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# Visual Preferences and Human Interactions with Shading and Electric Lighting Systems

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# VISUAL PREFERENCES AND HUMAN INTERACTIONS WITH SHADING AND ELECTRIC LIGHTING SYSTEMS

by

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*To Simin and Haji who spoil me with their endless love*

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# ABSTRACT


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Buildings in the United States are responsible for 40% of the primary energy use and 30% of carbon dioxide emissions. As awareness is being raised for the energy consumption and environmental impacts of buildings, it is not surprising that improving building performance has gained significant attention over the past years. Increasing the energy efficiency and reducing the emissions associated with buildings is possible through the use of high-performance building design and implementation of advanced building controls. Moreover, as part of the modern life style, people in developed countries spend most of their time inside the buildings. This fact necessitates consideration of two important requirements. First that energy saving achieved by efficiency methods in practice should not compromise occupants' comfort. Second, energy impacts of building users and their indoor environment preferences should be taken into account at both design and operation phases.

Therefore, understanding and modeling human-building interactions and their links to energy consumption and occupant satisfaction with the indoor environment is the main goal of this research. To this end and with a focus on the visual environment, systematic data collection from a large number of participants is undertaken and novel probabilistic modeling approaches are explored to provide new insights towards human-centered sustainable buildings. The specific research objectives of this thesis are:

1. Study human interactions with motorized roller shades and dimmable electric lights as well as human perception and satisfaction with the luminous environment in private offices with variable daylight and electric light conditions.
2. Develop a novel Bayesian approach to model the interrelated human interactions with window shades and electric lights.
3. Develop a Bayesian classification and inference modeling framework for occupants' visual preferences in daylit perimeter offices.

To this end, four identical private offices in a high performance building located in West Lafayette, IN were equipped with sensing network and online survey questionnaires to study almost 300 occupants during the two sets of field studies conducted for this thesis. The first field study extends the knowledge of human-building interactions to advanced building systems such as motorized roller shades and dimmable electric lights and reveals behavioral patterns enabled through side-by-side comparisons of different environmental controls and user interfaces ranging from fully automated to fully manual and from low to high levels of accessibility (wall switch, remote controller and graphical web interface). Results of the field study reveal: (a) occupational dynamics and human variables as two key features, in addition to environmental variables, in describing human-shading and -electric lighting interactions; (b) higher daylight utilization in offices with easy-to-access controls; (c) strong preference for customized indoor climate, along with a relationship between occupant perception of control and acceptability of a wider range of visual conditions.

With the insights gained from the first field study, the research extends to exploit the resulted dataset as a basis for the development of a hierarchical Bayesian approach which is used, for the first time, to model human interactions with motorized roller shades and dimmable electric lights. Bayesian multivariate binary-choice logit models have been constructed to predict shade raising/lowering and electric light increasing actions while Bayesian regression models with built-in physical constraints to estimate the magnitude of shading and electric lighting actions. The proposed models, in their structure, account for (a) intermediate operating states of the systems; (b) interrelated operation of shades and lights; (c) personal characteristics and human attributes. Moreover, the developed human-building interaction modeling framework benefits from the advantages of the Bayesian formalism as it (a) provides a systematic approach to identify significant features in describing the human-building interactions; (b) incorporates prior beliefs about the systems; (c) captures the epistemic uncertainty, which is important when dealing with small-sized datasets, a ubiquitous issue in human data collection in actual buildings.

The second field study was designed and conducted to collect data for occupants' satisfaction with the visual environment when exposed to different combinations of daylight and electric light conditions, along with data from room sensors, shading and light dimming states. The resulted dataset is then used as a basis to model occupants' visual preferences such as prefer darker, prefer brighter, or satisfied with current conditions. Bayesian multinomial logistic regression is augmented with Dirichlet process prior to encode within the model structure that occupants' visual preferences are influenced by a combination of environmental and control state variables as well as individual visual characteristics. The latter is treated as a hidden random variable which is used to cluster occupants with similar visual preference characteristics and to determine the optimal number of clusters among the observed population. Modeling results based on observations from 75 occupants in glare-free conditions suggest work plane illuminance, window unshaded area, and electric light ratio as significant features of the general visual preference model and reveal the existence of three distinct clusters with physical interpretation; preference for bright, moderate, and dark conditions. In the final step, a method for learning the visual preferences of new occupants is deployed which uses a mixture of the general probabilistic sub-models to infer new occupants' cluster values and personalized preference profiles. The proposed approach proves to be efficient as it is shown to predict personalized profiles with 81% prediction accuracy with very few observations (less than 16) from each new occupant.

In summary, the systematic data collection methods and prototype interfaces used in this dissertation establish a consistent and reliable approach for studying human interactions with building systems and satisfaction with the indoor environment. Unique datasets for human attributes towards the visual environment in perimeter building zones have been generated especially for the occupants' direct preference votes with different visual conditions which is currently lacked in the literature. The probabilistic models for human interactions with shading and lighting systems and occupants' visual preferences incorporate individual characteristics and account for uncertainties associated with limited data, thus, are to increase prediction accuracy when implemented in Building Performance Simulation tools. The research presented herein facilitates an effective pathway towards implementation of adaptive personalized environments and is a necessary precursor for future investigation and expansion to human-centered building controls.

# CHAPTER 1. INTRODUCTION

## 1.1 Background and Motivation

Occupant behavior in office buildings can be classified as (i) occupant presence/absence or so-called *occupancy*, which can make a difference in required temperature set points, ventilation requirements and energy consumption and (ii) their interaction with the building through thermal and visual control systems and/or devices that affect plug loads; *human-building interactions*. Interactions with comfort delivery systems include opening or closing windows/doors (Haldi and Robinson, 2009; Rijal et al., 2008(A)) and/or turning on/off fans (Haldi and Robinson, 2008; Rijal et al., 2008(B)), changing thermostat set points (Daum et al., 2011; Jazizadeh et al., 2013), controlling electric lights (da Silva et al., 2013; Newsham, 1994; Maniccia et al., 199; Reinhart and Voss, 2003; Lindelof and Morel, 2006; Mahdavi et al., 2008), and moving window shades (Rea, 1984; Inoue et al., 1988; Lindsay and Littlefair, 1993; Foster and Oreszcyn, 2001; Inkarojrit, 2005; Sutter et al., 2006; Inkarojrit, 2008; Haldi and Robinson, 2010(A); Zhang and Barrett, 2012). A typical framework used in occupant behavior studies is shown in Figure 1.1.

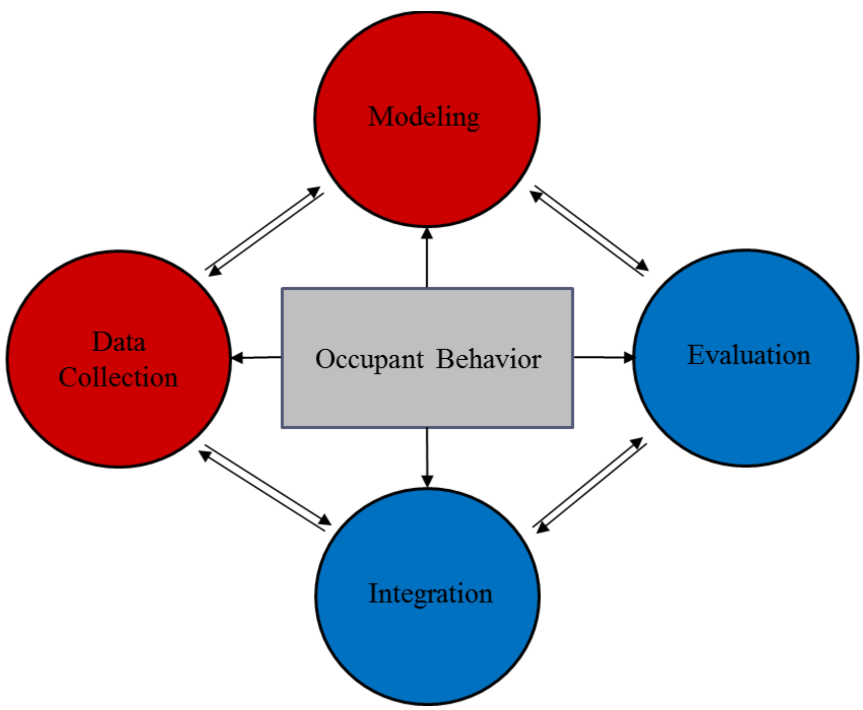


Figure 1.1 Typical framework of occupant behavior study (Yan et al., 2015)

Human-building interactions provide information on the energy impact of different control behaviors and sometimes are also used to infer occupant preferences and individual differences in experiencing thermal and visual environments; they reveal stimulus-response relationships for the integration of humans in sensing, control, and simulation frameworks. Among the building comfort delivery systems that occupants can usually interact with, window shades and electric lights are the main focus of this study.

Investigation of human interactions with shading and electric lighting systems has been designed around two main objectives: First, to attain an understanding of the reasoning behind the human-building interactions towards the development of adaptive control algorithms (Guillemin and Molteni, 2002; Guillemin and Morel, 2001; Daum and Morel, 2010; Lindelof 2009; Gunay et al., 2014). Second, to develop stochastic models based on probabilistic relationships between human-shading and -electric lighting interactions and environmental conditions that represent the random nature of occupant behavior (Haldi and Robinson, 2010; da Silva et al., 2013; Inkarojrit, 2008; Reinhart, 2004), and when used properly, achieve more reliable predictions in Building Performance Simulation (BPS) (Yan et al., 2015; da silva et al., 2014; Parys et al., 2011; Gunay et al., 2015; Gaetani et al., 2016).

Field studies conclude that maintaining acceptable visual comfort conditions for the majority of people is challenging, since perception of the visual environment varies significantly amongst individuals (Haldi and Robinson, 2010(A); Nicol et al., 2006; Moore et al., 2002; Moore et al., 2003; Galasiu and Veitch, 2006). An example of the occupant diversity is schematically illustrated in Figure 1.2. Suggested threshold values attempt to quantify lighting preference experienced by an average user as a function of lighting stimuli. This is while lighting preference is perception-based and as such, differences at preferred illuminance levels are to be expected between individuals (Nabil and Mardaljevic, 2006; Lindelöf and Morel, 2008; Haldi and Robinson, 2010(A); Nicol et al., 2006; Moore et al., 2002; Moore et al., 2003; Galasiu and Veitch, 2006).

Studies with shading/lighting automation systems suggest that occupants frequently override these systems, either indicating discomfort or implying their desire for customized indoor climate (Reinhart and Voss, 2003; Guillemin and Molteni, 2002; Vine et al., 1998; leaman and Bordass, 2001; Bakker et al., 2014; Meerbeek et al., 2014).

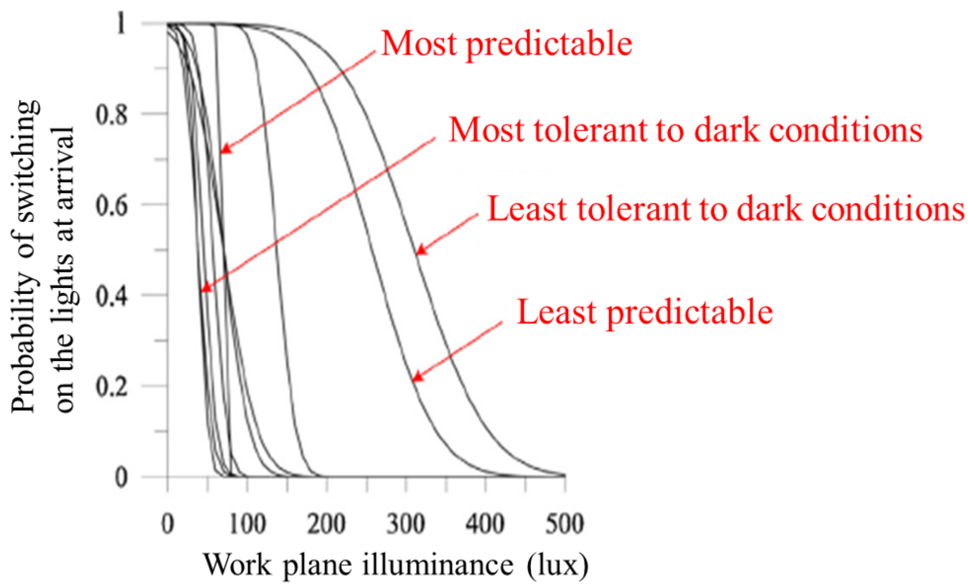


Figure 1.2 Example of occupant diversity: each line represents a logistic regression for the probability of an individual office occupant to turn on their lights upon arrival (Reinhart, 2004; Yan et al., 2015)

For high performance buildings, of particular importance are the energy impacts of different control behaviors and the relationship between occupant's perception of control and acceptability of a wider range of visual conditions. The dynamics of human interactions with shading and lighting systems need to be studied through the lenses of different user interfaces and environmental controls to reveal important behavioral patterns. This typically requires a large number of participants. However, previous human-shading and lighting interaction models are based on field studies and datasets collected from a relatively small number of human test-subjects and with limited potential for systematic evaluations and side-by-side comparisons.

There have been a few attempts to model visual discomfort assuming that human interactions with building systems that alter the luminous environment, such as window shades and electric lights, can be an indication of visual discomfort (Lindelöf and Morel, 2008; Zarkadis, 2015). Despite the clear strengths of these models in initiating the stochastic modeling of visual discomfort, the followings could be pointed out as drawbacks:

- Occupants' perception towards the luminous environment (discomfort or illuminance thresholds) is inferred from occupants' interactions with building systems. As theoretically shown in Figure 1.3, occupants' action is only one of the potential pathways to reflect the true attributes from human brain. Since actions taken by occupants are reported to be of low frequency (Foster and Oreszczyn, 2001; Reinhart and Voss, 2003; Inkarojrit, 2005; Mahdavi et al., 2008; Haldi and Robinson, 2010(A); Zhang and Barrett, 2012; Sadeghi et al., 2016), it is unlikely to have all visual preferences captured when following this path. Comparisons with other data collection processes based on direct feedback on occupants' lighting preferences votes such as "brighter", "dimmer", etc. can provide more insight in this manner.

- Models are built based on the assumption that the set of conditions immediately before and after occupant actions represent the transition from uncomfortable to comfortable conditions with visual discomfort being defined based on glare and light adequacy. However, it is known that not all the human interactions with shading systems are due to glare and illuminance levels; factors such as need for having a clear view to the outside and visual privacy can underlie occupant shading actions (Inoue, 1988; Foster and Oreszczyn, 2001; Reinhart and Voss, 2003; Inkarojrit, 2005; Mahdavi et al., 2008; Haldi and Robinson, 2010(A); Zhang and Barrett, 2012; Sadeghi et al., 2016).
- Stochasticity of human attitudes towards lighting conditions is taken into account through the development of probabilistic models for visual discomfort, however, no previous attempt have been made to develop a probabilistic visual preference model.

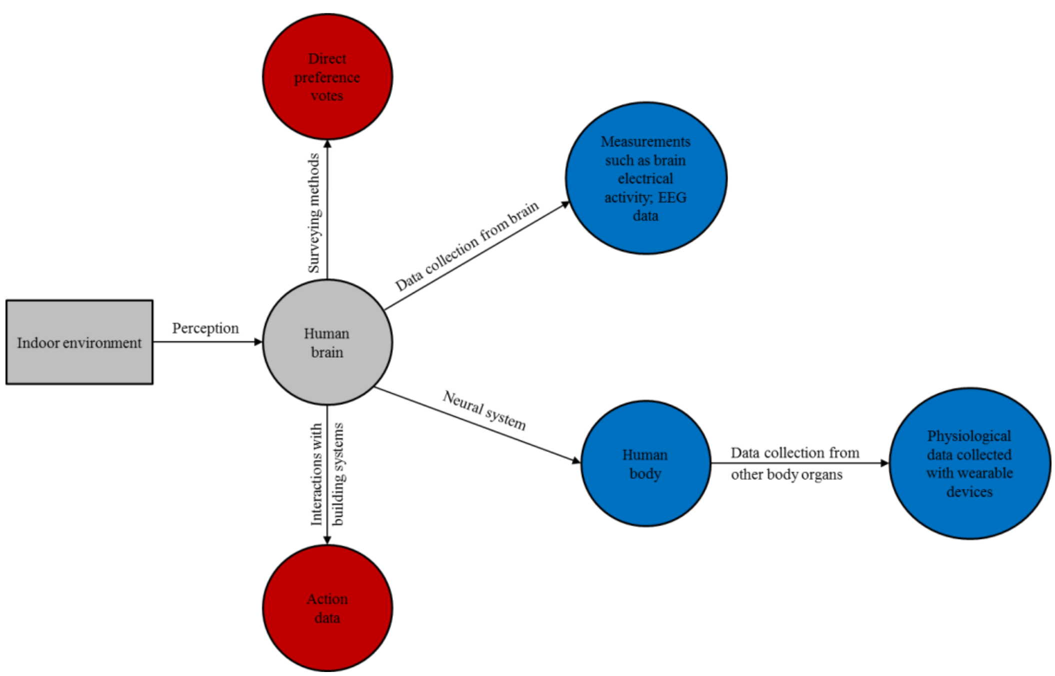


Figure 1.3 Human data collection methods

## 1.2 Objectives and Scope

Understanding human-building interactions is the overarching goal of this research. In this thesis, the focus is on visual preferences and human interactions with shades and electric lights in office environments. However, it is believed that the proposed experiment designs and modeling approaches could be applicable to occupant interactions with other comfort delivery systems. A perimeter zone of a high performance building with advanced envelope and HVAC systems, large window-to-wall ratio, motorized window shades, smart lighting controls, and Building Automation Systems (BAS) is selected as test-bed. The proposed research is extended to the following specific objectives:

1. Study human interactions with motorized roller shades and dimmable electric lights in private offices.
    a. Design field studies with a large number of participants for systematic data collection, including sensing of physical variables as well as surveys and prototype interfaces for occupants' feedback.
    b. Provide new insights for the energy impacts of occupant-shading and lighting interactions, and behavioral patterns enabled through side-by-side comparisons of different environmental controls and user interfaces.
2. Develop a novel Bayesian modeling approach to model human interactions with window shades and electric lights.
    a. Present a systematic method to identify significant features in describing the human interactions with motorized roller shades and dimmable electric lights.
    b. Predict the intermediate operating states of the shading and lighting systems as well as the potential interdependency in their operation.
    c. Incorporate human attributes and individual characteristics within the model structure.
3. Develop a general Bayesian probabilistic modeling/classification framework towards occupants' visual environment preferences.
    a. Incorporate occupant visual preference characteristics as a hidden random variable within the model structure, to cluster occupants based on that, and to determine the optimal number of clusters within the studied population.
    b. Demonstrate a new approach to infer visual preference profiles of individual occupants using a mixture of the general sub-models for each cluster.

The work proposed in this research is based on a Bayesian approach that was selected due to the following advantages: it allows uncertainty quantification, a ubiquitous issue when dealing with small-sized datasets such as in human data collection in actual buildings; allows encoding and testing our prior knowledge and beliefs about the relationships of the various variables; offers a systematic way to select amongst different models using the Bayes factor and the evidence for each model; can account for hidden (unobserved) variables such as occupant visual preference characteristics, cluster based on that and determine the optimal number of clusters within the data; and it can seamlessly combine data from heterogeneous sources (i.e. different experimental datasets) as they become available.

## 1.3 Document Overview

Chapter 2 contains an extensive literature review about visual preferences and human interactions with shading and electric lighting systems as well as the modeling efforts in these regards.

Chapter 3 includes the main experimental methodology and the field study designed to investigate human interactions with motorized roller shades and dimmable electric lights including different types of environmental control. This research relates to objectives 1a and 1b.

Chapter 4 presents key observations from the field study that provide the basis for developing models of human-shading and –electric lighting interactions, along with the modeling methodology and the performance evaluation results. This research relates to objective 2.

Chapter 5 presents the data collection for occupants' perception and satisfaction with the visual environment when exposed to variable daylight and electric light conditions along with modeling method for classification and inference of visual preferences. This research relates to objectives 1a and 3.

Chapter 6 summarizes the conclusions and main achievements of this thesis and also presents a future outlook in continuation of this work.

# CHAPTER 2. LITERATURE REVIEW

## 2.1 Occupant Behavior Impact on Building Performance

The building sector accounts for a significant portion (30%) of global energy consumption (IEA, 2015) and this reveals a great potential for energy conservation in this area. Climate, building envelope, building energy and services systems, building operation and maintenance, indoor design criteria, and occupant behaviors have been reported as the driving factors for energy consumption in buildings (IEA, 2015; EBC, 2013; Annex 66, 2013; Annex 53, 2013). Lighting represents a major energy-user in commercial buildings in U.S (DOE, 2015), and large amounts of energy can be saved by using well designed controls that can take advantage of the available natural light (Xiong and Tzempelikos, 2016; Shen et al., 2015; Chan and Tzempelikos, 2013; Tzempelikos and Shen, 2013; Shen and Tzempelikos, 2012; Tzempelikos and Athienitis, 2007). Occupant behavior is reported to account for up to 30% of the energy consumption in office buildings (Torcellini et al., 2004; Norford et al., 1994). It is often one of the main causes of "underperforming" green buildings (Torcellini et al., 2004) and can impact energy performance of offices by a factor of two or more (Norford et al., 1994; Reinhart, 2004; Haldi and Robinson, 2011; D'Oca and Hong, 2014; Feng et al., 2015). Therefore, occupant interactions with shading and electric lighting systems can significantly affect energy performance.

Automation algorithms with fixed set-points have been used for building systems such as window shades and electric lights as an attempt to mitigate the impact of occupant behaviors. However, better understanding of occupant interactions with shading and lighting systems is required in order to enable stochastic or adaptive controls and customized indoor environments rather than deterministic approaches with fixed set-points. At the same time, this understanding facilitates better representation of uncertainty of occupant behavior in buildings simulation tools. Recently, design practice and code compliance are relying on BPS tools to predict energy performance and comfort. Hoes et al. (2009) concluded that optimization of a building design is achievable by incorporating improved behavior modeling in building energy simulation during the design process.

It has been reported that actual occupants may behave differently from what designers indicate through modeling assumptions. Clevenger and Haymaker (2006) studied uncertainty in occupant behavior in building energy models, using various occupancy schedules and environmental preferences and found that the energy consumption differed 150% (or more) if the occupant-related inputs were maximized and minimized (even for typical occupant behavior patterns). At the same time, Parys et al. (2011) reported that the uncertainty of single office performance reported in previous research may exaggerate total uncertainty because of the diversifying effect of multiple offices at building scale. Gilani et al. (2016) compared conventional and stochastic modeling approaches for occupant interactions with shading and lighting systems in a simulation-based design. The study draws important conclusions with regards to the impact of assumptions but also highlights limitations of existing occupant interaction models with shading devices in terms of predicting blind occlusion rates for offices with different window-to-wall ratios and associated impacts on occupant perception of view and connection to outdoors.

Previous research has reported conflicting outcomes regarding the impact of conventional modeling assumptions in BPS tools; they can overestimate or underestimate building energy use depending on the specific case under consideration. Recent studies (Yan et al., 2015; Tahmasebi and Mahdavi, 2016) highlight general issues and misconceptions associated with the use of occupant behavior models in terms of their predictive performance, reliability and applicability in different building and geographical contexts. In fact, Tahmasebi and Mahdavi (2016) suggest that suggest that, while stochastic models can emulate the random character of occupant behavior and provide probabilistic distributions of performance indicators, their use does not guarantee more reliable predictions.

## 2.2 Observations of Human Interactions with Window Shades and Electric Lights

This section provides an overview of background information from experimental observations of human-interactions with shading and lighting systems in office buildings and outlines limitations that guided the methodology developed in this study.

### 2.2.1 Significant variables

In perimeter building zones, several physical or non-physical variables may affect occupants' visual perception and trigger their control actions –in these dynamic environments, understanding of stimulus-response relationships is a complex task. It is clear by analyzing previous studies that differences in building design (e.g., space layout, window size, orientation, glazing/shading type and properties) and indoor environmental control characteristics should be considered when comparing results.

Inkarojrit (2005) carried out a survey to identify the main motivations for closing window blinds in private offices. In this study, it was reported that the majority of occupants who closed their blinds do so to protect their workstations and screens from direct or reflected glare from sunlight, while 27.4% of the participants claimed that they use their blinds to reduce the heat from the sun and only 12.3% stated privacy and security as a reason for blind closure. Eilers et al. (1996) surveyed office occupants and confirmed that the majority of the subjects who closed their blinds do so to reduce the glare on their computer screen. Zhang and Barrett (2012) observed that window shade deployment did not follow the outdoor temperature. Arguably, Lindsay and Littlefair (1993) as well as Foster and Oreszczyn (2001) claimed that indoor temperature and external solar radiation cannot be a predictor variable for the window shade deployment. In order to quantify the intensity of solar radiation, they invented a simple "sunshine index". The sunshine index is a function of the horizontal global radiation and the time of the day. Its major limitation is that its maximum value (sunny conditions) tends to be in the middle of the day. Moreover, Foster and Oreszczyn (2001) limited the shade observation and analysis on the midday only. This is likely the explanation for them drawing conclusions that directly contradict the other studies that considered solar radiation as a factor (Mahdavi et al., 2008; Inoue et al., 1988; Inkarojrit, 2005; Sutter et al., 2006; Zhang and Barrett, 2012). Rubin (1978) considered sky conditions such as sunny, cloudy, and hazy 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. Reinhart and Voss (2003) and Inoue et al. (1988) found solar penetration depth -defined as the normal distance from the façade that the beam solar radiation reaches the work plane- to acceptably explain human-shading interactions and claimed that solar penetration depth can explain these interactions better than the mere incident solar radiation on the façade. A major advantage to the solar penetration depth metric is that it is independent of many other characteristics such as glazing type and can therefore be readily calculated using a geometrical relationship. However, the concept is less applicable for north-facing facades (in the northern hemisphere) because even when there is incident direct solar on the north façade, the surface-solar azimuth angle is very high (Reinhart and Voss, 2003). Several researchers also attempted to find correlations between illuminance and operation of window shades. Haldi and Robinson (2010 A) found that the greatest number of shade openings and closings occurred when the work plane illuminance was 200 lux and 1200 lux, respectively. Reinhart (2004) found the mean thresholds of exterior vertical illuminance to be 50 klux and 25 klux when occupants overrode the blinds for closing and opening respectively. In addition to illuminances, other variables explaining the luminous environment of occupants' visual field have also been notified by researchers in studies of human-shading and -electric lighting interactions. For example, Inkarojrit (2005) found luminance -both window and background- to explain the blind closing events properly while da Silva et al (2013) showed that daylight glare probability and index (DGP, DGI) could be correlated with occupants' shading actions. Daylight work plane illuminance (Hunt, 1979; Love, 1998), vertical illuminance on VDU screen (Sutter et al., 2006) and solar altitude are also among the physical variables used in the literature to describe occupant interactions with window shades.

Occupants may use shading devices to alleviate both visual and thermal discomfort, which can be caused by temperature, solar radiation, glare, etc. and a wide range of physical variables has been considered to identify the main drivers of these interactions with significant variations in findings (O'Brien et al., 2012). However, environmental variables are not the only drivers of human-building interactions. Personal characteristics and attributes, i.e. non-physical variables that are not measurable with typical sensors, have also been reported to describe occupant interactions with building systems. For example, view and connection to the outside as well as desire for privacy have been reported as non-physical motivations for human interactions with shading and electric lighting. It is evident that one of the main design purposes of windows is to provide a clear view and physical connection to the outside (Reinhart and Wienold, 2011). Inoue et al. (1988) reported that most occupants preferred to have seats close to the windows although these seats were known to be the most susceptible locations to glare and solar radiation. This finding can be interpreted as occupants prefer to tolerate some discomfort in order to have a better quality of view and connection to the outdoors. Window shading devices may obstruct the view to the outside. Haldi and Robinson (2010 (A)) carried out a study on window control with separate upper and lower blinds and reported that upper blinds were slightly more frequently used. The upper blinds were found to be fully drawn four times more than the lower blinds. However, the relationship between the view and window shade use was inconclusive due to variability introduced by the presence of anidolic reflectors. Other researchers (Inkarojrit, 2005; Zhang and Barrett, 2012; Mahdavi et al., 2008) have also acknowledged the view to the outside as a possible factor for triggering shading actions, yet a conclusive finding has not been suggested mainly because of the interferences from other variables. Rubin, et al. (1978) first introduced the concept of privacy by stating that the view to the other office buildings can conflict with the preference to maintain a private indoor space. Later on, Inkarojrit (2005) reported occupants' desire to maintain privacy as a secondary reason for choosing the blind positions. About 12% of participants stated that privacy and security concerns represent one of the reasons for deploying window shades. Moreover, Foster and Oreszczyn (2001) unexpectedly observed higher mean blind occlusion rates in the north facade than the west facade. This was attributed to the fact that north facade of the building was facing another office building, which in turn may be explained with the efforts of occupants to preserve their privacy. Similarly, Reinhart and Voss (2003) aimed to correct the bias in their observations due to the privacy concerns 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. Perception of daylight as important factor for health can also be another human attribute influencing occupant interactions with shading and electric lighting systems. Heerwagen (1986) carried out a survey on office occupants in a heating and cooling season and revealed that occupants widely believe daylight is crucial for their general health and essential for their work environment. Veitch et al. (1993) confirmed that people believe daylight is superior to artificial lighting for health. Participants reported that the quality of light sources is crucial for their well-being and the florescent lighting can cause headaches and eyestrain (Veitch and Gifford, 1996). Therefore, the occupants' preference to sit close to the windows in Inoue's study (1988) can also be explained with their health concerns related to the artificial lighting and desire to have more daylight. Visibility of energy use, which can be influenced with the availability of various feedback sources, can also be another human attribute affecting the behavioral adaptation of occupants (Janda, 2011). These direct and indirect feedbacks may emerge from simple and more intuitive energy use dashboards (Chetty et al., 2008), utility bills (Ayres et al., 2009), competitions or awards (Ayres et al., 2009). Darby (2001) estimated that savings of up to ten percent can be achieved through various feedback strategies, which suggests that occupants are likely to adapt their behaviors to save energy under specific conditions. In other words, the likelihood of undertaking a manual control action (e.g. turning off the lights before departure) can be influenced with the visibility of energy use.

Seasonal effects have been also studied by some of the researchers to investigate potential differences between occupants' interactions with shading and lighting systems in cooling and heating seasons. Mahdavi et al. (2008) carried out a survey on three office buildings, which revealed that the proportion of the mean shade deployment is up to 30% higher during the cooling season than the heating season. This was explained with the relatively higher solar radiation on the facade during cooling season. Even after substantial changes took place in the solar radiation and illuminance, occupants usually did not react to change the shade position (Barrett and Zhang, 2012). On the contrary, findings from some studies (Haldi and Robinson, 2010(A)) reported that the effects of seasonal changes rely on other physical variables, such as indoor temperature or daylight levels, thus they were found statistically insignificant. These suggest that considering the right triggering variables, one might be able to describe human-shading interactions throughout the year.

Facade orientation affects the magnitude and temporal distribution of the solar gains. For example, for the Northern Hemisphere, the north facades receive the least solar gains, while south facades receive the most useful solar radiation during the winter. Also, the solar penetration varies daily in zones adjacent to the east and west facades, but it varies more seasonally in the south zones. As a result, south facing offices tend to have higher indoor temperatures than the east, west, and north facing offices (Inkarojrit and Paliaga, 2004). In various studies mean window shade occlusion was reported lowest on north facades and highest on south facades (Foster and Oreszczyn, 2001; Inkarojrit, 2008; Eilers et al., 1996; Mahdavi et al., 2008; Rubin et al., 1978). Zhang and Barrett (2012) reported that the mean shade occlusion in the east and west facades were between that of the north facade and the south facade, however they were closer to that of the south facade. Given that the east and west facades are known to have greatest solar penetration depth during the occupied hours and the south perimeter zones often have the highest temperatures, the relative importance of the temperature and the beam solar radiation may be discernible at different facade orientations in offices that are not air-conditioned. For example, to avoid frequent blind use, occupants in the east and west facades can be more likely to leave their blinds fully closed. Inoue et al. (1988) reported significant diurnal patterns in the east and west facades. It was found that occupants in the east-facing offices close shades, upon arrival, and gradually open them up during the day, whereas, those in west facing offices opened their shades (which would have tended to be closed at the end of the previous day) and then close them over the course of the day. In spite of the observed variations in different façade orientations, it has been suggested that these effects can be addressed if proper related variables such as temperature, beam solar radiation or solar geometry are taken into account (O'Brien et al., 2012; Haldi and Robinson 2010 A; Rea, 1984).

Furthermore, HVAC system operation can affect the way occupants interact with shading and electric lighting systems. For example, results from (Inkarojrit, 2005) revealed that the mean shade occlusion rate for offices with air-conditioning (A/C) was 30% compared to 49% for offices without A/C. This can be interpreted that caution should be exercised when generalizing the results of monitoring campaigns and that the validity of these observations should be restrained with the context of the monitored building or similar buildings.

Occupation dynamics has been found to play role as a significant feature in studies of human-shading and -electric lighting interactions. That is, frequency and dynamics of shading/lighting interactions were found to be significantly different between arrival, intermediate, and departure periods. For example, Haldi and Robinson (2010 A) stated that the number of monitored blind deployments during arrival was 5.5 times more than that was during presence. da Silva et al (2013) also found occupancy state to be significant so that they had to look into arrival, intermediate and departure periods separately. These are in line with findings of relevant studies such as Hunt (1979), Eilers et al., (1996), and Love (1998). Likewise, the light switching was observed to take place during arrival and departure in different studies (Reinhart and Voss, 2003; Eilers et al., 1996; Hunt, 1979; Love, 1998). Switch-on actions during arrivals were frequently explained by the daylight illuminances in the work plane (Hunt, 1979; Love, 1998) while the switch-off actions upon departure were explained with length of absence (Reinhart, 2004; da Silva et al., 2013). Eilers et al. (1996) showed that only about half of the occupants switched off their lights if the departure was followed by an absence of two to four hours. Also, this ratio further decreased once there were occupancy sensors or dimmed, indirect lighting systems (Reinhart and Voss, 2003; Eilers et al., 1996). It is also worth noting that not all these occupant behaviors aim at adapting to their environment; instead, they can be habitual actions and human attributes. For example, occupants' action to turn on lights upon arrival, regardless of brightness, can attest their arrival in a habitual manner (Galasiu and Veitch, 2006). Therefore, not only the mere presence of the occupant, but also the state of presence (e.g. just arrived on a sunny day) should be incorporated in observational studies to be able to properly describe human interactions with window shades and electric lights.

### 2.2.2 Automated/manual controls

Low rates of shade movement for offices with manual (non-motorized) shading devices have been reported in previous research (Rubin et al., 1978; Inoue et al., 1988; Lindsay and Littlefair, 1993; Inkarojrit, 2005; Sutter et al., 2006; da Silva et al., 2013). Although very few studies considered occupant interactions with motorized blinds/roller shades, they all showed higher shade movement rates compared to manual control (Sutter et al., 2006; Bakker et al., 2014; Meerbeek et al., 2014; Kim et al., 2009). It is also important to monitor the preferred intermediate motorized shade positions selected by occupants (and not only fully open/closed positions), which of course varies with office layout, orientation and sky conditions among other factors summarized in (O'Brien et al., 2012). Studies focused on occupant interactions with electric lighting (Hunt, 1979; Newsham 1994; Maniccia et al., 1999; Reinhart and Voss, 2003; Lindelof and Morel, 2006; Nicol et al., 2006; da Silva et al., 2013) considered lights on/off switching without considering intermediate light levels, in parallel with shading positions. In addition to the frequency of electric light adjustment, selected dimming levels should be monitored as well, associated with visual comfort sensation and the nature of the office task.

To reduce occupants' energy impact, building systems with which occupants widely interact to adapt their indoor environments have been automated in many applications. However, evidence from these applications suggest that occupants frequently override the automation systems indicating their dissatisfaction. For example, Reinhart and Voss (2003) reported that in 1432 attempts to close the blinds automatically, the control algorithm was overridden by the occupants 1263 times (88%). Leaman and Bordass (2001) also stated that automation systems that exclude occupants from the control-loop (e.g. closing blinds before glare conditions exist for occupants) can infuriate occupants. Carter, et al. (1999) reported that manually controllable lighting fixtures which do not even meet the lighting standards were perceived more satisfactory than the daylight linked automated lighting controls. Other studies (Borgeson and Brager, 2008; Cole and Brown, 2009; Slater, 1996; Slater, 1995; Lee et al., 2013; Meerbeek et al., 2014; Bakker et al., 2014) confirmed these observations demonstrating the desire for customized indoor climate and access to control. Strong relationship between occupants' perception of control over their environment and their productivity is also reported (Leaman and Bordass, 2001; Leaman and Bordass, 1999). Related research highlighted a distinct difference between the effects of perceived and utilized control (Paciuk, 1990) and the fact that satisfaction benefits are contingent upon controls being simple and well-maintained (Leaman and Bordass, 2001; Veitch et al., 1993; Veitch and Gifford, 1996). This is also pronounced in (Langevin et al., 2012) where detailed statistical analysis has shown significant correlations between key thermal comfort and perceived control variables (ASHRAE RP-884 datasets) while conveying that occupants' understanding of controls plays a key role and simply having control over the environment is not enough to result in occupant satisfaction and comfort conditions. Some of the field studies have suggested that improved thermal satisfaction through perceived control is due to increased tolerance of wider ranges of thermal conditions (Brager and de Dear, 2001; Paciuk, 1990). Adaptive thermal comfort models also have the potential of making the comfort zone wider (de Dear and Brager, 1998). To date, there is no "adaptive visual comfort", but several studies investigated respective concepts (Jakubiec and Reinhart, 2012). Studies on luminous environment have recognized the importance of occupant control perception and interface design (Galasiu and Veitch, Yılmaz et al., 2015) but the details of occupant behavior remain to be investigated. Overall, it is believed that providing occupants with easy-to-use controls over comfort delivery systems would make them more eager to act for improving their comfort.

### 2.2.3 Office type

Compared to private offices, shared and open plan offices present further complexities to occupants' control of shades and electric lights. Occupants tend to be more unwilling to control their environments if others are present because of social constraints. Boyce's (1980) study about manual light control in large offices reported that switching actions are usually consistently performed by the same people (i.e. leaders) and that such actions occurred either when there was sufficient daylight or when the action was deemed to not impact anyone because most people had left. Not only could preferences vary by person under identical conditions, but the shade position and light level could result in different conditions for two different people (e.g., one person is further from the façade than the other or one person is sitting right under a lighting fixture) (Reinhart et al., 2006). The studied offices in the literature were predominantly private offices. However, about half of the buildings contain one or more shared offices or small open plan offices with up to nine occupants. Haldi and Robinson (2010) found that the shades of single occupancy offices were more adaptive of changing indoor illuminance levels than the double-occupancy offices. Reinhart and Voss (2003) stated that the applicability of their study is ideally used for open plan settings because people "loosen the perception of ownership over their immediate environment" under such conditions. Rubin et al. (1978) hypothesized that the social factors associated with offices with more than one occupant could impact shade movement, but were unable to test it. These research results prove that number of occupants in the office is another important aspect which can affect dynamics of their interactions with building comfort delivery systems such as window shades and electric lights, therefore, needs to be accounted for when studying human-building interactions.

Previous research has discussed the importance of cultural and social factors in the study of human-building interactions, highlighting the need for more and geographically broadly distributed office behavior monitoring campaigns (da Silva et al., 2013; Yan et al., 2015). Statistically high number of field studies have been conducted in several European countries (Haldi and Robinson, 2009; da Silva et al., 2013; Maniccia et al., 1999; Mahdavi et al., 2008; Foster and Oreszcyn, 2001; Sutter et al., 2006; Haldi and Robinson, 2010(A); Zhang and Barrett, 2012; da Silva et al., 2014) while studies in the United States are rather limited (Inkarojrit, 2005; Jazizadeh et al., 2013; Jazizadeh et al., 2014).

## 2.3 Modeling of Human Interactions with Window Shades and Electric Lights

This section provides an overview of background information on stochastic modeling of human interactions with shading and electric lighting systems and outlines important advances and limitations that guided the methodology developed in this study.

### 2.3.1 Modeling approaches

Occupant-shading interaction models have been developed upon observational studies with duration that varies between 5 days to six years and present significant variation in the selection of variables as well as model formulation and structure. In some cases, observations include occupant-shading and electric lighting interactions (da Silva et al., 2013; Reinhart, 2003) due to the obvious interdependency.

