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Designing Buildings for Real Occupants: An Agent-Based Approach

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***Abstract*—Building information modeling is only beginning to incorporate human factors, although buildings are sites where humans and technologies interact with globally significant consequences. Some buildings fail to perform as their designers intended, in part because users do not or cannot properly operate the building, and some occupants behave differently than designers expect. Innovative buildings, e.g., green buildings, are particularly susceptible to usability problems. This paper presents a framework for prospectively measuring the usability of designs before buildings are constructed, while there is still time to improve the design. The framework, which was implemented as an agent-based computer simulation model, tests how well buildings are likely to perform, given realistic occupants. An illustrative model for lighting design shows that this modeling approach has practical efficacy, demonstrating that, to the extent that users exhibit heterogeneous behaviors and preferences, designs that allow greater local control and ease of operation perform better.**

***Index Terms*—Buildings, design automation, human factors, simulation, usability.**

As Norman shared in *The Design of Everyday Things*, “technology changes rapidly, people change slowly.”[1]

I. Introduction

SEVERAL factors push the construction industry to become more innovative. Occupants demand distinctive high-quality spaces in which to live and work, economic globalization forces companies to cut operating costs to remain competitive, the green building movement seeks to reduce environmental impacts and improve occupant health, threats to energy affordability and security make national governments demand greater energy efficiency, and droughts and loss of snowpack do the same for water efficiency.

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This conservative industry has begun a cycle of innovation that will dramatically change the performance, look, and feel of buildings. However, change is not an easy process, and it is difficult to use some of the innovations in practice. Not all innovations will widely diffuse, and not all of them deserve to do so.

Characteristics of innovations that encourage their rapid diffusion include relative advantage (whether they are cheaper or better), compatibility (whether they fit well with the current system), complexity (whether they are easy to figure out), observability (whether they can be seen working somewhere nearby), and trialability (whether they can first be tested) [2]. For example, solar photovoltaics slowly diffuse, because they cost more than buying energy from the utility, and they sometimes seem complicated. Insulation, by contrast, rapidly diffuses, because it quickly pays back its installation cost in the form of reduced energy bills while also making the building thermally and acoustically more comfortable.

Standard design practices focus on the relative advantage and compatibility characteristics of candidate innovations. Thus, architects and engineers look for the most cost-effective solution that meets the client’s performance targets and their own customary system designs. Although designers and their clients agree on these basic practices, they may still argue about whether “cost effective” should be defined on a first-cost or life-cycle-cost basis and whether the appropriate target should be a building that meets or exceeds code.

Buildings, particularly innovative ones, do not always satisfy their occupants or perform as expected. Sometimes, these problems may be identified as straightforward design errors. For example, windows may directly be exposed to the late afternoon sun, or the energy management and control system may be misprogrammed. However, oftentimes, the problem lies in the way the building is used by occupants or operated by facilities staff. For example, a maintenance crew may force the economizer cycle on the heating–ventilating–air conditioning (HVAC) system into the “open” position but then forget to reset it so that it stays open all year long, or occupants may leave their window blinds closed all day rather than adjusting them according to the available daylight. In these cases, the users of the building behave in ways that the designer did not intend and that might be inconsistent with building performance goals. In such cases, the human presence may become a barrier to improved building performance.

Designers often wish for smarter, more orderly, and better behaved users, but real buildings need to accommodate real user behaviors. Indeed, among the lessons learned from earlier generations of energy-efficient passive solar buildings is that usability determines success, and the lack of usability hinders the diffusion of innovations [3]. This paper brings usability analysis to computer-based building information modeling and design.

II. Background

A. Usability

The premise of this paper is that, because the construction industry innovates, designers need to more systematically assess the usability of potential innovations. Usability is defined as the "...effectiveness, efficiency, and satisfaction with which a specified set of users can achieve a specified set of tasks in a particular environment" [4]. It is the ease with which humans, behaving normally, can operate a technology for its intended use.

Usability is associated with concepts such as functionality, comprehensibility, and convenience. It focuses on the characteristics of innovations, including complexity, observability, and trialability, which have more to do with human nature than with technological performance.

Usability is an attribute that people usually experientially assess. For example, we typically need to operate a building to determine whether keeping it comfortable is easy. We must usually occupy a space to understand how much effort goes into managing daylight to meet lighting needs or how comprehensible the interface on a thermostat is. Usability affects occupant satisfaction and productivity, as well as the building's performance.

A focus on usability is not new, of course, as architects from Vitruvius forward remind us. Norman [1] has addressed this issue for consumer products, [5] has become a bible to a generation of webpage designers, and [6] has done a similar job for large-scale systems. It is harder to find similar classics in the building industry, with [7] and [8], perhaps, coming the closest, but industry actors are interested (see, e.g., [9], [10]). Standard prescriptions for improving usability include the use of affordances (design an item so that it offers strong clues that it "is for" a specific purpose, no instructions required), clear conceptual models (ensure that visible evidence guides user to the correct mental model of how the item functions), visibility (do not have more functions than controls), mapping (take advantage of intuitive physical analogies and cultural understandings), feedback (send users immediate information about the result of their actions), and constraints (limit choices to reduce errors) [1].

Bevan and Macleod [11] identify the following three complementary perspectives: 1) a technology-centered view that usability is associated with a technology's (or product's) attributes and influenced by guidelines and checklists; 2) a context-centered view that places the characteristics of the user, technology, task, and environment foremost; and 3) a quality-of-use view that focuses on the interaction between user and technology in a specific context. The technology- and context-centered views identify necessary conditions, but only the quality-of-use view captures the sufficient conditions for measuring usability. The usable buildings literature echoes these distinctions in working toward designs that meet functional requirements, are serviceable in the context of actual use, and deliver a satisfactory user experience [9].

