likelihood* of the observed data set is:

$$p(\mathbf{z}_{1:N}|\mathbf{x}_{1:N}, \mathbf{b}) = \prod_{i=1}^N p(z_i|\mathbf{x}_i, \mathbf{b}). \quad (3)$$

To proceed, we need to specify our *prior* state of knowledge about the coefficients \mathbf{b} . Since we do not have much prior information about it, we will construct a vague hierarchical prior distribution. Specifically, we assign to \mathbf{b} a zero mean Gaussian prior,

$$p(\mathbf{b}|\alpha) = \mathcal{N}(\mathbf{b}|\mathbf{0}, \alpha^{-1}\mathbf{I}_{d+1}), \quad (4)$$

where $\mathcal{N}(\cdot | \boldsymbol{\mu}, \boldsymbol{\Sigma})$ is the probability density function of a multivariate Gaussian distribution with mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$ and \mathbf{I}_{d+1} is the $(d + 1)$ -dimensional unit matrix, and α is a priori unknown precision. Completing the model specification, we assign an exponential prior to α :

$$p(\alpha | \lambda) \sim \mathcal{E}(\alpha | \lambda), \quad (5)$$

where $\mathcal{E}(\cdot | \lambda)$ is the probability density function of an exponential random variable with rate parameter λ . Here, we fix $\lambda = 10000$.

Using Bayes rule, our *posterior* state of knowledge about the coefficients \mathbf{b} and the precision parameter α is given by:

$$p(\alpha, \mathbf{b} | \mathbf{x}_{1:N}, z_{1:N}, \lambda) \propto p(z_{1:N} | \mathbf{x}_{1:N}, \mathbf{b}) p(\mathbf{b} | \alpha) p(\alpha | \lambda). \quad (6)$$

Using the sum rule of probability theory, the *predictive distribution* at a new set of features \mathbf{x}^* is given by:

$$p(z^* | \mathbf{x}^*, \lambda) = \int p(z^* | \mathbf{x}^*, \mathbf{b}) p(\alpha, \mathbf{b} | \mathbf{x}_{1:N}, z_{1:N}, \lambda) d\mathbf{b} d\alpha. \quad (7)$$

This is intractable, but it can be approximated by sampling (see Sec. 4.3).

4.2 Bayesian Hierarchical Modeling – Multivariate Linear Regression (S3 and S4)

In the lower level models of hierarchy (S3 and S4), we are interested in addressing the following question -

“Given that we already know whether the person is going to raise/lower the shades and the current environment inside the office, what is the amount by which the person is going to raise or lower the shades?”

The model form we develop is identical for S3 and S4. Let y be a random variable indicating the position of the shades selected by the human after an action (either lowering or raising). We will be referring to y as the *target* variable. The probability of a shade position y conditioned on the observed features is modeled by:

$$p(y | \mathbf{x}, \boldsymbol{\beta}, \sigma^2) = \mathcal{N}(y | \boldsymbol{\beta}^T \mathbf{x}, \sigma^2), \quad (8)$$

Where $\boldsymbol{\beta} = (\beta_0, \beta_1, \dots, \beta_d)$ is the vector of regression coefficients to be determined from the data, and σ^2 is the noise variance. The role of the latter is to capture as random effects everything that cannot be explained by the observed features.

As in the previous section, let $\mathbf{x}_{1:N} = \{\mathbf{x}_1, \dots, \mathbf{x}_N\}$ and $\mathbf{y}_{1:N} = \{y_1, \dots, y_N\}$ be the observed features and targets, respectively. Assuming that the measurements are conditionally independent given the features, the *likelihood* of the observed data set is:

$$p(\mathbf{y}_{1:N} | \mathbf{x}_{1:N}, \boldsymbol{\beta}, \sigma^2) = \prod_{i=1}^N p(y_i | \mathbf{x}_i, \boldsymbol{\beta}, \sigma^2). \quad (9)$$