Deterministic models are used in studies of early researchers (Newsham, 1994; Lee and Selkowitz, 1994; Goller, 1998) and most of current practitioners to predict occupants' behaviors. Outcome of these models are such that probability of specific occupant behavior is zeros below a defined threshold value for predictor variable and becomes one once the variable reaches the threshold value. Later on in different observational studies it was shown that deterministic models fail in predicting the observed occupant behaviors (Inkarojrit and Paliaga, 2004; Inkarojrit, 2005; Sutter et al., 2006; Zhang and Barrett, 2012; da Silva 2013). The reason is that occupants' behaviors, although influenced by a set of definable features, are governed by a stochastic, rather than a precise deterministic relationship (Nicol, 2001).

Stochastic models estimate human-building interactions by assuming a probabilistic relationship with the predictor variable or variables. This probabilistic relationship is to capture the randomness in occupants' behaviors. Numerous researchers (Foster and Oreszczyn, 2001; Mahdavi et al., 2008; Van den Wymelenberg, 2012) proposed using linear-response (e.g. linear or polynomial regression) models, which assume a linear relationship between the response and predictor(s), to estimate the probability of the human-building interactions as a function of predictor variable(s). However, linear regression has been reported as a suboptimal method to model the human-building interactions because the linear regression model poorly predicts the upper and the lower bounds of the observations (Haldi and Robinson, 2009; Haldi and Robinson, 2010 A, Haldi and Robinson, 2011). This is due to the fact that linear-response models are not suitable for modeling response variables with non-normal distributions. Generalized linear models (e.g. logistic regression or probit) on the other hand, offer flexibility in such cases by allowing the response variables to be non-normally distributed. In generalized linear models, a linking function (e.g. logit function) of the response variable is a linear function of the predictor variables. Currently numerous researchers (Inoue et al., 1988; Rea 1984; Nicol, 2001; Clarke et al., 2006; Haldi and Robinson, 2008; Inkarojrit, 2008; Haldi and Robinson, 2009; Haldi and Robinson, 2010 A; Zhang and Barrett, 2012; da Silva, 2013; Sadeghi et al., 2016; Gunay et al., 2016) accept that logistic regression models are appropriate for estimating the probability of human-building interactions with respect to a particular predictor variable(s). With regards to the formulation, Bernoulli process (Haldi and Robinson, 2008), discrete-time Markov chain (Haldi and Robinson, 2009), and survival analysis (Reinhart, 2004; Haldi and Robinson, 2008; Haldi and Robinson, 2009) have been used previously. Most studies of human-shading interactions consider that shades are fully deployed or fully retracted although partial opening/closing events are important (Sadeghi et al. 2016) as daylight adequacy is not linearly related to shading position. The majority of the so-called stochastic models use input variables to predict the likelihood of a state change, e.g. blinds opening or closing action in the work by Haldi and Robinson (2010 A).

Recent studies (Gunay et al., 2014; Gunay et al., 2015; Yan et al., 2015; Tahmasebi and Mahdavi, 2016; Wang et al., 2016) highlight general issues and limitations associated with the development of occupant behavior models in terms of their reliability and applicability, including the validation process and the generality of estimate parameters (Yan et al., 2015). Moreover, data collection is often a costly process due to the amount of monitoring equipment and time required, while the selection of appropriate sample size for measurement duration, frequency, and the number of occupants remains an issue of debate.

To date, maximum likelihood estimation method has been used to develop classical logistic models for predicting occupants' shade raising and lowering actions (Haldi and Robinson, 2010 A; da Silva, 2013; Inkarojrit, 2008; Zhang and Barrett, 2012; Inoue et al., 1988; Rea 1984). This typically results in point estimates of the parameters without consideration of epistemic uncertainty induced by the limited availability of data. A different approach, based on Bayesian paradigm automatically incorporates epistemic uncertainties in a natural way. Probabilistic uncertainty quantification (UQ) addresses decision-making problems in a principled manner (Wald, 1956). Bayesian methods are useful in the sense that help us to combine existing knowledge (prior probability density distributions (PDFs)) with additional knowledge that is derived from the new data at hand (likelihood function). Bayes rule is used for combining prior knowledge with likelihood function, which results in the derivation of updated knowledge (posterior PDFs). These posterior PDFs can then be used as priors in subsequent analysis providing learning chains in science (Kuikka et al., 2014). The standard deviation (SD) of the posterior distribution quantify the uncertainty about the sampling distribution and is also defined as standard error (SE). The study by Lindelöf and Morel (2008) deployed the Bayesian formalism to infer the probability that any illuminance distribution should be considered by the user as visually uncomfortable. This was based on analysis of the past history of the user's interactions with the blind and lighting controls. However, Bayesian inference, despite of its advantages, has not been exploited in previously developed human-shading and lighting interaction models.

### 2.3.2 Model variables and considerations

Besides the modeling structure, selection of proper predictor variables is a critical task for developing models of human interactions with shading and electric lighting systems. In previous studies, a wide range of indoor variables was monitored to investigate the triggers of occupant interactions with shades and lights as described in section 2.1.1. Overall, findings (Haldi and Robinson, 2010; O'Brien et al., 2012) suggest that considering local stimuli (indoor illuminances) offers promise for extension to other shading and building configurations as well as façade orientation (Haldi and Robinson, 2010). However, some of the variables that have been reported to describe human-shading and –electric light interactions can be highly correlated (e.g. DGP and window luminance or solar penetration depth and indoor illuminances) and systematic selection of features is critical in order to avoid multicollinearity that may result in model inefficiency and overfitting.

The occupation dynamics was reported to be significant in the study by Haldi and Robinson (2010 A) and different models were developed for the arrival and intermediate occupation period, supported by an extended dataset corresponding to a period of six years. This approach was adopted in subsequent studies (da Silva, 2013) despite the significantly lower density of actions during the intermediate occupation period and the relatively small dataset on which the models were based. In this case, it is very likely for the model to treat the low number of actions as disturbances. That is, the model might still describe the general characteristics of the phenomenon, such as significant variables and their directional attributes, but its predictive power might drop significantly.

Beside the environmental variables, individual characteristics and human attributes, such as desire for view and connection to the outside as well as visual privacy have been reported as motives of occupant interactions with shading systems as described in section 2.1.1. However, these variables have not been incorporated as model inputs for predicting human-shading interactions.

In an attempt to represent occupants' behavioral diversity, Haldi and Robinson (2010 A) examined individual behaviors by estimating different regression parameters for all the 23 participants in the study. However, this approach only investigates variations among the observed occupants and does not provide generalized outcomes. That is, the reasoning behind the variations remains vague and related explanatory variables cannot be identified. Therefore, when applying the models to a new set of occupants in building simulation or control algorithms, it is required to randomly choose from observed behaviors, assuming transferability for individual differences. Instead, individual characteristics can be treated as model inputs in stochastic models of occupant behaviors, by deploying a consistent data collection of human attributes, in addition to the observations of human-building interactions and environmental state variables. This approach quantifies human attributes, enables classification of behaviors and as a result, improves model generality. As a first step in this direction, Inkarojrit (2005) included the sensitivity to brightness as an input variable in a shade lowering model and demonstrated improved performance.

## 2.4 Occupants' Visual Preferences

This section provides an overview of background information on observational and modeling studies of occupants' visual preferences in office environments and outlines important advances and limitations that guided the methodology developed in this study.

### 2.4.1 Observations

Studies of occupants' satisfaction with the visual environment in office spaces can be classified into two main groups. The first group focuses on examining the acceptance of automated shading and lighting controls (Reinhart, 2004; Galasiu and Veitch, 2006; Meerbeek et al., 2014; Bakker et al., 2014; Konis, 2013) and field studies report that automation systems are not well received unless occupants' preferences are somehow included within the control loop. The second group, where the objectives of thi thesis lay in, investigates occupants' visual environment preferences and satisfaction as it relates to the underlying variables such as environmental, physiological, and psychological factors. Important aspects of data collection are the *measurement* of environmental variables such as indoor illuminances, luminance variation in the field of view, etc., and the *observation* of occupants, that may include online surveys (de Korte et al., 2015; Sadeghi et al., 2016; Konis, 2013) or their interactions with building systems such as window shades and electric lights, e.g. manual controls, overrides on system controls using web-enabled interfaces, etc. (Gunay, 2017; Lindelöf and Morel, 2008; Despenic et al., 2017; Meerbeek et al., 2014; Bakker et al., 2014; da Silva et al., 2013; Sadeghi et al., 2016; Zarkadis, 2015). Personalized adaptive controls have been explored by inferring occupants' preferences from their interactions with shading and lighting systems, aiming to improve their satisfaction with the visual environment while reducing energy consumption (Guillemin and Molteni, 2002; Gunay et al., 2017; Gunay et al., 2014; Guillemin and Morel, 2001). Learning is associated with adapting parameters in a model or a control logic based on data collected from an individual occupant. As such, the learning approach is essential and determines the effectiveness of this solution, since system control is based on the learning outcomes. Nonetheless, developing visual preference profiles may require information that can be difficult to collect from occupants in real buildings.

Previous research has shown that lighting preference is perception-based and as such, differences at preferred illuminance levels are to be expected between individuals (Nabil and Mardaljevic, 2006; Lindelöf and Morel, 2017; Reinhart, 2004; Yan et al., 2015; Despenic, 2017; Haldi and Robinson, 2010(A), Nicol et al., 2006; Moore et al., 2002; Moore et al., 2003; Galasiu and Veitch, 2006). Occupant preferences for light levels have been studied by considering the indoor illuminance as an important characteristic of the visual environment. Work plane (horizontal) illuminance has been widely investigated, since it is the simplest measure, and generally preferred ranges are reported (Sadeghi et al., 2016; Konis, 2013; IESNA, 2012; Rea, 2000; Escuyer and Fontoynont, 2001; Begemann et al., 1997; Halonen and Lehtovaara, 1995; Laurentin et al., 1998; Laurentin et al., 2000; Roche et al., 2001). These studies introduce a broad range of work plane illuminance up to 1000 lux as occupants' general preference for light level while suggesting values higher than 1000 lux to be less frequently preferred. However, research findings suggest that occupants' visual preferences cannot be predicted solely based on work plane illuminance but the effect of several –indoor and outdoor- environmental variables that define the visual environment, as well as physiological, psychological and contextual factors associated with space layout, shading/lighting/glazing systems, etc. (Galasiu and Veitch, 2006, sahin et al., 2014; Borisuit et al., 2014; O'Brien and Gunay, 2014; de Korte et al., 2015). Recent studies have emphasized on the complexity of user satisfaction and occupant perceived control of daylighting/shading systems for that reason (Meerbeek et al., 2014; Bakker et al., 2014; da Silva et al., 2013; Sadeghi et al., 2016). In previous research on occupant visual environment, the preferred type of lighting (natural versus artificial) has been investigated and it has been widely reported that people believe daylight is superior to electric lights in terms of its positive effects on humans (Cuttle, 1983; Heerwagen and Heerwagen, 1986; Veitch et al., 1993). Window characteristics and properties (size, number, position in wall, and degree of transparency) have been also investigated by researchers to identify occupant preferences towards these physical features that affect the visual environment (Ne'eman and Hopkinson, 1970; Keighley, 1973(A); Keighley, 1973(B); Wotton and Barkow, 1983; Butler and Biner, 1989; Boubekri et al., 1991; Leather et al., 1998; Christoffersen et al., 2000). These early studies also introduce outside view as an important aspect. Connection to outdoors includes the quality (Hellinga and Hordijk, 2014), quantity, and clarity of outside view which is directly related to window and shading optical characteristics (Konstantzos et al., 2015(B)). Outside view has been reported to influence occupants' visual satisfaction and the perception of glare (Aries et al., 2010; Tuaycharoen and Tregenza, 2007). Similar findings also indicate impacts of the connection to outdoor on well-being, job stress, and health recovery (Leather et al., 1998; Shin et al., 2012; Raanaas et al., 2012).

### 2.4.2 Modeling

Using results of field studies, researchers have attempted to evaluate occupants' visual discomfort that is attributed to glare (Wienold and Christofferson, 2006) and unsatisfactory illuminance levels (CIE, 1992). Although daylight discomfort glare has been extensively studied in the past few years, there is a lack of studies on occupant satisfaction towards the overall visual environment in daylit spaces.

Lindelöf and Morel (2008) used the observations from 20 office rooms to develop a general visual discomfort model. It was assumed that human interactions with building systems that alter the visual environment, such as window shades and electric lights, could be an indication of visual discomfort. In this approach, the authors used a Bayesian binary classifier to model whether any given visual condition was comfortable for the occupants. Similarly, Zarkadis (2015) used a Hidden Markov Model (HMM) to develop a three-state model. In their HMM framework, the Markov process includes observable outputs (indoor illuminance) which are dependent on hidden states (comfort state: comfortable, uncomfortable due to insufficient illuminance, uncomfortable due to excessive illuminance). Despite the apparent strengths of these models, the followings could be pointed out as opportunities for improvement:

(i) Data collection and assumptions: Occupants' perception towards the visual environment (discomfort or illuminance thresholds) is inferred from their interactions with shading and electric lighting systems by making explicit assumptions about the trigger and state transition. Use of web-enabled interfaces (Sadeghi et al., 2016) can facilitate information acquisition for the reasoning of the interaction along with other triggers such as the need for having outside view (Haldi and Robinson, 2010(A); Sadeghi et al., 2016; Inoue et al., 1988; Foster and Oreszcyn, 2001; Reinhart and Voss, 2003; Inkarojrit, 2008; Mahdavi et al., 2008; Zhang and Barrett, 2012) or the long term perception of weather/incident solar radiation (Rea, 1984).

(ii) Model variables: The work plane illuminance is the only variable from the visual environment which has been used in the developed models to describe visual comfort. This is while other variables such as vertical illuminance at eye level, window and background luminance, solar penetration depth and window view (unshaded portion) can also influence the visual perception.

(iii) Model implementation: The outcome of the binary visual discomfort model developed by Lindelöf and Morel (Lindelöf and Morel, 2008) represents the probability of being uncomfortable while the reason for the discomfort is not clear. The three-state model developed by Zarkadis (2015) is improved as it indicates the probability of discomfort due to low or high illuminance. In any case, modeling satisfaction with the visual environment without extracting conclusions from discomfort-based assumptions is desired.

Furthermore, considering feedback from a large number of occupants is necessary for developing stochastic models for general visual comfort or preferences. Personal differences have been pointed out in (Lindelöf and Morel, 2008; zarkadis, 2015) which were based on observations from 20 offices half of which were occupied by a single user and the other half with two. These differences, however, were not explicitly considered within the general model structure. A recent study (Despenic et al., 2017) presents a clustering method for occupants' attitudes towards electric lighting conditions in open-plan office spaces based on observations from 16 occupants. Classification of activeness (level of activity of each user determined by the number of occupant controls) and dominance (fraction of time electric light levels match occupant lighting preference) was conducted based on the authors' assumptions of threshold values for these features. However, the number of clusters for tolerance (determined based on the breadth of illuminance range acceptable by occupant) and lighting preference are not known a priori. Therefore, the K-means clustering algorithm along with *silhouette* criterion has been used to find the number of clusters for these factors. This study is a first step towards the classification of occupant lighting preferences, but it is subjected to limitations of the selected clustering method. More specifically, K-means clustering does not provide probabilistic outcomes to account for the stochastic nature of occupants.

In other observational studies, it was attempted to cluster occupants into passive and active users based on the frequency of their actions on building systems (Reinhart, 2004; Rijal et al., 2007;

Parys et al., 2011). Nonetheless, as a compromise, a few studies account for the diversity of occupant behaviors through probabilistic models that allow for probabilistic distributions of model coefficients (Sadeghi et al., 2017; O'Brien et al., 2017; Haldi et al., 2016).

# CHAPTER 3. OCCUPANT INTERACTIONS WITH SHADING AND LIGHTING SYSTEMS USING DIFFERENT CONTROL INTERFACES: A PILOT FIELD STUDY

## 3.1 Overview

This chapter presents a field study on human interactions with motorized roller shades and dimmable electric lights in private offices of a high performance building. The experimental study was designed to (i) extend the current knowledge of human-building interactions to different and more advanced systems, including intermediate shading positions and light dimming levels, and (ii) reveal behavioral characteristics enabled through side-by-side comparisons of environmental controls ranging from fully automated to fully manual and interfaces with low or high level of accessibility (wall switch, remote controller and web interface).

## 3.2 Methodology

The field study was designed to address the following set of key research questions:

1. How do occupants interact with motorized roller shades and dimmable electric lights using different control interfaces (including manual operation modes and overrides on automated operation)? What are the resulting shade positions and electric light levels?
2. What are the underlying physical and non-physical variables for describing human interactions with motorized shading and electric lighting systems?
3. What are the preferred visual conditions in offices with different shading and lighting control setups?
4. What are the effects of shading and lighting control setups on occupant visual comfort and satisfaction with the indoor environment?

## 3.3 Field Study Details

### 3.3.1 Building description

Four identical south-facing private offices (3.3m×3.7m×3.2m high) in a new high performance building (Herrick Laboratories) located in West Lafayette, Indiana, were selected for the purpose of this study. The building was awarded LEED Gold certificate in 2013. A Building Management

System (BMS) is available through the installed Tridium JACE controllers and Niagara/AX software framework, which in addition to a variety of internet-enabled features gives the ability to monitor, control, and automate all the building systems regardless of manufacturer or communication protocols. Figure 3.1 shows the arrangement of the monitored offices. The offices have 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 windows are equipped with dark-colored motorized interior roller shades that have a total visible transmittance equal to 2.53% (measured with an integrating sphere) and an openness factor of 2.18%. The low openness factor combined with the low visible transmittance was a decision to reduce daylight glare (Chan et al., 2015), while the dark color is associated with clearer view to the exterior (Konstantzos et al., 2015(B)). Each office has two electric lighting fixtures with two 32-watt T5 fluorescent lamps (total of 128 watts). During the field study, the temperature in each office was well kept within ±0.5 $^{o}$C of the set point using feedback from two sensors installed close to the person. This is only important for ensuring that there were no other thermal impacts potentially affecting human interaction with shading.


Figure 3.1 The four offices used in the study

### 3.3.2 Office control setups and interfaces

Four different arrangements (control setups) were considered to investigate human-building interactions with shading and lighting in the offices:

- Setup 1: Manual control with low level of accessibility (wall switches)

In this setup, participants used commercially available wall switches (Figure 3.2, left) 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.

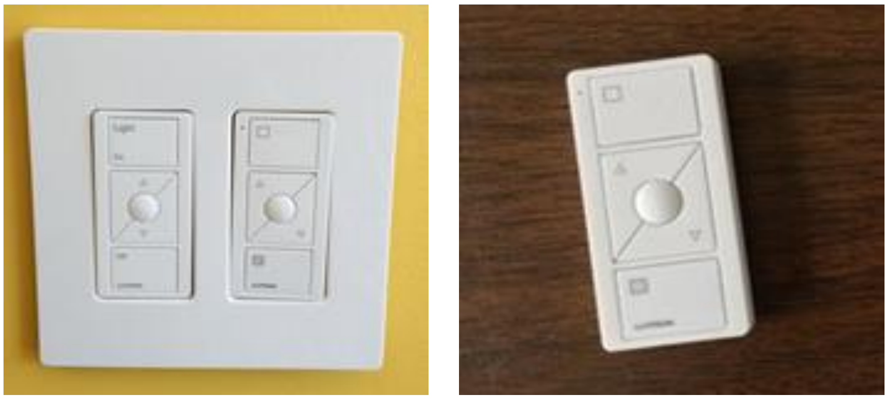

Figure 3.2 Wall switches for manual control of electric lights and roller shades (left); remote controller for shading control in setup 4 (right)

- Setup 2: Manual control with high level of accessibility (web interface)

  In this setup, participants used a modular web-based graphical interface (designed by the authors) to control shade position and electric lighting levels. Usability tests of the interface were performed in a preliminary study before starting the main monitoring campaign. Figure 3.3 presents the graphical interface in its final design form (note that occupants were also able to change thermostat set points but this aspect is outside of the scope of this study). Participants could use sliders or click on buttons to control roller shade position (right side) and electric light levels (left side) in 25% increments.

  As shown in Figure 3.3, other important features (that proved to be critical) were designed on the interface. These include 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. The selection of non-physical triggers included on the interface was based on a preliminary study before the main monitoring campaign, which was done with a small group of participants. This revealed that “increasing visual privacy”, “getting a better outside view”, and “increasing room spaciousness” were the most important non-physical drivers of human-shading interactions.

The interface features and the way data was collected is crucial for understanding the triggers of human interactions. This was achieved by collecting information when those interactions occur, i.e. participants moved the comfort sliders right before taking any action. In addition, they only moved the reasoning slider before moving the shades, based on one of the indicated reasons; otherwise, the slider would remain untouched. The sliders incorporated a snapping feature, which was designed to bring the slider back to its default position (in the middle for comfort sliders and at the left end for the reasoning slider) three minutes after each movement. All comfort votes and actions were continuously monitored. The developed web interface is a first step towards standard methods for studying human interactions with building systems in a consistent and reliable way.

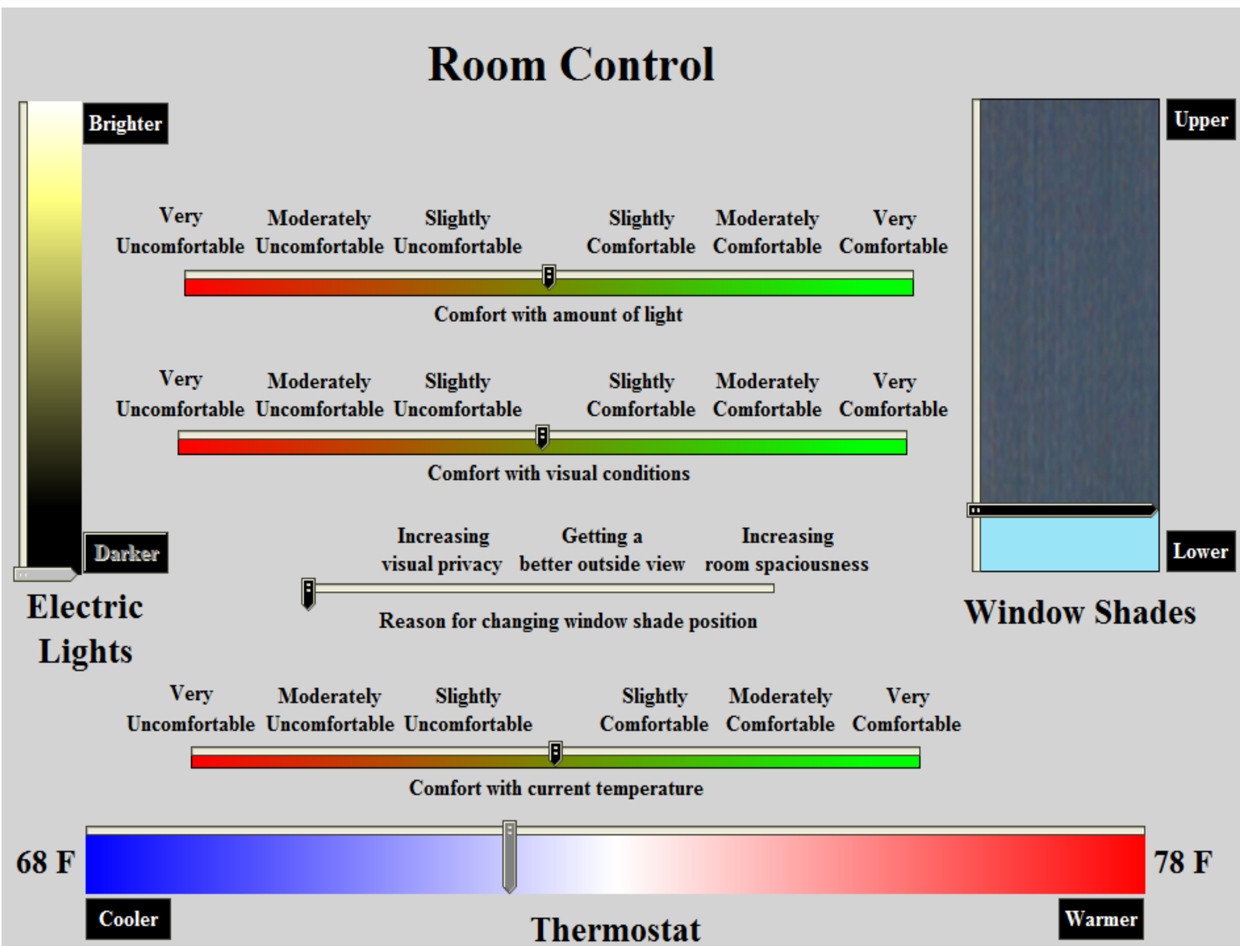


Figure 3.3 The modular web-based graphical interface for environmental controls in setup 2

- Setup 3: Fully automated control

  In this setup, occupants did not have any control over their environmental conditions. Roller shades were controlled automatically 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. This operation depends on the solar path and the room orientation (Shen and Tzempelikos, 2012; Lutron Electronics Co. Inc.); having intermediate positions is better than fully opening/closing shades, since it allows more daylight and outside view. Electric lights were automatically controlled in order to always provide 500 lux on the work plane, using a commercially available ceiling daylight sensor.

- Setup 4: Automated control with manual overrides

  In this setup, shading and lighting were automatically controlled as in setup 3, but occupants could override the shade position using a remote controller (Figure 3.2, right). The controller had buttons for completely opening/closing shades as well as for continuous intermediate positions, by holding the increase/decrease buttons and releasing them once the desired position was reached. The automatic control was disabled for 15 minutes after each override and then enabled again.

  Upon arrival in the morning (9:00 am), the room air temperature was 22 $^{o}$C in all offices. Occupants could precisely control the room temperature in all manual setups (using a wall switch in setup 1 and the web interface in setups 2 and 4) -the Variable Air Volume (VAV) system in each office was fine-tuned for that reason. In setups 3 and 4, the initial shading position upon arrival was set automatically following the control logic described above, and electric lights were initially turned off. In setups 1 and 2, where there was no automatic control, different initial conditions for the roller shade position and electric light levels were implemented over the course of the study. However, to enable side-by-side comparison between setups 1 and 2, the same initial conditions were used in these two setups every day.

### 3.3.3 Instrumentation, physical data acquisition, and communications

This section presents the data acquisition framework designed to investigate occupant interactions with shading and lighting systems. This includes the sensors used to monitor physical variables and the communication protocols for actuation and operation status of the building systems. The following physical variables were monitored during the field study:

- Shade position, electric light levels, and room temperature set point: shading and lighting systems in the building were connected to a lighting control hardware. VAV boxes, with thermostat set-point information, were connected to thermal systems controllers. Both control hardware communicate with the building's JACE controllers through the Niagara framework (Tridium Inc.) and BACnet protocol.
- Occupancy: wireless vacancy sensors connected to lighting controller were used to monitor and store the state of occupancy in each room and as mentioned above, lighting control hardware communicates with building JACE controllers and Niagara framework. All other sensors described below were connected to national Instrument (NI) data acquisition input modules, and through a wireless connection, to the NI main data acquisition (DAQ) controller, which communicates with JACE controllers through the Niagara framework and Modbus protocol.
- Work plane illuminance: measured using one LI-COR 210-SL photometric sensor in each office. Facing upwards, the sensor was located on the desk and in a central position of occupant working area. Occupants were advised to keep the sensor unobstructed. All illuminance sensors had an accuracy of 3%.
- Work plane daylight illuminance: calculated from the difference between measured total work plane illuminance and work plane illuminance due to electric lighting (the latter measured separately at night).
- Vertical illuminance (near eye level): measured using LI-COR 210-SL photometric sensors mounted vertically (on the camera) adjacent to the occupant's head (30 cm away) to capture representative values without obstructing their actions.
- Transmitted global solar radiation through window: measured using a LI-COR 200-SL pyranometer vertically mounted on the inside of the glazing, facing outside. The sensor had a resolution of 0.1 W/m$^2$ and accuracy of 3%.
- Transmitted illuminance through window: measured using a LI-COR 200SL photometric sensor vertically mounted on the inside of the glazing, facing outside, next to the pyranometer.

Average window and background luminance: a calibrated dSLR camera (Canon T2i) equipped with fisheye lenses (Sigma 4.5) was mounted at 30 cm from the occupants' head in each office to capture the luminance distribution within their visual field, using HDR imaging. This methodology is based on previous work on Daylight Glare Probability or DGP (developed by Wienold and

Christoffersen, 2006) that was analyzed for the case of roller shades by Konstantzos et al., 2015(A) and Chan et al., 2015, proposing alternate criteria for the case of low openness fabrics. To avoid manual operation and occupant distraction, a firmware (Magic Lantern, 2013) was used with the cameras to automate the shooting sequence. To extract the average luminance of the visible part of the window, the respective area was masked from the HDR images using Adobe Photoshop and then used as input for Evalglare (Wienold, 2012) marking the area of interest as a glare source. This enabled the software to output the average luminance of the area of interest, in addition to the average luminance of the entire visual field. Due to the large number of data throughout the experiment, automation scripts were created for running all the necessary image-processing routines involved. Cameras were calibrated using a Konica LS-100 luminance spot meter and a Macbeth Color Chart, extracting the response curve. As the cameras were located close to the subject's head, it was of the essence to create the least possible distraction, a goal that affected both the number of LDR photographs consisting each HDR image, decided to be 5, and the period between each shooting sequence, decided to be 15 minutes. For that reason, Magic Lantern firmware (2013) was used in the cameras to automate the shooting sequence. The LDR photographs were merged into HDR images using the response curve of Figure 3.4 along with the HDRgen UNIX command line tool and an automation script to handle the high number of measuring instances throughout the whole experiment. As wider apertures are responsible for more controlled light penetration in the sensor, leading to less apparent vignetting distortions (Inanici and Galvin, 2004), an aperture of F11 was used for all the photographs. Authors assumed that with a wide aperture of F11 and by applying the generic correction included in the firmware of the camera, vignetting errors would be negligible, an assumption which was confirmed by evaluating the extent of vignetting as suggested by Inanici and Galvin (2004). Validation of the calibration performed with the luminance spot meter could be case sensitive, depending on the target chosen. For that reason, a side-by-side comparison of vertical illuminance values was performed, using the values extracted by the HDR images through Evalglare and the values recorded by either the photometers or Konica T10 illuminance sensors, attached on the top of the lens and having the same measuring span as the camera. The results showed a good calibration fit, including some outliers that are always present in HDR approaches (Figure 3.5).

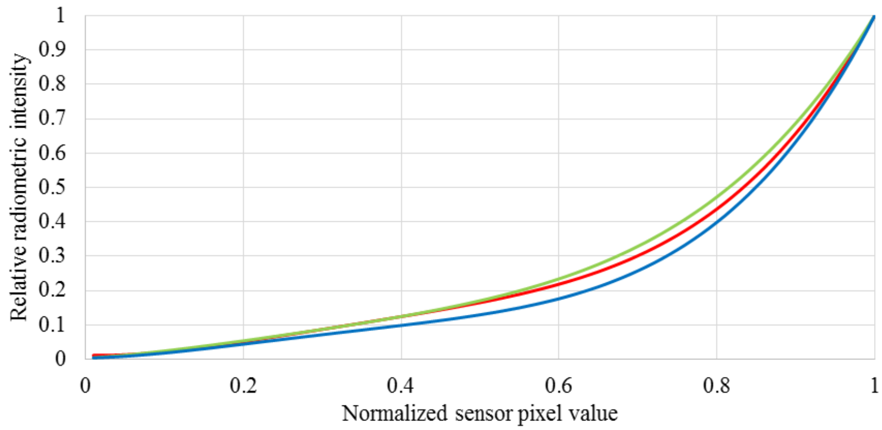


Figure 3.4 Extracted response function for the combination of camera and lens

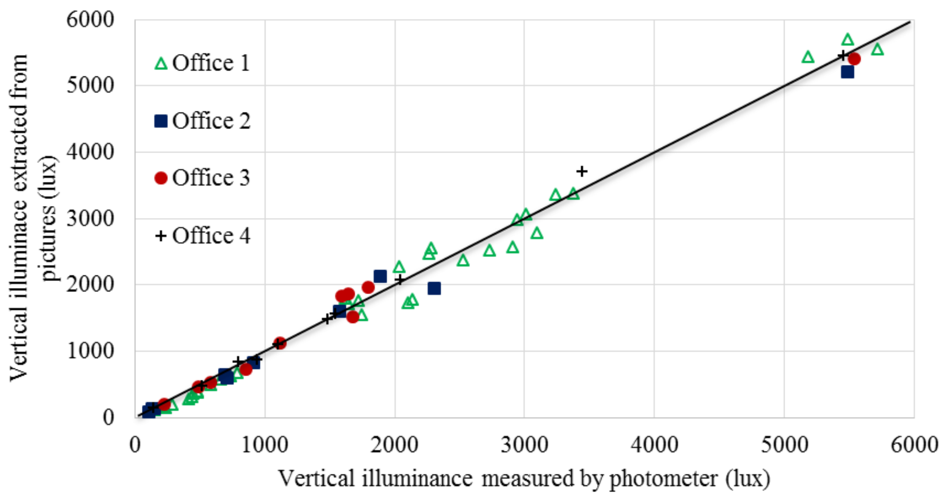


Figure 3.5 Validation of illuminance readings from the camera

- Daylight Glare probability: DGP was calculated by processing the HDR images in Evalglare. There were some differences in terms of focus area between different subjects as some participants were also using their laptop screens along with the monitors provided. Therefore, the glare source identification method was based on the average luminance of the entire visual field rather than the task areas.
- Indoor air temperature: two shielded J-type thermocouples (resolution of 0.01 $^{o}$C, 0.4% accuracy) were mounted in each office at seating height and on two sides of occupant regular work position. The average reading of the two is used to reduce the influence of spatial temperature distribution.

Figure 3.6 shows a typical layout with part of the monitoring instrumentation described above. The seating position of the occupant, with partial window view (wall-facing office layout), which represents a typical setting for office environments, along with the location of sensors and control devices are shown in Figure 3.7. The framework of sensor integration to Building Management System (BMS) is presented in Figure 3.8. Measurements of relative humidity, globe and room air temperature were included to ensure proper equipment operation. Using proper communication protocols, all sensor readings were discovered in Niagara framework and recorded every five minutes; DGP and luminance data were measured every 15 minutes.

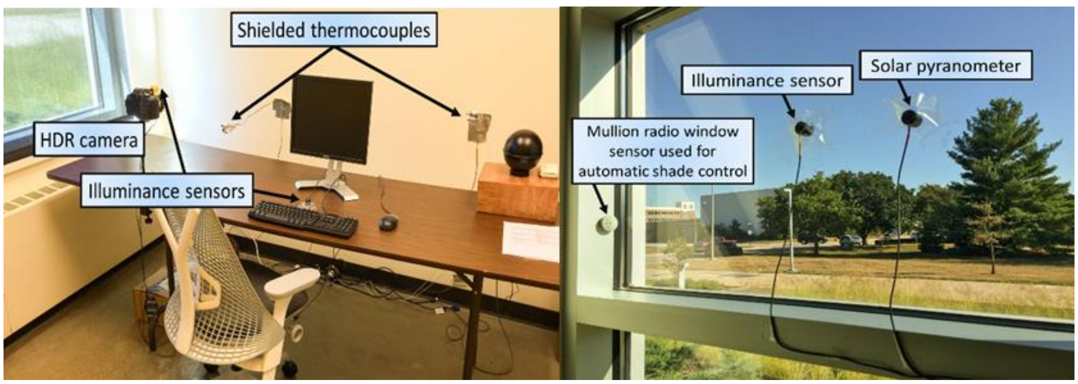


Figure 3.6 Typical layout of monitoring instrumentation in each office

### 3.3.4 Occupant surveys

Two types of web-based survey questionnaires were designed in order to capture data that are not measurable with sensors. Survey-A includes questions about both human-building interactions and occupant satisfaction with indoor environment and was completed four times a day. A six-point scale from "very uncomfortable" to "very comfortable" was used, while a seven-point Likert scale was utilized for questions related to satisfaction with window view and overall lighting conditions. Survey-B refers to personal characteristics and attributes. Survey questionnaires were sent to participants at specific times during the day. Occupants were reminded to answer the web surveys by phone alarms set in the morning. Table 3.1 presents a summary of the survey questions.

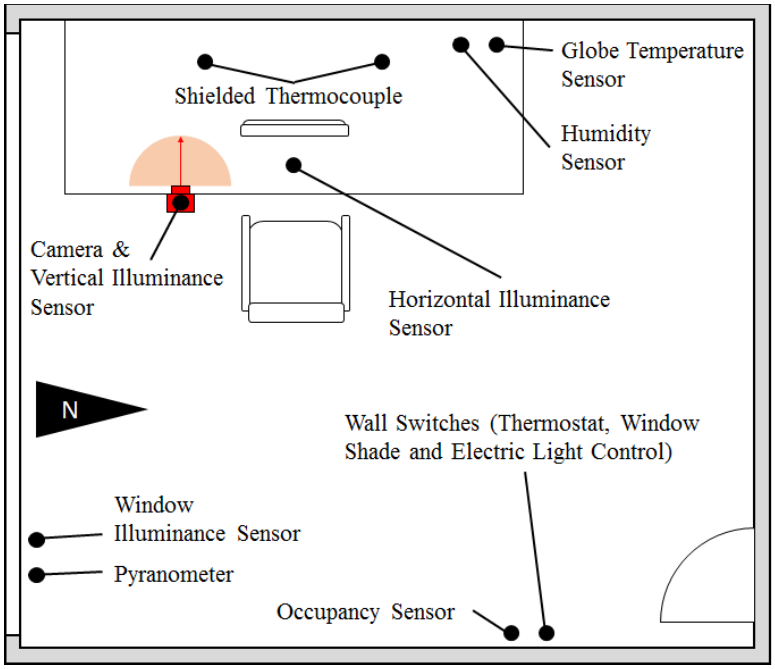


Figure 3.7 Schematic view of identical offices showing occupant's seating position, location of sensors and control devices

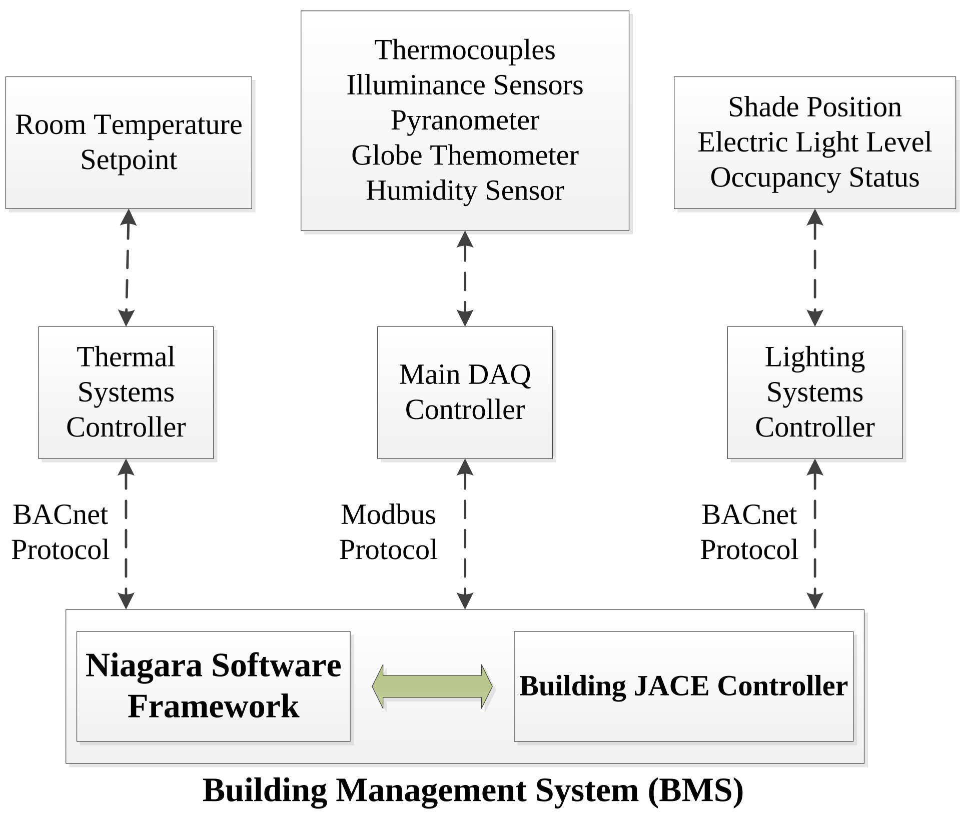


Figure 3.8 Sensor integration to BMS

Table 3.1 Summary of survey questionnaires

| **Questions** | **Answer options** |
|---|---|
| **Survey A** | |
| 1a) Did you lower/close roller shades during last section? | Yes/No |
| 1b) If yes, what was the reason for that? | To increase visual privacy<br>To reduce overall brightness of workspace<br>To reduce glare on computer screen<br>To reduce glare on the desk<br>To reduce glare on the floor<br>To reduce glare from the sun (directly into my eyes)<br>To reduce heat from sun<br>Other, (please specify) |
| 2a) Did you raise/open roller shades during last section? | Yes/No |
| 2b) If yes, what was the reason for that? | To get a better outside view<br>To increase room spaciousness<br>To increase level of daylight in workspace<br>To get heat from sun<br>Other, (please specify) |
| 3a) Did you adjust electrical lights during last section? | Yes/No |
| 3b) If yes, what was the reason for that? | To reduce overall brightness of workspace<br>To reduce glare on computer screen<br>To reduce glare from electrical lights (directly into my eyes)<br>To reduce heat from electrical lights<br>To save energy<br>To increase level of lights in workspace<br>To make interior surfaces (walls, ceiling etc.) almost as bright as window<br>Other, (please specify) |
| 4) How comfortable are you with current amount of light? | 1. Very uncomfortable, 2. Moderately uncomfortable, 3. Slightly uncomfortable, 4. Slightly comfortable, 5. Moderately comfortable, 6. Very comfortable |
| 5) How comfortable are you with current visual conditions (e.g. glare, reflections, and contrast)? | 1. Very uncomfortable, 2. Moderately uncomfortable, 3. Slightly uncomfortable, 4. Slightly comfortable, 5. Moderately comfortable, 6. Very comfortable |
| 6) How satisfied are you with your current window view? | 1. Very dissatisfied, 2. Moderately dissatisfied, 3. Slightly dissatisfied, 4. Neutral, 5. Slightly satisfied, 6. Moderately satisfied, 7. Very satisfied |
| 7) Please describe the current lighting condition at your workspace | 1. Very dark, 2. Dark, 3. Slightly dark, 4. Neutral, 5. Slightly bright, 6. Bright, 7. Very bright |
| **Survey B** | |
| 1) In general how important is it for you to have a clear view to outside? | 1. Least important … 5. Most important |
| 2) In general how important is it for you to have visual privacy? | 1. Least important … 5. Most important |
| 3) In general how sensitive are you to brightness? | 1. Least sensitive … 5. Most sensitive |
| 4) In general what is your preference for lighting conditions at your work space? | 1. Very dark, 2. Dark, 3. Slightly dark, 4. Neutral, 5. Slightly bright, 6. Bright, 7. Very bright dark |
| 5) Overall, how would you rate your today's work productivity? | 1. Poor, 2. Fair, 3. Good, 4. Very good, 5. Excellent |
| 4) What is your gender? | Male/female |

### 3.3.5 Experimental procedure

The field study was conducted over a period of 40 days (9:00 am – 4:00 pm), covering a wide range of sky conditions (Figure 3.9) and solar paths between April 1$^{st}$ and June 15$^{th}$ 2015 (including 22 sunny days, 10 cloudy days, and 8 mixed sky days). Overall, 147 office occupants participated in the field study (98 males and 49 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. 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.). This would create realistic occupation dynamics and would allow investigation of its impacts on human-shading and –electric lighting interactions. To enable side-by-side comparisons, contextual factors such as monitor type and size, monitor position, seat position, sensor positions, office desks, and other furniture were identical in the four offices. The only difference was the control interface provided to participants for interacting with shading and electric lighting systems. At the beginning of the day, details regarding the environmental control setups were explained thoroughly to each participant in order to help them become quickly familiar with the setup. 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.