Postoccupancy evaluations (POEs) of buildings that measure operators' and occupants' perceptions of building performance and usability are becoming more common. Along with the commissioning of building systems, POEs help owners improve building performance and increase tenant satisfaction. Both POE and commissioning are currently required to earn certain green building certifications, for example.

The problem with waiting to assess usability until after the structure is built and occupied is, that, by then, fixing a usability flaw is much harder. What is needed is a way to do prospective usability evaluation. Computer simulation modeling offers this possibility.

B. Building Information Modeling

According to [12], "a building information model (BIM) is a digital representation of physical and functional characteristics of a facility." BIM 1.0 focuses on visualization and drawings, i.e., the stage that most architectural offices have reached, whereas large firms and specialists have advanced to BIM 2.0, which focuses on analysis, and they are investigating BIM 3.0, which focuses on simulation [13]. This case represents an exciting, if slowly advancing, shift in possibilities from representation to interoperable data to virtual-building sandbox [14]. BIM 4.0 for managing facilities seeks to marry the BIM and building management system industries [15], [16].

BIM tools currently offer sophisticated views of key building systems to aid the design process. Available products—some stand alone, others integrated—analyze structural needs, wind loading and microclimate impacts, massing, shading and shadows, lighting needs, HVAC needs, energy use, acoustics, quantity takeoffs, and costing, among others. Emerging tools can simulate construction phasing, emergency evacuation, and a few other dynamic phenomena. Missing from most models is a meaningful representation of human agency. Instead, each occupant is a passive object that, illustratively, adds 150 W/h to the cooling load and accepts the system designer's target levels of illumination, temperature, humidity, and outside air.

Richer representations of the human side of the human–technology interactions in buildings are needed for usability analysis. This paper introduces an agent-based modeling approach that shows promise for integrating usability analysis into standard BIM tools. It provides a straightforward way of portraying realistic human behavior in buildings, calibrating and validating this portrayal with POE survey data when some are available, and testing the prospective usability of alternative designs.

C. Usability Metrics

As the aforementioned definition implies, usability relates to effectiveness, efficiency, and satisfaction. We define three associated sets of usability metrics. There is strong support from empirical studies in a variety of domains that that these items measure a single underlying construct of usability [17]. Previous building researchers have measured effectiveness in terms of whether users can achieve what they want to do with the building, efficiency in terms of how long it takes them to achieve it, and satisfaction in terms of their feelings and attitude toward the building [18]. Our slightly different operationalizations follow.

Effectiveness measures the extent to which a person who uses a technology can achieve a specified end-use performance target, such as a lighting level of 300 lx on a desk in an office building or an indoor air temperature of 20 °C in a home. Software usability studies often subdivide effectiveness into an error count and a task completion count [19], but for buildings, a single success rate is more appropriate. Standard analysis tools for the design of building systems, e.g., lighting and HVAC, are well equipped to calculate in a deterministic manner the outcomes that such technologies deliver, given specific inputs. Those inputs will, however, be stochastic and take the form of scenarios to be simulated, perhaps in a Monte Carlo analysis. Hence, one measure of usability is the probability that the technology effectively performs, given the distribution of user behaviors.

Efficiency measures the ratio of the output of a system to its input. It indicates whether a design wastes resources, including the human resources of time, effort, and attention. Again, several standard tools for designing building systems can help, because they calculate efficiencies in the engineering sense, as in energy efficiency and water-use efficiency. A usability analysis will need to augment these efficiency calculations with measures of human resource use.

Satisfaction measures the utility that a user derives from a system. It indicates the level of contentment or gratification that a user feels when operating a system to fulfill a desire, need, or expectation. Standard design tools are of little direct use here, because the calculation of satisfaction depends on understanding the user's preferences and perceptions. A typical utility function would incorporate effectiveness and efficiency alongside other factors that give satisfaction to a user. Building owners, operators, and occupants typically have very different interests and concerns and, therefore, will have different utility functions.

D. Occupant Behavior

Different disciplines emphasize different aspects of human decision making. Economics emphasizes external factors, such as prices, that drive specific decision outcomes. Psychology, instead, more often emphasizes internal factors, such as values and beliefs. Computer science emphasizes procedural steps in the decision-making process. Here, we synthesize the theory to guide a data collection and modeling effort based on the three disciplinary traditions.

Economic Models: Neoclassical economics employs an extremely simple model of human agency, i.e., the self-interested rational maximizer. By assumption, a microeconomic agent has full knowledge and perfect foresight, is asocial, and behaves in a way that maximizes its own utility. Modern behavioral economists accept this basic model but qualify it by identifying cognitive and perceptual limits to rationality and the possibility that satisfaction can derive from social and other considerations. Economists are typically more interested in system-level properties of the interactions of microeconomic agents than they are in detailed explanations for particular agent behaviors.

Psychology Models: Psychologists are explicitly interested in explaining agent behavior, and they pay relatively less attention to the resulting socioeconomic system dynamics. Psychologists do not have the luxury of programming human brains to follow a specific decision-making framework. Instead, they usually theorize about human cognition and behavior from outside the black box and test those theories in a limited fashion based on indirect evidence. There is less orthodoxy in characterizing how human agents make decisions than in economics and computer science. Most researchers develop and test theories that focus on specific parts of the decision process. In the environmental psychology literature, which focuses on human–environment interactions, including nonselfish altruistic behaviors, this topic is dominated by the following two theories that share some elements: 1) the norm activation theory [20] and 2) the theory of planned behavior (TPB) [21].