Similarly, we assign a hierarchical prior to $\boldsymbol{\beta}$:

$$p(\boldsymbol{\beta} | \psi) = \mathcal{N}(\boldsymbol{\beta} | \mathbf{0}, \psi^{-1} \mathbf{I}_{d+1}), \quad (10)$$

where, as before, ψ is an unknown precision parameter distributed exponentially,

$$p(\psi | r) = \mathcal{E}(\psi | r), \quad (11)$$

with rate parameter $r = 10000$, and

$$p(\sigma | \gamma) = \mathcal{E}(\sigma | \gamma), \quad (12)$$

with $\gamma = \frac{1}{25}$. Using Bayes rule, our posterior state of knowledge about the parameters is:

$$p(\psi, \boldsymbol{\beta}, \sigma | \mathbf{x}_{1:N}, \mathbf{y}_{1:N}, r, \gamma) \propto p(\mathbf{y}_{1:N} | \mathbf{x}_{1:N}, \boldsymbol{\beta}, \sigma) p(\boldsymbol{\beta} | \psi) p(\psi | r) p(\sigma | \gamma). \quad (13)$$

Using the sum rule of probability theory, our *predictive distribution* at a new set of features \mathbf{x}^* is given by:

$$p(y^* | \mathbf{x}^*, \lambda) = \int p(y^* | \mathbf{x}^*, \mathbf{b}) p(\psi, \boldsymbol{\beta}, \sigma | \mathbf{x}_{1:N}, \mathbf{y}_{1:N}, r, \gamma) d\psi d\boldsymbol{\beta} d\sigma. \quad (14)$$

This is also intractable, but it can be approximated by sampling (see Sec. 4.3).

4.3 Training and Sampling Approximation to the Predictive Distributions

We implemented our models using the Python package PyMC 2.3.0 (Patil et al. 2010) and used Markov chain Monte Carlo (MCMC) to sample from the posterior of \mathbf{b} ($\boldsymbol{\beta}$). After monitoring the traces and the autocorrelations of the chain, we decided to burn the first 1,000,000 samples, and gather 200 samples by keeping one MCMC sample out of every 1,000. Using these samples, we can approximate the predictive distributions at new sets of features. For example, if $\mathbf{b}_{1:S} = \{\mathbf{b}_1, \dots, \mathbf{b}_S\}$ are samples from Eq. (6), then the predictive distribution of Eq. (7) is approximated by:

$$p(z^*|\mathbf{x}^*, \lambda) = \frac{1}{S} \sum_{i=1}^S p(z^*|\mathbf{x}^*, \mathbf{b}_i). \quad (15)$$

In our numerical results, we summarize the predictive distribution by computing its median 5- and 95-percent predictive quantiles. This is accomplished numerically by computing the empirical percentiles of a z_i^* , $i = 1, \dots, S$, sampled from $p(z^*|\mathbf{x}^*, \mathbf{b}_i)$.

5. ESTIMATION RESULTS AND DISCUSSION

All the variables in Figures 3 and 5 were considered within the multivariate structure of models. Python 2.3.0 was used for programming all models and the forward selection method was applied to determine the most statistically significant variables. As mentioned earlier, only the arrival time is considered for model development. Table 2 presents descriptive statistics of variables selected in the models used to normalize the data. Table 3 presents the estimate parameters for two different forms for model S1. Form 1 represents a shade raising model only including physical variables. Form 2 represents the model constructed using significant human variables. Variable “SV” in this model accounts for the interactive impacts of outside view and shade position. The variable is created by dividing the shade position by the importance level of clear view to outside reported by occupants in survey type-B. An increase in probability of shade raising is expected as this variable decreases, which is confirmed by the negative sign of parameter estimate. Lighting preference is also included as an individual characteristic reported by occupants in survey type-B. The positive sign for this variable indicates that the probability of shade raising increases for occupants who prefer to have brighter conditions.