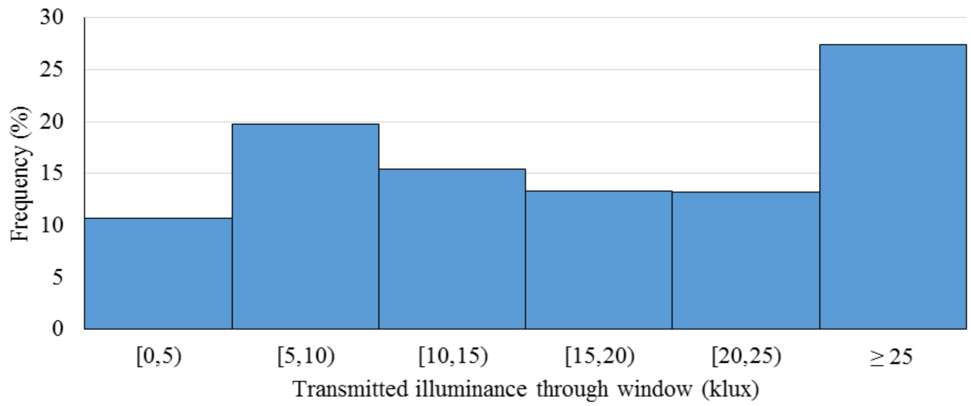


Figure 3.9 Frequency distribution of measured transmitted illuminance through the window during the field study

During the preliminary phase of the field study (before starting the main monitoring campaign), the impact of test duration, in terms of the number of days that human test-subjects stay in the office, was examined to ensure that occupant interactions with building systems would be consistent when human test-subjects stayed more than one day in the office. For this purpose, human test subjects attended the same office with the same control setup for three consecutive days and their interactions were monitored. Consistent behaviors were observed for all participants during this test. Representative results (Figures 3.10 and 3.11) show the work plane illuminance along with the selected shade position by a human test-subject for three consecutive days in control setup 2. For example, it is clear from Figure 3.10 that this participant preferred a slightly dark lighting condition at his/her workspace and interacted with building systems accordingly on all three days. The average value of work plane illuminance remained in the same range between the days. The occupant's preference towards dark conditions was also reflected by the answer to a question in the online survey asked at the end of day three (In general, how would you prefer the lighting conditions at your workspace? 1. Very dark … 7. Very bright). Similarly, as shown in Figure 3.11, the participant preferred moderately bright conditions on all three days. Therefore, occupants showed consistent behavior in all consecutive days and our findings also support the conclusions made in previous studies (Rubin et al., 1978; Hunt, 1979; Rea, 1984; Inoue et al., 1988; Lindsay and Littlefair, 1993; Love, 1998; Maniccia et al., 1999; Reinhart and Voss, 2003; Reinhart, 2004): Even though occupants behave differently, they use their lighting and blind controls consciously and consistently. In addition, comparisons of our findings in terms of daily human-shading interactions with those reported in previous studies (Bakker et al., 2014; Meerbeek et al., 2014; Kim et al., 2009) that investigated motorized shade movement rates in office spaces (reported in Section 4.2.1) indicate good agreement, despite of the differences in the duration of stay of the occupants in the offices. Similarly, good agreement is found with results reported in (Inoue et al., 1988; Reinhart and Voss, 2003; Haldi and Robinson, 2010(A); da Silva et al., 2013) regarding the significance of occupation dynamics for interactions with shading and lighting systems. Therefore, it is anticipated that the results of this study are representative of typical office occupants. The field study with human subjects was approved by the Institutional Review Board (IRB Protocol #: 1503015873).

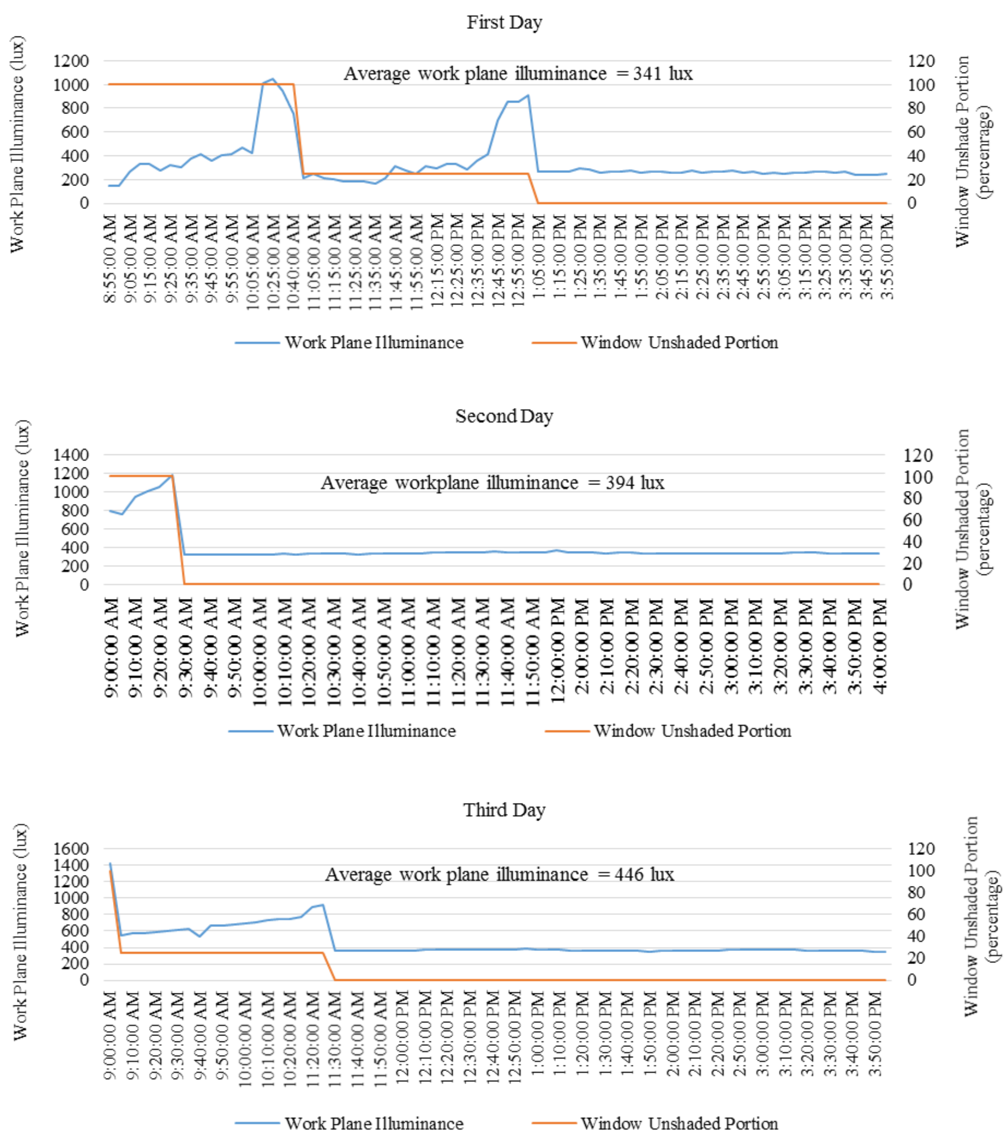


Figure 3.10 Investigating the consistency in human-building interactions in control setup 2 (lighting preference: slightly dark)

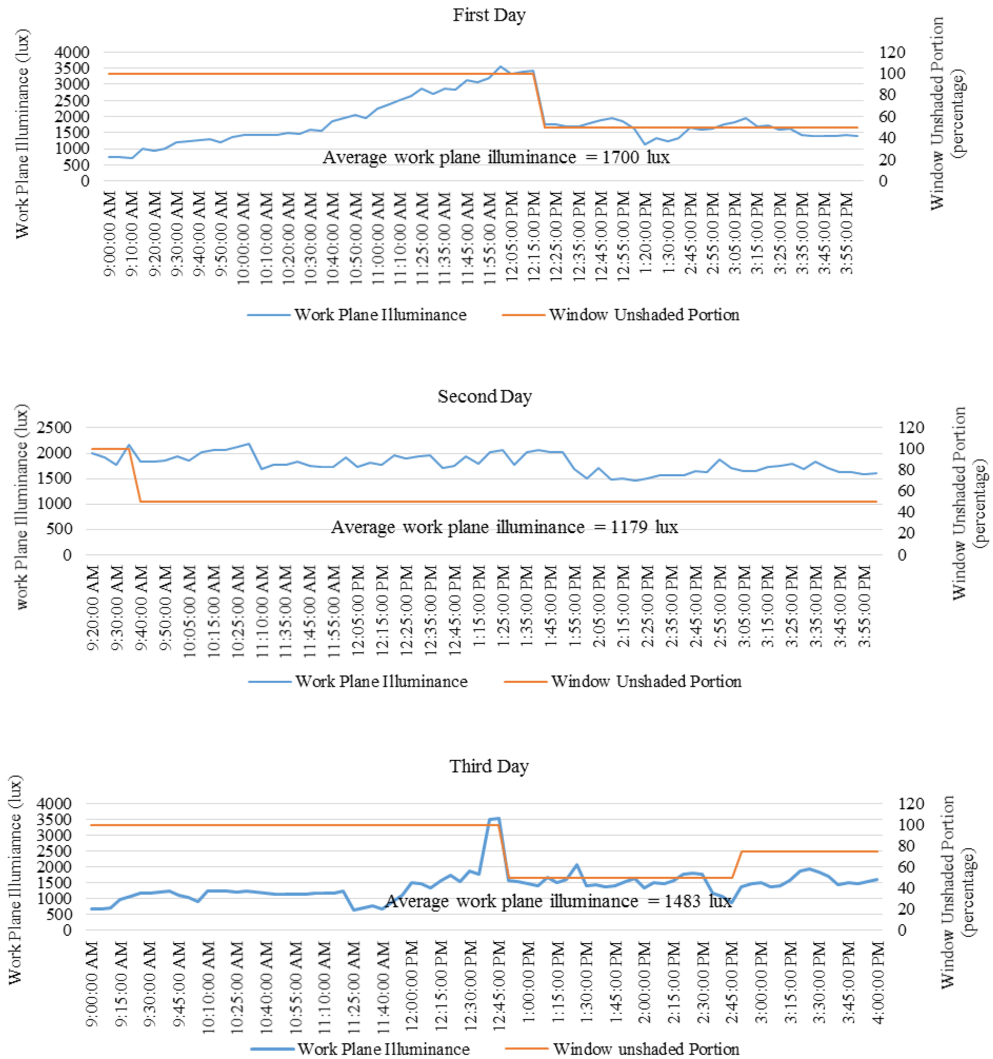


Figure 3.11 Investigating the consistency in human-building interactions in control setup 2 (lighting preference: moderately bright)

## 3.4 Results

This section presents the experimental data from the monitoring campaign structured to address the set of key research questions presented in Section 3.2.

### 3.4.1 How do occupants interact with motorized roller shades and dimmable electric lights?

3.4.1.1 Interactions with motorized roller shades

Table 3.2 presents the summary of test cases under different sky conditions and metrics for interactions with motorized shades for each control setup. It should be noted that setups 1 and 2 were examined throughout the whole period of the field study with the same outdoor conditions. To increase the number of observations in control setup 2, this setup was sometimes used in multiple offices during the field study, resulting in 54 cases with different participants. Setup 4 was evaluated for a shorter period. For the results presented in Table 3.2, the same percentages of sunny/cloudy/dynamic days were considered for setups 1, 2 and 4, representing statistically equivalent conditions in order to enable meaningful comparisons.

A total number of 53 shading adjustments were recorded when occupants had to use the wall switch (setup 1) to control the motorized roller shade (1.36 shade adjustments/day on average). These results are in agreement with other studies (Bakker et al., 2014; Meerbeek et al., 2014; Kim et al., 2009) that investigated motorized shade movement rates in office spaces. A significantly higher number of interactions (2.63/day) was observed when the web interface was used (setup 2), proving that the ease of control access results in increased interactions with motorized shading (or more generally, reduces the effort required to control/improve indoor environmental conditions). This is also the reason why the shade movement with wall switches presented here is still higher than what has been reported in studies with non-motorized manual shading devices, operated by turning a rod, pulling a chain or cord (Rea, 1984; Inoue et al., 1988; Lindsay and Littlefair, 1993; Inkarojrit, 2005; Zhang and Barrett, 2012; da Silva et al., 2013; da Silva et al., 2014). Raising and lowering could happen in 25% increments with setups 1 and 2; but with setup 4 (overrides to automated control), all intermediate positions were available using the remote controller. The rate of occupant overrides (2.24/day on average) in this case is an indication of the desire to have personalized control over the luminous environment.

Table 3.2 Observed shading system events

| | **Control setup 1 (wall switches)** | **Control setup 2 (web interface)** | **Control setup 4 (automated shades/remote controller overrides)** |
|---|---|---|---|
| **Total number of tests** | 39 | 54 | 25 |
| **Tests during sunny days** | 21 | 31 | 14 |
| **Tests during cloudy days** | 10 | 11 | 5 |
| **Tests during mixed sky conditions** | 8 | 12 | 6 |
| **Total number of human-shading interactions** | 53 | 142 | 56 |
| **Average number of daily human-shading interactions** | 1.36 | 2.63 | 2.24 |
| **Number of shade raising events** | 31 | 61 | 30 |
| **Number of shade lowering events** | 22 | 81 | 26 |

Figure 3.12 (top) shows the frequency of shade positions selected with control setups 1 and 2. Motorized shades remain in intermediate positions for a considerable amount of time; therefore, studies investigating only fully open/closed positions may not be adequate. This is more pronounced in setup 2 (web interface with easier access) where occupants tend to fine-tune their environmental conditions through a higher number of interactions with shading and selection of intermediate positions. Consequently, control interfaces play an important role in both the number of interactions and selected shade positions, which have a profound effect on energy use.

3.4.1.2 Interactions with dimmable electric lights

The frequency of selected light levels is depicted in Figure 3.12 (bottom). On average, occupants adjusted their electric lights 1.33 times per day using wall switches and 1.52 times per day using the web interface. Higher frequencies of intermediate light levels with setup 2 show the desire towards improving environmental conditions when exposed to easy-to-access and high-level personalized controls (web interface). Moreover, for both interfaces, the high frequency of keeping electric lights off and interacting with motorized shades implies that occupants prefer natural light –nevertheless, this statement should be interpreted cautiously as shading interactions might be triggered by other non-physical variables (e.g. visual privacy, outside view), rather than desire for daylight as explained in sections 3.4.2 and 3.4.3.

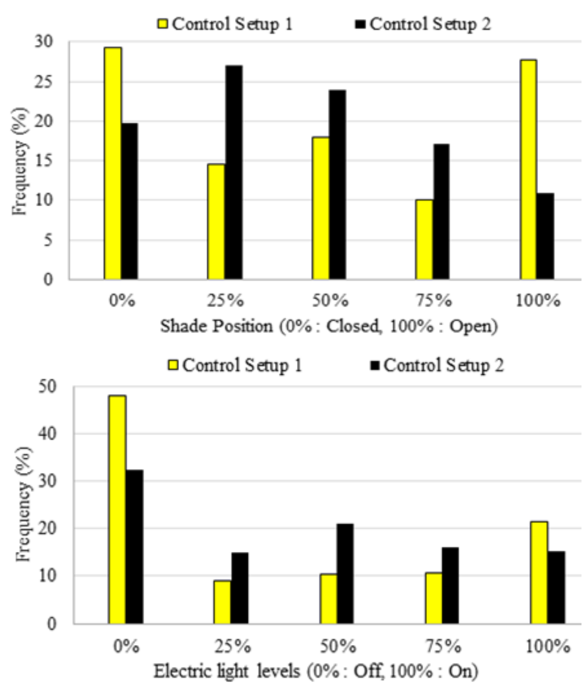


Figure 3.12 Frequency of selected shade positions (top) and electric light levels (bottom) with control setup 1 (wall switches) and control setup 2 (web interface)

### 3.4.2 What are the underlying variables for describing human interactions with shades and lights?

3.4.2.1 Environmental variables and modeling considerations

Human interactions with shading and lighting systems are governed by a combination of variables (physical and non-physical) rather than a single variable, some of which might be affecting each other's attribute in explaining the interactions (dependent variable in statistical terms) within a network structure. Table 3.3 presents Pearson correlation coefficients between nine physical variables and corresponding changes in the operation status of roller shades and electric lights based on the data collected from control setup 1 and 2 (results for the two setups were similar to each other, therefore only one correlation coefficient is shown for each variable). It is clear that indoor illuminances and solar penetration depth show the strongest correlations with shading and lighting interactions. However, due to multicollinearity issues, these variables cannot be included in the same modeling framework. Moreover, despite the high inter-correlation, their attributes need to be further investigated in presence of other significant variables (e.g., direct solar radiation or occupation dynamics and non-physical variables) within a multivariable modeling framework.

Table 3.3 Pearson correlation between physical variables and operating status of roller shades and lights

| | Work plane illuminance | Work plane daylight illuminance | Vertical illuminance at eye level | Average window luminance | Average luminance of visual field | DGP | Transmitted global solar radiation | Transmitted direct solar radiation | Solar penetration depth | Room temperature |
|---|---|---|---|---|---|---|---|---|---|---|
| Roller shades | -0.453 [a] | -0.401 [a] | -0.427 [a] | -0.326 [a] | -0.293 [a] | -0.367 [a] | -0.143 [c] | -0.248 [b] | -0.487 [a] | -0.078 [d] |
| Electric lights | -0.151 [a] | -0.336 [a] | -0.264 [a] | -0.234 [a] | -0.262 [a] | -0.243 [a] | 0.088 [d] | 0.023 [c] | -0.335 [a] | 0.091 [b] |

*([a] Statistical significance at 0.001, [b] Statistical significance at 0.05, [c] Statistical significance at 0.1, [d] Not statistically significant)*

To investigate the existence of endogeneity between the operating status of roller shades and electric lights, Figure 3.13 explores the interaction between their usages, considering aggregated datasets from control setups 1 and 2. The figure presents selected electric light levels for each roller shade position and shows that increased electric light levels are more frequently selected with lower shade positions (and vice versa). Table 3.4 shows the Pearson correlation matrix for the operating status of roller shades, electric lights, and thermostats. Results for the thermostat set point adjustment were considered, showing independent operation with the shading and electric lighting, which confirms the quality of the experimental dataset used in this paper. Overall, electric lights and roller shades are operated interdependently. This should be considered when developing predictive models to describe the human interactions with shading and electric lighting systems whether modeling their operating status directly or occupant actions on the systems (raising, lowering, etc.) as the interdependent operation can be reflected on human actions as well.

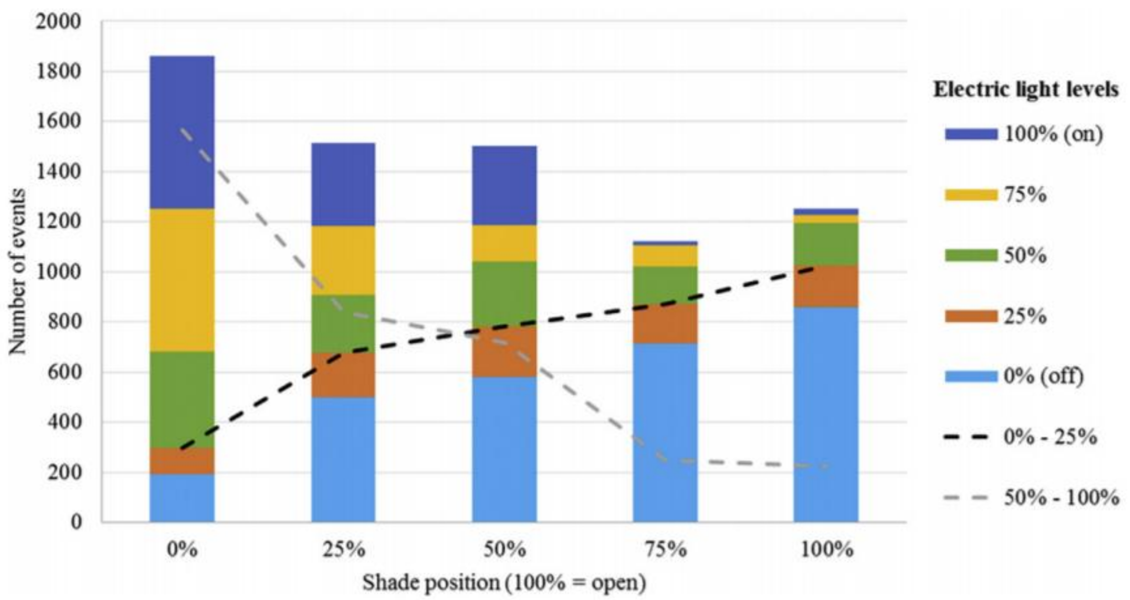


Figure 3.13 Interdependency between occupant interactions with motorized roller shades and electric lights

Table 3.4 Pearson correlation between operating status of building systems

| Variable | Roller shade operating status | Electric light operating status | Thermostat set point |
|---|---|---|---|
| Roller shade operating status | 1.000 [a] | -0.423 [a] | 0.005 [a] |
| Electric light operating status | -0.423 [a] | 1.000 [a] | 0.110 [b] |

*([a] Statistical significance at 0.001, [b] Statistical significance at 0.05)*

Effects of occupation dynamics and control access on shading and lighting actions are depicted in Figure 3.14. The first ten minutes after arrival and the last ten minutes before the departure were selected as threshold limits for arrival and departure time intervals. The same threshold was used for determining events before and after intermediate absences. Based on these results, a considerable portion of shading and electric lighting adjustments in both setups occurs outside the intermediate time interval with continuous occupation (49% with setup 1 and 35% with setup 2 for shading interactions; and 65% and 42% for electric light interactions respectively). Among the occupation dynamics outside the intermediate time interval, arrival and departure times show the highest frequencies of shading and electric lighting interactions in both setups 1 and 2 (orange and blue in small pies) except for departure shading interactions in setup 1. This is in agreement with findings of previous studies (Inoue et al., 1988; Reinhart and Voss, 2003; Haldi and Robinson, 2010(A); da Silva et al., 2013) and suggests that occupation dynamics is a significant variable for interactions with shading and lighting systems, and should be considered in relevant models. In addition, the results of Figure 3.14 imply that the type of control interface, -or "ease-of-access"- should be considered as another important variable. Occupants using a web interface (setup 2) interact more with both shades and lights during intermediate time intervals with continuous occupation, compared to setup 1 (wall switches). This finding demonstrates the importance of human-building interface design, which should be incorporated in predictive models for human-building interactions.

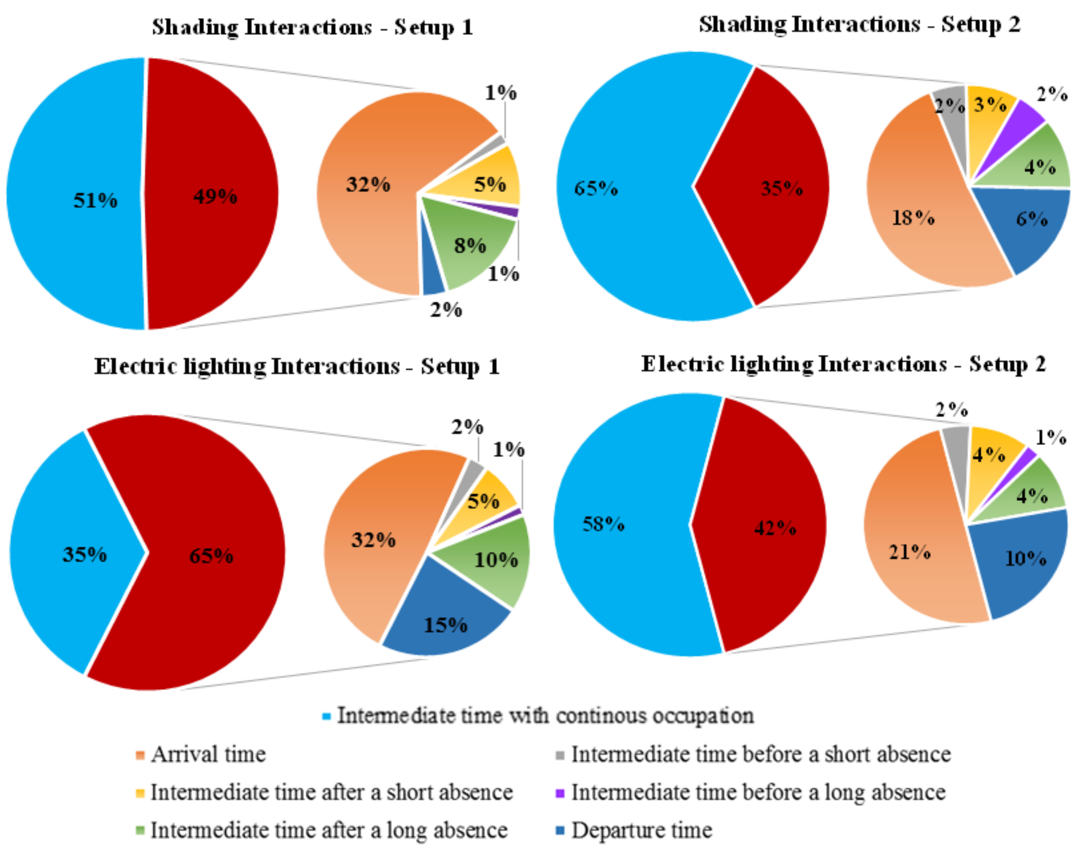


Figure 3.14 The effect of occupation dynamics on interactions with motorized shades (top) and electric lights (bottom), comparing control setups 1 (wall switches) and 2 (web interface). In the big pie charts, the blue area demonstrates the overall portion of the intermediate time with continuous operation. For the remaining portion of time, a more detailed overview can be observed in the smaller pie charts

3.4.2.2 Survey results: human variables and reasons for interactions with shades and lights

Figure 3.15 illustrates the reasons for shading interactions based on the data collected from the survey type-A (Table 3.1) with setups 1, 2 and 4. Reducing overall brightness and increasing daylight levels were the main reasons for lowering and raising roller shades respectively with all control setups. Reducing glare on computer screens and desks are also two other frequent shade-lowering reasons, which can be also described by physical variables (e.g. glare indices or luminance values). Significant and relatively high Pearson correlation for these physical variables (Table 3.3), shows a good agreement between outcomes of survey type-A and monitored behaviors. With control setup 4 (overrides to automated shading operation), a higher rate of actions to reduce brightness was observed, due to the fact that shades automatically reset their position 15 min after each override, allowing 1 m of sunlight on the floor –which seemed too bright for the occupants.

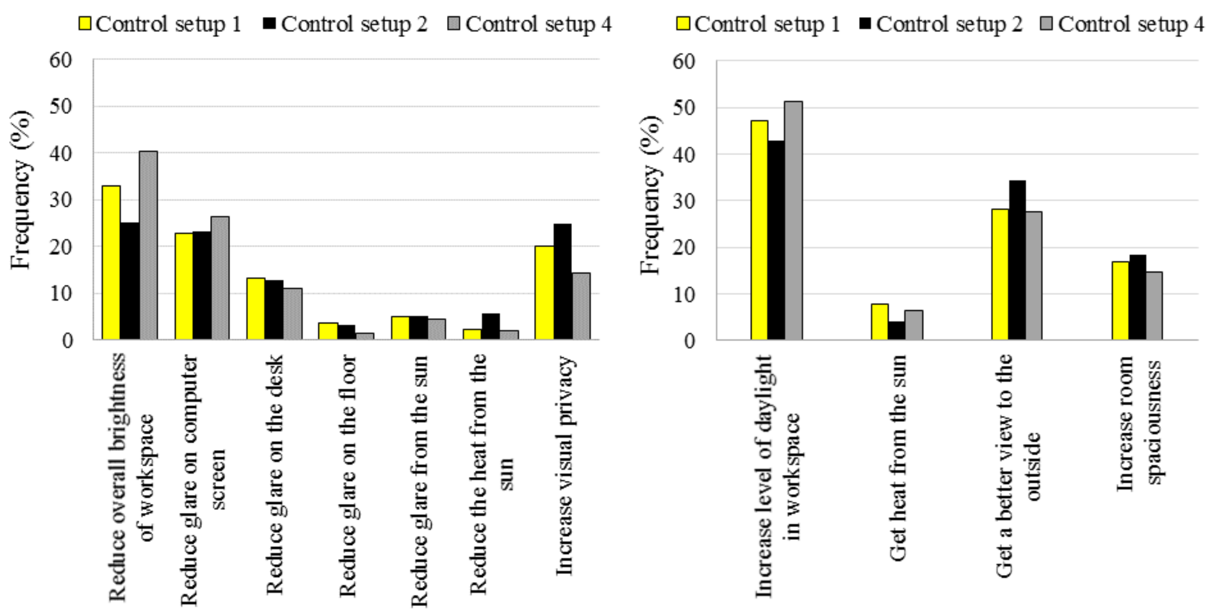


Figure 3.15 Survey results: reasons for lowering/closing roller shades (left) and raising/opening roller shades (right) with control setups 1, 2 and 4

The desire to increase visual privacy was another significant motive for lowering/closing window shades. Achieving a better outside view, as well as increasing room spaciousness were also reported by participants as reasons for window shade raising/opening events –these are all non-physical or human variables. Connection to the outdoors, directly related to shade position, is an important but not adequately studied aspect of the visual environment (Aries and Veitch, 2010;

Tuaycharoen and Tregenza, 2007; Shin et al., 2012; Hellinga and Hordijk, 2014), especially for the case of motorized shades, which affect the amount and clarity of outside view (Konstantzos et al., 2015(B)). For that reason, questions related to outside views were included in survey type-A, while some more general questions were answered once per day in survey type-B. Figure 3.16 presents a distribution of survey type-B results relevant to connection to the outdoors. More than 60% of the participants prefer to be close to windows; the great majority want to have a window, while only 3% of the participants specifically stated that they want to face the window. These results, combined with other studies focused on the spatial characteristics of visual discomfort (Chan et al., 2015; Jakubiec and Reinhart; Aries and Veitch, 2010; Tuaycharoen and Tregenza, 2007; Shin et al., 2012) support the fact that people are satisfied with partial window views (i.e., wall-facing layout in offices), which decrease visual discomfort sensation while still provide adequate daylight.

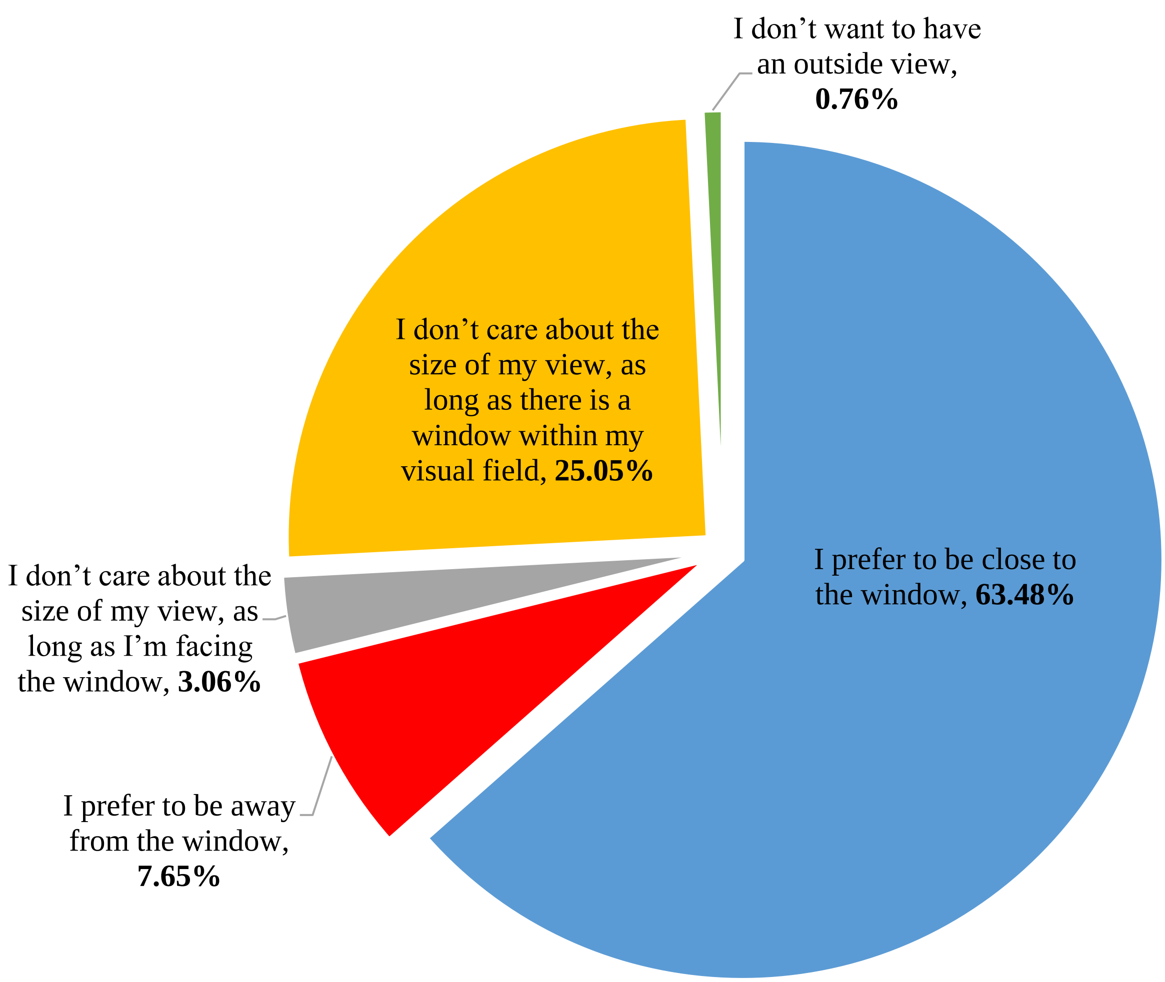


Figure 3.16 Survey results related to outside view and connection to outdoors

To examine the effect of outside view and visual privacy, Figure 3.17 illustrates boxplots of selected shade positions with control setups 1, 2, and 4 versus occupant's self-reported level of importance of clear outside view and visual privacy (importance level of one is excluded due to low frequency). An average line as well as error bars are also shown. Higher unshaded 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. Therefore, the impact of human variables –such as visual privacy and outside view- on the dynamics of human-shading interactions is noticeable.

Among the reasons for adjusting electric light levels (Figure 3.18), participants reported increasing and reducing the light level in workspace, as expected. Saving energy and making interior surfaces brighter were also noticed in both setups 1 and 2. Most of the reasons for interactions can also be represented by physical variables, except for "saving energy".

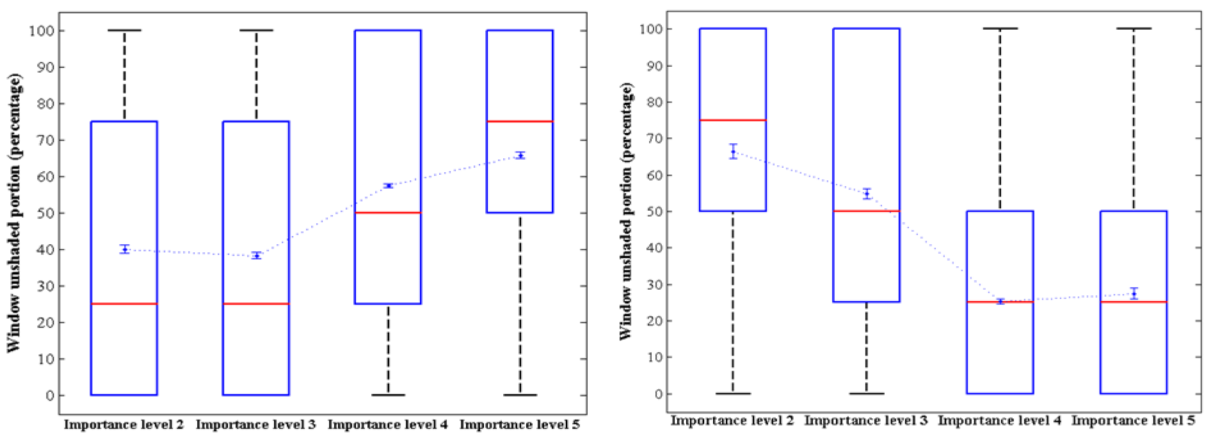


Figure 3.17 Survey results for different shade positions (window unshaded portion) related to different importance levels of outside view (left) and visual privacy (right)

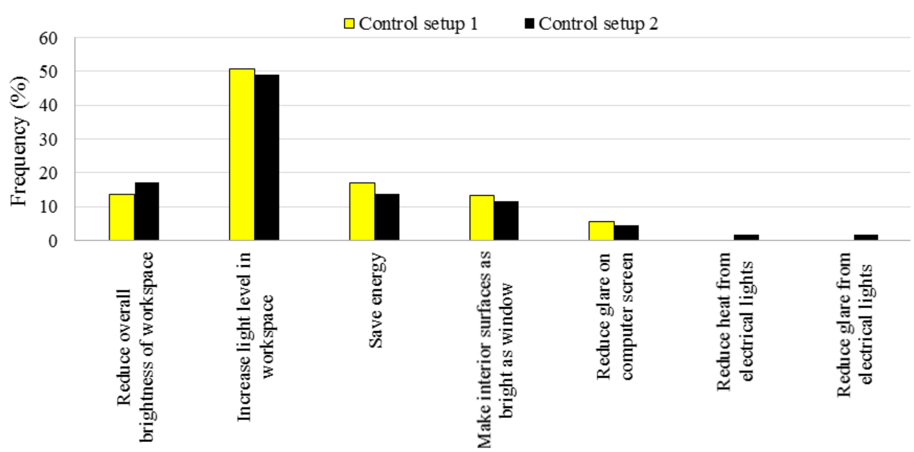


Figure 3.18 Survey results: reasons for adjusting electric light levels with control setups 1 and 2

### 3.4.3 What are the preferred visual conditions in offices with different control setups?

Figure 3.19 (top) shows the distribution of total work plane illuminance for all control setups during the monitoring campaign. Setup 3 represents fully automated control and visual conditions, which are not associated with occupant interactions. The rest of this section focuses on setups 1, 2, and 4 where indoor illuminances would result from occupant interactions with shading and electric lighting systems. It is clear from the results that work plane illuminances up to 1000 lux are preferred for all control setups. This is while outdoor conditions during the field study were bright enough to achieve higher values (Figure 3.9) but people preferred to control shades and lights to follow the frequency distribution of Figure 3.19. Although there is a difference in the dynamics of interactions between setups 1 and 2, as described earlier, the general illuminance preferences were within similar ranges between all setups. In other words, occupants seek similar preferences using different dynamics. The only difference between setups 1 and 2 is that occupants using the web interface (control 2) preferred total illuminances up to 500 lx over higher illuminances; the opposite was observed for occupants using wall switches (control 1), as well for the remote control overrides (control 4). Overall, work plane illuminances higher than 1000 lux are less frequent, while values higher than 2000 lux are rare.