The norm activation theory posits that altruistic acts follow from the development of personal norms to accept responsibility for acting altruistically, which are, in turn, due to developing an awareness of a behavior's consequences and holding beliefs about personal responsibility [20], [22]. This line of theorizing emphasizes the role of personal factors, and it links bedrock values, beliefs about the necessity and efficacy of action, attitudinal disposition, and the development of personal norms to environmentally significant behavior.

Stern *et al.* [23] extend the values-focused thread by developing a value–belief–norm (VBN) theory of environmentalism. Core values (which may be egoistic, altruistic, or biospheric) influence beliefs (with regard to one's ecological worldview, awareness of adverse ecological consequences of human behavior, and perceived ability to reduce such threats), which, in turn, help establish personal norms (with regard to a sense of obligation to take proenvironmental actions), which finally lead to specific behavioral outcomes. In his synthesis, Stern [24] seeks to go beyond attitudinal factors to include contextual forces (interpersonal influences, physical constraints, and legal strictures) and personal capabilities (knowledge, skills, wealth, time, and power) as key determinants of environmentally significant behavior.

Social psychologists have long been concerned about the weak empirical links between attitudes and behavior [25]. A well-known attempt to improve the predictive power of attitudes is TPB [26], which develops a model of behavior that incorporates additional complementary factors such as social norms and perceptions of control. TPB proposes a causal chain that starts with beliefs about behaviors, norms, and personal control of events, and these beliefs respectively influence attitudes, subjective norms, and perceived control. These factors, in turn, establish a person's behavioral intentions, and the intentions, interacting with perceived control, predict actual behavior (see Fig. 1).

Formally, according to TPB [27], we have

$$B \sim BI = w_1\, AB + w_2\, SN + w_3\, PBC \tag{1}$$
$$AB = \Sigma b_i e_i \tag{2}$$
$$SN = \Sigma n_i m_i \tag{3}$$
$$PBC = \Sigma c_i p_i \tag{4}$$

where

B	behavior;
BI	behavioral intention;
AB	attitude toward the behavior;
SN	subjective (social) norm with regard to the behavior;
PBC	perceived behavioral control over behavior;
$w_{1,2,3}$	weights applied to key factors AB, SN, and PBC;

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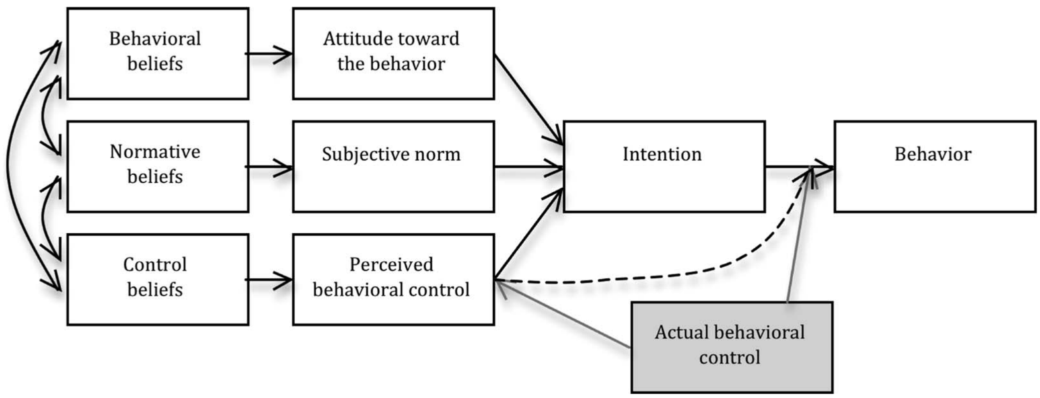

Fig. 1. TPB [27].

b_i belief strength with regard to the outcome of performing behavior i;
e_i evaluation of the desirability of the outcome of behavior i;
n_i strength of normative belief about the behavior (what others think);
m_i motivation that the individual has to comply with that norm;
c_i strength of control belief, which measures how much control an individual expects to have over a factor that governs the behavior;
p_i power of a control belief, given the presence of a factor that governs behavior (e.g., information, opportunities, and barriers), which measures its power in determining that the behavior will happen.

TPB is a robust formulation that has inspired a large literature and a series of meta-analyses that provide broad-based empirical support [21], [28]–[30]. However, TPB models typically account for only about 1/3 of the variance in observed behavior, suggesting that there is considerable room for improvement [30].

TPB is closer to the traditional economic model of personal utility maximization compared to Schwartz's model of norm-activated behavior, because it emphasizes personal utility (an egoistic perspective) and not primarily altruistic values. TBP also highlights perceived control over behavior, thereby recognizing the importance of external contextual factors such as cost and availability. Several recent articles have grafted elements of the norm-activated behavior and VBN models onto TPB, creating new syntheses that address both internal and external determinants of environmentally significant behavior [22], [24], [31]–[33]. Of particular importance for this paper are recent efforts to tie TPB to the belief–desire–intention (BDI) framework in agent-based models (e.g., [34]), as discussed in the following sections.

Computer Science Models: Artificial intelligence is a branch of computer science that attempts to mimic or improve upon human decision-making processes. One essential human characteristic is agency, i.e., the ability to demonstrate autonomous behavior [35]. Agent-based models specify how agents interact with one another and with their environment, and the specification includes the agent's attributes, behavioral rules, memory, resources, decision-making sophistication, and any rules for modifying current behavioral rules [36]. A wide range of human agent models are now available in the literature, including zero-intelligence (nonadaptive) agents, agents subject to reinforcement- or belief-based learning, and agents that can evolve new behaviors and modes of learning and behavior [37].