Table 2: Descriptive statistics of explanatory variables (features)

Variable	Minimum	Mean	Max	Std.
Work plane ill. (lx)	78.11	801.39	7052.8	1526.49
Vertical ill. (lx)	75.78	982.34	12331.6	1056.66
Shade position (%)	0	44.05	100	37.08
SV	0	17.91	100	20.36
SP	0	22.39	100	26.01

Table 3 also presents estimation results for shade lowering actions. Among the environmental variables, vertical illuminance at eye level was found to be the best predictor for shade lowering actions. “SP” is included in model S2 to represent the interaction between the shade position and need to have visual privacy. To create variable “SP”, the votes on importance of visual privacy are manipulated to reflect symmetry. That is, “the most important” votes were assigned to level 1 and “the least important” votes to level 5 (1. The most important ... 5. The least important). Variable “SP” is created by dividing the shade position by the new representation of votes on visual privacy need. It is expected for probability of shade lowering to increase as this variable increases which is confirmed by the positive sign of the parameter estimate for this variable in Table 3.

Table 3: Shade raising and lowering models (S1 and S2)

Parameter Estimates (β 95% HPD interval)				
	Shade raising models		Shade lowering models	
	Form 1	Form 2	Form 1	Form 2
Work plane ill.	-11.112 (-10.635,-5.622)	-6.665 (-9.627,-3.855)	N/A	N/A
Vertical ill.	N/A	N/A	1.046 (0.692,1.288)	1.153 (0.766,1.431)
Lighting preference	N/A	1.343 (0.752,1.635)	N/A	-0.701 (-1.110,-0.201)
SV	N/A	-2.662 (-3.748,-1.042)	N/A	N/A
SP	N/A	N/A	N/A	0.955 (0.635,1.311)
Constant	-4.501 (-5.544,-3.328)	-5.834 (-7.232,-4.846)	-2.000 (-2.373,-1.654)	-2.631 (-3.098,-1.979)
Observation No.	569		397	

The data is divided into training and testing sets and a separation plot for the testing set (10% of data) is shown in Figure 7. The separation plot for binary classifiers is resulted from sorting the data points based on estimated probabilities. Black lines show the estimated probability for each data point while the vertical blue lines indicate occurrence of raising/lowering actions (1s in dependent variable). It is expected that estimated probability increases as density of vertical lines does. It is clear from figure 7 (left) that unlike model form 2 (based on physical and human variables), model form 1 (based on physical variables) mostly fails to estimate high probabilities corresponding to events where raising actions have occurred. Better performance of the lowering model in form 2 is also evident from figure 7 (right). That is, including human variables adds to the power of the model in describing the phenomenon and improves its performance.

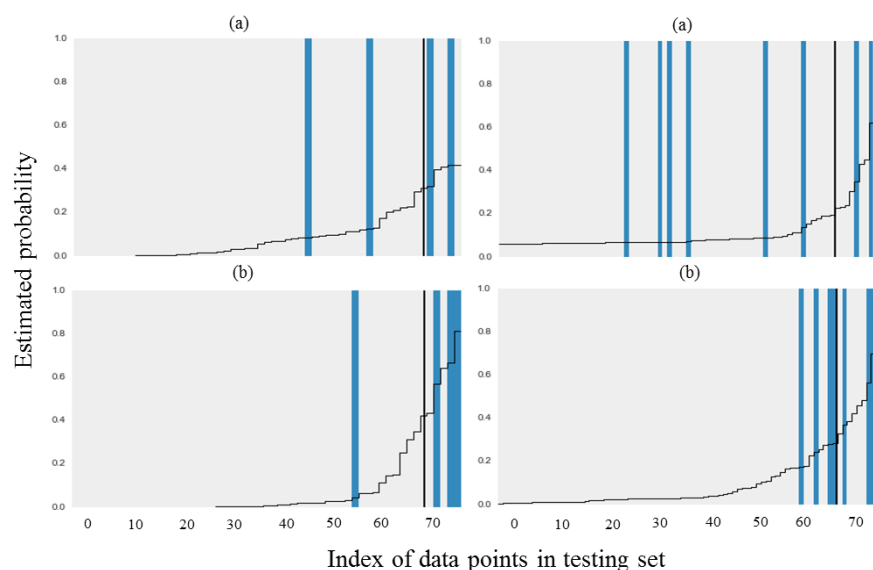


Figure 7: Separation plots for shade raising (left) and lowering (right) models; (a): model with physical variable, (b): model with both physical and human variables