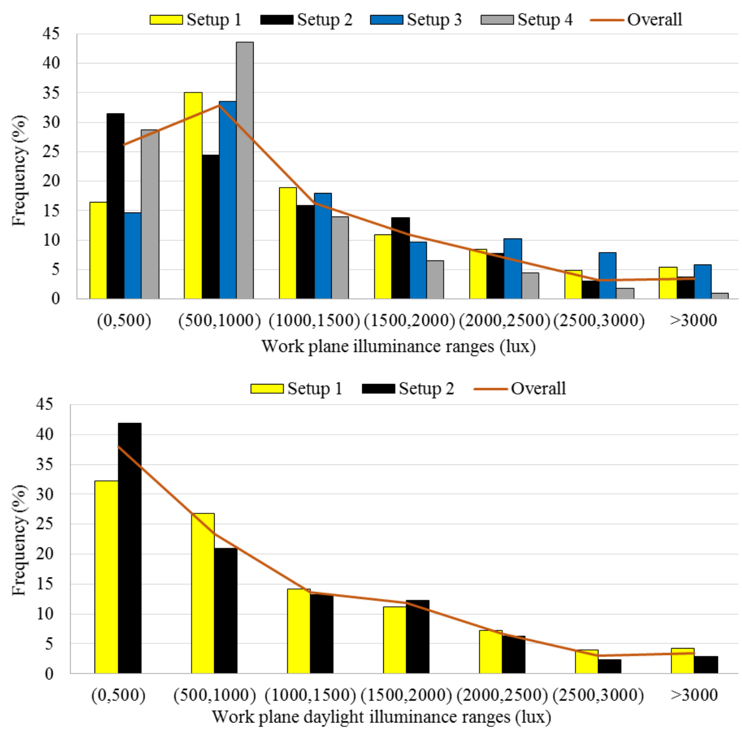


Figure 3.19 Frequency distribution of total work plane illuminance (top) and work plane illuminance from daylight (bottom) for different control setups

Figure 3.19 (bottom) shows the distribution of daylight illuminance for control setups 1 and 2, showing that occupants preferred daylight illuminances within the range of 100-2000 lux for almost two-thirds of the times (72% in setup 1 and 65% in setup 2). This confirms findings of previous studies (Nabil and Mardaljevic, 2006), generally supporting simplified comfort criteria such as useful daylight illuminance bins. Daylight illuminance was investigated for different levels of electric lighting. With setup 1, on average, the daylight illuminance was 1675 lux for low levels of electric light (0% and 25%) while it was 700 lux for higher levels (50%, 75% and 100%). The respective average with setup 2 were 1852 lux and 564 lux. The easier access with the web interface of Setup 2 results in a wider range on average values, implying more use of daylight.
To further assess occupant preferences when controlling electric lights using different interfaces, electric light dimming levels were correlated with daylight illuminance levels for setups 1 and 2 (Figure 3.20). Office occupants tend to choose natural light (low electric light levels) if a preferable range of daylight is available to them, as expected. However, the way that they interact with electric lights seem to depend on the control interface with implications on lighting energy use. Figure 3.20 shows that higher electric light levels (>75%) are used when daylight levels are less than 1000 lux with setup 1 (wall switches). For higher daylight values, low electric light levels are preferred. This behavior occurs around 600 lux (daylight levels) when a web interface is used (setup 2). These results emphasize the significance of interaction dynamics using different control interfaces and show that there is a noticeable impact on light energy use.

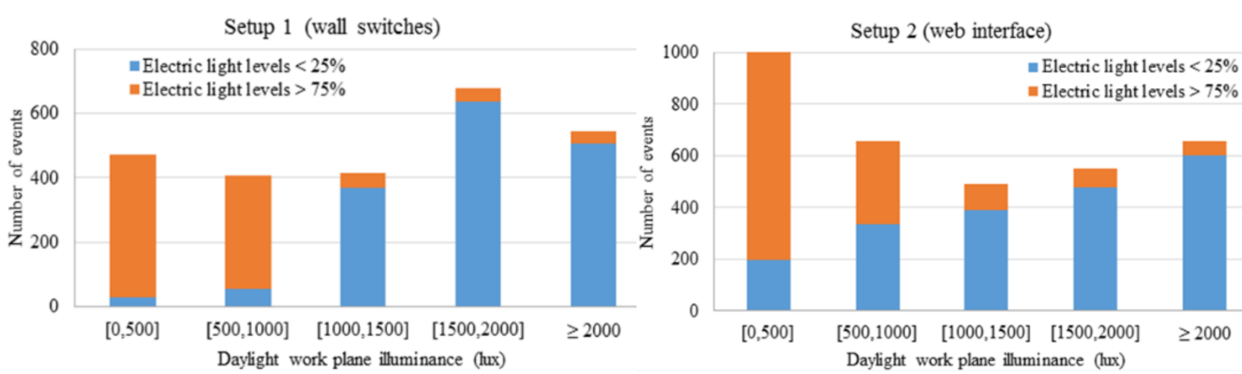


Figure 3.20 High and low electric lighting levels correlated with daylight illuminance levels for setups 1 (left) and 2 (right)

To assess the potential impact of daylight discomfort glare, the DGP index was calculated by post-processing luminance distributions with the different control setups. Figure 3.21 demonstrates distributions of DGP resulted from shading and lighting settings selected by occupants with all control setups. Noticeable glare is supposed to occur for DGP values higher than 0.35 (Wienold and Christoffersen, 2006). The average value of DGP was 0.2 (M= 0.2, S.D= 0.07, n= 916) in setup 1, 0.16 (M= 0.16, S.D= 0.08, n=1468) in setup 2 and 0.2 (M=0.2, S.D=0.04, n= 678) in setup 4. DGP values are mostly between 0.15 and 0.25 in all setups with occupant controls and rarely exceed 0.35. Note that the shades have a low openness factor and visible transmittance, and that the sun is not within the field of view of the occupants for a significant amount of time – nevertheless, sunlight enters the space when the shades are partially open during sunny days. Experiments with lower sun angles might show higher discomfort values, however occupants are expected to interact more with shades to reduce glare in that case; moreover, alternate glare criteria might be more suitable for cases with roller shades of low openness factors (Chan et al., 205). Vertical illuminance on the eye of the observer is also a critical metric associated with discomfort (Wymelenberg and Inanici, 2014; Chan et al., 2015l; Wienold, 2009). Through the simplified DGPs index, vertical illuminances over 2760 lux indicate noticeable glare. The findings of this field study show that occupants prefer much lower values (Figure 3.22) for all the control setups.

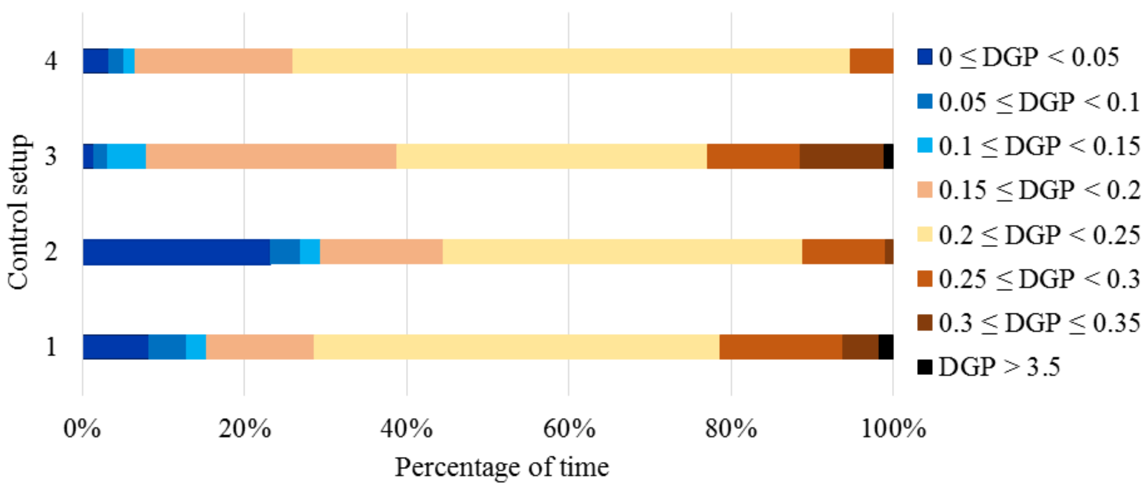


Figure 3.21 Measured DGP index with different setups during the course of field study

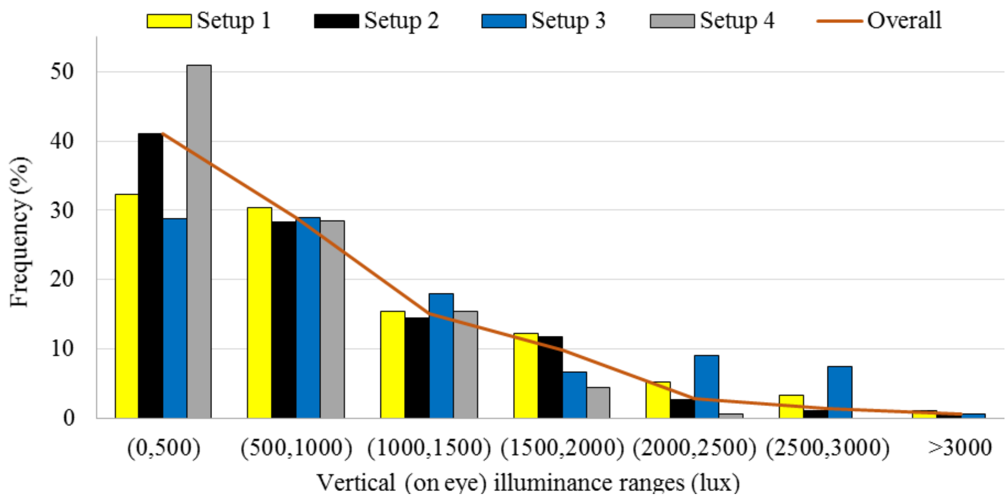


Figure 3.22 Frequency distribution of vertical illuminance (at the eye level) for different control setups

### 3.4.4 What are the effects of control setups on occupants' visual satisfaction?

Data from web surveys during the field study were analyzed to provide an initial understanding of occupant satisfaction with the visual environment under different control setups. Figure 3.23 presents boxplots of votes for comfort (i) with amount of light (ii) with visual conditions (iii) with outside view and (iv) a subjective assessment of productivity, for all different control setups. Average lines along with an error bar for the mean value are also shown for each case. Overall, the lowest comfort votes occur when there is no occupant control (setup 3), indicating that there is a preference for customized indoor climate and a relationship between occupants' perception of environmental control and productivity (Figure 3.23d). Comfort votes are significantly improved when occupants are allowed to override the automated system (setup 4), while controlling lights and shades manually through wall switches or a web interface (setups 1 and 2) show the best performance. However, the effect of ease of access (control interface) on comfort experience and productivity was not found to be significant, at least for the comfort votes presented here. The average line and non-overlapping confidence intervals of mean in Figure 3.23a rank control setup 2 as the highest comfortable in terms of light adequacy, followed by setups 1, 4, and 3. Except for a few votes considered as outliers, participants were mostly comfortable with the amount of light in control setups 1, 2, and 4. This is also true for comfort votes with visual conditions in control setups 1 and 2 (Figure 3.23b). Comfort votes are high mainly because occupants had full control over their visual environment (motorized shades and controlled lights) and partially because they had about one third of the window within their visual field (when looking at the computer screen) with no significant glare issues reported. Very high illuminance values were rarely experienced in this field study –as should happen in well-designed, occupant-controlled indoor environments.

The distribution of comfort votes based on data gathered with the graphical web interface (setup 2) at the moments of shading or electric lighting interactions are shown in Figure 3.24. The lower levels of comfort at moments of actions is obvious. "Comfortable" votes still exist because some of the actions were due to discomfort with only one of the visual conditions/amount of light or even none of them in cases when participants used the reasoning slider to report non-physical variables as the reason for their interaction.

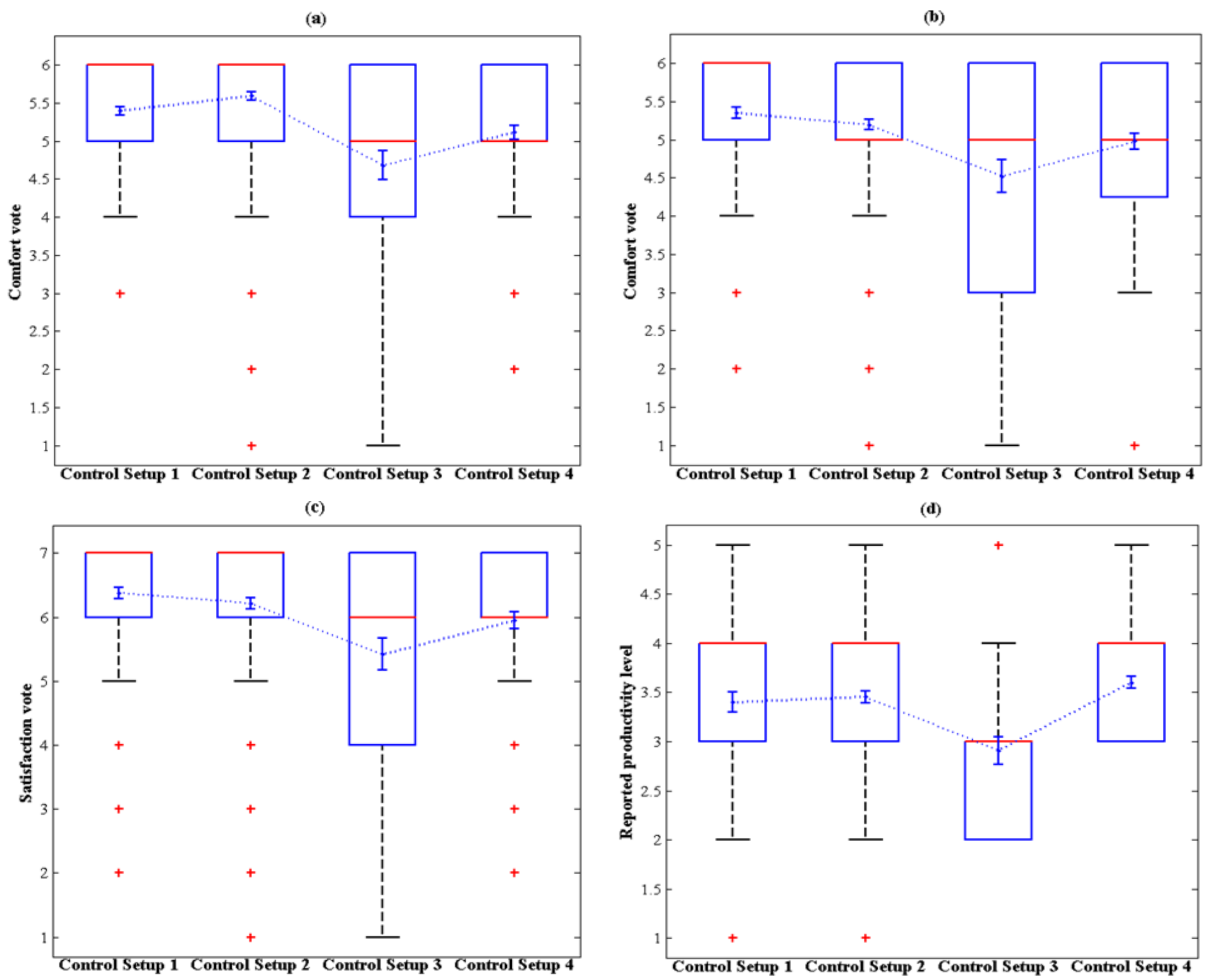


Figure 3.23 Comfort vote distributions with (a) amount of light (b) visual conditions(c) satisfaction with outside view and (d) subjective productivity, for different control setups

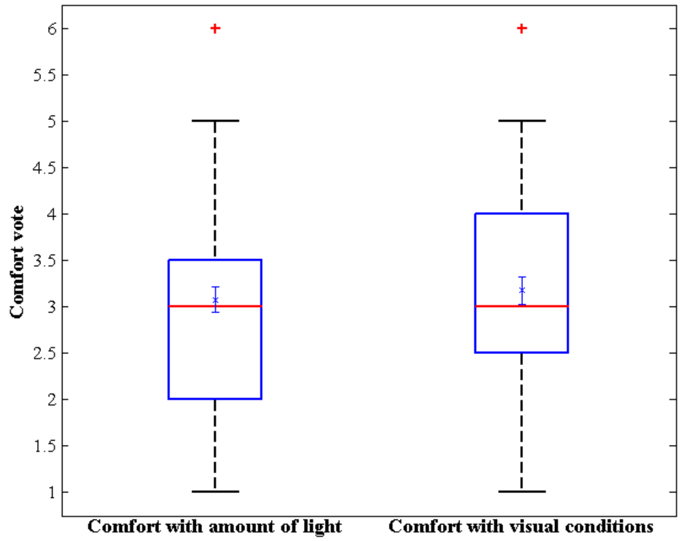


Figure 3.24 Comfort votes at moments of actions with setup 2

Figure 3.25 presents the distribution of "perceived" lighting conditions for each control setup, based on responses on a seven-scale question in survey type-A (Table 3.1, question 7). The perceived conditions with control setup 3 (fully automated shades) and setup 1 (manual wall switches) are almost the same. But lower comfort votes with the amount of light for control setup 3 (Figure 3.23a) imply that lack of personalized controls can result in lower comfort levels even under the same range of perceived physical conditions. This is also clear from Figure 3.26, which shows the level of comfort with amount of light in control setups 1 and 3, disaggregated by values of work plane illuminance greater and less than 2000 lux. It is clear that in setup 1, participants remained comfortable for the whole range of work plane illuminance. In setup 3, on the other hand, comfort level drops dramatically for work plane illuminance values greater than 2000 lux. These results, along with similar physical conditions observed for setups 1 and 3 in Figure 3.19, tend to suggest that in setup 1, occupants reported to be comfortable almost for the whole range of experienced work plane illuminances only because they had full control over their luminous environment. These results present "occupants' access to environmental controls" as an important parameter to be accounted for when evaluating visual comfort.

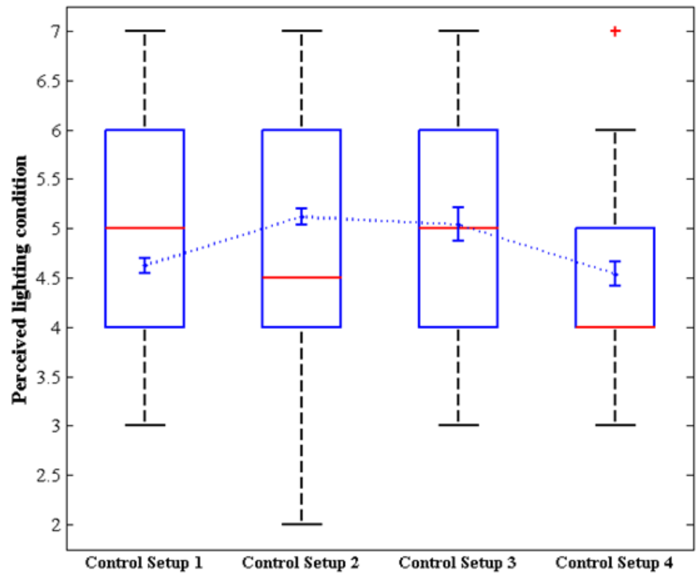


Figure 3.25 Perception of lighting conditions with different control setups

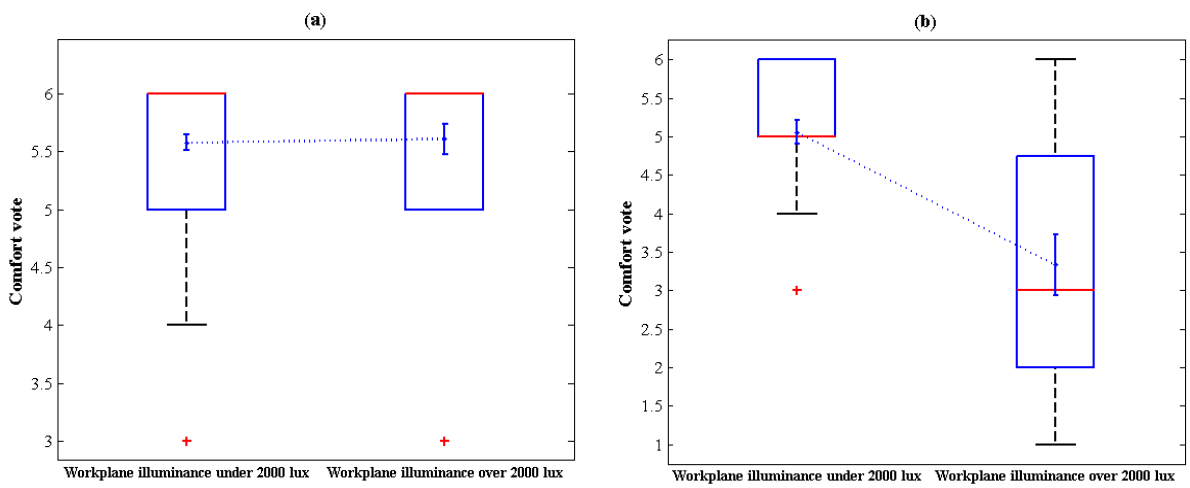


Figure 3.26 Comfort with amount of light for setup 1 (a) and setup 3 (b)

## 3.5 Summary

This chapter presented a pilot study to investigate occupant interactions with motorized shading and dimmable electric lighting systems in private offices of a high performance building. Four different control setups were explored ranging from fully manual to fully automatic. Occupants could move shades to intermediate positions and select intermediate light dimming levels using manual (wall switches, remote controllers) or web interfaces. The modular web interface was specially designed to (i) enable interactions with shading and electric lighting (ii) capture comfort levels when the actions occur and (iii) consider non-physical variables, in parallel with occupant surveys. In addition to extending the current knowledge of human-building interactions to different and more advanced systems, this study provides new insights that support the development of new modeling representations and personalized controls.

Based on the field study and presented results in this chapter, several conclusions can be summarized as follows:

- The dynamics of human interactions with motorized roller shades and dimmable electric lights are different from those found in studies without these advanced control options. The results indicate the need for developing predictive models of occupant interactions with these systems. The importance of non-physical variables (e.g., outside view, privacy, etc.) in shading and electric lighting interactions was demonstrated along with the need to incorporate such variables in modeling frameworks, in addition to the consideration of occupational dynamics.
- Window shades and electric lights were found to be operated interdependently, with increased electric light levels more frequently selected with lower shade positions (and vice versa), and resulting implications on daylight utilization of the space. This interdependency needs to be checked and accounted for when deriving predictive models to describe human interactions with shading and electric lighting systems, whether modeling their operating status directly or occupant actions on the systems.
- Different dynamics in occupant interactions with different control interfaces (wall switches and web-interfaces) pronounce the need to incorporate the "ease of access" to building systems when constructing models of human-building interactions. These dynamics result in similar lighting preferences in both setups but have different energy impacts. Higher daylight utilization in offices with easy-to-access controls was observed, which implies less frequent use of electric lights and less energy consumption accordingly. This finding shows advantages in providing office users with higher level of accessibility to environmental controls.
- Differences in occupant responses, in terms of comfort with the amount of light and visual conditions, between offices with different accessibility to shading/lighting control, reveal a strong preference for customized indoor climate along with a relationship between occupant perception of control and acceptability of a wider range of visual conditions. Under the same physical conditions, participants showed different levels of comfort with different control setups. Therefore, the access to control is an important parameter when evaluating occupant visual comfort and should be further investigated.

# CHAPTER 4. A BAYESIAN MODELING APPROACH OF HUMAN INTERACTIONS WITH SHADING AND ELECTRIC LIGHTING SYSTEMS IN PRIVATE OFFICES

## 4.1 Overview

This chapter presents a hierarchical Bayesian approach to model human interactions with motorized roller shades and dimmable electric lights. At the top level of hierarchy, Bayesian multivariate binary-choice logit models predict the probability of shade raising/lowering actions as well as the actions to increase the level of electric light. At the bottom level, Bayesian regression models with built-in physical constraints estimate the magnitude of actions, and hence the corresponding operating states of shading and electric lighting systems. The models are based on a dataset from a field study conducted in private offices designed to facilitate a large number of participants and to collect data on environmental parameters as well as individual characteristics and human attributes governing human-shading and –electric lighting interactions. A practical algorithm for simulating the use of window shades and dimmable electric lights at arrival instances and then evaluate the performance of the modeling framework is also presented.

## 4.2 Field Study

This section presents the field study that was conducted to support the data collection required for developing the models of human-shading and -electric lighting interactions. The experimental setup is the same with that explained in section 3.3 but the findings reported in chapter 3 were based on a monitoring campaign with solar paths between April 1st and June 15th 2015. In order to address potentially different dynamics of occupant behaviors within the model structures and to enrich the data set, the field study was extended to December 2015. That is, models presented in this chapter are based on a field study which 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 19th and December 10th 2015 covering 21 sunny days, 11 cloudy days, and 6 mixed sky conditions. Overall, 208 test-subjects participated in the field study (131 males and 77 females). Figure 4.1 illustrates the variation of outdoor conditions over the course of the whole field study. Control setup 3 was not used in the second round of experiment as occupants did not have any control over the systems in this setup and it would not be helpful for the development of human-building interaction models. Moreover, for consistency purposes and more efficient data collection, occupants used the graphical interface to override the automatic controls during the second round. Thus, the three control setups used for collecting data required for model development are as follows: (a) Manual control with commercially available wall switches (Figure 3.2, left) to control motorized roller shades and electric lights (setup 1 in chapter 3); (b) Manual control of lights and shades with a web-enabled computer interface (Figure 3.3) that includes comfort sliders and a four-scale reasoning slider to capture non-physical motives of human-shading interactions (setup 2 in chapter 3). (c) Automated control with manual overrides using the graphical web-enabled interface (Figure 3.3). The automatic controller set the roller shade on any continuous position while occupants' overrides were in 25% increments. Once overridden, the automatic controller would remain disabled one hour in the second round of field study.

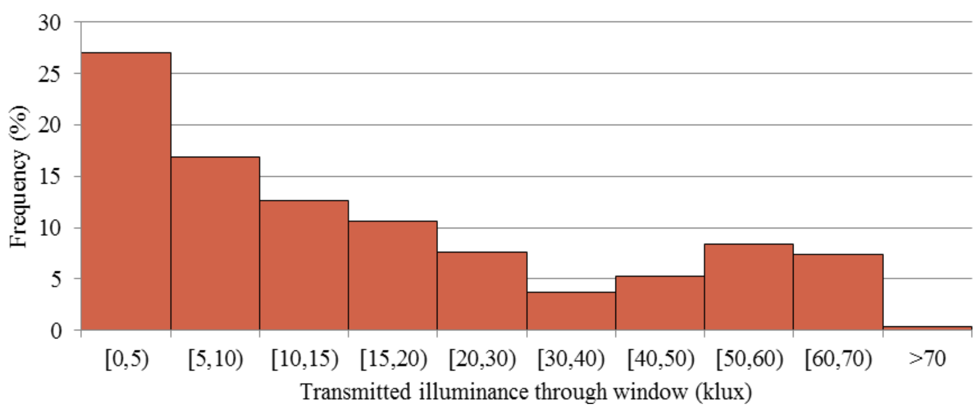


Figure 4.1 Overall frequency distribution of measured transmitted illuminance through the window during the two rounds of field study

## 4.3 Experimental Results

This section presents key observations from the field study that provide the basis for developing models of human-shading and –electric lighting interactions.

As an extension to Table 3.2 which was focused only on first round of field study, Table 4.1 presents the summary of test cases under different sky conditions and metrics for interactions with motorized shades and electric lights for each control setup. The same percentages of sunny/cloudy/dynamic days were considered for all setups, representing statistically equivalent conditions, in order to enable consistency.

Table 4.1 Observed shading and electric lighting system events during the whole field study

| | Wall switches | Web interface | Automated with overrides |
|---|---|---|---|
| Total number of tests | 77 | 105 | 36 |
| Tests during sunny days | 45 | 64 | 18 |
| Tests during cloudy days | 20 | 24 | 12 |
| Tests during mixed sky conditions | 12 | 17 | 6 |
| Total number of human-shading interactions | 121 | 223 | 116 |
| Number of shade raising events | 61 | 109 | 38 |
| Number of shade lowering events | 60 | 116 | 78 |
| Total number of human-electric light interactions | 108 | 190 | 65 |
| Number of electric light increasing events | 73 | 121 | 37 |
| Number of electric light decreasing events | 35 | 69 | 28 |

Table 4.2 Shading and electric lighting interactions in different occupation intervals

| | **Morning arrival** | **End-of-the-day departure** | **Intermediate departure** | **Intermediate arrival** | **Intermediate, continuous occupation** |
|---|---|---|---|---|---|
| **Wall switches:** | | | | | |
| Shading interactions | 37.2% | 1.6% | 0% | 15% | 46.2% |
| Electric lighting interactions | 31.6% | 15.3% | 7.4% | 12.6% | 33.1% |
| **Web interface:** | | | | | |
| Shading interactions | 34.9% | 1.8% | 0% | 9% | 54.3% |
| Electric lighting interactions | 28.1% | 18% | 1.2% | 12.1% | 40.6% |
| **Automated with overrides:** | | | | | |
| Shading interactions | 28.8% | 0.0% | 0.0% | 13.1% | 58.1% |
| Electric lighting interactions | 29.6% | 26.1% | 0.0% | 9.5% | 34.8% |

The occupation dynamics was found to have an impact on how participants interact with shading and electric lighting systems. The first ten minutes after arrival to the office and the last ten minutes before the departure from the office were selected as threshold limits to determine arrival and departure time intervals. As shown in Table 4.2, in all control setups, a considerable portion of shading and electric lighting interactions occurs outside the intermediate time interval with continuous occupation (53.8%, 45.7%, and 41.9% of shading actions when using wall switches, web interface, and automated with overrides respectively; 66.9%, 59.4%, and 65.2% of electric lighting actions respectively for wall switches, web interface, and automation with overrides).

High frequency of shading interactions is observed in arrival instances, 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). Among the arrival human-shading interactions, 53% lowering and 47% raising actions were recorded. High frequency of actions in arrival period was also recorded for electric lights and it was observed that almost all of these actions were to increase level of electric lights (less than 1% was dedicated to turning off or decreasing level of electric lights). Overall, compared to actions throughout the day, the number of shading and electric lighting actions per unit of time is significantly higher upon arrival. Therefore, only arrival actions have been considered for modeling purposes in this study. A similar approach is undertaken elsewhere (Reinhart and Voss, 2003; Inkarojrit, 2005). Due to the low density of actions in intermediate time with continuous occupation, more observations are required for developing probabilistic action models while also avoiding inefficiencies in their predictive power.

Figure 4.2 shows the frequency of selected shade positions and level of electric lights during arrival. It was observed that 53% of times, the selected positions of motorized window roller shades were different from extreme positions of 0% and 100% (0% being fully lowered and 100% being fully raised). Electric lights were also selected to be on intermediate levels 45% of times. These findings indicate that behavioral models for occupant interactions with window shades and dimmable electric lights should predict intermediate operating states in addition to fully lowered/raised positions for shades and completely on/off events for electric lights.

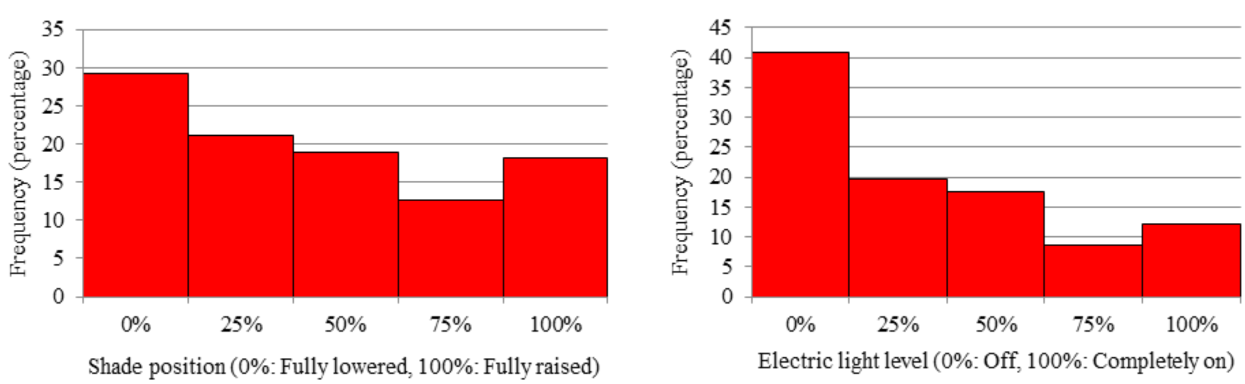


Figure 4.2 Frequency of selected shade positions (left) and electric light levels (right)

Among the reasons for human-shading interactions reported in survey A, reducing the overall brightness and glare of workspace were found to be the main motives for lowering the motorized roller shade (respectively reported with frequency of 28% and 43%). Increasing the amount of daylight was also reported to be the main reason for raising the roller shade (with frequency of 44%). Actions governed by these motives can be described by environmental variables (e.g. work plane illuminance, vertical illuminance, glare indices, luminance values etc.). Figure 4.3 presents the boxplots of environmental variables during the arrival time during the whole course of the experiment and at the moments right before raising and lowering actions. An average line is also overlaid.

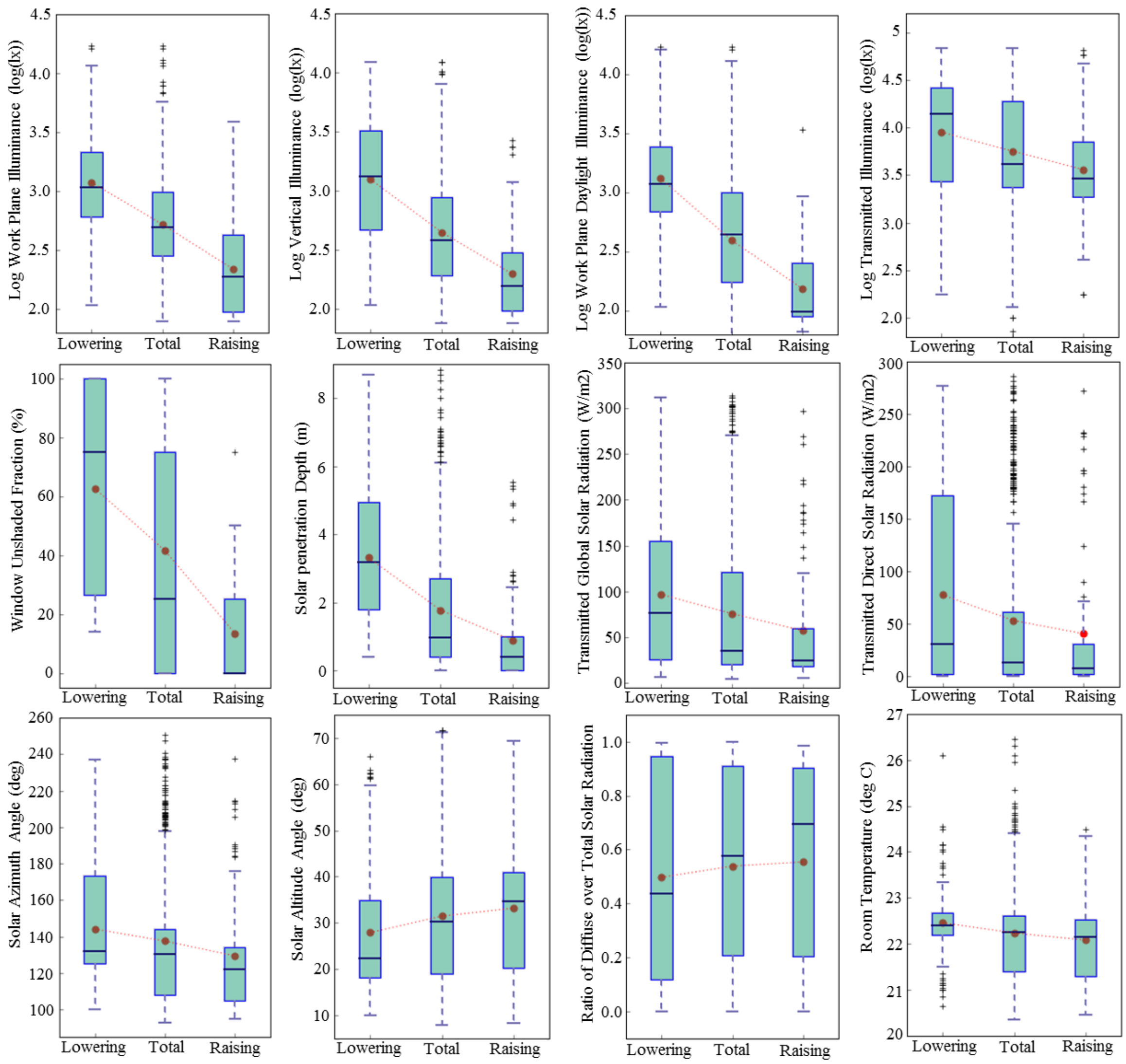


Figure 4.3 Distribution of environmental variables at moments of actions and over the whole field study

As shown in the figure, variables such as indoor illuminances, window un-shaded fraction, solar penetration depth, transmitted global solar radiation and ratio of diffuse over total solar radiation can explain lowering actions to some extent. This is inferred from the differences in distributions at lowering moments compared to the distributions over the whole course of the study. Similar trends are observed for 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. All these variables are investigated within the multivariate modeling framework described in section 4.4.

Participant responses to the survey questionnaires reveal that achieving a better outside view was reported as significant motive for raising/opening the window roller shades (with frequency of 37%). The desire to increase visual privacy was also another important reason for window shade lowering/closing actions (with frequency of 26%). To further investigate the impacts of window view and visual privacy on human-shading interactions, questions 1 and 2 in survey B (Table 3.1) were used to filter the selected shade positions during the field study. Figure 4.4 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). This is the updated form of Figure 3.17 when looking at the whole duration of filed study (both rounds) at once. It is clear that the trend lines are even smoother in Figure 4.4 with more data collected and the same conclusion can be drawn; higher window 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 4.5 presents the overall distribution of human variables collected from survey B and their distribution when actions occurred. The significance of human variables on shade raising and lowering actions is clear from Figures 4.4 and 4.5 and thus, they are incorporated in the human-shading interaction models presented in section 4.4.

For interactions with electric lights, as expected from the first round of field study, participants mainly reported increasing the light level in workspace (with frequency of 71%, survey A) to be the only reason. This motive can be represented by environmental variables (e.g. indoor illuminances) in human-electric light interaction models.