To characterize the behaviors of building occupants, one appropriate agent modeling framework is the BDI model as inspired by [38] and formalized by [39]. BDI models seek to mimic the practical reasoning processes by which humans make "right" decisions, given the structure of their personal values and society's norms [34], [40], [41]. Agents in these models are "rational and have certain mental attitudes of belief, desire, and intention, representing, respectively, the informational, motivational, and deliberative states of the agent" [39: 293]. We summarize the common elements of extant definitions as follows [39], [42], [43].

Belief. This informative component provides the model with information on the state of the external world, particularly system-level information. Beliefs about the world may differ from the actual state of the world due to incomplete understanding or poor data. The belief processor in the model converts a set of perceptions into a set of beliefs. The belief processor answers the questions: "What do I understand to be the state of affairs, and implicitly, what are the possibilities?"

Desire. This motivational component provides the model with information on the objectives to be accomplished and what priorities or payoffs are associated with various current objectives. Desires describe the state of affairs that the agent wishes to bring about and its goals. The desire processor in the model performs cognitive work by evaluating whether possible states of affairs are more or less preferable, given current beliefs and preference structures. The desire processor answers the questions: "What are my preferences, and implicitly, which possibilities do I like better?"

Intention. This deliberative component represents the currently chosen courses of action, i.e., the plans that the agent currently executes. Intentions are desires or objectives that the agent has committed to achieve, whereas plans are recipes or sequences of actions for achieving desired outcomes. An agent forms an intention to satisfy a subset of desires, creates some plans, and then selects a plan to meet those specific goals. The deliberation processor in the model filters the set of desires to select one intention. A subsequent planning processor develops a library of plans that address current intentions. Finally, the

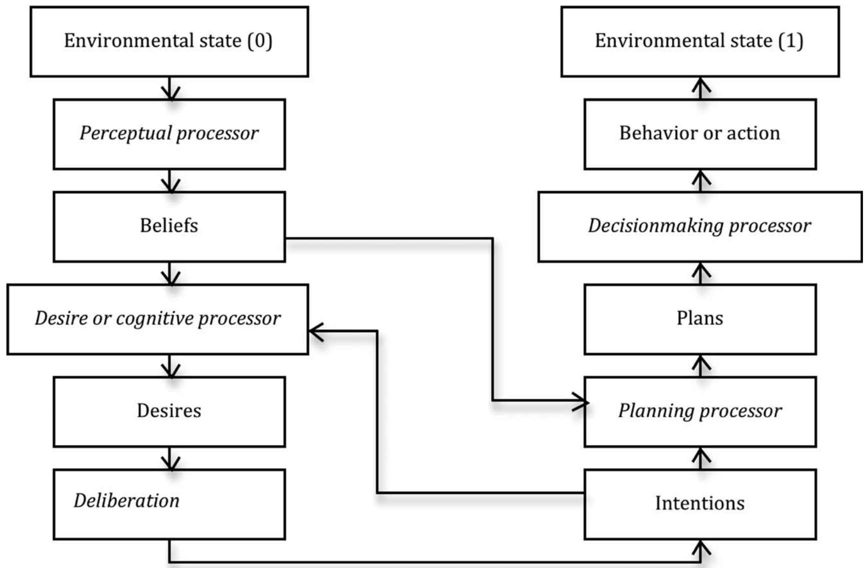

Fig. 2. BDI model framework. Note that italicized items are processes and normally printed items are outputs [44].

decision-making processor selects a plan of action. The deliberation, planning, and decision-making processors (forming and carrying out intentions) answer the question: "Toward which possibility am I working?"

Thus, the BDI framework includes a series of reasoning tasks that grow and then prune a decision tree. Given data on the external environment, the agent must establish its beliefs. Given updated beliefs, it must establish the structure of its preferences. Given updated beliefs and preferences, it must select the desire that it intends to satisfy, the range of possible plans for doing so, and the preferred plan of action. Then, the cycle repeats. Fig. 2 summarizes the model.

In the BDI framework, agents are not omniscient optimizers, but rather, they are situated actors with bounded rationality, multiple goals, and intentions that they sometimes do not fulfill. BDI agents exhibit "goal-directed behavior, whereby an agent's actions are motivated by a hierarchy of goals rather than being purely reactive . . . this model is based in folk psychology, i.e., the way that we think we think" [42: 2, 6].

Synthesis: The TPB and BDI frameworks are similar enough in approach and scope such that we can reasonably combine them. TPB provides a tested framework for questionnaire design and offers relatively detailed categories of beliefs. BDI provides a tested framework for agent-based simulation modeling and offers relatively detailed procedural steps that link beliefs, intentions, and behaviors. Robbins and Wallace [34: 1576]argue that "a software implementation of the dynamic BDI model can be used to simulate the process that is implicitly suggested by the static TPB." Fig. 3 shows the combined BDI/TPB framework used in this paper.

Decision Making in the BDI Framework: Five processes in the BDI framework contribute to decision making and action. First, the perceptual processor translates information from the environment into beliefs, and here, we assume that the translation is perfect. (We could, instead, add noise to the system by representing fixed environmental observations as stochastic variables and taking random draws from the distribution.) Second, the desire or cognitive processor translates a set of beliefs into a preference structure for measuring the relative desirability of alternative outcomes. Third, the deliberation processor selects a desired outcome or intention. Fourth, the planning processor generates several courses of action or plans that could achieve the desired outcome. Finally, the decision-making processor selects a plan and executes it.

Each of these BDI processes depends on the building occupant's preferences, leading us to need an operational measure of what makes the occupant happy. Relative satisfaction or happiness is typically measured with a utility function that calculates how many "utils" an occupant enjoys in a particular situation.