Figure 8 presents the median of estimated probabilities resulted from models S1 and S2 for shade raising and lowering actions versus the change in explanatory variables. Outcome probabilities have been filtered based on lighting preference so that three plots are presented for each model; preferences for dark, moderate, and bright lighting conditions (used vote values of 2, 4, and 6 for lighting preference variable in the models). It is clear from the top plots that shade raising probability increases as the need for window view (SV) increases and the level of work plane illuminance decreases. However, this variation is also influenced by the lighting condition preference conditions. It can be seen that when dark conditions are preferred, shade raising action is of a low probability after the threshold value of 500 lx for the work plane illuminance while this happens around 1200 lx when there is a preference for bright lighting conditions. The same concept can be seen for shade lowering actions in bottom plots. That is, a shade lowering action is more likely to happen when dark conditions are preferred. It is evident from the plots that increase in vertical illuminance and need for visual privacy increases the likelihood of shade lowering actions.

Table 4 presents the estimated linear regression models for the magnitude of shading actions (models S3 and S4) while their performance is evaluated on the testing set (10% of the data) and shown in Figure 9. As a feature of Bayesian estimation, the uncertainty of predicted values is quantified and shown as a box plot for each data point. In this plot, we are only looking at the mean of the response with the Gaussian noise excluded and the uncertainty is the epistemic uncertainty induced by the finite amount of data. It is worth mentioning that the number of data points in the testing set is rather small, which might be the reason for off predictions and wide distributions of predicted values in some data points.