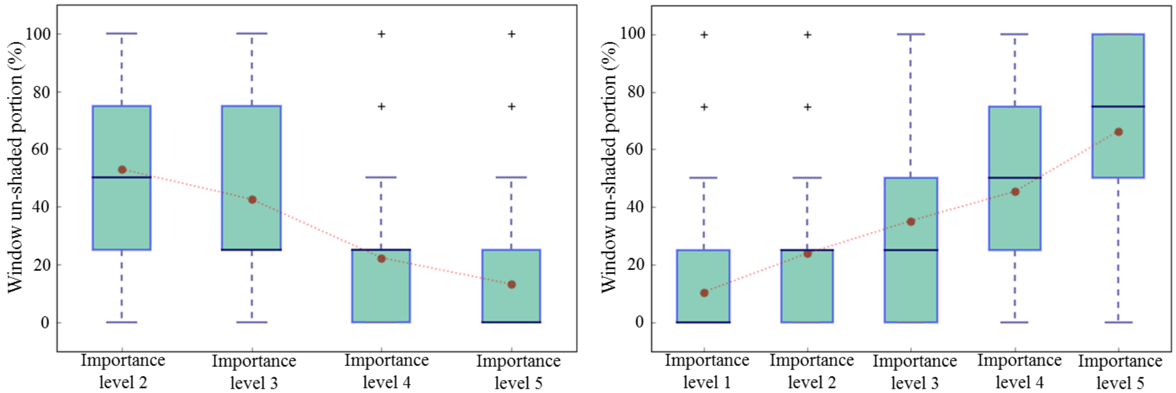


Figure 4.4 Selected shade positions with different level of reported need for visual privacy (left) and window view (right)

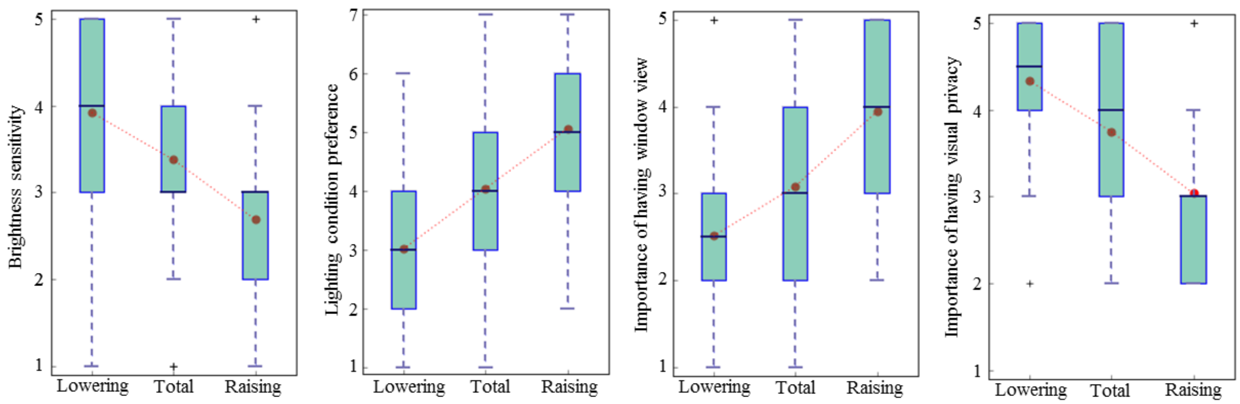


Figure 4.5 Distribution of human variables at moments of actions and over the whole field study

## 4.4 Modeling Methodology

Four sub-models have been developed to construct a probabilistic model that predicts the interdependent human-shading and lighting interactions while considering intermediate operating states of the systems. 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 attributes and environmental state variables) for which occupants decided to undertake the action. Only looking at moments of actions, models S3 and S4 respectively predict the magnitude of shade movement in case of raising and lowering. Figure 4.6 indicates the hierarchy within which models S1, S2, S3, and S4 work together to predict human-shading interactions given all the explanatory variables.

A multivariate binary-choice logit modeling form along with Bayesian parameter estimation has been used for models S1 and S2. For the magnitudes of shade movements, the dependent variable consists of four discrete alternates in fully manual control setups (25%, 50%, 75%, and 100%). In automated control setup with overrides on the other hand, other values are possible due to continuous operation of the automatic controller. However, since deviations from 25% increments were negligible, the observations were rounded in this control setup. Therefore, a discretized version of multivariate Bayesian regression was used to estimate the magnitude models, S3 and S4. The same methodology was used to model human interactions with the electric lighting system. However, as mentioned in section 4.3, almost no action was observed to decrease the level of electric light in arrival, and therefore, only two models were estimated; model L1 predicts binary actions of electric light increase and L2 predicts the corresponding magnitude.

In what follows, $\mathbf{x} = (1, x_1, \ldots, x_d)$ 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*.

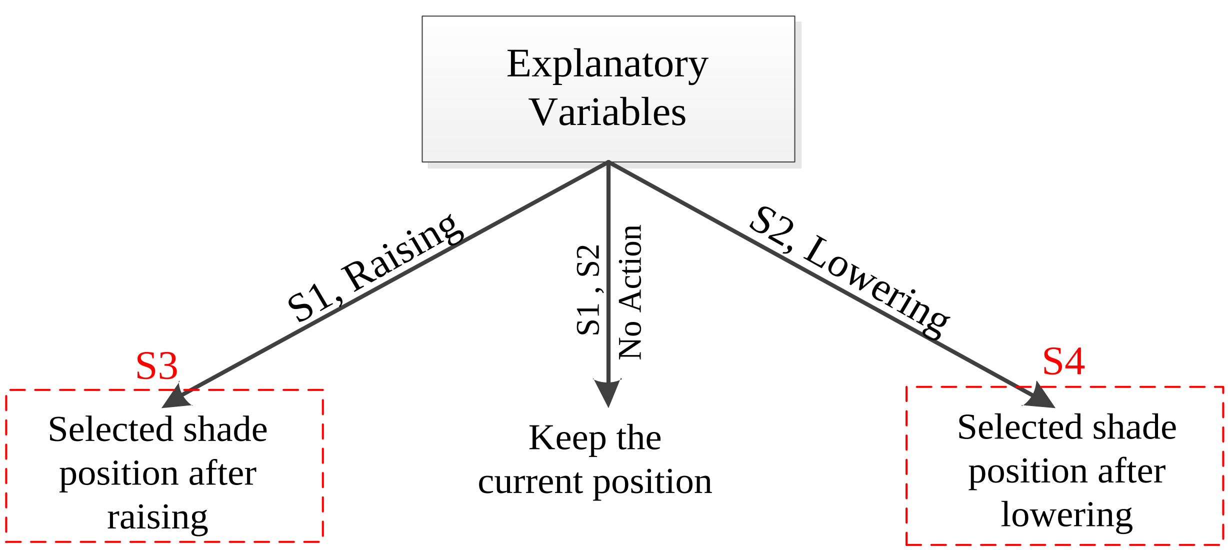


Figure 4.6 Structure of human-shading interaction model

### 4.4.1 Bayesian hierarchical modeling – multivariate logistic regression (S1, S2, and L1)

For the models at the top level of hierarchy (S1, S2, and L1), we address the following question: *"Given the current environmental states and human attributes, what is the probability that the occupant will raise/lower the shade (or increase electric light level)?"*

The model form we propose is identical for S1, S2 and L1. 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:

$$p(z = 0|\mathbf{x}, \mathbf{b}) = \text{sigm}(\mathbf{b}^T\mathbf{x}), \qquad \text{(Eq. 4.1)}$$

Where $sigm(x) \coloneqq \frac{1}{1+e^{-x}}$ 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 $\boldsymbol{b}^T\boldsymbol{x}$ 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:

$$p(z = 1|\mathbf{x}, \mathbf{b}) = 1 - p(z = 0|\mathbf{x}, \mathbf{b}) \qquad \text{(Eq. 4.2)}$$

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:

$$p(\mathbf{z}_{1:N}|\mathbf{x}_{1:N}, \mathbf{b}) = \prod_{i=1}^{N} p(\mathbf{z}_i|\mathbf{x}_i, \mathbf{b}). \qquad \text{(Eq. 4.3)}$$

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,

$$p(\mathbf{b}|\alpha) = \mathcal{N}(\mathbf{b}|\mathbf{0}, \alpha^{-1}\mathbf{I}_{d+1}), \qquad \text{(Eq. 4.4)}$$

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

$$p(\alpha|\lambda) \sim \mathcal{E}(\alpha|\lambda), \qquad \text{(Eq. 4.5)}$$

Where $\mathcal{E}(\cdot\,|\lambda)$ is the PDF of an exponential random variable with rate parameter $\lambda$. Here, we set $\lambda = 10000$.

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

$$p(\alpha, \mathbf{b}|\mathbf{x}_{1:N}, z_{1:N}, \lambda) \propto p(\mathbf{z}_{1:N}|\mathbf{x}_{1:N}, \mathbf{b})p(\mathbf{b}|\alpha)p(\alpha|\lambda). \quad \text{(Eq. 4.6)}$$

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

$$p(z^*|\mathbf{x}^*, \lambda) = \int p(z^*|\mathbf{x}^*, \mathbf{b})p(\alpha, \mathbf{b}|\mathbf{x}_{1:N}, z_{1:N}, \lambda)d\mathbf{b}\mathrm{d}\alpha. \quad \text{(Eq. 4.7)}$$

This integral is intractable, but it can be approximated by sampling (see section 4.4.3).

### 4.4.2 Bayesian hierarchical modeling – discretized multivariate regression (S3, S4, and L2)

For the models at bottom level of hierarchy (S3, S4, and L2), we address the following question: *"Given that we already know the occupant is going to raise/lower the shade (or increase the level of electric light) and the current environmental states, what is the amount by which the occupant will move the shade (or increase electric light level)?"*

The model form we propose is identical for S3, S4, and L2. Let $y$ be a random variable indicating the amount of shade raising/lowering and electric light increasing. We will be referring to $y$ as the *target* variable. For our analysis and models, $y$ can only take discrete values of 25, 50, 75, and 100 percent. From prior knowledge, we also know that the current shade position and electric light level restrict values of the target variable. For example, if the current shade position is at 25%, magnitude of shade movement for raising action can only be equal to or less than 75%. That is, the predicted $y_{\text{raise}}$ values cannot take the value of $100\%$ in this case, as it is not possible physically. Similar is the case for shade lowering and electric light increase. We can incorporate this prior knowledge of physical systems in our models by means of characteristic function $\chi_{\text{raising}}(x_{\text{CSP}}, y)$ for shade raising action, $\chi_{\text{lower}}(x_{\text{CSP}}, y)$ for shade lowering action and $\chi_{\text{increase}}(x_{\text{CEL}}, y)$ for electric light increasing action; where $x_{\text{CSP}}$ refers to shade position and $x_{\text{CEL}}$ refers to electric light level at current time-step. The characteristic function is then defined as follows:

$$\chi_{\text{raising}}(x_{\text{CSP}}, y) = \chi_{[0,100]}(x_{\text{CSP}} + y), \quad \text{(Eq. 4.8)}$$

$$\chi_{\text{lower}}(x_{\text{CSP}}, y) = \chi_{[0,100]}(x_{\text{CSP}} - y), \quad \text{(Eq. 4.9)}$$

$$\chi_{\text{increase}}(x_{\text{CEL}}, y) = \chi_{[0,100]}(x_{\text{CEL}} + y), \quad \text{(Eq.4.10)}$$

where $\chi_A(x)$ is the characteristic function of the set $A$ defined as: $\chi_A(x) = 1$ if $x \in A$ and zero otherwise.

In standard linear regression, the probability of a continuous predicted variable $t$ conditioned on the observed features is modeled by:

$$p(t|\mathbf{x}, \boldsymbol{\beta}, \sigma) = \mathcal{N}(t|\boldsymbol{\beta}^T\mathbf{x}, \sigma^2), \quad \text{(Eq. 4.11)}$$

where $\boldsymbol{\beta} = (\beta_0, \beta_1, \dots, \beta_d)$ is the vector of regression coefficients to be determined from the data, and $\sigma^2$ is the noise variance. The role of the latter is to capture as random effects everything that cannot be explained by the observed features. The predicted variable $t$ is continuous with no upper or lower bound values. However, since we want our models to predict the probabilities of discrete values 25, 50, 75 and 100% for our target variable $y$, we need to bin the probabilities of $t$. Specifically, we will bin the probability mass of $t < 37.5$ to $y = 25$, $37.5 < t < 62.5$ to $y = 50$, $62.5 < t < 87.5$ to $y = 75$ and $t > 87.5$ to $y = 100$. To achieve this goal, we model the probability of shade raising/lowering or electric light increase magnitude $y$ conditioned on the observed features as:

$$p(y = 25|\mathbf{x}, \boldsymbol{\beta}, \sigma) = \chi_M(x_C, y) \times \Phi\left(\frac{(37.5 - \boldsymbol{\beta}^T\mathbf{x})}{\sigma}\right), \quad \text{(Eq.4.12)}$$

$$p(y = 50|\mathbf{x}, \boldsymbol{\beta}, \sigma) = \chi_M(x_C, y) \times \left(\Phi\left(\frac{(62.5 - \boldsymbol{\beta}^T\mathbf{x})}{\sigma}\right) - \Phi\left(\frac{(37.5 - \boldsymbol{\beta}^T\mathbf{x})}{\sigma}\right)\right), \quad \text{(Eq.4.13)}$$

$$p(y = 75|\mathbf{x}, \boldsymbol{\beta}, \sigma) = \chi_M(x_C, y) \times \left(\Phi\left(\frac{(87.5 - \boldsymbol{\beta}^T\mathbf{x})}{\sigma}\right) - \Phi\left(\frac{(62.5 - \boldsymbol{\beta}^T\mathbf{x})}{\sigma}\right)\right), \quad \text{(Eq.4.14)}$$

$$p(y = 100|\mathbf{x}, \boldsymbol{\beta}, \sigma) = \chi_M(x_C, y) \times \left(1 - \Phi\left(\frac{(87.5 - \boldsymbol{\beta}^T\mathbf{x})}{\sigma}\right)\right), \quad \text{(Eq.4.15)}$$

where $\Phi(\cdot)$ is the cumulative distribution function of a standard normal distribution. Based on the model type, whether it is shade raising, lowering or electric light increase, $\chi_M(x_C, y)$ is $\chi_{\text{raising}}(x_{\text{CSP}}, y)$, $\chi_{\text{lower}}(x_{\text{CSP}}, y)$ or $\chi_{\text{increase}}(x_{\text{CEL}}, y)$, respectively. 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:

$$p(\mathbf{y}_{1:N}|\mathbf{x}_{1:N}, \boldsymbol{\beta}, \sigma^2) = \prod_{i=1}^{N} p(y_i|\mathbf{x}_i, \boldsymbol{\beta}, \sigma^2). \quad \text{(Eq.4.16)}$$

We assign a hierarchical prior to $\boldsymbol{\beta}$:

$$p(\boldsymbol{\beta}|\psi) = \mathcal{N}(\boldsymbol{\beta}|\mathbf{0}, \psi^{-1}\mathbf{I}_{d+1}), \quad \text{(Eq.4.17)}$$

where $\psi$ is an unknown precision parameter distributed exponentially,

$$p(\psi|r) = \mathcal{E}(\psi|r), \quad \text{(Eq.4.18)}$$

with rate parameter $r = 10000$, and

$$p(\sigma|\gamma) = \mathcal{E}(\sigma|\gamma), \quad \text{(Eq.4.19)}$$

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

$$p(\psi, \boldsymbol{\beta}, \sigma|\mathbf{x}_{1:N}, \mathbf{y}_{1:N}, r, \gamma) \propto p(\mathbf{y}_{1:N}|\mathbf{x}_{1:N}, \boldsymbol{\beta}, \sigma)p(\boldsymbol{\beta}|\psi)p(\psi|r)p(\sigma|\gamma). \quad \text{(Eq.4.20)}$$

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

$$p(y^*|\mathbf{x}^*, r, \gamma) = \int p(y^*|\mathbf{x}^*, \psi, \boldsymbol{\beta}, \sigma)p(\psi, \boldsymbol{\beta}, \sigma|\mathbf{x}_{1:N}, \mathbf{y}_{1:N}, r, \gamma)d\psi d\boldsymbol{\beta}\mathrm{d}\sigma. \quad \text{(Eq.4.21)}$$

Same as Eq. (4.7), this integral is also intractable but be approximated by sampling (see section 4.4.3).

### 4.4.3 Training and sampling

Python PyMC 2.3.0 (Patil et al. 2010) package was used to code all the models as well as sample from the posterior of $\mathbf{b}$ ($\boldsymbol{\beta}$) using Markov chain Monte Carlo (MCMC). After analyzing the traces and autocorrelations of the chain, we decided to burn the first 1,000,00 samples, and gather 2000 samples by keeping one MCMC sample out of every 100. Using these samples, we approximate the predictive distributions at new sets of features. For the logistic regression models, if $\mathbf{b}_{1:S} = \{\mathbf{b}_1, \dots, \mathbf{b}_S\}$ are samples from Eq. (4.6), then the predictive distribution of Eq. (4.7) is approximated by:

$$p(z^*|\mathbf{x}^*, \lambda) \approx \frac{1}{S}\sum_{i=1}^{S} p(z^*|\mathbf{x}^*, \mathbf{b}_i, \alpha, \lambda). \quad \text{(Eq. 4.22)}$$

Similarly, for the discretized regression models, if $\boldsymbol{\beta}_{1:S} = \{\boldsymbol{\beta}_1, \dots, \boldsymbol{\beta}_S\}$ and $\sigma_{1:S} = \{\sigma_1, \dots, \sigma_S\}$ are samples from Eq. (4.20), then the predictive distribution of Eq. (4.21) is approximated by:

$$p(y^*|\mathbf{x}^*, r, \gamma) \approx \frac{1}{S}\sum_{i=1}^{S} p(y^*|\mathbf{x}^*, \boldsymbol{\beta}_i, \sigma_i, r, \gamma). \quad \text{(Eq. 4.23)}$$

In our numerical results, we summarize the predictive distribution by computing its mean.

### 4.4.4 Model evidence and comparison

After defining the models in Sections 4.4.1 and 4.4.2, we address the following question: *"Given that we use certain features for defining the model, how confident are we that the model is representative of the data and is the model better than other models with different features?*

Suppose that we wish to compare a set of $L$ models $\{M_i\}$ where $i = 1, \ldots, L$. From Bayesian model selection (Bishop, 2006), we can compare different models using evidence for each model. The model evidence is defined to be:

$$p(D|M_i) = \int p(D|\theta, M_i)p(\theta|M_i)d\theta, \qquad \text{(Eq. 4.24)}$$

where $D$ is the observed data and θ are the parameter values used in context of the particular model $M_i$. The mode evidence is analytically intractable and its computation with MCMC is unstable. Here, we will compute it using sequential Monte Carlo (SMC) (Doucet et al., 2000; Chen et al., 2015; Del Moral and Doucet, 2002). Suppose that we are comparing two models $M_j$ and $M_k$ and that we wish to determine which one is best. This can be achieved by computing the Bayes factor (Kass and Raftery, 1995) defined as the ratio of the model evidence:

$$B_{jk} = \frac{p(D|M_j)}{p(D|M_k)}, \qquad \text{(Eq. 4.25)}$$

where $p(D|M_j)$ is the evidence for the model j found in Eq. (4.24). When $B_{jk} > 1$, the data favor model $j$ over $k$, and vice versa when $B_{jk} < 1$. If instead of the Bayesian model evidence, the likelihood corresponding to maximum likelihood estimate is used, the test becomes the classical likelihood-ratio test. Bayes factors in Bayesian statistics play a similar role to p-value in Frequentist statistics. P-value, however, may produce misleading results (Wasserstein and Lazar, 2016; Kass and Raftery, 1995). Unlike the likelihood-ratio test, Bayesian model comparison does not depend on particular set of parameters, as it integrates over all parameters in each model with respect to priors. An advantage of using Bayesian model comparison is that this comparison automatically takes into account the model complexity when assessing the degree to which one should believe in the model.

## 4.5 Estimation Results and Discussion

This section presents results of the parameter estimation for the models along with their interpretation.

### 4.5.1 Shade raising and lowering models (S1, S2)

All the variables in Figures 4.3 and 4.5 (Section 4.3) were considered as potential features within the multivariate structure of models. A forward selection method along with Bayesian model evidence was utilized to determine the most statistically significant variables in each model. All the models presented in this section are in their final form of calculation. As mentioned earlier, only the arrival time is considered for model development. Table 4.3 presents descriptive statistics for the selected variables. In order to avoid scaling issues in model estimations, descriptive statistics are used to normalize the data.

Table 4.3 Descriptive statistics of explanatory variables (features)

| Variable | Minimum | Mean | Maximum | Std. |
|---|---|---|---|---|
| Work plane ill. (lx) | 78.1 | 872.2 | 7796.9 | 856.7 |
| Vertical ill. (lx) | 75.8 | 927.4 | 12331.6 | 1547.3 |
| Shade position (%) | 0 | 41.8 | 100 | 36.1 |
| Electric light level (%) | 0 | 24.8 | 100 | 34.9 |
| Lighting condition preference | 1 | 4.7 | 7 | 1.5 |
| SV | 0 | 16.6 | 100 | 19.1 |
| SP | 0 | 20.5 | 100 | 24.6 |

Table 4.4 presents the parameter estimates for shade raising (S1) and lowering (S2) models. 95% high probability interval for each parameter estimate is shown in the table along with the mean value of estimated distributions. This is an advantageous feature of Bayesian approach which compared to maximum likelihood estimation method with point estimates, provides more information on each parameter and enables capturing the uncertainty of features' attributes within the model. As a result, when implementing the models in building controllers or building performance simulation, desired quantiles of posterior distributions can be readily selected and analyzed at each time step to determine performance bounds (e.g. energy flow) due to occupant interactions with building systems.

Table 4.4 also shows two different forms for each model. Form 1 represents the model constructed using significant environmental and human variables while form 2 represents binary action models only based on environmental variables. Variable "SV" in form 1 of model S1 accounts for the interactive impacts of outside view and shade position. This variable is created by dividing the shade position by the importance level for having clear view to outside which was reported by occupants in survey B. As schematically illustrated in Figure 4.7, when exposed to the same position of window shade and range of work plane illuminance, occupants to whom having a clear outside view matters more, can be more likely to take raising actions. Intuitively, an increase in probability of shade raising action is expected as variable SV decreases and it is confirmed by the negative sign of parameter estimate for this feature in Table 4.4. Self-reported preference for lighting conditions (survey B) is another human variable included in form 1 of shade raising model. The positive sign for this variable indicates that the probability of shade raising action correctly increases for occupants who prefer to have brighter conditions.

Table 4.4 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. | -2.065\|(-3.532,-0.806) | -3.898\|(-5.328,-2.588) | N/A | N/A |
| Vertical ill. | N/A | N/A | 0.891\|(0.601,1.18) | 0.915\|(0.719,1.138) |
| Lighting preference | 1.168\|(0.785,1.512) | N/A | -0.679\|(-0.998,-0.303) | N/A |
| SV | -2.639\|(-3.652,-1.598) | N/A | N/A | N/A |
| SP | N/A | N/A | 0.781\|(0.539,1.095) | N/A |
| Constant | -4.282\|(-5.023,-3.514) | -3.074\|(-3.557,-2.513) | -2.126\|(-2.528,-1.741) | -2.106\|(-2.38,-1.872) |
| Log model evidence | -108.78 | -922.30 | -111.68 | -887.88 |
| Observation No. | 786 | | | |

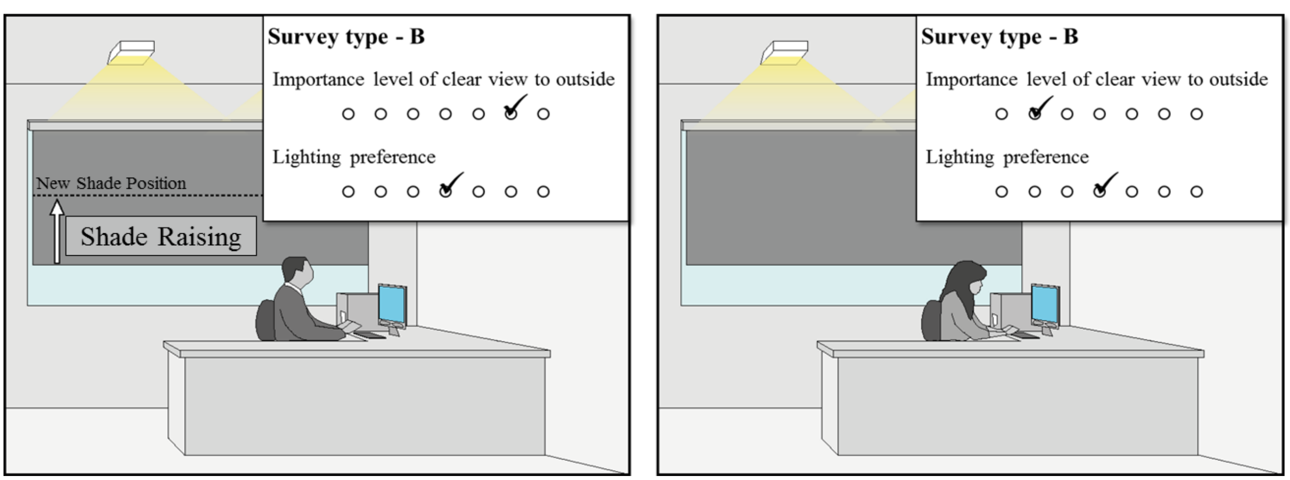


Figure 4.7 Need for having a clear view to outside as a triggering for shade raising actions

Among the environmental variables, vertical illuminance at eye level was found to be the best predictor for shade lowering actions. This is due to the fact that most of shade lowering actions are undertaken to alleviate discomfort conditions imposed by glare (Sadeghi et al., 2016) which is directly related to vertical illuminance at eye level (Konstantzos et al., 2015(A)). However, there are also lowering actions which are triggered by the need for having visual privacy. Variable “SP” is included in model S2 to capture this interaction. 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 the probability of shade lowering to increase as SP increases, which is confirmed by the positive sign of the parameter estimate for this variable in Table 4.4.

To investigate how inclusion of human variables can improve model performance, the data is divided into training (90% of data) and testing (10% of data) sets. Models are constructed with the training set while their performance is evaluated with the testing set and shown with a separation plot. A separation plot for binary classifiers is presented in Figure 4.8 from sorting the data points based on estimated probabilities from smallest to largest (Greenhill et al., 2011), i.e. from left to right on the plots of Figure 4.8. Black lines represent the estimated probability for each data point in the testing set while the vertical blue lines indicate occurrence of raising/lowering actions (1s in dependent variable); wherever there is no vertical line it means that no action has happened (0s in dependent variable). It is expected that the density of vertical lines increases as the estimated probability does, that is towards the right side of the separation plot. It is clear from Figure 4.8 (left) that unlike model form 1 (based on both environmental and human variables), model form 2 (only based on environmental variables) mostly fails to estimate high probabilities corresponding to events where raising actions have occurred. Moreover, vertical lines are more scattered rather than dense on the right side of the plot for the shade raising model without human attributes (form 2). Better performance of the lowering model in form 1 is also evident from Figure 4.8 (right). That is, including human variables adds to the predictive power of human-shading interactions models and improves their performance.

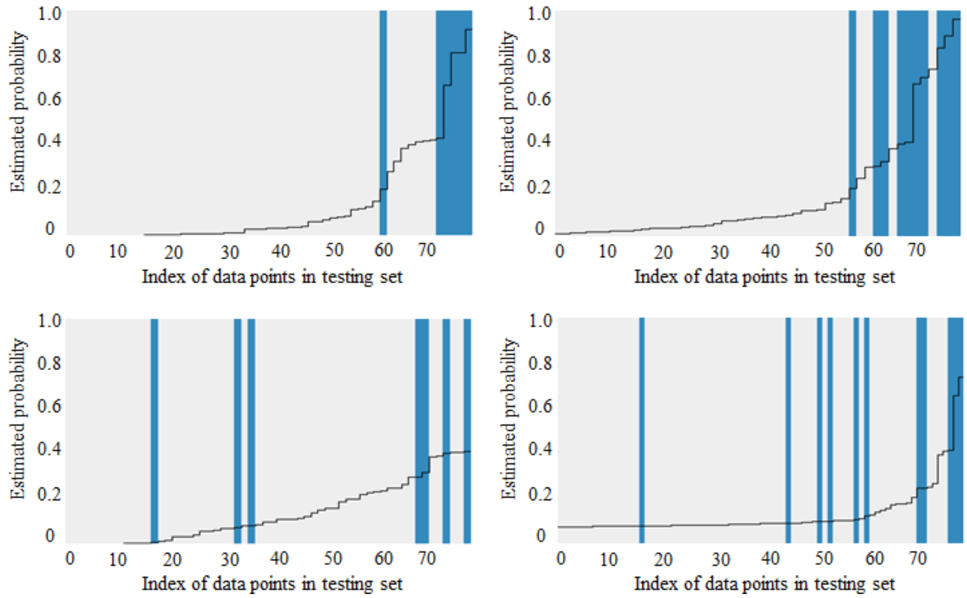


Figure 4.8 Separation plots for shade raising (left) and lowering (right) models; top: models with both environmental and human variables (form 1), bottom: models with only environmental variables (form 2)

To further investigate the impact of personal characteristics on human-shading interactions, Figure 4.9 presents the median of estimated probabilities resulted from models 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 (corresponding to vote values of 2, 4, and 6 for the lighting preference variable in the models). It is clear from the plots (Figure 4.9, left) that the shade raising probability increases as work plane illuminance and variable “SV” decrease. However, this variation is also influenced by the preference for lighting conditions. For example, it can be seen that the maximum probability of shade raising is close to 0.1 when dark conditions are preferred while it can be as high as 0.9 when there are preferences towards brighter conditions. Furthermore, when dark conditions are preferred, a shade raising action does not occur (zero probability) when the threshold value of 500 lx for the work plane illuminance is exceeded while this value is around 700 lx and 1050 lx when there is preference for moderate and bright lighting conditions. The same concept can be seen for shade lowering actions (Figure 4.9, right). Increase in vertical illuminance and variable “SP” increases the likelihood of shade lowering action but the likelihood is also affected by the lighting preference and it increases when darker conditions are preferred.

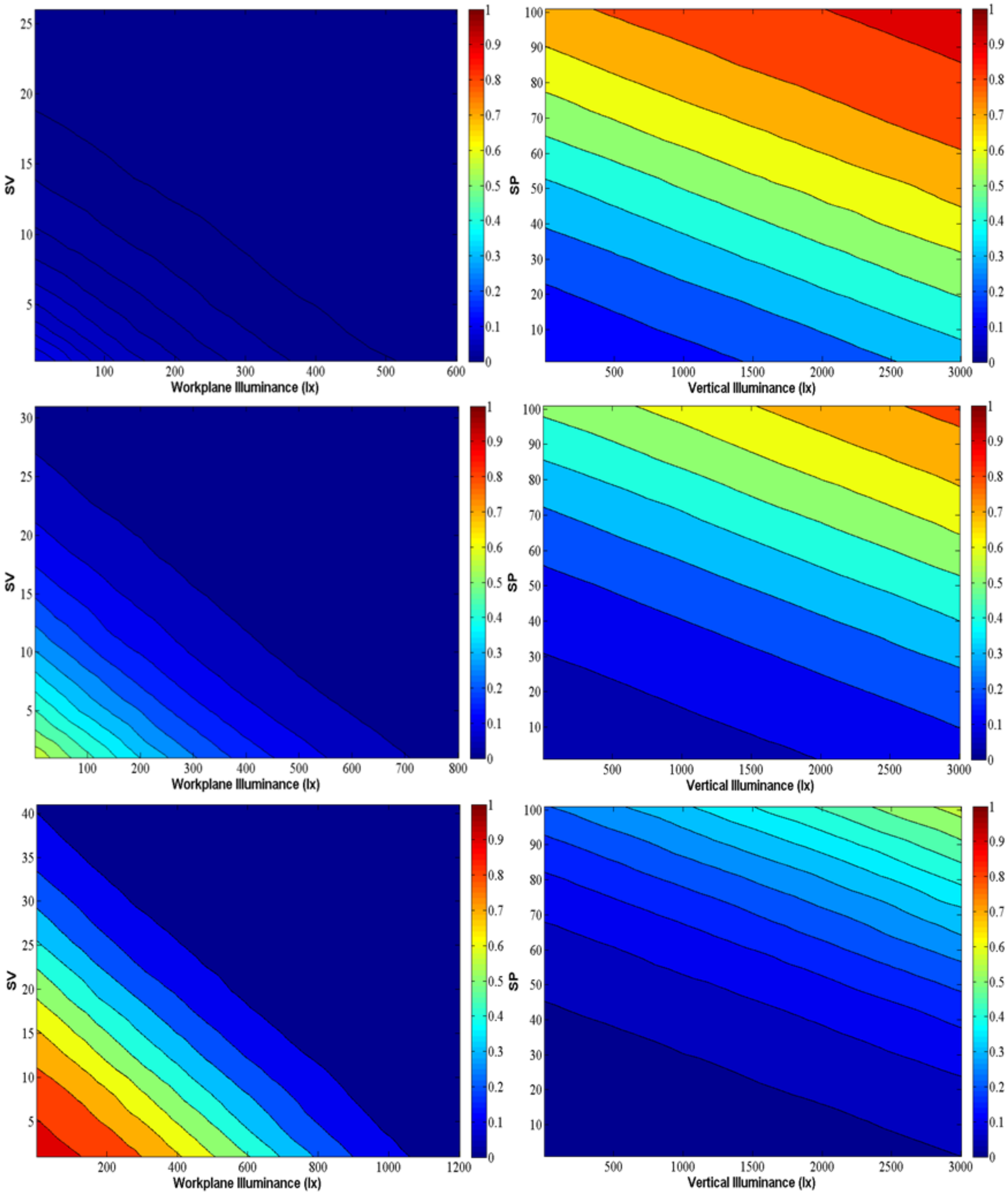


Figure 4.9 Level plots of estimated outcome probabilities for shade raising (left) and lowering (right) filtered based on lighting condition preferences (top: preference for dark conditions, middle: preference for moderate conditions, bottom: preference for bright conditions)

Although human variables improve model performance, may result in reduced practicality as direct measurements might not be available *a priori*. However, depending on the use, human attributes can be reproduced. For instance, for model implementation in adaptive building controllers, this information can be obtained from responses of the occupants to short surveys. When simulating building performance, a suitable approach might be to define different scenarios for occupant types and investigate potential differences in the outcomes. Another proposed solution for both simulation and control would be to randomly sample from distributions of human variables based on observations in monitoring campaigns. To this end, Figure 4.10 presents histograms of votes on lighting condition preferences as well as the need for having window view and visual privacy based on surveyed participants in this study.

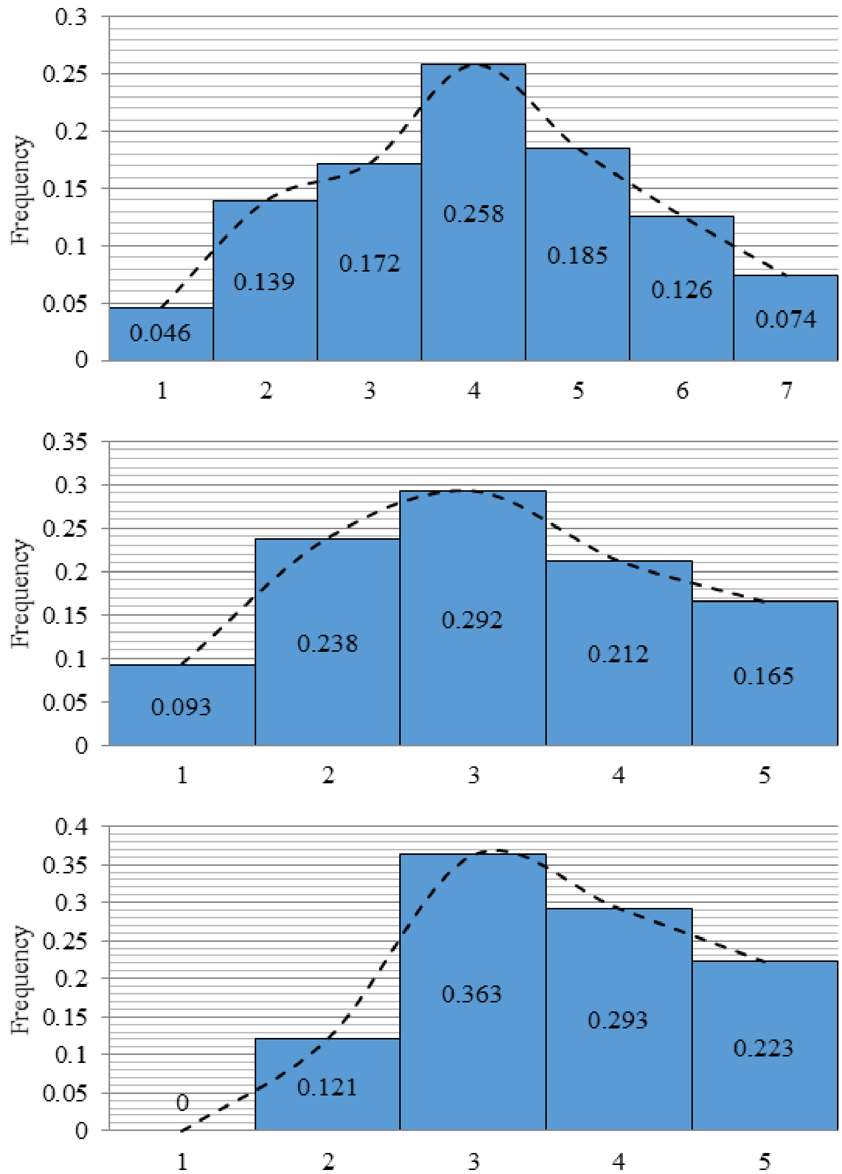


Figure 4.10 Top: histogram of lighting condition preference votes (1: very dark … 7: very bright), middle: histogram of votes on importance of having an outside view (1: least important … 5: most important); Bottom: histogram of votes on importance of having visual privacy (1: least important … 5: most important)

### 4.5.2 Model of occupant interactions with electric lights (L1)

Table 4.5 presents the estimate parameters of the binary model for occupant interactions with the electric lighting system. As mentioned in section 4.3, very few (less than 1%) events of decreasing actions on electric lights were observed in arrival intervals during the field study, and therefore, models were not developed for this case. Features in the final model form are the work plane illuminance along with the simultaneous binary shade lowering action. The latter can be interpreted as occupants' awareness of the state of the room when a shade lowering action is undertaken. That is, occupants know that a shade lowering will result in darker conditions and take a simultaneous electric light raising action to avoid such conditions. This concurrent dynamic of actions results in electric light increasing actions that correspond to high values of work plane illuminance due to the interdependency of human-shading and –electric lighting interactions, which is also reported elsewhere (Reinhart and Voss, 2003; Sadeghi et al., 2016). As discussed previously, shade lowering and raising actions can be adequately described using environmental and human variables. That is, shading interactions can be predicted first and then used to predict occurrence of electric lighting actions.

Table 4.5 Electric light increasing model (L1)

| | Parameter Estimates (β\|95% HPD interval) |
|---|---|
| Work plane illuminance | -1.298\|(-1.901,-0.739) |
| Binary shade lowering action | 1.614\|(1.404,1.808) |
| Constant | -1.791\|(-2.068,-1.578) |
| Log model evidence | -323.27 |
| Observation No. | 786 |

### 4.5.3 Magnitude models (S3, S4, and L2)

Bayesian discrete regression models for shade movement and electric light increase magnitudes are developed, considering only the moments of actions. Parameter estimates are shown in Table 4.6.

None of the human variables were found to be significant in magnitude models while interdependency of the shading and electric lighting interactions found to be important. It is clear from Table 4.6 that the electric light increasing action is a significant feature for predicting the magnitude of shade movement in raising actions. The negative sign of the parameter estimate for this feature indicates that shade raising magnitude is less when undertaken concurrently with an electric light increasing action. When occupants perceive low levels of light in their workspace and decide to take a raising action they might interact with both shading and electric lighting systems to alleviate these conditions (based on results of survey A, and Tables 9 and 10, light level at work plane is a motive for shade raising and electric light increasing actions). In this case, the magnitude of shade movement is less compared to the case when only the shading system is utilized. In the implementation of the whole modeling framework, all input variables for models at the bottom level of the hierarchy (S3, S4, and L2), will be available once the models at top level of hierarchy are run.