In the economics literature, human agents classically operate as selfish atomistic optimizers with perfect foresight. More recent theories have modified this caricature by acknowledging myopia, satisfying behavior, social embeddedness, and bounded rationality [45]. Most economic decision-making models exogenously specify their utility functions rather than depending on an endogenous theory of preference formation.

Among the drivers of innovation mentioned at the beginning of this paper, the green building movement exists, in part, to overcome market failures that are not fully explained by microeconomics—particularly with regard to the provision of public goods. Rational-choice models (e.g., [46]) tend to underestimate the actual level of private provision of public goods [47]. Economic explanations of proenvironmental behaviors arguably need to account better for altruism and other "psychological" motives not captured by a short-term selfish conception of utility [48].

Economists have responded by hypothesizing a variety of values that could be incorporated into utility functions, e.g., the "existence value" of knowing that Mount Everest is there even if you never visit it or the "warm glow" value of having reduced your carbon footprint [49]. Measuring these values is a technical challenge that researchers approach by estimating revealed preferences from actual behavior or by eliciting stated preferences using questionnaires [50].

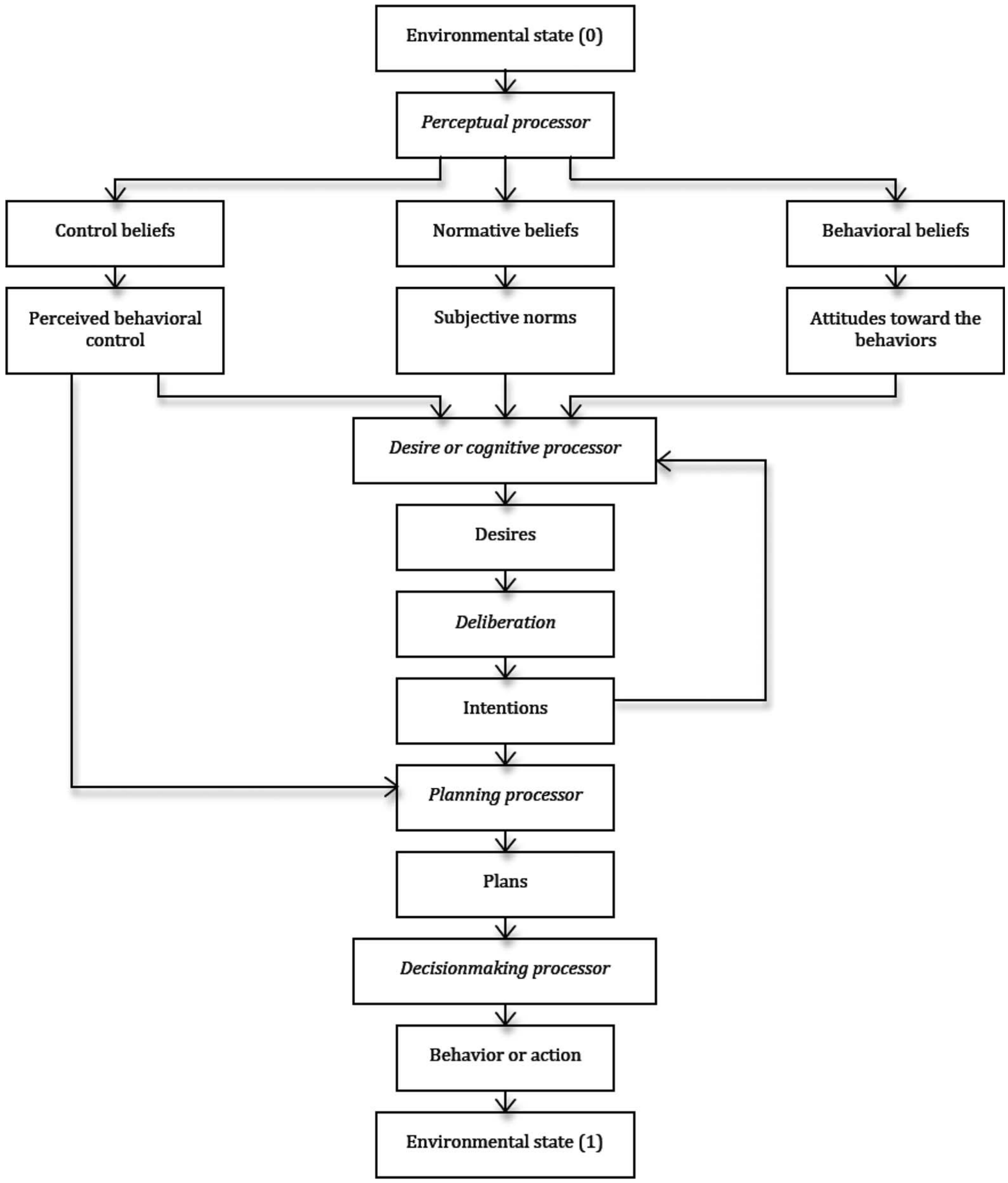

Fig. 3. Combined BDI and TPB framework. Note that italicized items are processes and normally printed items are outputs.

Social psychologists have identified "universal" value sets related to power, achievement, hedonism, stimulation, self direction, universalism, benevolence, tradition, conformity, and security [51]. Value conflicts can therefore arise within and among individuals. To show that people, in fact, settle on different predominant tradeoffs, Schwartz [51] clusters these values along two dimensions. The first dimension extends from self enhancement (SE) to self transcendence (ST), and the second dimension extends from openness to change (O) to conservativeness (C) [52]. The following four types of environmentally significant behavior may result [31]:

1) activism (ST, O);
2) good citizenship (ST, C);
3) healthy consumerism (SE, O);
4) conventional consumerism (SE, C).