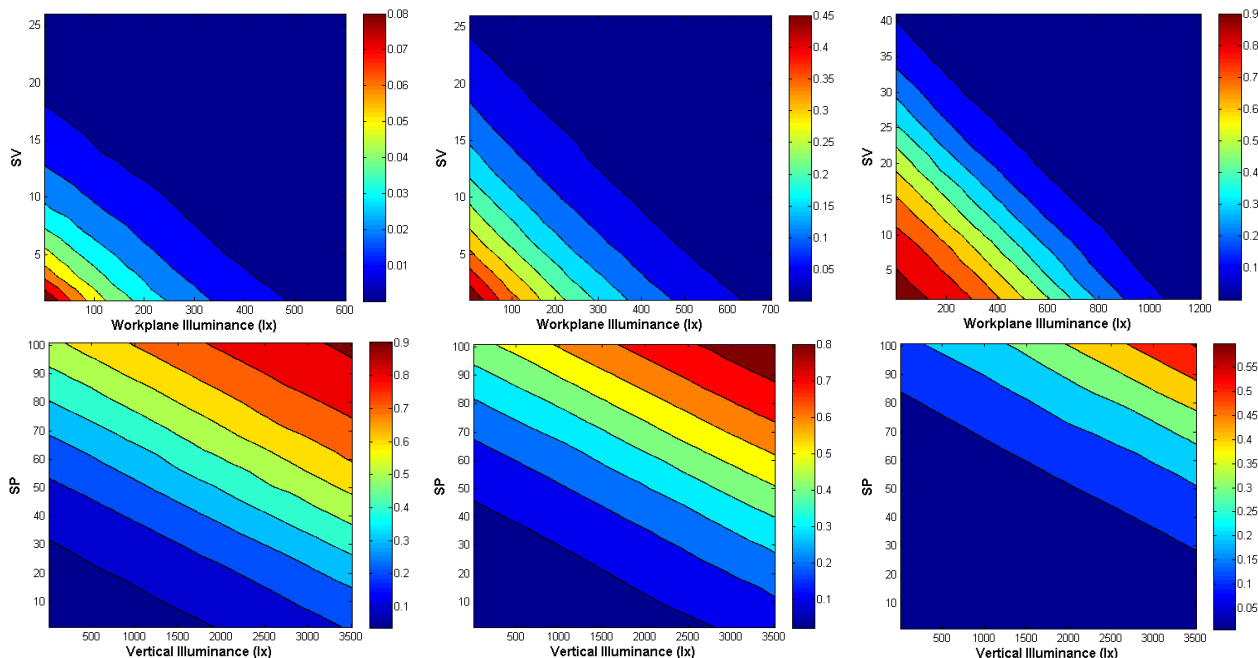


Figure 8: Level plots of estimated outcome probabilities for shade raising (top) and lowering (bottom) filtered based on lighting condition preferences (left: preference for dark conditions, middle: preference for moderate conditions, right: preference for bright conditions)

Table 4: Models for magnitude of shade raising and lowering (S3 and S4)

Parameter Estimates (β 95% HPD interval)		
	Raising magnitude	Lowering magnitude
Work plane ill.	-3.153 (-9.241,3.413)	N/A
Vertical ill.	N/A	6.234 (1.356,11.040)
Shade position	-3.710 (-8.956,3.537)	17.101 (11.363,22.096)
Constant	40.353 (33.824,45.113)	45.332 (40.234,50.543)
Observation No.	71	69

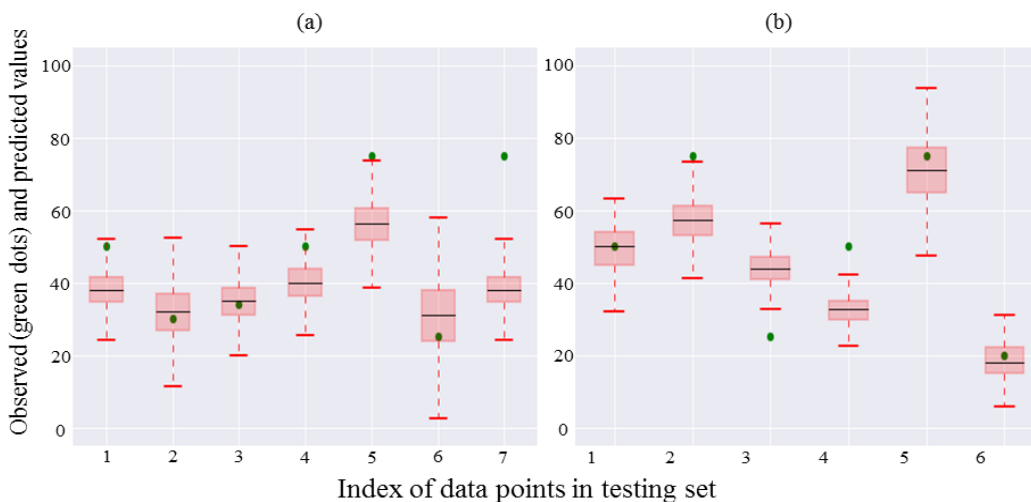


Figure 9: Observed and estimated magnitude of raising (a) and lowering (b) actions

6. CONCLUSIONS

This paper presented a contribution to characterization of human-shading interactions in private offices. Bayesian multivariate binary-choice logit models have been developed to predict shade raising/lowering along with Bayesian linear regression models to estimate the magnitude of shading actions, thus, allowing for prediction of continuous intermediate operating states of the shading system. Based on the findings of our field study, intermediate positions are frequently selected by the occupants and therefore, the new modeling framework is expected to increase the prediction accuracy of human-shading interactions in BPS tools. Human variables proved to have a significant impact on the operation of shading systems. Our findings prove that it is a combination of physical variables along with human attributes and individual characteristics that underlie human interactions with building systems such as window shades and both should be considered in modeling structures and BPS tools. It should be noted that the experimental dataset corresponds to a private office with a south façade orientation and the predicted probabilities to 5 min intervals. Occupant interactions with electric lighting will be incorporated in the modeling framework in future work by the authors.

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