Table 4.6 Magnitude models for shade raising/lowering and electric light increasing (S3, S4 and L2)

| | **Parameter Estimates (β\|95% HPD interval)** | | |
|---|---|---|---|
| | Shade raising magnitude | Shade lowering magnitude | Electric light increase magnitude |
| Work plane ill. | -17.556\|(-40.266,9.096) | N/A | -3.012\|(-8.801,2.776) |
| Vertical ill. | N/A | 7.802\|(-0.199,17.579) | N/A |
| Current Shade position | -10.856\|(-41.246,19.534) | 19.878\|(2.026,32.239) | N/A |
| Current electric light level | N/A | N/A | -34.788\|(-50.384,-23.373) |
| Binary electric light increasing action | -20.781\|(-36.104,-11.179) | N/A | N/A |
| Constant | 23.888\|(-3.492,41.919) | 44.705\|(35.501,57.638) | 43.463\|(32.856,50.694) |
| Sigma | 42.084\|(27.089,59.257) | 26.012\|(19. 964,32.453) | 31.967\|(28.194,40.525) |
| Observation No. | 91 | 103 | 135 |
| Log model evidence | -101.851 | -72.183 | -68.555 |

The performance of magnitude models for shading actions is evaluated based on a sample testing set (10% of the data) and visualized in Figure 4.11. The predictive models in this case only allow for discrete values of raising/lowering in 25% increments. Bayesian estimation enables the quantification of the uncertainty of predicted values through probability distributions on possible magnitudes of shade movement for each data point in the testing set. Figure 4.11 indicates these probability distributions as stacked bars. Current positions of window shade and observed shade movement magnitudes are reported for each point. In our Bayesian approach, prior beliefs have been used to exclude infeasible events. For example, it is clear from the lowering plot (Figure 4.11, bottom) that when the window shade is fully open (100%), all the four categories of lowering magnitude (25%, 50%, 75%, 100%) are feasible. However, when the current shade position is 25%, the only feasible lowering amount is 25%, therefore, it has 100% likelihood of happening while other categories follow zero probability in the estimated distribution. High output probabilities are expected for the magnitude categories which correspond to observed values. This is violated in some data points especially in the shade raising magnitude model. This is due to epistemic uncertainty induced by finite amount of data and variation in observations, which is inherently more pronounced in shade raising events, and is captured by the probability responses of the models. It is also demonstrated with the wider range of the high density interval for the standard deviation (Sigma in Table 4.6) estimated for this model. To explore how the uncertainties from all the models (S1, S2, S3, S4, L1, and L2) impact the predictions of the window shade and electric light states, performance of all the models is investigated within the simulation framework presented in section 4.6.

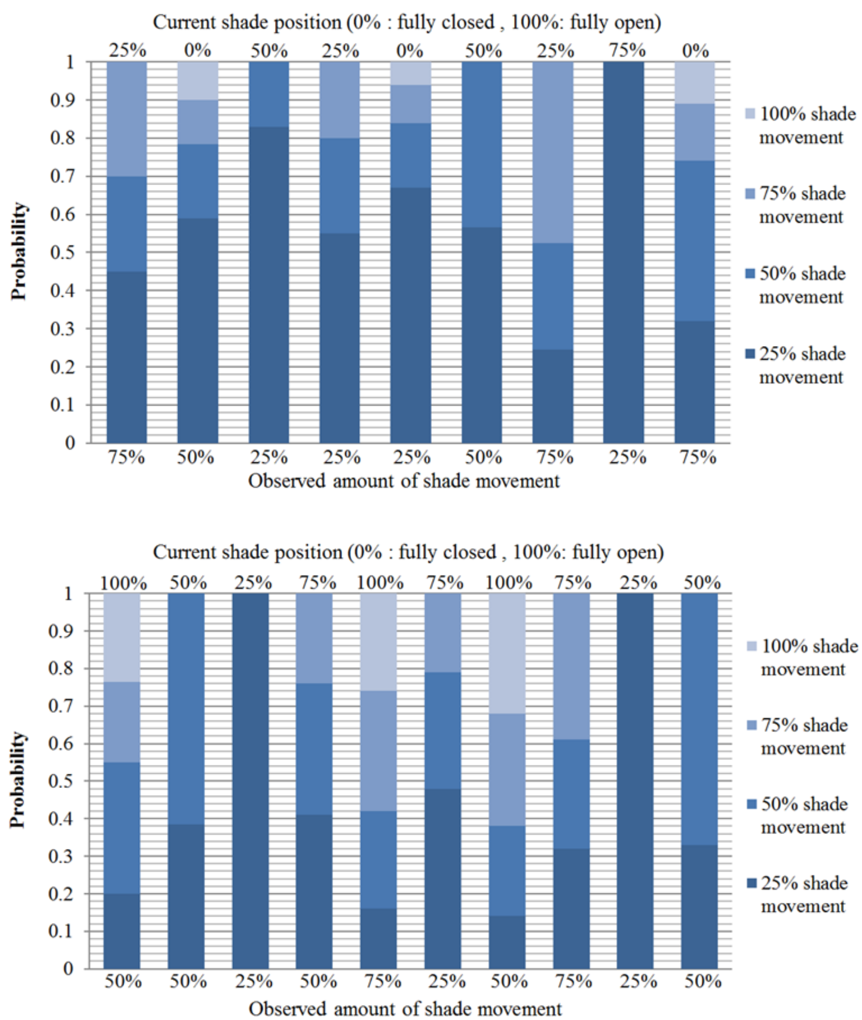


Figure 4.11 Observations versus estimated probability distributions for magnitude of shade raising (top) and lowering (bottom) actions

## 4.6 Implementation and Performance Evaluation

In this section, we first present a practical algorithm for simulating the use of window shades and dimmable electric lights at arrival instances and then evaluate the performance of the modeling framework which integrates all the models presented in section 4.5. Performance evaluation metrics are discussed.

### 4.6.1 Implementation algorithm

The algorithm has three main steps as follows:

- After detecting an arrival, a daylight model provides indoor illuminances given the current shade position and level of electric light. Indoor illuminances are then used along with human variables to run models S1 and S2. Following basic probability rules, outcome probabilities resulted from S1 and S2 are used to calculate the probability of no action happening as: $P_{no\text{-}action} = 1 - P_{raise} - P_{lower}$. A general method of simulating a random process is then undertaken for the predictions. That is, the three probabilities are sorted and stacked from the smallest value forming three likelihood ranges. Then a randomly generated number from a uniform distribution between zero and one is compared with the threshold values to determine the predicted outcome (raising, lowering, or no action), corresponding to the range that the random number lays in. If no action is predicted, the shade position remains the same.
- The predicted binary action (0,1) for shade lowering along with the work plane illuminance are then used to run model L1. The outcome probability is compared with a random uniform number between zero and one to determine whether or not an electric light increasing action happens. If no increasing action is predicted, the state of electric lights remains the same.
- The current shade position, indoor illuminances, and predicted binary action for electric light increasing are used in models S3 and S4 to predict the magnitudes of window shade movement when shade raising or lowering is predicted in step 1. The current state of electric lights along with work plane illuminance is also used to run model L2 when an electric light increasing action is predicted to happen. In order to get predictions from magnitude models with four categories of probability outcomes, stacked bars of probabilities are constructed for each observation as shown in Figure 4.11 and the same approach as in step one is followed.

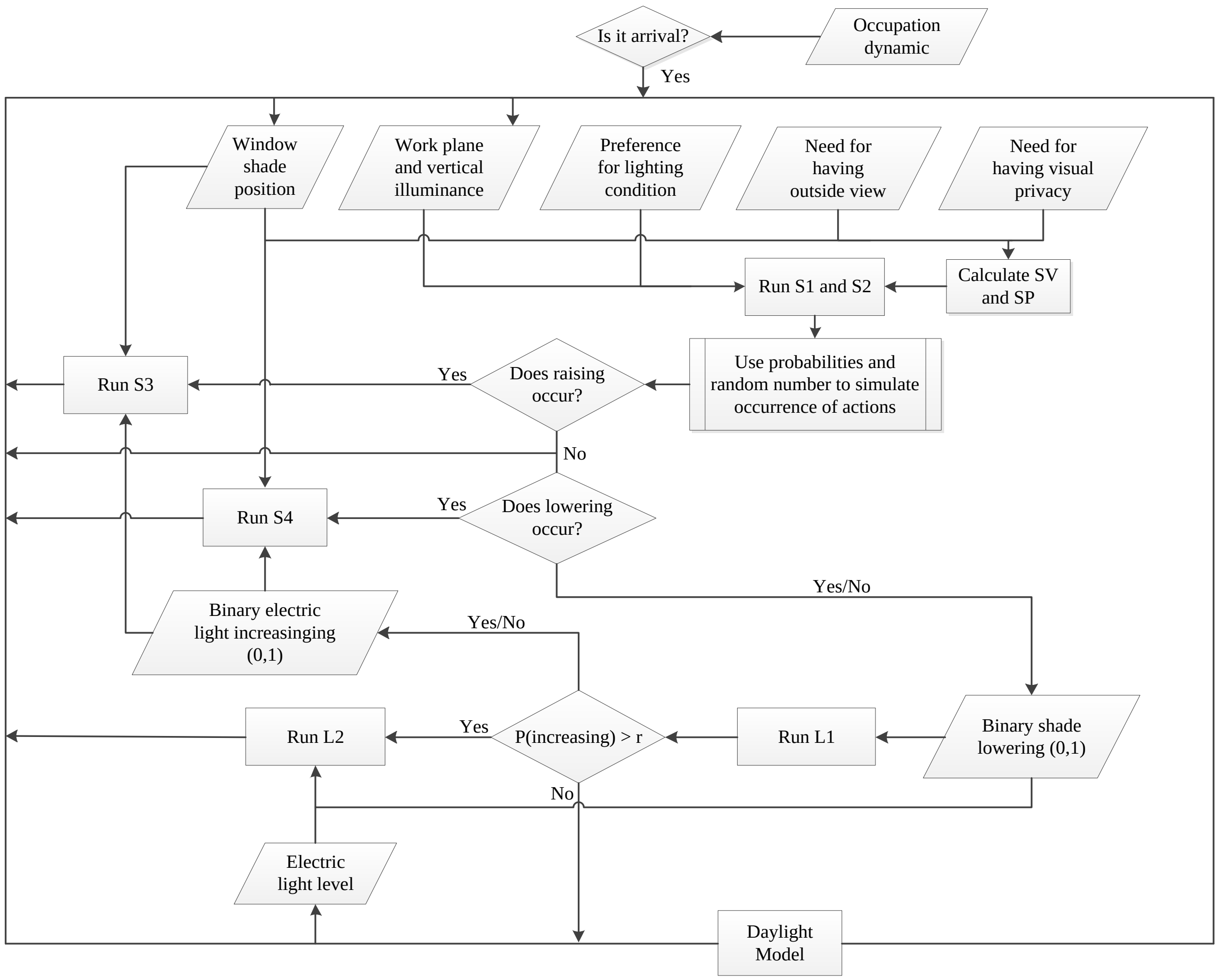


Figure 4.12 Graphical scheme for implementing models of window shade and electric light use in arrival time instances

Figure 4.12 visualizes the flow chart of this algorithm. For the analysis presented in this section, we were able to use measurements of indoor illuminances as inputs; therefore, no coupled daylight model was required. However, for implementation in building performance simulation, coupling with a daylight model would be necessary (Figure 4.12). Our analysis focuses on the arrival time interval, that is, only one instance of actions is predicted. In accordance, feedback from simulated occupants is not applicable in this case. However, when models for intermediate time intervals are considered, feedback from simulated occupant behaviors should be incorporated.

### 4.6.2 Performance evaluation

Herein, to evaluate the predictive power of the models all together, we randomly divide the data into training (90% of data corresponding to 196 days) and testing (10% of data corresponding to 22 days) sets and use the developed models (Section 4.5) along with suggested simulation algorithm (Section 4.6.1) to predict occupants' actions in testing set. The process is repeated 100 times for two sets of models, with and without consideration of human attributes, and we use this comparison as an example for performance evaluation of the proposed modeling framework. The predicted number of actions along with mean values of shading and electric lighting systems' operating state are investigated to evaluate consistency of predictions with observations. Moreover, the prediction success in detecting occurrence of an action, error in shade position and electric light level throughout the simulation, and overall predicted distributions are utilized to further assess whether or not human interactions with shades and electric lights are acceptably reproduced. Use of these metrics is suggested in other studies of occupant behaviors (Mahdavi and Tahmasebi, 2016; Tahmasebi and Mahdavi, 2015; da Silva et al., 2013; O'Brien et al., 2012; Haldi and Robinson, 2010(A)). It should be noted that the impact of human variables on performance of shading raising and lowering models is discussed separately in section 4.5.1 while prediction of shade movement and electric light increase magnitudes using Bayesian discrete regression models is discussed in section 4.5.3. As explained in section 4.5.1, if no prior information is available for personal characteristics such as lighting preferences, need for having a clear view to outside and visual privacy, then different scenarios can be defined or they can be randomly sampled from reported distributions such as those provided in Figure 4.10 based on our field study. However, for the analysis presented here, measurements of human variables were available through the occupant surveys.

Table 4.7 summarizes information on the predictive power of the models while considering two different scenarios. Models S3, S4, L1, and L2 are the same in both cases but form 1 (Table 4.4) of models S1 and S2 are implemented in case 1 while form 2 of these models are applied in case 2. That is, scenario 1 considers human attributes in predicting window shade raising/lowering actions. As shown in Table 4.7, both modeling scenarios predicted fewer actions than actual observations and the simulated average value for the operating state of window shades and electric lights were found to be only slightly closer to actual observations when human variables were considered in scenario 1. However, the mean value may not be the best metric for the purpose of performance comparison. To examine the differences between scenario 1 and 2, the Root Mean Squared Error (RMSE) for the shade position and electric light level is presented in Table 4.7 while distribution of predicted operating states of systems is plotted along with actual observations in Figure 4.13. The significant difference between RMSE of scenario 1 and 2 is clear from Table 4.7 indicating the improved performance when considering human attributes. This can also be seen from Figure 4.13. Both scenarios were able to correctly capture the interdependency of shading and electric lighting systems in their predictions i.e. where high values of window un-shaded portion are predicted, lower levels of electric lights are anticipated and vice versa. However, dissimilarity between distributions of observations and results generated by scenario 2 indicate the poor performance of models without consideration of human attributes and individual characteristics. As another metric of comparison, the percentage of correctly detected actions is investigated and reported in Table 4.7. Better performance of scenario 1 is observed. Finally, it should be mentioned that despite the wide range of standard deviation estimated for model S3 (Table 4.6) which is due to limited amount of data, it can be seen from Table 4.7 that the RMSE for predictions of shade positions is relatively low (14.9%) when all the six models (S1, S2, S3, S4, L1, and L2) run together and human attributes are considered. However, further analysis is required to evaluate energy impacts of errors in predicting shade positions.

Table 4.7 Performance metrics

| | Observations in 100 test sets | Case scenario 1 | Case scenario 2 |
|---|---|---|---|
| Total number of shade raising actions | 605 | 563<br>Prediction success (“0”\|”1”) = (90%\|74%) | 503<br>Prediction success (“0”\|”1”) = (86%\|39%) |
| Total number of shade lowering actions | 858 | 800<br>Prediction success (“0”\|”1”) = (92%\|71%) | 745<br>Prediction success (“0”\|”1”) = (79%\|43%) |
| Total number of electric light increasing actions | 941 | 847<br>Prediction success (“0”\|”1”) = (84%\|52%) | 916<br>Prediction success (“0”\|”1”) = (72%\|27%) |
| Average window un-shaded portion | 36.4% | 38.1% | 42.8% |
| RMSE for window un-shaded portion | --- | 14.9% | 27.6% |
| Average electric light level | 35.4% | 33.2% | 29.3% |
| RMSE for electric light level | --- | 25.3% | 39.1% |

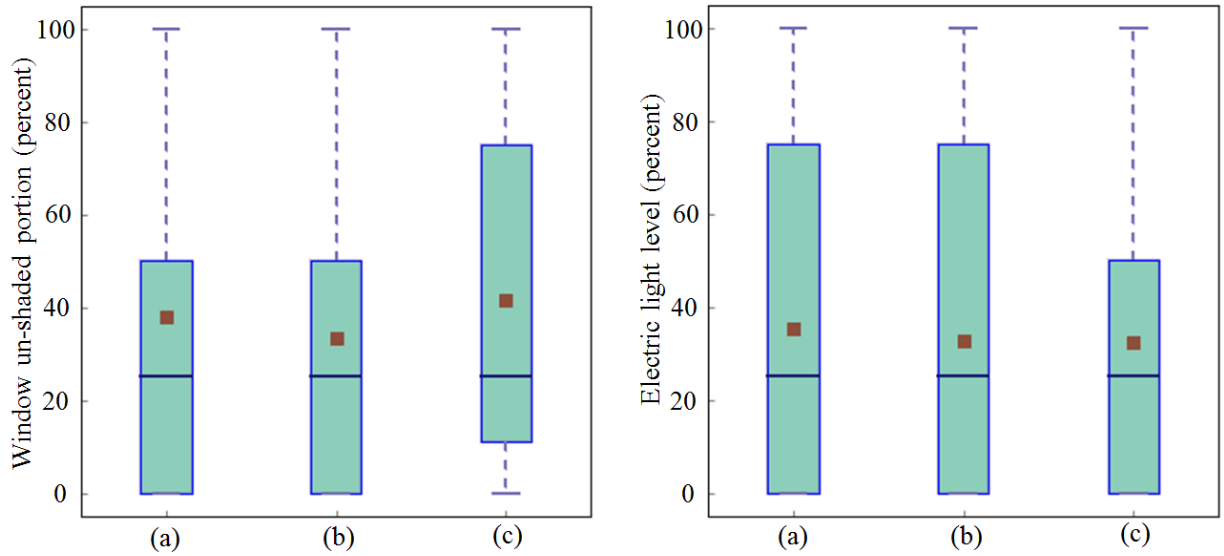


Figure 4.13 Distribution of shade position (left) and electric light level (right) for observations in testing set (a) and predicted values in that set using models of scenario 1 (b) and 2 (c)

## 4.7 Summary

A contribution to modeling of human-shading and –electric lighting interactions in private offices has been presented in this chapter. Bayesian multivariate binary-choice logit models have been developed to predict shade raising/lowering and electric light increasing actions. Bayesian regression models were also used to estimate the magnitude of shading and electric lighting actions, thus, allowing for prediction of intermediate operating states of the systems. Based on the observations in 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 interactions with window shades and electric lights in BPS tools. Interrelated operation of window shades and electric lights was observed and incorporated within the structure of human interaction models with these systems. Human variables proved to have a significant impact on the operation of shading systems. Our findings reveal that it is a combination of environmental 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. The methodology presented in this chapter demonstrates the advantages of the Bayesian formalism for developing human-building interactions models based on limited data. These include, feature selection based on Bayesian model evidence, the use of prior knowledge in the development of magnitude models for human shading/lighting interactions and the discussion of epistemic uncertainty in their performance analysis. Further comparative analysis may be considered in future research.

Our experimental dataset corresponds to a private office with a south façade orientation and the predicted probabilities to 5 min intervals during arrival times. Human-building interaction models were only developed for arrival periods due to the low frequency of actions during intermediate time intervals with continuous occupation and consequently the lack of sufficient observations for model estimation. Nonetheless, due to different dynamics of occupants' interaction with shading and electric lighting systems during intermediate occupancy, separate sets of models need to be developed for this period. The impacts of control interface on occupant-building interactions in arrival period was not significant so none of models presented in this chapter incorporated this factor. However, human-building interactions during intermediate period can be affected by control interfaces may require different model dynamics.

# CHAPTER 5. BAYESIAN CLASSIFICATION AND INFERENCE OF OCCUPANT VISUAL PREFERENCES IN DAYLIT PERIMETER OFFICES

## 5.1 Overview

This chapter further investigates the complex interactions related to visual environment control in private offices of perimeter building zones and presents a novel method developed for learning occupant visual preferences. In the first step of the methodology, field observations of occupants' perception and satisfaction with the visual environment are collected when exposed to variable daylight and electric light conditions, along with data from room sensors, shading and light dimming states. Consequently, a Bayesian classification and inference model is formulated, using the Dirichlet process prior and multinomial logistic regression, to develop probability distributions of occupants' preference, such as prefer darker, prefer brighter, or satisfied with current conditions. Based on field observations, it is encoded within the model structure that occupants' visual preferences are influenced by a combination of measured environmental and control state variables describing the luminous environment, as well as latent human characteristics. The latter represent hidden random variables used to determine the optimal number of possible clusters of individuals with similar visual preference characteristics in the studied office building population. In the final step, the visual preferences of new occupants in the dataset are learnt by inferring their cluster values, and the personalized profiles are derived using a mixture of the general probabilistic sub-models.

## 5.2 Data Collection

To collect data on occupants' lighting preferences under a wide range of visual conditions, we designed and conducted field observations using two of the identical perimeter south-facing private offices shown in Figure 3.1. As described in Section 3.3, the offices have 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 windows are equipped with dark-colored motorized interior roller shades (total visible transmittance = 2.53%, measured with an integrating sphere, and openness factor = 2.18%). There are two electric lighting fixtures with two 32-watt T5 fluorescent lamps (total of 128 watts, correlated color temperature of 4100 K) in each office which can provide a maximum of 500 lx on the work plane.

During the data collection for the purposes of this chapter, each office was occupied by one participant every day between 10:00 AM and 4:00 PM. Upon arrival in the morning, the room air temperature was 22 $^{o}$C in both offices. Occupants utilized typical wall thermostats to precisely control the room temperature as they wished. The Variable Air Volume (VAV) system in each office was fine-tuned to maintain the temperature within ±0.5 $^{o}$C of the set point using feedback from two sensors installed close to the occupant. In this way, potential interactions between thermal effects and occupant visual preferences were eliminated as much as possible.

Each test-day included a morning and afternoon session, with a 60 min lunch break in between. During each session occupants were exposed to four different combinations of daylight and electric light conditions, each lasting for 25 minutes. At the end of each test-condition, a short web-based survey questionnaire was sent to participants by e-mail to collect their feedback. Phone alarms were used as reminders for this task. Table 5.1 presents a summary of the survey completed after each test-condition. Additional information for occupants' general attitudes towards the visual environment is obtained through the exit survey (Table 5.1) at the end of the test-day.

Table 5.1 Summary of survey questionnaires

| Questions | Answer options |
|---|---|
| Survey after each lighting condition | |
| **1) How would you describe the current lighting condition at your workspace?** | 1. Very dark, 2. Dark, 3. Slightly dark, 4. Neutral, 5. Slightly bright, 6. Bright, 7. Very bright |
| **2) How satisfied are you with the current lighting condition?** | 1. I prefer brighter, 2. I prefer darker, 3. I am satisfied with the current lighting condition |
| Exit survey at the end of the day | |
| **3) In general, how sensitive are you to brightness?** | 1. Least sensitive, …, 5. Most sensitive |
| **4) In general, what is your preference for lighting conditions at your workspace?** | 1. Very dark, 2. Dark, 3. Slightly dark, 4. Neutral, 5. Slightly bright, 6. Bright, 7. Very bright |

A sensor, communication, and data acquisition framework was deployed to measure and record the following environmental variables and control states during the field study:

- Shade position and electric light levels: shading and lighting systems in the building were connected to lighting control hardware which records data and communicates with the building's JACE controllers through the Niagara framework (Tridium Inc.) and BACnet protocol.

- Work plane illuminance, vertical illuminance and transmitted illuminance through the window were measured with calibrated LI-COR 210 photometric sensors, which have a cosine correction and an error percentage of less than 3%. The work plane illuminance sensor was placed on the desk, facing upwards, in a central position of the working area. Participants were advised to keep the sensor unobstructed. The vertical (on eye) illuminance sensor was mounted vertically adjacent to the occupant's head (30 cm away) to capture representative values without obstructing the work area. The amount of transmitted light through the window was measured with a sensor vertically mounted on the inside of the glazing, facing outside.

All the sensors described above were connected to data acquisition input modules, and through a wireless connection, to the main data acquisition (DAQ) controller that communicated with JACE controllers through the Niagara framework and Modbus protocol. Figure 5.1 shows a typical layout of the offices along with the monitoring instrumentation. Using proper communication protocols, we discovered all sensor readings in Niagara framework where they were recorded every minute.

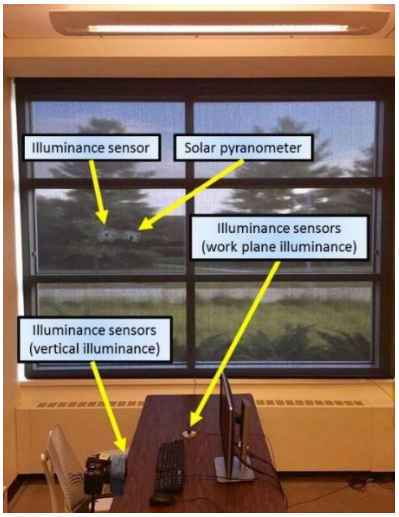


Figure 5.1 Typical office layout and monitoring instrumentation

Real-time readings of the illuminance sensor at work plane were used as a control variable to achieve specific light levels using combinations of daylight and electric light. Work plane illuminance levels produced by electric lights were measured at nighttime for different light dimming levels. A shading control algorithm was developed and implemented in the BMS system. This algorithm controlled the position of motorized roller shades so that reading of work plane illuminance was kept within 50 lux of any specific set-point. Depending on the outdoor conditions, up to eight different lighting conditions (presented in Table 5.2) were tested each day, and their sequence was randomized to avoid any carry-over effects in the data.

As mentioned earlier, dissatisfaction with visual conditions may be attributed to glare or unsatisfactory light levels (inadequate or excessive illuminance levels). To distinguish between these two, focus on preferences, and reduce the complexity, we conducted the experimental study in glare-free conditions. To achieve this, the sun was not in the field of view of occupants (by using west-facing direction in the morning and east-facing direction in the afternoon), while work plane illuminance levels did not exceed 2000 lux (Table 2). The latter has proved to satisfy general discomfort glare criteria (Shen and Tzempelikos, 2017) in accordance with the UDI concept (Nabil and Mardaljevic, 2006), but cannot be used alone as a safe measure. Vertical illuminance thresholds (typically 2760 lux) have proven to be adequate measures of visual discomfort in the absence of sunlight and high contrast (Chan et al., 2015; Konstantzos et al., 2015(A); Karlsen et al., 2015). During our field observations vertical illuminance did not exceed 1500 lux to ensure comfortable conditions. Sample luminance measurements with a HDR camera were also taken to ensure that resulting DGP values are lower than 35%.

Table 5.2 Experimented lighting conditions

| Illuminance Level (lux) | Combination 1 | Combination 2 | Combination 3 |
|---|---|---|---|
| 500 | 250 E + 250 D | 0 E + 500 D | --- |
| 1000 | 500 E + 500 D | 250 E + 750 D | 0 E + 1000 D |
| 1500 | 500 E + 1000 D | 0 E + 1500 D | --- |
| 2000 | 0 E + 2000 D | --- | --- |

E: Electric Light, D: Daylight

The field study was conducted over a period of 42 days between October 2016 and January 2017 including 17 sunny days, 15 cloudy days and 10 days with mixed sky conditions. Overall, 80 office occupants (49 males and 31 females), graduate students and staff (between 20 and 40 years old) not familiar with this research, participated in the study. All participants were asked to perform their usual workload (computer-related work, reading, writing, etc.) during the day and advised to avoid any direct contact with the monitoring instrumentation. To eliminate any bias in the results, each occupant participated only for a single day. This sampling method facilitates the participation of a large number of human test subjects, which is necessary for the purpose of this study and does not require the installation of experimental equipment in a large number of offices.

Before starting the actual field study, the impact of test duration, in terms of the number of days each human test-subject stays in the office, was examined by investigating visual preferences in three consecutive days. In this way, occupants' feedback is representative of their true visual preferences. To this end, 10 human test-subjects were recruited to participate in the field study for three consecutive days, and their visual preference votes were monitored along with environmental conditions. Consistent votes were observed for all participants during this test. Representative results (Figures 5.2, 5.3, and 5.4) show the visual preference votes along with work plane illuminances. The window unshaded portion is also included to indicate how the work plane illuminance set point is achieved.

It is clear from Figure 5.2 that this specific participant preferred a slightly dark lighting condition at his/her workspace and voted accordingly on all three days. He/she reported to be satisfied with lower shade positions and work plane illuminance levels while almost always preferred to have darker conditions when work plane illuminance exceeded 500 lux. The occupant's preference towards dark conditions was also reflected by the answer to a question in the online survey asked at the end of day three (In general, how would you prefer the lighting conditions at your workspace? 1. Very dark … 7. Very bright). Similarly, as shown in Figure 5.3, the participant preferred very bright conditions and voted consistently on all three days. Figure 5.4 shows consistent visual preference votes from a participant who preferred moderate lighting conditions at his/her workspace. As shown in the figure, in all three days, the participant preferred darker conditions when work plane illuminance was higher than 1000 lux while consistently voted to be satisfied for lower illuminance levels. The preference vote for darker conditions with 1000 lux of work plane illuminance (500D + 500E) on the first day can be explained by the high window unshaded portion.

This will be further explained in Section 5.3 where it is shown that window unshaded portion can impact visual preference profiles which is why it is incorporated within the model structure presented in Section 5.4.

In overall, observations from the initial tests indicate that the results of this study can be representative of typical office occupants. The field study with human test-subjects was approved by the Institutional Review Board (IRB Protocol #: 1507016229).

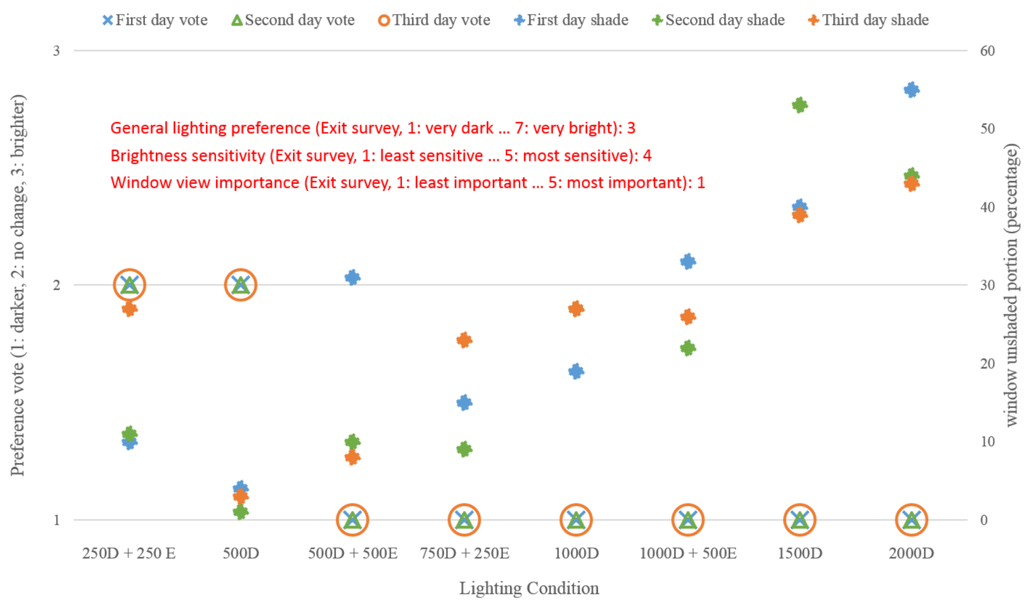


Figure 5.2 Consistency in occupants' visual preferences (lighting preference: slightly dark)

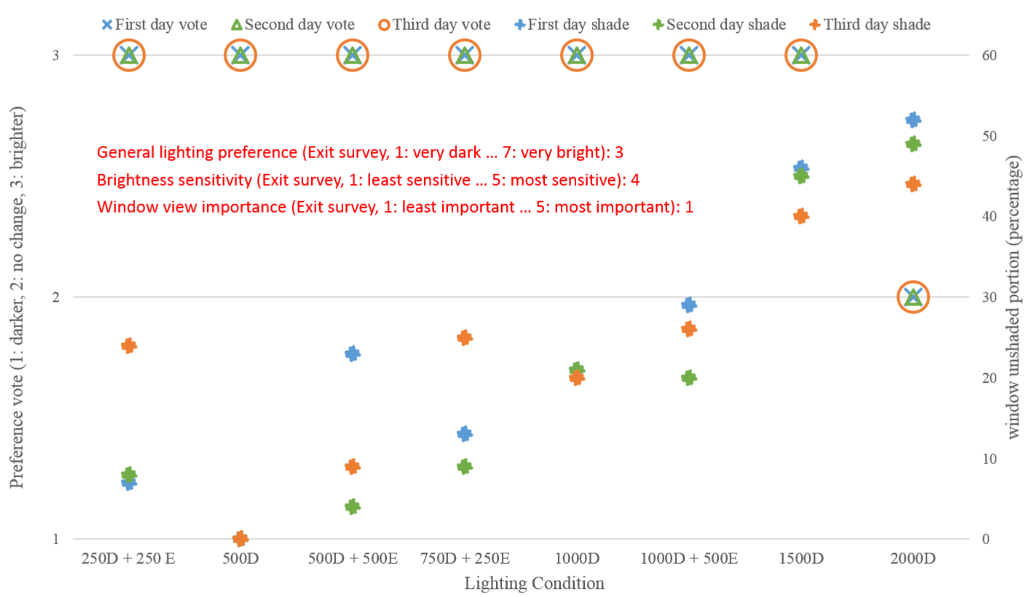


Figure 5.3 Consistency in occupants' visual preferences (lighting preference: very bright)

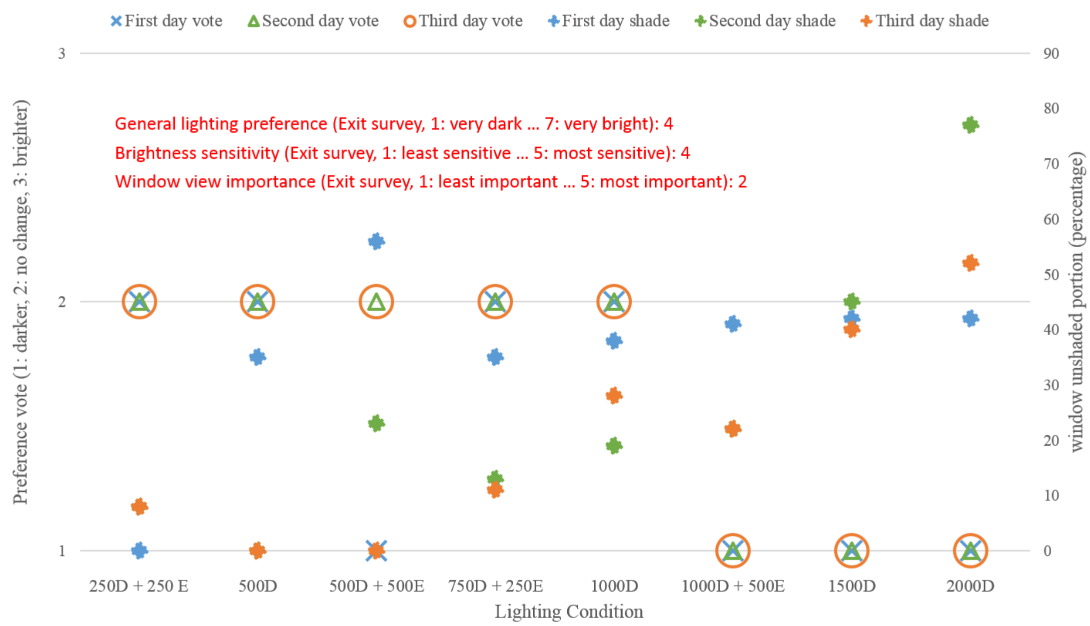


Figure 5.4 Consistency in occupants' visual preferences (lighting preference: moderate)

## 5.3 Experimental Observations

In this section, we discuss key experimental observations that provide the basis for developing probabilistic models of occupants' visual preferences. In Figure 5.5, we present the frequency of preference votes collected during the field study (Table 5.1). The frequency of preferring brighter conditions is the highest at 500 lux of work plane illuminance while preference for darker conditions has the lowest frequency at this light level. The highest frequency of occupants' satisfaction with the current condition is observed at 1500 lux of work plane illuminance followed by 1000 lux and 500 lux.


Figure 5.5 Distribution of lighting preference votes

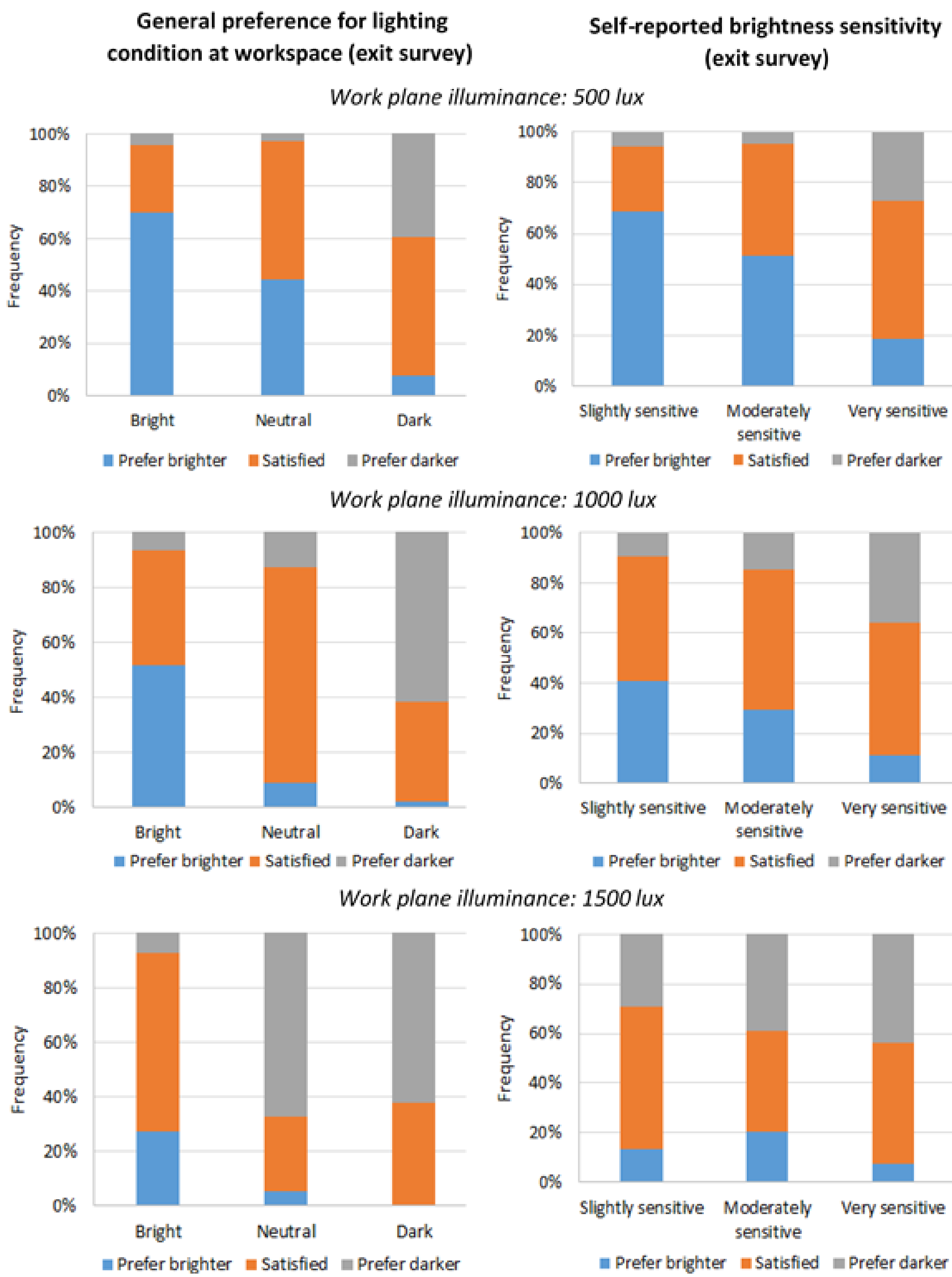


Figure 5.6 Lighting preference votes for different lighting conditions filtered based on human attributes collected in the exit survey. Left: filtered based on responses to the question "In general, what is your preference for lighting conditions at your workspace?"; Right: filtered based on responses to the question "In general, how sensitive are you to brightness?"