Environmental psychologists find some empirical evidence that there are distinct egoistic, altruistic, and biospheric value orientations and that these values carry through to behavior [53], [54], although the clearest case is for an egoistic (SE) versus broadly altruistic (ST) distinction [55]. Situational factors may moderate (inhibit or facilitate) the effect of these personal variables such that an attitudinal disposition toward a proenvironmental behavior is a good predictor of that behavior when the situation encourages it but is a poor predictor otherwise [31], [56].

III. Methods and Data

This section introduces the modeling and data collection activities performed for this paper. The scope of the modeling activities is to represent the performance of building systems accurately and in a way that highlights both the determining role of occupant behavior and the links between building performance and occupant satisfaction (see Fig. 4). The scope of data collection includes the objective measures of building performance, the objective measures of occupant behavior if

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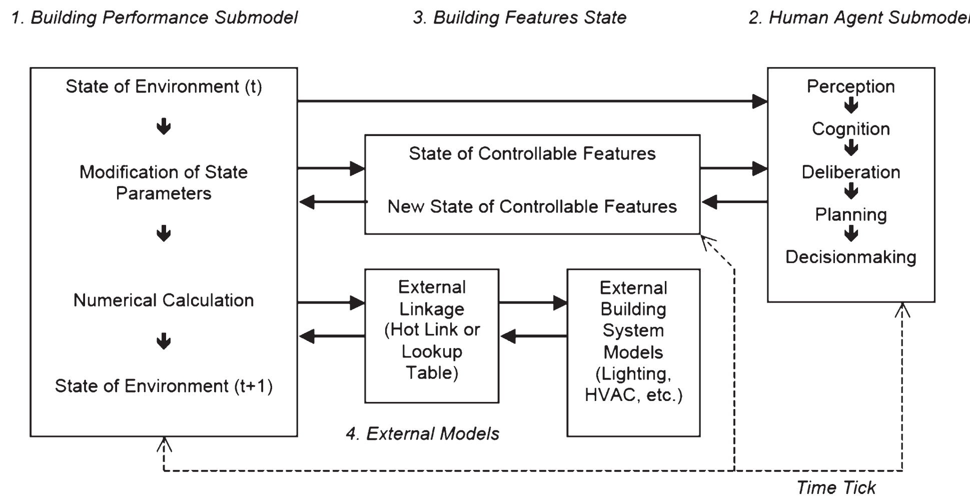

Fig. 4. Modeling framework.

available, and the occupants' subjective perceptions of their experience in a case study building.

A. Simulation Modeling Framework

Computer simulation models that characterize complex systems to inform better decision making originated more than 30 years ago and are currently widely used in construction-related fields [57]–[60]. Detailed engineering systems analysis tools are widely used in HVAC, lighting, building orientation, building envelope, and structural system design [61]–[66]. They are used much less often for plumbing (water and wastewater), with choices limited to public utility-scale tools for water and wastewater [67], [68], and simple CAD-based estimating tools [e.g., [69] and [70]]. Whole-building integrated design tools are mostly confined to spreadsheet- or Matlab-based models that were idiosyncratically developed by engineers for their own use [e.g., [71] and [72]].

The most powerful of these tools provide extremely detailed engineering estimates of system performance and equipment needs, but they suffer from simplistic representations of occupant behavior. For example, most models assume homogeneous building occupants who like the same temperature set points, lighting levels, and appliance loads, although survey data and observations reveal great heterogeneity [73], [74].

Microsimulation models of commercial building energy demand [75] and more recent agent-based models of various human behaviors [76] have blazed pathways for improving these representations of behavior, but they have just begun to appear in building-level models. The most significant advances have been in studies of emergency building evacuations, where models currently have rich detail and usability [77]. By contrast, HVAC and lighting applications are limited to research-level models of highly stylized one- to two-room buildings [78], [79]. Part of our agenda is to advance this marriage of engineering and behavioral analyses.

We have developed a research-level computer-based simulation modeling framework that will ultimately support integrated characterizations of lighting, water, wastewater, energy, and indoor air systems in buildings. It currently delivers dynamic representations of interactions among occupants and specific systems in case study buildings and allows the prospective study only of lighting design tradeoffs in hypothetical buildings. The special feature of this framework is that it enhances the modeling of human factors, using a multiagent simulation (MAS) approach to more realistically represent occupant behavior.

The integrated modeling framework is incrementally built by integrating standard packaged engineering models and a new human factors model created using NetLogo [80]. The MAS model has undergone quality assurance testing as suggested in [81] but is subject to the limitations described in [82]. The MAS model is linked to the aforementioned engineering models using a common set of input and output files and a Common Object Request Broker Architecture interface. However, the current implementation, as described in this paper, is not hot linked. Instead, the occupant behavior model accesses a lookup table that contains results from running a wide variety of scenarios through the packaged engineering model.

As shown in Fig. 4, in the MAS model, we build upon the approach pioneered in [78] to represent human and environmental interactions within a computational structure. It contains the following submodels:

1) a building performance simulation submodel that tracks environmental conditions;
2) a human action simulation submodel that contains a representation of agency;
3) a mediating submodel that tracks the state of the building's controllable components and links the building and its human occupants;
4) external industry-standard building system models that help submodel 1 calculate the state of the environment within the building.

Submodels 1 and 4 manage a set of standard engineering calculations to determine the state of the architectural environment, e.g., workspace illumination levels, as functions of the building's technical state and occupant behavior.

Submodel 3 describes the building's technical state as a function of occupant behavior and the state of the building's environment, i.e., it describes objects such as windows and faucets and whether they are open or shut. In submodel 2, the human agents, i.e., the building's occupants, respond to environmental conditions within the building through chained processes of sensation, cognition, deliberation, planning, and decision making that lead to changes in the states of the building's controllable features and in its performance. Humans are heterogeneous in their sensations, perceptions, desires, causal beliefs, and prescriptive/planning beliefs; hence, they heterogeneously act, given similar stimuli. The aforementioned combined TPB and BDI framework forms the core of submodel 2. This modeling framework allows *in silico* tests of behavior modification proposals, as well as tests of the efficacy of technical innovations such as occupancy sensors.

Modeling inputs include building site conditions and design choices, and occupant preferences and capabilities. Outputs include the usability measures of effectiveness, efficiency, and satisfaction. The model has been calibrated and validated using occupant survey responses and design data from a case study building. Half of the occupants were randomly assigned to the calibration group, and the other half became part of the validation group.

B. Packaged Engineering Design Tool

This paper is limited to an illustrative application to lighting design questions, particularly the choice among lighting technologies in commercial buildings. It uses in modeling step 4 the virtual lighting simulator based on the well-known lighting design simulation modeling tool RADIANCE [83]. This tool is "for predicting the distribution of visible radiation in illuminated spaces . . ., which takes as input a 3-D geometric model of the physical environment and produces a map of spectral radiance values [using] the technique of ray-tracing [which] follows light backwards from the image plane to the source(s)" [83: 1].

The lighting design problem is illustrative of numerous other problematic human–technology interactions in commercial buildings. Behaviorally robust solutions to this problem will be relevant to plumbing, HVAC, indoor air quality, solid waste management, and integrated building design topics. One particularly valuable aspect of the modeling efforts is to repackage the insights from case studies, which are necessarily backward looking and contextualized, in a way that is forward looking, formally explicit, and more general. In prospective evaluations, the identities of the actual users are unknown. However, it is possible to specify typical distributions of occupant characteristics likely to be found among the users of a building.

C. Model of Human Behavior

By simulating both occupant behavior and the performance of building systems, the overall modeling framework can deliver the usability metrics of effectiveness, efficiency, and satisfaction. The model of human behavior (modeling step 2) implements a version of the aforementioned BDI theory using an agent-based modeling approach. Building occupants perceive their indoor environment, develop preferences, select a desired outcome and course of action, and implement it. Behavior may vary from one occupant to another, because perceptions, preference structures, and the ability to act may vary.

The human behavior model incorporates a utility function that serves two purposes. First, it plays a role in simulating human behavior by allowing exogenously established beliefs to guide the occupant's choice of action. Second, it measures occupant satisfaction.

Some building occupants may hold ST values and be open to change, even if such values require them to devote more effort to operating the building and to endure more discomfort. Indeed, some occupants may enjoy the novelty of operating innovative features despite the effort required, whereas other occupants may not. The utility function for measuring occupant satisfaction should therefore account for these possibilities, along with more traditional factors such as comfort and cost. In short, occupant utility $= f$ (benefits to self, benefits to others, costs to self, and costs to others).

The BDI desire or cognitive processor specifies this utility function for each occupant. The deliberation processor selects a desired outcome that reflects the priorities embedded in the occupant utility function. The planning processor generates plans that increase the occupant utility relative to the status quo. The decision-making processor selects the plan that yields the largest increase in occupant utility and implements it.

Several considerations govern the selection of the utility function's form. First, because occupant satisfaction depends on four components, it must be a multiattribute utility function. Second, by making a strong simplifying assumption that the occupant views the four components as having preferential, utility, and additive independence, it is reasonable to specify an additive formulation [84]. Third, it is reasonable to assess weights on the four components based on occupants' responses to survey questions. Despite its simplifications, decision scientists view this approach as accurate, trustworthy, and easy to use [85]. The form of the additive multiattribute utility function is

$$\text{Occupant utility} = U(x) = \sum k_i U_i(x_i) \tag{5}$$

where

x_i performance level of attribute i (normalized by a max–min range);

$\underline{U}_i(x_i)$ single attribute utility for attribute i (the range is 0–1);

k_i weighting constant for the utility of attribute i (the range is 0–1, $\Sigma k_i = 1$);

I 1 (benefits to self), 2 (benefits to others), 3 (costs to self), and 4 (costs to others).

Thus occupant multiattribute utility has a range from 0 to 1.

D. Operationalization

This utility function may be operationalized by redefining the concepts to have a common directionality and the potential to be normalized. Each attribute may operationally be defined as something occupants do not want. This operational choice also reflects observed behavior, because building users "tend to not worry about comfort as such, but discomfort . . . [and] they react when a 'crisis of discomfort' has been reached" [86: 664]. Therefore, operationally, we measure

$$\begin{aligned}\text{Occupant disutility} = f(&\text{lack of benefits to self}\\ &\text{lack of benefits to others}\\ &\text{costs to self}\\ &\text{costs to others})\end{aligned} \tag{6}$$

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Set up simulation

- Establish graphical user interface (GUI), building shape (5-zone), and number of occupants (11)
- Use GUI to specify runtime, parameters, initial conditions:
  - site conditions (sunrise/sunset, cloud cover, electricity price)
  - design options and available controls (% window on each exterior wall, shading devices, illumination devices, technology performance parameters, target illumination levels)
  - occupant characteristics (location in building, light sensitivity, utility function)

↓

Perform simulation

- Cycle through hourly time ticks
- Calculate sun position, daylight illumination initially reaching occupants
- For each occupant:
  - Perceptions: acquire occupant's characteristics, room's illumination level
  - Cognition: compare illumination level to target light level modified by occupant's light sensitivity
  - Deliberation: check status of controllable features, determine whether room should be darker or lighter
  - Planning: create alternative plans of action (e.g., first turn lights on/off, then raise/lower blinds if light still isn't right)
  - Decisionmaking: select a plan that maximizes utility and act on it
- Resolve conflicts among occupants in same room (last one to act wins)
- Given the resulting changes in conditions, calculate usability metrics (energy used for lighting, cost of that energy, lighting sensation felt by each occupant, resulting comfort level of each occupant, effort expended by each occupant in adjusting controllable features, and from these, utility enjoyed by each occupant)
- Report the results of this hourly time tick, accumulate results over time on GUI
- Continue to the next time tick, repeat until end of simulation period

Fig. 5. Programming steps in the simulation model.