To investigate the possibility of classification in lighting preferences, we utilize the outcomes of the exit survey (Table 5.1) to filter the preference votes, and show the results in Figure 5.6. Specifically, we use responses of “slightly dark,” “dark,” and “very dark” to the question of “In general, what is your preference for lighting conditions at your workspace?” in the exit survey to define occupants who prefer dark conditions. Also, we use responses “slightly bright,” “bright,” and “very bright” to filter occupants with a preference towards bright conditions and the “neutral” vote to represent people who prefer moderate visual conditions. Similarly, we use responses 1 and 2 to the question of “In general, how sensitive are you to brightness?” to define slightly sensitive occupants while response 3 defines moderately sensitive people and responses 4 and 5 indicate occupants who consider themselves to be very sensitive to brightness. Figure 5.6 shows that distributions of lighting preference votes vary significantly with human characteristics in almost all lighting conditions (note that 2000 lux work plane illuminance is not shown in this plot due to a low relative frequency of this condition compared to the rest). For instance, when occupants are exposed to 1000 lux of work plane illuminance, the percentage of “satisfied” votes is significantly lower for occupants that expressed a preference for bright conditions compared to those who prefer moderate conditions (Figure 5.6, middle left plot). As another example, when occupants are exposed to 500 lux of work plane illuminance, the percentage of the vote for preferring brighter conditions decreases as occupants are more sensitive to brightness (Figure 5.6, top right plot). Moreover, the frequency of the vote for dark preferring conditions increases when more sensitive occupants are exposed to the same level of light. These observations provide evidence for the existence of clusters in occupants’ visual preferences, attributed to individual characteristics; this is further discussed in Section 5.4.

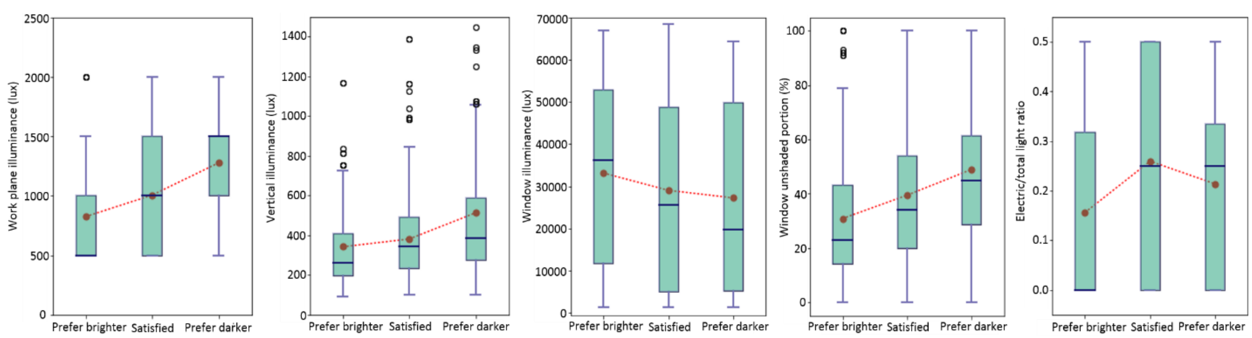


Figure 5.7 Distribution of observed environmental variables for different lighting preference votes during the field study

To examine how visual preferences are influenced by environmental variables, we present in Figure 5.7 the distributions of observed environmental variables for each class of preference vote (Prefer brighter, Satisfied, and Prefer darker on the x-axis). A line connecting mean values in each distribution is also overlaid. A clear trend is observed for some of the variables (i.e. work plane illuminance, vertical illuminance, and window unshaded portion) suggesting these variables as inputs of a visual preference model. A systematic investigation of the preference sensitivity to these variables is presented in Section 5.4.

In perimeter building zones, the shading position along with the ratio of daylighting and electric light may affect occupants' perception of the visual environment. To investigate this effect, we depict in Figure 5.8 the distributions of window unshaded portion for different perceptions under each lighting condition. Responses of "slightly dark," "dark," and "very dark" to the question of "How would you describe the current lighting condition at your workspace?" are grouped together to represent conditions perceived as dark; and similarly for responses of "slightly bright," "bright," and "very bright". "Neutral" votes are used to filter out the perception of neutral conditions. We observe that when occupants are exposed to 500 lux and 1000 lux of work plane illuminance, they perceive the same lighting condition as brighter for larger window unshaded portion. As expected, this effect is not observed in high levels of work plane illuminance such as 1500 lux and 2000 lux. Intuitively, the impact of the window unshaded portion is also expected to affect the visual preferences. Figure 5.9 depicts this effect for two light levels (500 lux and 1000 lux): under the same lighting level, the frequency of the preference vote for brighter conditions decreases when the window unshaded portion is higher while preference for darker conditions increases. It is worth mentioning that, similar to the perception votes, this impact is not significant for higher light levels (1500 lux and 2000 lux). These findings provide clear evidence that the window shade position is also an important feature in a visual preference model.

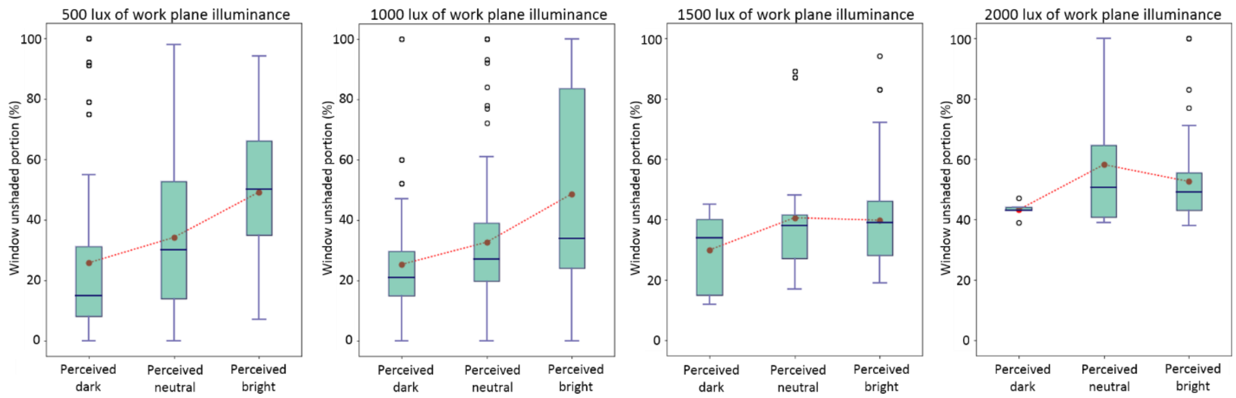


Figure 5.8 Distributions of window unshaded portion filtered based on lighting perception under different lighting conditions

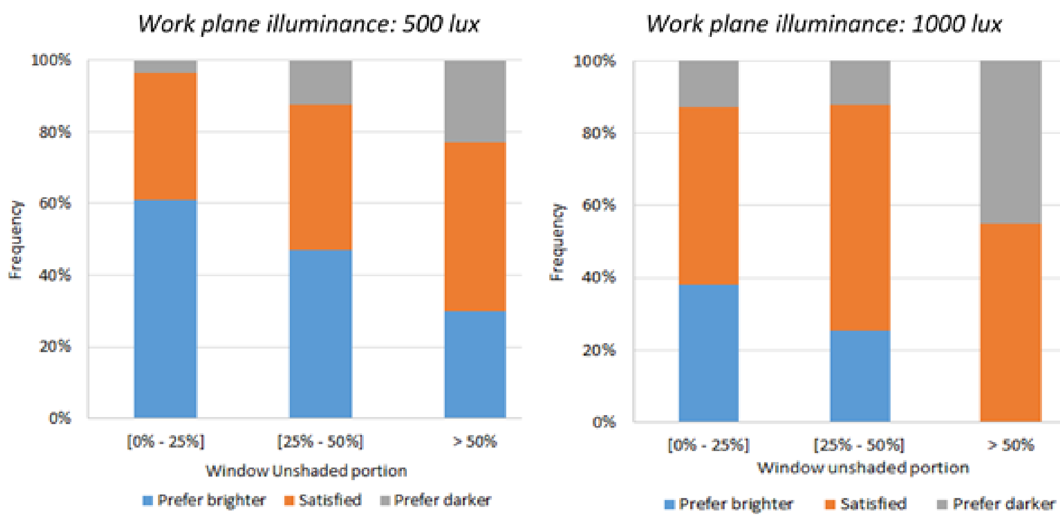


Figure 5.9 Distributions of lighting preference vote filtered based on window unshaded portion

Figure 5.10 shows the distribution of occupant perception votes collected after exposure to each lighting condition for cases with the electric lights ON and OFF. We observe that for work plane illuminances up to 1000 lux, occupants tend to perceive the same lighting level brighter when it is provided by the combination of natural and artificial lighting sources compared to cases with daylight only. These results suggest that the electric lighting ratio may be a significant feature in visual preference models. However, observations might be affected by the specific range of the spectrum or color temperature of the lights used in this study (32-watt T5 fluorescent lamps with correlated color temperature of 4100 K) and further investigation with different lamps is recommended.

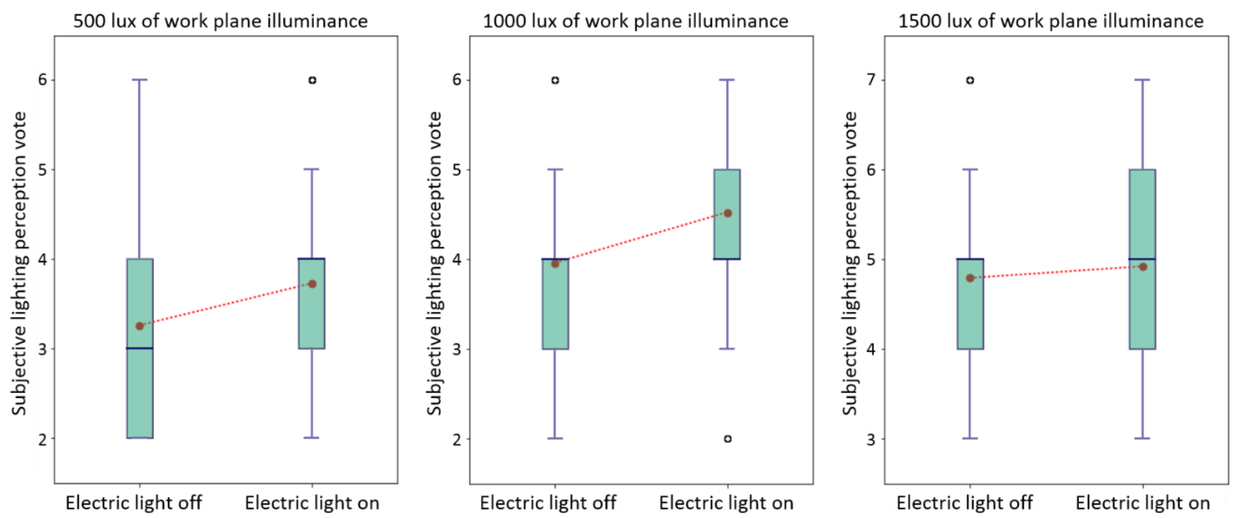


Figure 5.10 Distribution of the responses to the question "How would you describe the current lighting condition at your workspace?" (1. Very dark … 7. Very bright) for electric light ON and OFF cases

## 5.4 Discovering Clusters of Occupants with Similar Visual Preference Characteristics

Based on the experimental observations presented in Section 5.3, we develop a general visual preference model by encoding the following hypothesis: "different people prefer different visual environments". We assume that there is an unknown number of possible clusters of individuals with similar visual preference characteristics. Thus, developing the preference model becomes a clustering problem, i.e., discovering groups of people in a dataset and developing sub-models for each cluster.

### 5.4.1 Modeling methodology

We postulate that the graph in Figure 5.11 represents our knowledge and beliefs regarding occupants' visual preferences. Yellow nodes are the observed potential input variables (features), and the green node stands for the observed output variable. The white node represents personal visual characteristics, which are treated as unobserved features within the model structure, as collecting related data in actual buildings could be impractical. Variables such as brightness sensitivity or general preference for lighting conditions at work space, observed through surveys in our field study, may be related to these visual preference characteristics. This hypothesis is tested in Section 5.4.2

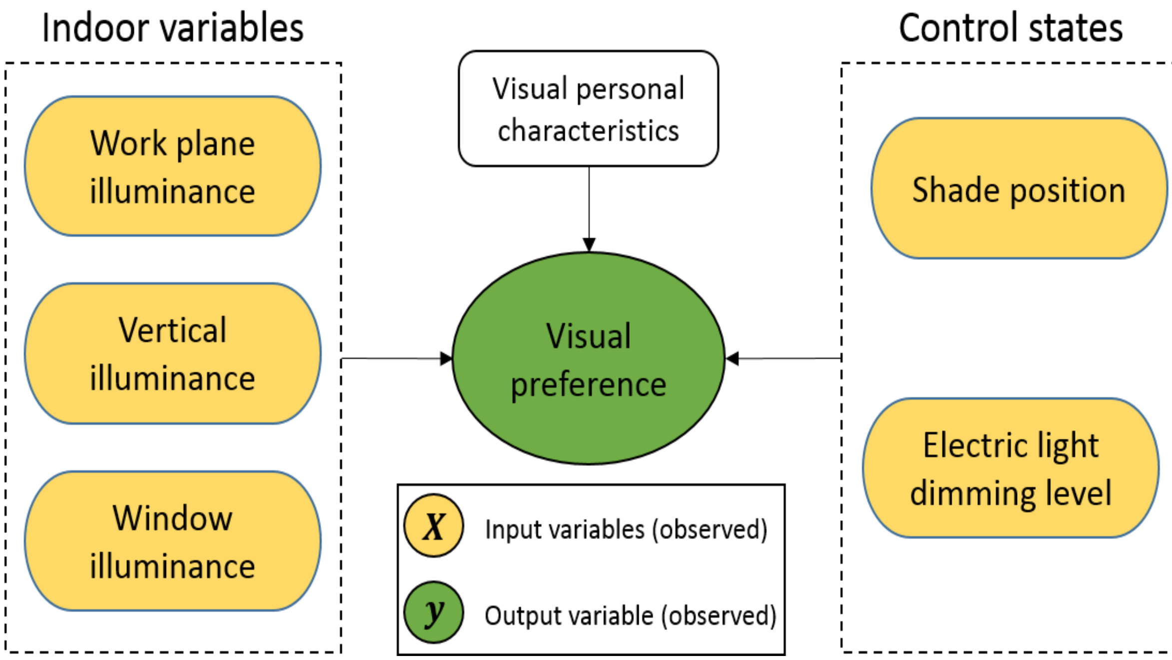


Figure 5.11 Visual preference and potential underlying features

Mathematically, we denote the features by $\mathbf{x} = (1, x_1, \ldots, x_m)$, the preference vote by $y$, and the hidden personal characteristics by $z$. Note that we have prepended a constant unit feature to simplify the notation of the preference model presented below. The preference vote $y$ is a discrete random variable such that $y = 1$ corresponds to "prefer brighter", $y = 2$ to "prefer darker", and $y =$ 3 to "satisfied with current conditions". The latent visual characteristics are represented by the variable $z = 1, \ldots, K$, where $K$ is the (unknown) number of possible visual preference clusters. We hypothesize that the probability of an individual expressing a preference vote $y = c$ given the environmental conditions $\mathbf{x}$ and their preference profile $z$ is given by the multinomial logistic regression model:

$$p(y = c|\mathbf{x}, \mathbf{B}, z) = \frac{\exp(\boldsymbol{\beta}_{z,c}^{\mathrm{T}}\, \mathbf{x})}{\sum_{c'=1}^{C} \exp(\boldsymbol{\beta}_{z,c'}^{\mathrm{T}}\, \mathbf{x})}. \qquad \text{(Eq. 5.1)}$$

Here, $\mathbf{B} = \{\mathbf{B}_1, \ldots, \mathbf{B}_{\mathrm{K}}\}$ denotes all the model parameters, $\mathbf{B}_k = \{\boldsymbol{\beta}_{k,1}, \boldsymbol{\beta}_{k,2}, \boldsymbol{\beta}_{k,3}\}$ are the parameters corresponding to cluster k, and $\boldsymbol{\beta}_{k,c}$ is the $(m + 1)$-th dimensional vector of the $c$-class coefficients in $k$-th multinomial logistic regression model. Without loss of generality, we take $\boldsymbol{\beta}_{k,3} = \mathbf{0}$ for all $k$.

Let $\mathbf{y}_{1:D} = \{\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_D\}$ and $\mathbf{X}_{1:D} = \{\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_D\}$

$$p(\mathbf{y}_{1:D}|\mathbf{X}_{1:D}, \mathbf{B}_{1:K}, z_{1:D}) = \prod_{d=1}^{D} p(\mathbf{y}_d|\mathbf{X}_d, \mathbf{B}_{z_d}, z_d) = \prod_{d=1}^{D}\prod_{i=1}^{n_d} p(y_{d,i}|\mathbf{x}_{d,i}, \mathbf{B}_{z_d}, z_d), \quad \text{(Eq. 5.2)}$$

where i stands for each sample and $\prod_{i=1}^{n_d} p(y_{d,i}|\mathbf{x}_{d,i}, \mathbf{B}_{z_d}, z_d)$ represents the likelihood of a single occupant. To proceed, we need to specify our *prior* state of knowledge about the coefficients $\mathbf{B} = \{\mathbf{B}_1, \dots, \mathbf{B}_K\}$ in the model. Since we do not have much prior information about them, we will construct a vague hierarchical prior distribution. Specifically, we assign to $\boldsymbol{\beta}_{k,c}$ a zero mean Gaussian prior,

$$p(\boldsymbol{\beta}_{k,c}|\tau) = \mathcal{N}(\boldsymbol{\beta}_{k,c}|0, \tau^{-1}\mathbf{I}_{m+1}), \quad \text{(Eq. 5.3)}$$

where $\mathcal{N}(\cdot|\boldsymbol{\mu}, \boldsymbol{\Sigma})$ is the PDF of a multivariate Gaussian distribution with mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$, $\mathbf{I}_{m+1}$ is the $(m+1)$-dimensional unit matrix, and $\tau > 0$ is an a priori unknown precision. Completing the model specification, we assign the following prior to $\tau$:

$$p(\tau|\lambda_1, \lambda_2) \sim G(\tau|\lambda_1, \lambda_2), \quad \text{(Eq. 5.4)}$$

where $G(\cdot|\lambda_1, \lambda_2)$ is the PDF of a gamma random variable with parameters $\lambda_1, \lambda_2$. Here, we set $\lambda_1 = \lambda_2 = 0.001$.

To investigate existence of clusters of visual preferences, we employ the machinery of the Dirichlet process prior. Understanding how the DP allows us to model an arbitrary number of clusters is beyond the scope of this work. The interested reader is directed to the discussions in (Chen et al., 2015; Lee et al., 2017). It suffices to say that the DP prior enables us to infer the probability of each cluster being active, while automating the discovery of the optimal number of clusters (Lee et al., 2017). Avoiding the cumbersome rigorous DP definition, we proceed directly to the "stick-breaking" construction (Sethuraman, 1994). The "stick-breaking" construction of DP is equivalent to assigning the following prior over the cluster value $z$ (Chen et al., 2015),

$$p(z_{1:D}|\mathbf{v}) = \prod_{d=1}^{D} \pi_{z_d}(\mathbf{v}), \quad \text{(Eq. 5.5)}$$

where

$$\pi_k(\mathbf{v}) = v_k \prod_{i=1}^{k-1} (1 - v_i), \quad \text{(Eq. 5.6)}$$

and the auxiliary random variables $v_i$ are Beta distributed:

$$p(v_k|\alpha_0) = \mathcal{B}\text{eta}(v_k|1, \alpha_0). \quad \text{(Eq. 5.7)}$$

The weights $\pi_k$ decay at a rate specified by the concentration parameter $\alpha_0 \geq 0$ which controls our prior belief about the number of clusters a priori. Small $\alpha_0$ corresponds to the prior belief that the number of clusters is small, and large $\alpha_0$ to the prior belief that the number of clusters is large. A choice of $\alpha_0 = 0$ corresponds to the belief that there is a single cluster. In other words, the $\pi_k$'s can be interpreted as the probability of cluster $k$ being active. To close the model, we need to pick a value for the $\alpha_0$. Since we do not have prior information about it, we employ a hierarchical Bayesian approach and assign to an exponential distribution with rate parameter equal to 1, i.e., $p(\alpha_0) = \mathcal{E}(\alpha_0|1)$. In principle, the DP allows for an infinite number of clusters. In practice, however, all components are truncated at a large, but finite, upper number of clusters $K$. To ensure allowing enough flexibility for revealing clusters, this value must be selected to be bigger than the maximum number of clusters we anticipate finding. Based on several initial attempts of model development, we find that the choice $K = 5$ is adequate for our work.

Figure 5.12 shows the overall model structure using standard plate notation (Buntine, 1994). Using the Bayes rule, the posterior distribution given the data can be written as:

$$p(z_{1:D}, \mathbf{B}_{1:K}, \tau, \nu_{1:K}, \alpha_0 | \mathbf{y}_{1:D}, \mathbf{X}_{1:D}) \propto$$
$$p(\mathbf{y}_{1:D}|\mathbf{X}_{1:D}, \mathbf{B}_{1:K}, z_{1:D}) p(\mathbf{B}_{1:K}|\tau) p(\tau) p(z_{1:D}|\nu_{1:K}) p(\nu_{1:K}|\alpha_0) p(\alpha_0). \quad \text{(Eq. 5.8)}$$

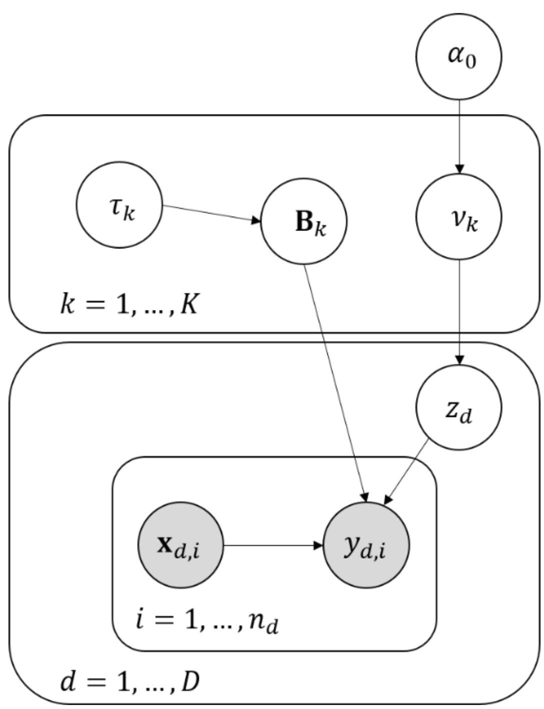


Figure 5.12 Plate notation of overall model structure. Shaded: observed; plain: unobserved

### 5.4.2 Model training

To train the general visual preference model, we use the dataset obtained from the field study described in Section 5.2. This dataset includes 565 observations collected from 75 occupants. To estimate the model parameters with a fully Bayesian approach, we sample the parameters and the hidden cluster values from the posterior distribution. Since the posterior distribution is intractable analytically, sampling techniques such as sequential Monte Carlo (SMC) can be used (Sadeghi et al., 2017; Lee et al., 2017; Bilion and Koutsourelakis, 2102). Although SMC is more efficient than standard sampling techniques such as Markov chain Monte Carlo (MCMC) (Bilion and Koutsourelakis, 2102), it still remains very costly and suffers from the label switching problem (Lee et al., 2017). To overcome these issues, we are going to use variational inference; a deterministic approximation method which instead of drawing samples from the posterior, fits a distribution to it and turns the sampling problem into an optimization problem (Bishop, 2006). Assume $\boldsymbol{\theta}$ collects all the model parameters. Variational Inference fits a distribution $q(\mathbf{s})$ to the posterior $p(\mathbf{s}|\mathbf{Data})$, where $\mathbf{s}$ is a set of parameters $(\boldsymbol{\theta})$ and unobserved variables $(z_{1:D})$ while $\mathbf{Data}$ represents the all the observations $(\mathbf{y}_{1:D}, \mathbf{X}_{1:D})$. The distribution $q(\mathbf{s})$ is restricted to belong to a family of distributions simpler than $p(\mathbf{s}|\mathbf{Data})$. Variational inference attempts to minimize the information loss as measured by Kullback-Leibler divergence (KL-divergence) between $p(\mathbf{s}|\mathbf{Data})$ and $q(\mathbf{s})$:

$$D_{KL}(q(\mathbf{s})||p(\mathbf{s}|\mathbf{Data})) = \int q(\mathbf{s}) \log \frac{q(\mathbf{s})}{p(\mathbf{s}|\mathbf{Data})} d\mathbf{s}, \qquad \text{(Eq. 5.9)}$$

where $p(\mathbf{Data})$, written as below, is known as the *evidence*.

$$p(\mathbf{Data}) = \int p(\mathbf{Data}, \mathbf{s})\, d\boldsymbol{s}. \qquad \text{(Eq. 5.10)}$$

This minimization problem is equivalent to maximizing the evidence lower bound (ELBO):

$$L(q) = \int q(\boldsymbol{s})\, ln \frac{p(\mathbf{Data}, \mathbf{s})}{q(\boldsymbol{s})} d\boldsymbol{s} \leq \log p(\mathbf{Data}). \qquad \text{(Eq. 5.11)}$$

Although the maximization of ELBO can be conducted analytically if we design the model carefully (i.e., conditionally conjugate model), the algorithm should be manually derived for each model structure. However, unlike the traditional algorithms of Variational Inference, there are new methods which can automate this process (Ranganath et al., 2014; Salimans and Knowles, 2014; Titsias and Lázaro-Gredilla, 2014; Kucukelbir et al., 2015) and promote the Bayesian approach in large-scale machine learning problems. In this study, Automatic Differentiation Variational Inference (ADVI) (Kucukelbir et al., 2016) is used. Since ADVI does not support discrete variables, first we marginalize $z_{1:D}$ out from the posterior (Eq. 5.8) as:

$$p(\boldsymbol{\theta}|\mathbf{y}_{1:D}, \mathbf{X}_{1:D})$$
$$\propto \sum_{z_{1:D}} p(\mathbf{y}_{1:D}|\mathbf{X}_{1:D}, \mathbf{B}_{1:K}, z_{1:D}) p(\mathbf{B}_{1:K}|\tau) p(\tau) p(z_{1:D}|\nu_{1:K}) p(\nu_{1:K}|\alpha_0) p(\alpha_0). \quad \text{(Eq. 5.12)}$$

ADVI transforms the support of the parameters ($\boldsymbol{\theta}$) to the real coordinate space and deal with the transformed variables $\boldsymbol{\zeta}$. Thereafter, ADVI fits a mean-field Gaussian distribution to the posterior of $\boldsymbol{\zeta}$ as:

$$q(\boldsymbol{\zeta}|\boldsymbol{\phi}) = \mathcal{N}\left(\boldsymbol{\zeta}\middle|\boldsymbol{\mu}, \mathrm{diag}(\boldsymbol{\sigma}^2)\right) = \prod_{n=1}^{N} \mathcal{N}(\zeta_n|\mu_n, \sigma_n^2), \quad \text{(Eq. 5.13)}$$

where $\boldsymbol{\phi} = (\mu_1, \dots, \mu_N, \sigma_1^2, \dots, \sigma_N^2)$. The PyMC3 Python package was used to implement and train all the models (Fonnesbeck et al., 2015; Salvatier et al., 2016). Since the default stochastic gradient descent algorithm, Adagrad, exhibited relatively slow convergence, we used instead the stochastic gradient descent Adam (Kingma and Ba, 2015) algorithm. We have also implemented random initialization (100 initial points) in model training to get closer to global solution of the variational inference problem.

### 5.4.3 Model estimation results

We consider as potential features within the multivariate model structure all the observed environmental variables (Figure 5.11). To avoid scaling issues in model estimations, we scale all features using the empirical statistics, presented in Table 5.3. Specifically, we are subtracting from all features the empirical mean and divide them with the empirical standard deviation. The window unshaded portion in the monitored offices can correspond to different window unshaded areas compared to other offices. To improve the transferability of the model, we use the unshaded window area instead of the unshaded portion. We discuss limitations associated with this variable in Section 5.6.

Table 5.3 Descriptive statistics of considered variables as model features

| Variable | Minimum | Mean | Maximum | Std. |
|---|---|---|---|---|
| Work plane illuminance (lux) | 457.6 | 1033.6 | 2090.8 | 470.5 |
| Vertical illuminance (lux) | 91.0 | 406.1 | 1511.2 | 313.5 |
| Window unshaded area ($m^2$) | 0 | 2.58 | 6.59 | 2.73 |
| Electric light ratio | 0 | 0.2 | 0.5 | 0.2 |
| Window illuminance (lux) | 1392.2 | 31919.8 | 68505.5 | 21962.1 |

We develop different models resulting from different combinations of variables. Bayesian model selection (Bishop, 2006) dictates that the best model is the one that has the maximum evidence. However, in ADVI only a lower bound to the model evidence is available. Thus, in this work, we use this model evidence lower bound to perform model selection. Indeed, we verified that this process does select the model with the highest prediction accuracy. To assess the prediction accuracy of models, we use a five-fold validation. Models are trained based on a training set (80% of the data) and their prediction accuracy is evaluated on a testing set (20% of the data). We draw 3000 samples, $\hat{\boldsymbol{\theta}}_m, m = 1, \ldots, 3000$, from the posterior of the model parameters, $p(\boldsymbol{\theta}|Data)$, and calculate the predictive probability associated with each sample for each observation of the testing set, $\mathbf{x}_j$, as:

$$p(y|\mathbf{x}_j, z_j. \hat{\boldsymbol{\theta}}_m) = \sum_{z_j} p(y|\mathbf{x}_j, z_j, \hat{\boldsymbol{\theta}}_m) p(z_j|\hat{\boldsymbol{\theta}}), \quad j = 1, \ldots, N_{obs}. \qquad \text{(Eq. 5.14)}$$

Subsequently, one sample, $\hat{y}_{j,m}$, is drawn from each predictive probability and the prediction accuracy is calculated as:

$$Prediction\ accuracy = \frac{\sum_{j=1}^{N_{obs}} \sum_{m=1}^{3000} f(y_j, \hat{y}_{j,m})}{N_{obs} \times 3000}, \qquad \text{(Eq. 5.15)}$$

where

$$f(y_j, \hat{y}_{j,m}) = \begin{cases} 1, & y_j = \hat{y}_{j,m} \\ 0, & otherwise. \end{cases} \qquad \text{(Eq. 5.16)}$$

Table 5.4 presents a performance summary for some of the models. Based on the model evidence lower bound and prediction accuracy, Model 8 with work plane illuminance, window unshaded area, and electric light ratio as features performs better in terms of describing occupants' visual preferences. Since there are three classes of model outcome (prefer brighter, being satisfied, prefer darker), an entirely random choice would result in almost 0.33 of prediction accuracy. Therefore, the prediction accuracies reported in Table 5.4 are satisfactory if they are significantly higher than this value. The reported results show that all models perform better than an entirely random prediction and Model 8 (0.69 prediction accuracy) is the best. As can be seen in Table 5.4, the evidence lower bound of this model (395.52) is also the highest among the others. Figure 5.13 shows the $p(z = k|\mathbf{Data})$ for Model 8. $p(z = k|\mathbf{Data})$ can be interpreted as the probability that a new occupant has preferences compatible with cluster $k$. We conclude that three clusters can explain the dataset with high probabilities, $p(z = k|\mathbf{Data}), k = 1,2,3$.

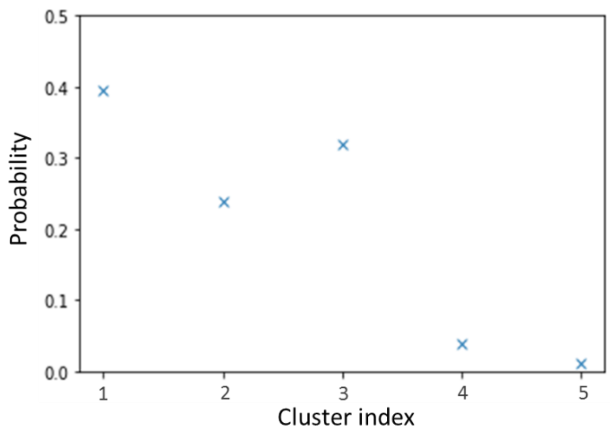


Figure 5.13 $P(z|\mathbf{Data})$ inferred by Dirichlet process

Table 5.4 Model feature selection (ticks mean variable inclusion; bold line represents the best model)

| No. | Model features | | | | | Model lower bound | Prediction accuracy |
|---|---|---|---|---|---|---|---|
| | **Work plane illuminance** | **Vertical illuminance** | **Window unshaded area** | **Ratio of electric over total light** | **Window illuminance** | | |
| 1 | ✓ | | | | | -425.89 | 0.54 |
| 2 | | ✓ | | | | -454.68 | 0.41 |
| 3 | | | ✓ | | | -466.44 | 0.48 |
| 4 | ✓ | | ✓ | | | -424.90 | 0.54 |
| 5 | ✓ | | | ✓ | | -452.86 | 0.46 |
| 6 | | ✓ | ✓ | | | -445.39 | 0.43 |
| 7 | | ✓ | | ✓ | | -497.13 | 0.38 |
| **8** | **✓** | | **✓** | **✓** | | **-395.52** | **0.69** |
| 9 | ✓ | | ✓ | | ✓ | -429.08 | 0.51 |
| 10 | ✓ | | | ✓ | ✓ | -454.84 | 0.42 |
| 11 | | ✓ | ✓ | ✓ | | -413.28 | 0.54 |
| 12 | | ✓ | ✓ | | ✓ | -433.05 | 0.47 |
| 13 | | ✓ | | ✓ | ✓ | -481.64 | 0.44 |
| 14 | ✓ | | ✓ | ✓ | ✓ | -397.94 | 0.65 |
| 15 | | ✓ | ✓ | ✓ | ✓ | -417.43 | 0.56 |
| 16 | ✓ | ✓ | ✓ | ✓ | ✓ | -409.73 | 0.61 |

Table 5.5 Parameter estimates for the visual preference model

| Class | Features | Parameter Estimates ($\boldsymbol{\beta}_{k,c}$\|95% HPD interval) | | |
|---|---|---|---|---|
| | | Cluster 1 | Cluster 2 | Cluster 3 |
| Prefer brighter | Work plane ill (lx) | -2.78\|(-3.59,-1.98) | -5.45\|(-6.87,-4.05) | 0.07\|(-2.16,2.41) |
| | Window unshaded area | -0.16\|(-0.23,-0.10) | -0.13\|(-0.26,0.00) | -0.08\|(-0.30,0.14) |
| | Electric light ratio | -4.03\|(-4.92,-3.14) | -1.67\|(-3.01,-0.33) | 2.10\|(-0.08,4.39) |
| | Constant | -0.33\|(-0.73,0.06) | -2.82\|(-3.47,-2.18) | -3.45\|(-4.49,-2.41) |
| Prefer darker | Work plane ill (lx) | 1.72\|(0.33,3.06) | 5.5\|(4.29,6.67) | 1.63\|(0.65,2.61) |
| | Window unshaded area | 0.16\|(0.09,0.23) | 0.05\|(-0.07,0.18) | 0.15\|(0.07,0.24) |
| | Electric light ratio | 2.06\|(0.56,3.55) | 2.03\|(0.73,3.30) | 0.65\|(-0.25,1.54) |
| | Constant | -3.50\|(-4.24,-2.75) | -2.17\|(-2.67,-1.68) | 0.45\|(0.0,0.89) |

Parameter estimates of the selected visual preference model corresponding to three significant clusters (and sub-models) are presented in Table 5.5. In this table, 95% credible interval for each parameter estimate ($\boldsymbol{\beta}_{k,c}$) is shown along with the mean value of estimated distributions. Given distributions for each model parameter represent one of the advantageous feature of Bayesian modeling which compared to point estimate methods, such as maximum likelihood estimation, provides more information on each model parameter and enables capturing the uncertainty within the model structure. Figure 5.14 shows the approximate posterior distributions of model parameters. The blue curves represent the samples for the first cluster while the green and red colors represent second and third clusters. The three distinct sets of parameter estimates in Figure 5.14 illustrate that the model has revealed three significant clusters among the population of the occupants.

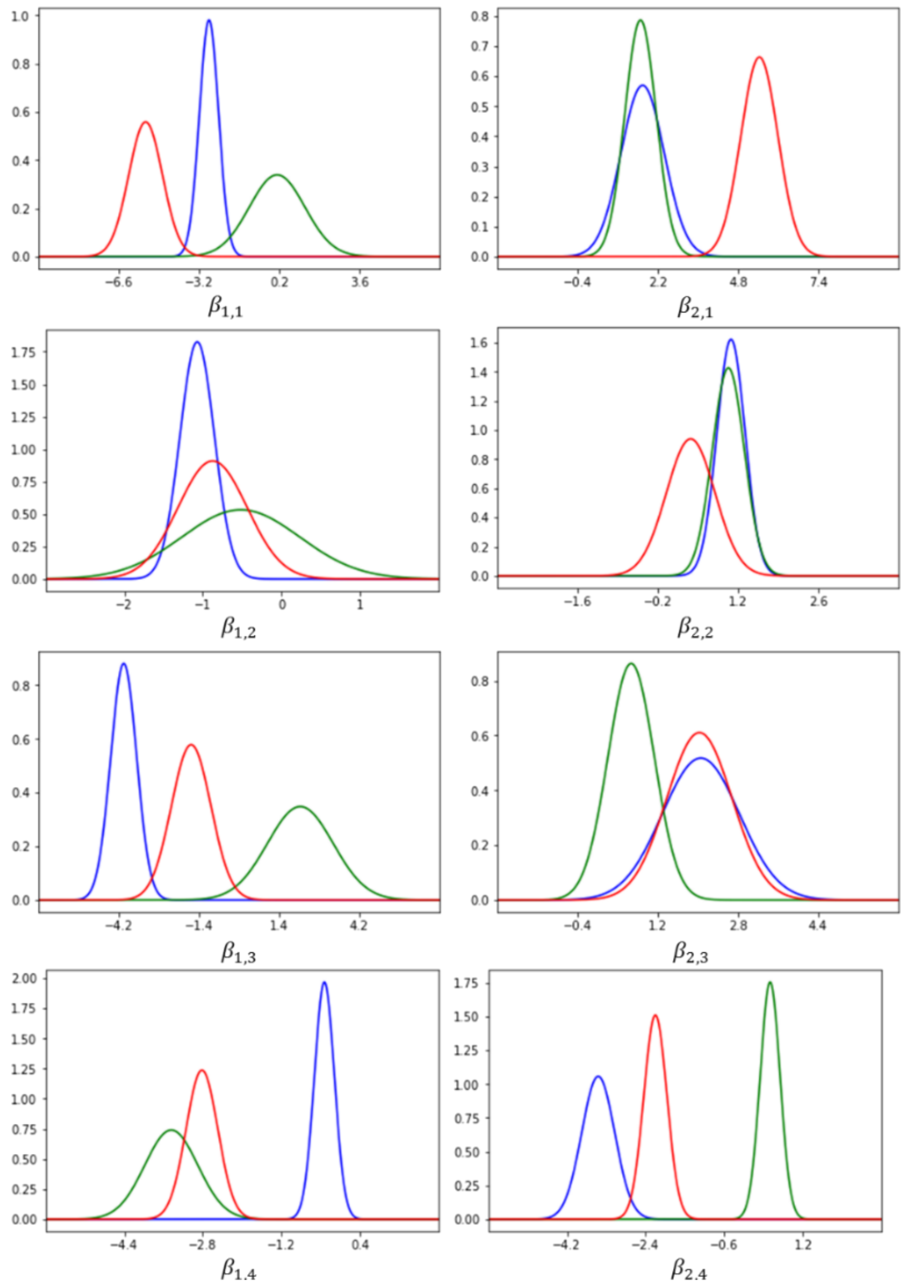


Figure 5.14 Approximated posterior distributions of model parameters. Blue: cluster 1; Green: cluster 2; Red: cluster 3

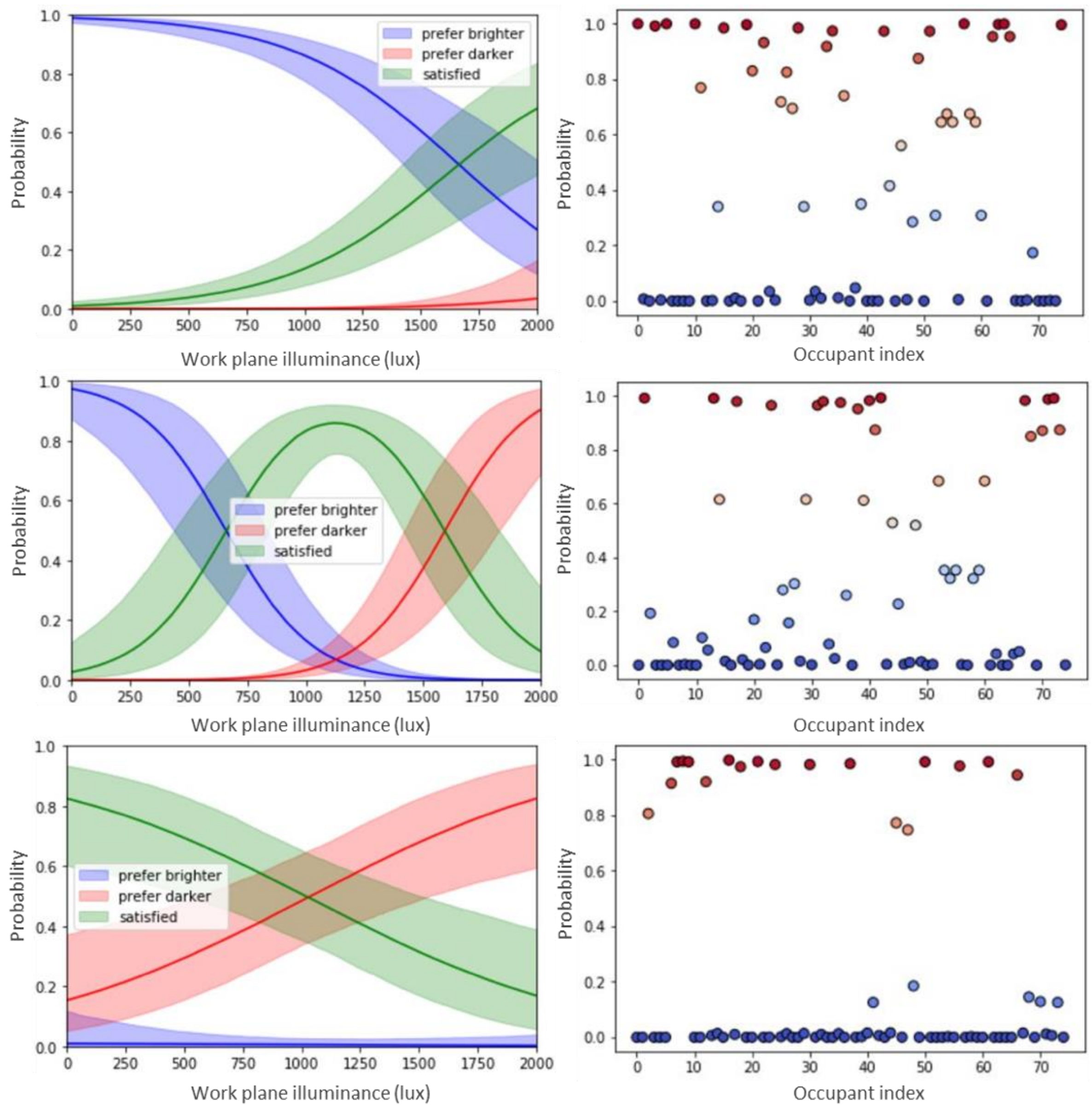


Figure 5.15 Left: Probability distributions calculated for each cluster with following settings: window unshaded portion equals to 30% (corresponding to 1.98 m2 unshaded area) and electric light is off; Right: Probability of each occupant belonging to each cluster; Top: Cluster 1; Middle: Cluster 2; Bottom: Cluster 3

In Figure 5.15, we investigate the properties of each of the clusters. The left column shows a section of the probability distribution surface for occupant visual preferences as a function of the work plane illuminance for the three significant clusters. To plot this figure, we set the electric light ratio to zero (electric lights off) while the window unshaded portion is set to 30% (corresponding to 1.98 $m^2$ unshaded area), which is close to the visor position (the shade position where the bottom of the shade is approximately at the occupant's eyes level). The solid line represents the median of the predictive distribution while the uncertainty bounds (95% prediction interval) are shown with the shaded area indicating the limits of epistemic uncertainty, resulting from limited data. The limits of epistemic uncertainty can shrink as more data become available. Epistemic uncertainty is further discussed in Section 5.6.

The differences among the clusters are illustrated in Figure 5.15 (left). In cluster 1, the probability of preferring brighter conditions (blue curve) is very high up to 1000 lux of work plane illuminance and then gradually decreases. However, this probability starts to decrease at lower values of work plane illuminance for cluster 2 and has low values for cluster 3. Along the same lines, the probability of preferring darker conditions (red curve) is low in cluster 1 while it follows very different trends in clusters 2 and 3. Overall, it seems that cluster 1 describes occupants who prefer "bright" conditions while clusters 2 and 3 include occupants with preferences for "moderate" and "dark" conditions respectively. It should be noted that the probability values presented for work plane illuminances lower than 500 lux arise from extrapolation of the predictive distributions. Intuitively, it can be expected for the curves in clusters 1 and 2 to have similar shapes as shown in Figure 5.15 (left). However, this might be different for cluster 3 (occupants preferring dark conditions) especially for low illuminance values, as it is expected for the probability of preferring brighter conditions (blue curve) to increase for these values due to the insufficient amount of light. An important observation from Figure 5.15 (left) is related to the green curve that represents the probability of being satisfied with the current conditions and is crucial for the implementation of personalized shading and lighting controls. This specific section of the visual preference surface has a peak in cluster 2 (occupants preferring moderate lighting conditions) around 1150 lux of work plane illuminance. This peak value is significantly higher or lower for cluster 1 and 3 respectively.

We investigate how each occupant is assigned to the visual preference clusters, by calculating the probability of each occupant belonging to cluster k, $p(z_d = k|\mathbf{y}_{1:D}, \mathbf{X}_{1:D})$, and plotting the results in Figure 5.13 (right column). In this figure, the color of each circle corresponds to the probability value, i.e., dark red denotes high probability and dark blue means low probability. Each circle represents an occupant, that is, there are 75 circles in each figure (note that out of the 80 occupants who participated in this study, 75 are used for model training purposes). Therefore, summing up the probabilities for one occupant in each figure would be equal to 1. According to Figure 5.15

(right), the calculated probabilities are mostly close to either 0 or 1, which means that occupants are clearly classified into one of the three clusters. Distinct classification of occupants is even more pronounced for cluster 3.

To further investigate the revealed classification in occupants' visual preferences, we use the human characteristics collected in the exit survey (Table 5.1) to filter the probabilities of occupants belonging to each cluster (probability values in Figure 5.15, right), and we show the results in Figure 5.16. In this figure, boxplots of probability distributions are presented along with an overlaid line connecting the mean values. Responses of 4 and 5 to the question "In general, how sensitive are you to brightness?" in the exit survey are grouped together to create the "most sensitive" group on the x-axis. Response 3 represents the "moderate" group and responses 1 and 2 are used to reflect the "least sensitive" group (Figure 5.16, top). To draw the bottom plots in Figure 5.16, we gather the responses of "slightly bright", "bright", and "very bright" to the question "In general what is your preference for lighting conditions at your workspace" in the exit survey to represent the group with preference towards "bright" conditions (x-axis). The answer "neutral" to this question represents "moderate" and responses "slightly dark", "dark", and "very dark" define the "dark" preferring group. As shown in Figure 5.16 (top), the estimated probabilities of belonging to clusters 1 and 2 are small for occupants who have voted to be most sensitive to brightness while the estimated probabilities of belonging to cluster 3 are high for these occupants. It is also evident that occupants who are least sensitive to brightness have very small probabilities of belonging to cluster 3. Figure 5.16 (bottom) indicates a definite trend between occupants' self-reported preference for lighting conditions at workspace and model's assignment of each occupant to the three revealed clusters.

It is noticeable that occupants who have voted to have a general preference towards bright, moderate, or dark conditions for their workspace are also found by the model to have high probabilities of belonging to clusters 1, 2, and 3 respectively. These findings indicate good agreement between the model results and the survey data, that were not used for model training, and confirm the validity of the model outcomes. Moreover, the significant correlations shown in Figure 5.16 indicate that the clustering revealed in the visual preference model is directly linked to individual differences in perception and preferences of the visual environment, implying that there are probably no other significant unobserved features in the field study governing the classification.

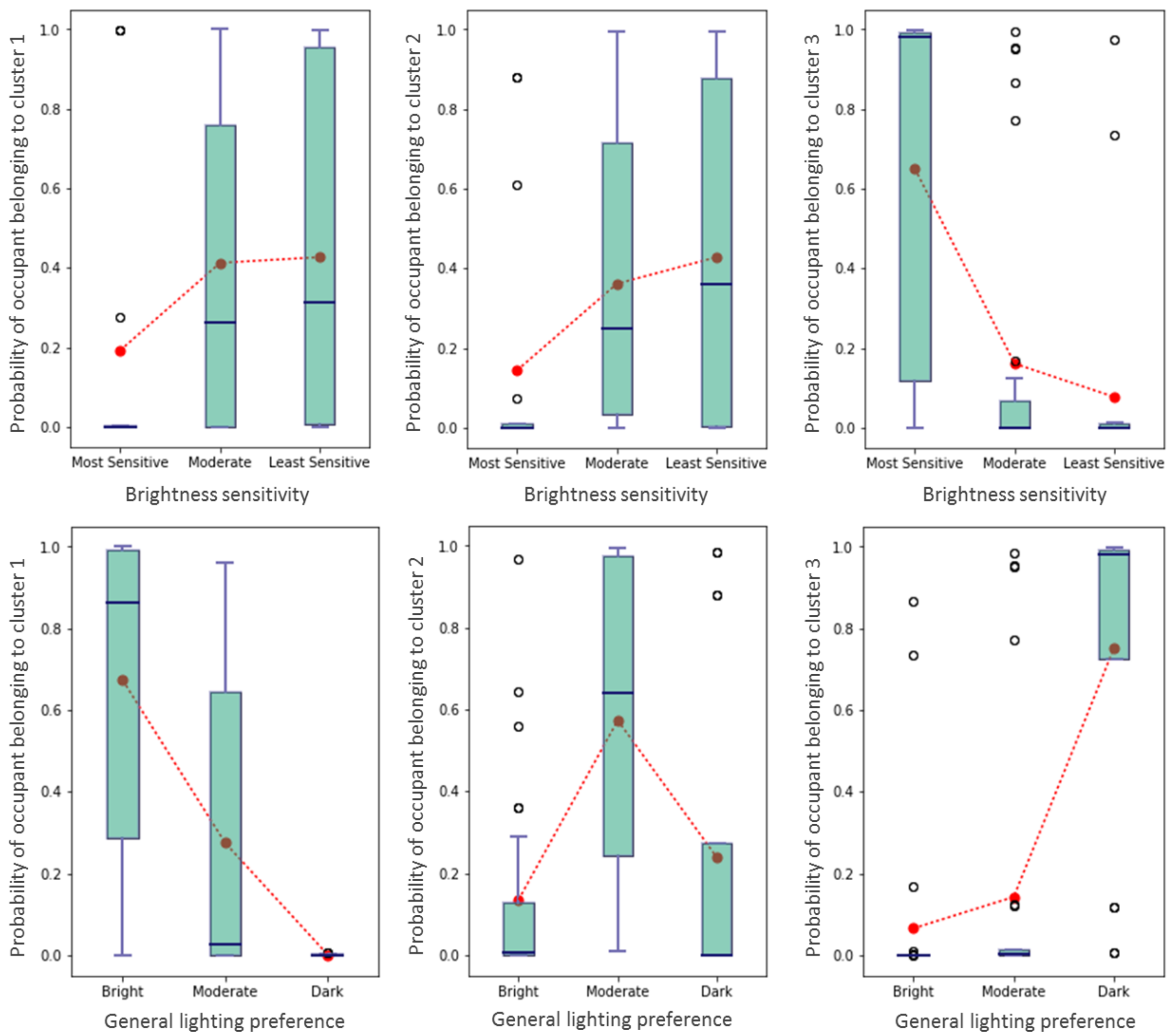


Figure 5.16 Correlating the subjective votes of human characteristics (exit survey) with probabilities of occupants belonging to each cluster. Top: self-reported brightness sensitivity; Bottom: self-reported general preference for lighting conditions at workspace

To explore the influence of window unshaded portion and electric light ratio in the predictive distributions of the model we present in Figure 5.17 two sections of the occupants' visual preference surface to be compared with that shown in Figure 5.15 (left). The plots on the left side of Figure 5.17 indicate the predictive distributions with similar window unshaded portion as in Figure 13 (left), i.e. 30% (corresponding to 1.98 $m^2$ unshaded area), but a higher electric light ratio (0.33). Comparing these two figures, one can notice that in cluster 1, the probability curve for preferring brighter conditions decreases with increasing ratio of electric light while with this condition the satisfaction curve shows higher probabilities for the same values of work plane illuminance. Moreover, in cluster 2, the peak of the satisfaction curve occurs around 950 lux with 0.33 ratio of electric light while this value was observed to be around 1150 lux when electric light was off (Figure 5.15, left). These results imply that the same light levels are perceived as brighter when the electric lights are ON leading to different profiles of visual preference. As mentioned earlier, different ranges in electric light spectrum should be investigated in future research.

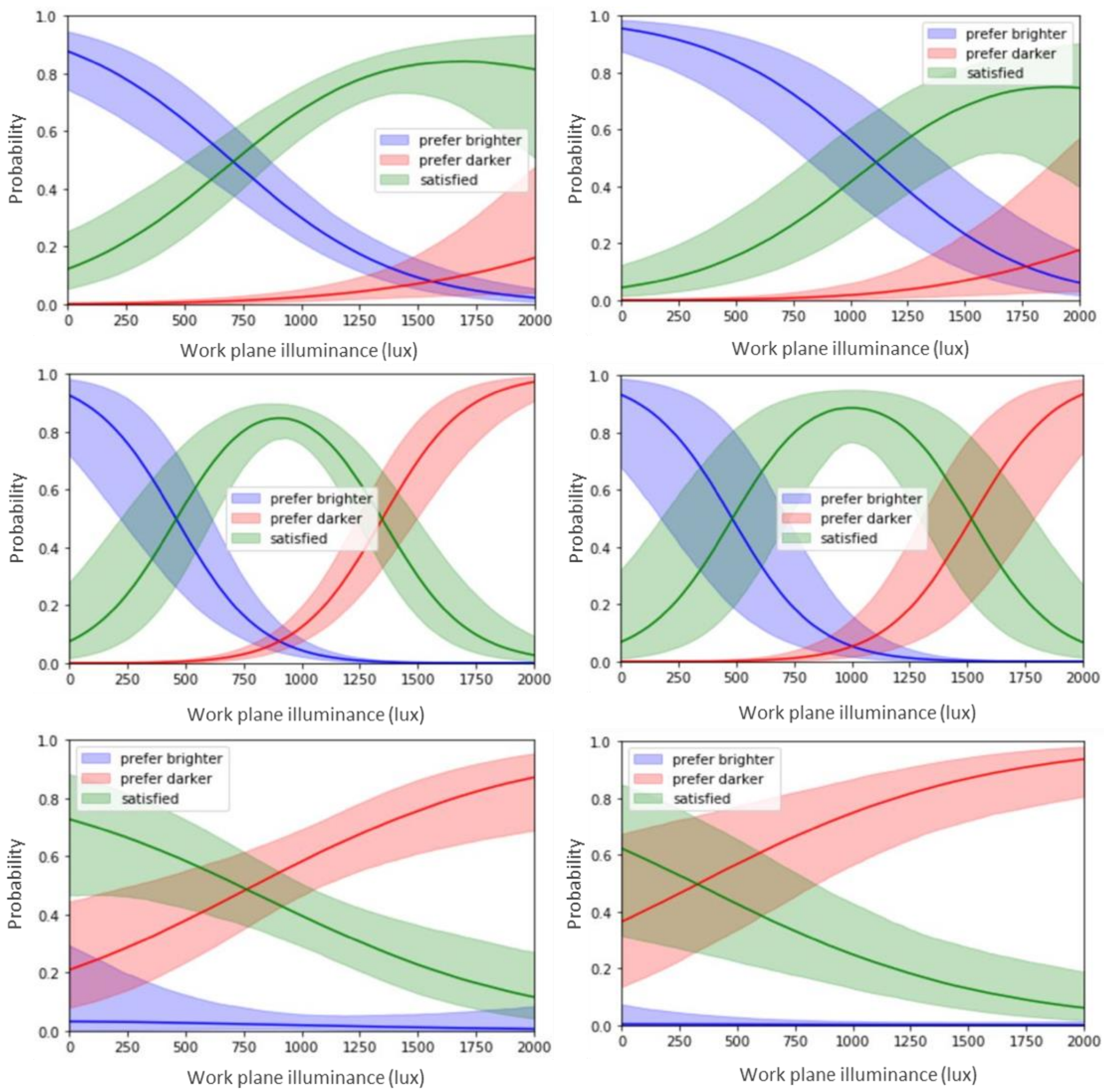


Figure 5.17 Probability distributions calculated for each cluster. Left: 30 % of window unshaded portion and electric light ratio of 0.33; Right: 70 % of window unshaded portion (corresponding to 4.61 m2 unshaded area) and electric light ratio of zero (electric light off); Top: Cluster 1; Middle: Cluster 2; Bottom: Cluster 3

We examine the impact of window unshaded portion/area on visual preference profiles by comparing Figure 5.17 (right) and Figure 5.15 (left). Unlike Figure 5.15 (left), which corresponds to 30% window unshaded portion and 1.98 m$^2$ of unshaded area, the plots in Figure 5.17 (right) are based on conditions with 70% of window unshaded portion (corresponding to 4.61 m$^2$ unshaded area). The datasets in both figures represent cases with the electric lights OFF. For the same values of work plane illuminance in cluster 1, the lower probabilities of the blue curve and higher probabilities of the green curve are obvious when the unshaded portion is higher. Furthermore, the peak of satisfaction curve in cluster 2 occurs around 1000 lux of work plane illuminance in Figure 5.17 (right) which is almost 150 lux less than that with window unshaded portion 30%. Finally, in cluster 3, the probability curve for preferring darker conditions is higher and the satisfaction curve is lower with the higher window unshaded portion. All these agree with the findings presented in Section 5.3 implying that under the same work plane illuminances, the visual environment is perceived as brighter for higher shade positions and this perception results in different shapes of visual preference profiles. These results confirm that impact of window unshaded portion on visual preferences is successfully captured by the model.

## 5.5 Learning the Visual Preferences of New Occupants

### 5.5.1 Learning methodology

In this section, we demonstrate our modeling approach for learning the visual preferences of new occupants. That is, we present how to infer a new occupants' cluster value (i.e., personal characteristic towards visual conditions, $z_{\text{new}}$) and derive occupant's visual preference profile under certain conditions for use in personalized visual environment control. First, the probability of a new occupant belonging to each cluster can be calculated via:

$$p(z_{\text{new}}|\mathbf{y}_{\text{new}},\mathbf{X}_{\text{new}},\mathbf{y}_{1:D},\mathbf{X}_{1:D}) \propto \int p(\mathbf{y}_{\text{new}}|\mathbf{X}_{\text{new}},\boldsymbol{\theta},z_{\text{new}})p(z_{\text{new}}|\boldsymbol{\theta})p(\boldsymbol{\theta}|\mathbf{y}_{1:D},\mathbf{X}_{1:D})\,d\boldsymbol{\theta}, \qquad \text{(Eq. 5.17)}$$

where, $\mathbf{Data} = \{\mathbf{y}_{1:D},\mathbf{X}_{1:D}\}$ are data used to train the general preference model and $\mathbf{Data}_{\text{new}} = \{\mathbf{y}_{\text{new}},\mathbf{X}_{\text{new}}\}$ are data collected from the new occupant. The standard plate notation presented in Figure 5.18 shows the hierarchy in this equation. Similarly, predicting the visual preference of a new occupant (i.e., $y_{\text{p}}$) under certain conditions (i.e., $\mathbf{x}_{\text{p}}$) can be computed using a mixture of sub-models from each cluster, as follows (plate notation shown in Figure 5.18):

$$p(y_p = c|\mathbf{x}_p, \mathbf{y}_{\text{new}}, \mathbf{X}_{\text{new}}, \mathbf{y}_{1:D}, \mathbf{X}_{1:D})$$

$$= \int \sum_{z_{\text{new}}} p(y_{\text{p}} = j|\mathbf{x}_{\text{p}}, z_{\text{new}}, \boldsymbol{\theta}) p(\mathbf{y}_{\text{new}}|\mathbf{X}_{\text{new}}, \boldsymbol{\theta}, z_{\text{new}}) p(z_{\text{new}}|\boldsymbol{\theta}) p(\boldsymbol{\theta}|\mathbf{y}_{1:D}, \mathbf{X}_{1:D})\, d\boldsymbol{\theta}.\ c = 0,1,2 \qquad \text{(Eq. 5.18)}$$

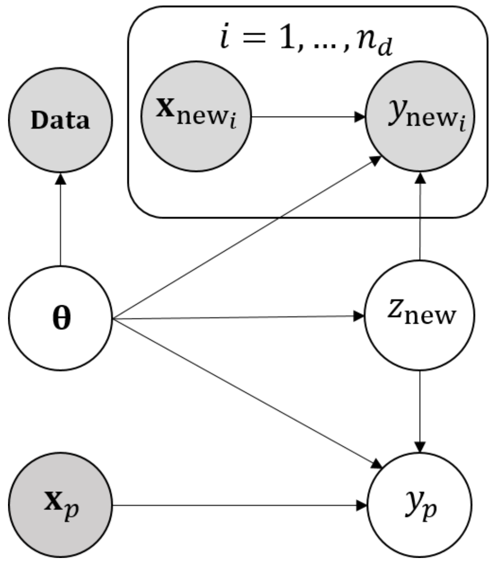


Figure 5.18 Graphical representation of the joint probability for learning visual preferences of a new occupant. Shaded: observed; plain: unobserved

### 5.5.2 Implementation and evaluation

We use the visual preference model presented in Section 5.4 to learn the profiles of the new occupants, and we adopt a validation process based on the prediction accuracy to evaluate its performance. That is, the data collected from the new occupants is split into training (80% of the data) and testing set (20% of the data). To ensure sufficient data for training and validation, we had five test-subjects participated in the field study for three days (24 observations). The resulted dataset was only used for the learning purpose in this section and not for training the general model presented in Section 5.4. Table 5.6 presents the prediction accuracy when the learning process is conducted with 8, 16, and 24 observations from each occupant. The high accuracy on the testing set indicates that the model and learning method have been successful in identifying the profiles of the new occupants. As expected, the model becomes more accurate as more data become available. However, the difference between 16 and 24 observations is not significant in terms of the prediction accuracy, implying the efficiency and success of the method even with fewer data points (16 observations). These findings demonstrate that the proposed method is practical and can be implemented in actual buildings.

Table 5.6 Model performance in learning the preferences of new occupants

| Number of observations | Number of samples collected from each new occupant | Prediction success in learning the new occupants |
|---|---|---|
| 8 | 8 | 71.5 % |
| 16 | 16 | 80.8 % |
| 24 | 24 | 83.4 % |

We present in Figure 5.19 the probabilities of the five new occupants belonging to each of the three clusters, $P(z_{\text{new}}|\mathbf{y}_{\text{new}}, \mathbf{X}_{\text{new}}, \mathbf{y}_{1:D}, \mathbf{X}_{1:D})$, along with their visual preference profiles. To visualize the results in 2-D figures, we plot visual preference profiles for different work plane illuminances while the window unshaded portion is set to the visor position (30%, corresponding to 1.98 $m^2$ unshaded area) and electric light ratio is zero. We observe that occupant 1 belongs to cluster 1 with high probability, preferring bright conditions, while the derived personalized visual preference profile resembles the one for this cluster shown in Figure 5.15 (left). This is also reflected in the response of occupant 1 in the exit survey presented in Table 5.7. Similarly, occupant 4 has a high probability of belonging to cluster 1 which is in agreement with the survey results (Table 5.7). The learning algorithm assigns, occupant 2 to cluster 2 (preference toward moderate conditions), with high probability. The inferred visual preference profile for this occupant is similar to the profile shown for cluster 2 in Figure 5.15 (left) and consistent with the responses to the survey question for general lighting preference (Table 5.7). Occupant 3 reported to be sensitive to brightness and also to generally prefer dark conditions at the workspace (Table 5.7). We show in Figure 5.19 that the learning algorithm has correctly assigned this occupant to cluster 3, with high probability. For occupant 5, the learning algorithm has identified comparable probabilities for belonging to both clusters 1 and 2. That is, this occupant has shown preferences for both bright and moderate lighting conditions during the field study.

Table 5.7 Responses of new occupants to personal characteristic questions in exit survey

| Occupant ID | In general, what is your preference for lighting conditions at your workspace? 1. Very dark … 7. Very bright | In general, how sensitive are you to brightness? 1. Least sensitive … 5. Most sensitive |
|---|---|---|
| 1 | 6 | 2 |
| 2 | 4 | 2 |
| 3 | 3 | 4 |
| 4 | 5 | 5 |
| 5 | 5 | 2 |

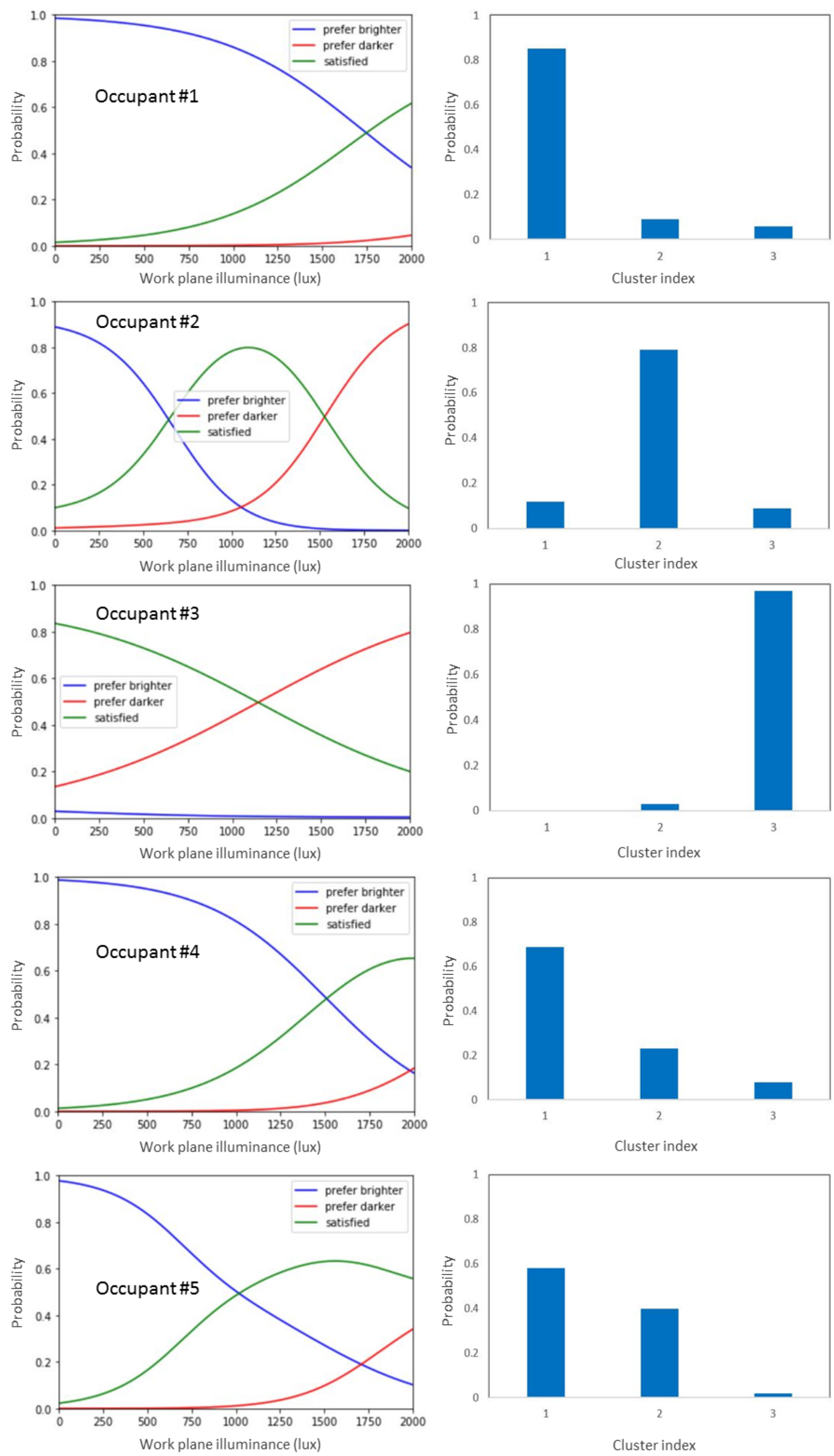


Figure 5.19 Visual preference profiles learned for five new occupants (left); Probability of new occupants belonging to each of the three clusters (right).

## 5.6 Discussion

In our field study, occupants' visual preferences were found to be influenced by both environmental variables and human characteristics. The derived visual preference model correctly captured occupants' visual preference characteristics as clusters of preferences among the population while environmental variables were included for as model features. Luminance ratios within the visual field as well as window maximum and average luminance were not monitored in our study. These may be considered in future research to investigate potential correlations with visual preferences and possible improvements of the epistemic uncertainty due to the incorporation of additional features within the model structure. In our study, both work plane illuminance and vertical illuminance at eye level were measured and their contribution in describing the occupants' visual preferences was tested along with other variables within a multivariate model structure. The model with work plane illuminance was shown to outperform the one with vertical illuminance which can be due to the fact that vertical illuminance is more associated with discomfort glare and the field study was conducted in glare free conditions. One sensor was deployed on the desk to record work plane illuminance and control the shade position, although significant variations can be observed in the work plane in sunny conditions. Additional sensors may be considered in future research. Alternatively, with the use of hidden variables, one can incorporate the measurement process within the model structure to reduce the epistemic uncertainty associated with noisy data and improve the prediction performance of the model. Finally, data collection from a similar or larger number of occupants in other locations and different office setups would help quantify the epistemic uncertainty in model outcomes due to limited data.

The model training method used in this study (ADVI) is a deterministic approximation that fits a distribution to the posterior and solves a practical optimization problem to estimate the model parameters. By selection of the approximating family, posterior correlations between the parameters is disregarded. Therefore, due to the approximation and underlying assumptions, it is likely for uncertainty bounds of model outcomes to be wider when parameter estimates are conducted through sampling techniques such as Markov Chain Monte Carlo (MCMC) or sequential Monte Carlo (SMC).

The model evidence along with prediction accuracy have been used in this study to select the best model for describing the visual preferences. It is worth mentioning that variable selection is only a part of the process for determining the best model. The model structure needs to be identified too. To this end, different model structures with linear, polynomial, and sigmoid functions were tested and the logistic regression model with the three selected features as reported in Table 5.4 was found to outperform all the other models. Use of model evidence and prediction accuracy as model selection criteria proved to be crucial as these metrics could allow for comparison of different model structures. However, if the best model structure is known (or assumed) and only the variable selection is desired, methods such as Automatic Relevance Determination (ARD) can readily determine the most significant features without the need for comparison of different models using model evidence and prediction accuracy (Bishop, 2006). ARD can be a powerful method when variable selection needs to be conducted with a large number of features, which was not the case in this study. However, this method was still used to confirm the significance of the three features identified with use of model evidence and prediction accuracy (Table 5.4).

Our experimental dataset was collected in private offices in a perimeter building zone with a south façade orientation with 54% window-to-wall ratio. Although the window unshaded area has been used to improve the transferability of the model, the impact of contextual factors such as glazing and shading type remains to be investigated. Moreover, further investigation is required to evaluate potential impacts of different electric light spectrums and colors, façade orientations/sun paths, climatic conditions and daylighting/shading systems on clusters of visual preferences. Similar field studies are needed in different locations around the world for a larger database with longer duration. Since the Bayesian approach can be used to seamlessly combine data from heterogeneous sources as they become available (Jaynes, 2003; Lee et al., 2018), all the data from different field observations can be merged to develop a more transferable visual preference model. The overall approach presented in this paper is a first step towards personalized visual environments in office buildings using real-time feedback from occupants.

## 5.7 Summary

In this chapter, we have presented a new method for learning occupant visual preferences in private offices of a perimeter building zone. This was achieved by collecting a dataset from field observations and adopting a Bayesian modeling approach to map indoor environmental conditions and occupant visual preference votes and demonstrating its advantages. These include a systematic method to identify significant features in describing the visual preferences and to capture the epistemic uncertainty within the model parameters; the ability to incorporate occupant visual preference characteristics as a hidden random variable, to cluster occupants based on that, and to determine the optimal number of clusters within the studied population. Moreover, we have demonstrated a new approach to infer visual preference profiles for individual occupants using a mixture of the general sub-models for each cluster.

Our multinomial logistic regression model augmented with the Dirichlet process prior that includes work plane illuminance, window unshaded area, and electric light ratio as features, revealed the existence of three distinct clusters with physical interpretation; preference for bright, moderate, and dark conditions. These were directly linked to individual differences in perception and preferences of the visual environment, and it was confirmed that there were no other significant unobserved features in the field study governing the classification.

Our field observations revealed complex interactions between occupant electric light and daylighting perception including the impacts of shading position and connection to outdoors on perceived lighting conditions. Under the same work plane illuminances, the visual environment was perceived as brighter for higher shade positions while the same light levels were perceived as brighter when the electric lights were used. These interdependencies were successfully captured in our model structure, leading to different shapes of visual preference profiles for the studied office building population.

Our modeling approach predicts personalized profiles with 81% prediction accuracy on the validation set, and it is efficient, as it only requires less than 16 observations from each new occupant; this is a significant benefit for implementation of personalized visual environments in actual buildings based on occupant feedback. The probabilistic form of the model accounts for the variability in occupant preferences while the directional outcome (prefer brighter, satisfied, prefer darker) determines the required action for the shading and lighting controller.

# CHAPTER 6. CONCLUSION AND OUTLOOK

## 6.1 Main Achievements

With a focus on visual environment, the main contributions of this doctoral thesis revolve around understanding and modeling human-building interactions and their links to energy consumption as well as occupant satisfaction with the indoor environment. More specifically, key achievements of this doctoral thesis are:

- A systematic field study design for comprehensive data collection from human-building interactions and occupant satisfaction with the visual environment. This includes efficient sensor network deployment for sensing environmental variables as well as online surveys and prototyped cyber-physical interfaces for occupants' feedback. The efficient field study design allowed for investigation of large number of human test-subjects, which proves to be necessary for the purpose of occupant studies, and did not require the installation of experimental equipment in a large number of offices.
- Insights on dynamics of human interactions with motorized roller shades and dimmable electric lights as advanced control options which are widely adopted in high performance buildings but studies on their performance are rather limited. Through side-by-side comparisons of different environmental controls and user interfaces, our field investigations reveal behavioral patterns and provide insights on (a) influence of ease-of-access to control on human-building interactions and related energy impacts; (b) interdependent operation od window shades and electric lights; (c) impacts of perception of control on satisfaction with indoor environment and acceptability of wider ranges of visual conditions; (d) role of individual characteristics in human-building interactions.
- A novel Bayesian modeling approach for human interactions with window shades and electric lights. The developed modeling framework exploits the advantages of Bayesian formalism to its full extent. These include systematic feature selection based on Bayesian model evidence, the use of prior knowledge in model development, and quantification of epistemic uncertainty induced by limited observations which proves to be a ubiquitous issue in human data collection in actual buildings and needs to be accounted for. Our findings reveal that it is a combination of environmental variables along with human

attributes and individual characteristics that underlie human interactions with building systems such as window shades. The developed model incorporates, for the first time, human attributes and individual characteristics within its framework. Moreover, the new modeling framework considers the interrelated operation of window shades and electric lights and is able to predict their intermediate operating states, thus, is expected to increase the prediction accuracy of human-building interactions when used in BPS tools.

- A novel Bayesian probabilistic modeling framework for classification and inference of occupants' visual preferences. The developed framework is based on a rich data set collected from a well-designed field study for investigation of occupant satisfaction with the visual environment through direct preference votes and without extracting conclusions from discomfort-based assumptions. The resulted dataset, itself, is a contribution to the body of knowledge as the current literature lacks such a database. The general probabilistic visual preference model takes full advantage of the Bayesian formalism by adopting systematic methods for identification of significant features and capturing the epistemic uncertainty within the model parameters. Moreover, it incorporates, for the first time, occupant visual preference characteristics as a hidden random variable and cluster occupants based on that while determining the optimal number of clusters within the studied population. Using a mixture of the general sub-models for each cluster, the classification and inference framework is used to demonstrate a novel approach for learning visual preference profiles of new individual occupants with high level of accuracy based on very few observations.

## 6.2 Future Outlook

All the observational results and developed modeling frameworks presented in this doctoral thesis are tied back to one common core which is human feedback collection from the built environment. As shown previously in Figure 1.3, occupant feedback from the indoor environment can be collected through subjective votes reported in surveys or from observations of human interactions with building comfort delivery systems. It is of great importance to evaluate these two different occupant feedback collection methods when studying the same phenomenon. For instance, occupants' direct votes on surveys were used in chapter 5 to study and develop modeling frameworks to describe and predict occupants' visual preferences. Human interactions with building systems that alter the luminous environment, such as window shades and electric lights, can also be interpreted to describe visual preferences. In spite of the few attempts in the literature to use occupants' actions to describe visual preferences, due to the drawbacks mentioned in Section 2.4.2, the produced results cannot provide a reliable source of comparison with our visual preference model presented in Chapter 5. Nonetheless, as continuation of the work in this thesis, a field study is designed to investigate visual preferences of occupants when they are learnt through occupants' subjective votes versus observations of occupant actions. Results of such field study can reveal potential similarities and differences of these two data collection methods and provide insights on how occupants transfer their preferences to actions. This can also be extended to providing feedback to occupants on related automation systems and energy impacts associated with their preferences or their behavior. That is to investigate how information delivery can make occupants aware of different aspects of the built environment and help them adopt rational behaviors that would impact their interactions with building systems.

Both forms of occupant feedback collection (subjective votes and observation of interactions with building systems) are to reflect occupant mental state in perception of the built environment. Therefore, to further investigate the practicality of the data collection methods, one can evaluate their accuracy in representing the true mental state under different combinations of environmental conditions. For instance, nonintrusive sensing methods such as neural-signal electroencephalogram (EEG)-based method can be used to record the electrical activity of the brain and such unbiased measurements from the human brain can be related to occupants' reflection of it through different feedback collection methods.

Due to dynamic nature of the built environment and high dimensionality of influencing factors, a holistic study of human factors can be complex and costly. Therefore, human factor studies within the built environment are usually compromised. For instance, in this doctoral thesis, investigations are only limited to the visual environment. However, occupants in buildings are simultaneously exposed to many different stimuli such as thermal dynamics, noise, and air quality. Thus, in order to consider the effect of the indoor environment on human perception and satisfaction, it is important to account for combined effects of all influencing factors. To this end, systematic experiment designs should be adopted to facilitate efficient learning processes with minimal observations from the time varying factors. Preferential Bayesian optimization can be used to construct sequential learning algorithms which can efficiently guide the data collection process. In the proposed approach, the built environment will be mapped to a domain of time-variant factors and divided into pairwise comparisons of duels. Gaussian process (GP), which is a probability measure over functions such that any linear restriction is multivariate Gaussian, can be used to learn the desired utility with N duels and afterwards, the next region for data collection is identified by selecting a duel which would move towards the maximum of utility function value. Such efficient search algorithm allows for gaining sufficient information with minimal number of sensing trials.

Finally, use of Immersive Virtual Environments (IVE) for study of human-building interactions can be helpful to reduce the need for extensive resources such as office test-beds used for the purpose of this thesis. However, potential of IVE in representing the actual built environment and resembling longitudinal field studies, such as this thesis, needs to be confirmed first. To this end, one can combine IVE with BPS to create dynamic visual environments over the course of days and conduct a comparative study to reproduce results of visual preferences reported in Chapter 5. With the lessons learned from such study one can extend the use of IVEs to a holistic investigation of human factors within the built environment.

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# PUBLICATIONS

**Journal papers**

Sadeghi S.A., Karava P., Konstantzos I. and Tzempelikos A., 2016. Occupant interactions with shading and lighting systems using different control interfaces: a pilot field study. Building and Environment 97: 177-195.

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**Conference papers**

Sadeghi S.A., Karava P., 2014. Stochastic model predictive control of mixed-mode buildings based on probabilistic interactions of occupants with window blinds. 3rd High Performance Buildings Conference, West Lafayette, IN (1st place in student paper competition).

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