Occupants prefer scenarios with less disutility.

The first reason for calculating the occupant's multiattribute utility function is to make a BDI modeling framework operational based on the TPB. In addition, it provides a relative basis for measuring satisfaction.

IV. Application in Lighting Design

To illustrate how our framework performs, we model the behavior of a building's inhabitants with regard to lighting systems and measure their satisfaction with the chosen design. In addition, the illustrative model gauges the efficiency and effectiveness of the building's lighting system. Empirical relationships established in the literature on lighting-related occupant behavior, as summarized in [87], guided the formulation of the model. The major programming steps in the model are summarized in Fig. 5.

The application uses a simplified five-zone single-story commercial building layout (see Fig. 6) that approximates a real building, with appropriately specified site conditions (sunrise/sunset times, cloudiness, electricity prices, and the number of occupants). The graphical user interface (GUI) allows the user to input design choices and occupant characteristics. Key design choices include the size of each room, the percentage of the exterior wall facing in each cardinal direction that is glazed with windows, whether a shading device is employed on each window (none, overhangs and fins, and overhangs), the type of illumination device used in each room (ceiling troffer, indirect pendent light, or portable task light), and the target illumination level (based on code requirements for the expected use). The user can enter technological performance specifications, including illuminance and rates of energy consumption. Occupant characteristics include their location (in one of the five rooms), light sensitivity (prefer the target illumination level, more light, or less), value structure, and utility function weights. The modeler specifies the characteristics of up to ten occupants from the GUI.

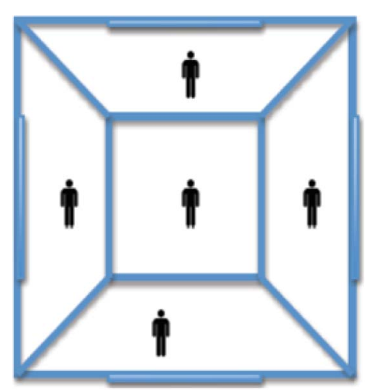

Fig. 6. Simplified representation of building in the model.

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TABLE I
OPERATIONAL DEFINITIONS

Item/ Concept	**Benefit to self**	**Benefit to others**	**Costs to self**			**Cost to others**
Definition	Service received	Green innovation	Effort	Discomfort	Cost	Environmental impact
Operational measure	% of time desired service is unavailable	Energy use (kWh)	Number of times the occupant has to adjust controls	% difference between actual and desired performance	Utility bill ($)	Energy use (kWh)
Direction of "goodness"	Less is better	Less is better	Less is better	Less is better	Less is better	Less is better

The GUI provides an animation to help the user understand what is happening. Building-level outputs, e.g., energy consumption for lighting, are reported for each time tick and are also tracked over time. Outputs for each occupant and room are also reported and accumulated.

A. Model Calibration

We set the initial model parameters to simulate an office building (with some classrooms) located in New Brunswick, NJ, USA, with design choices as specified in the building plans. Percent window coverage for the building was determined to be 10% for the east-facing side of the building, 20% for the north-facing side of the building, 40% for the west-facing side of the building, and 32% for the south-facing side of the building. With regard to shading, the building does not possess overhangs or fins.

Troffer lighting is the most prevalent type of indoor lighting throughout the building. Autumnal mid-day light levels within the building were measured and determined to be between 344 lx and 938 lx in the classrooms, between 219 lx and 276 lx in the hallways, and 503–601 lx in the offices.

We surveyed building occupants to ascertain their values, beliefs, preferences, and self-reported actions. Based on an opportunity sample of 91 responses, we used 45 responses for calibrating the model and 46 responses for validating it.

Table I summarizes the measures used to operationalize the occupant utility functions. The benefit-to-others (green innovation) and cost-to-others (environmental impact) categories are collapsed into one measure that is operationalized as the energy consumption for lighting (in kilowatthours).

Table II summarizes the value structures of occupants included in the calibration sample. Based on occupant responses to a ten-question scale (the short version of Stern's portrait values survey [88]), occupants are categorized as green activists (ST, O), good citizens (ST, C), healthy consumers (SE, O), or traditional consumers (SE, C) [31]. For comparison, their proportions in the U.S. population are 64%, 9%, 23%, and 4%, respectively, based on the analysis of data in [88]. These

TABLE II
CALIBRATION SAMPLE AND WEIGHTS $(k_I)/100$

Occupant Value Set Type	**% of sample**		**Service rec'd**	**Env. impact**	**Effort**	**Discomfort**	**Cost**
Green Activist	51		27	23	11	21	18
Good Citizen	24		23	17	16	19	25
Healthy Consumer	18		28	16	13	26	19
Traditional Consumer	7		23	10	12	15	40

TABLE III
CALIBRATION SAMPLE ILLUMINATION PREFERENCES

Occupant Value Set Type	**% of sample**		**% Prefer Darker**	**% Normal**	**% Prefer Brighter**
Green Activist	51		64	14	22
Good Citizen	24		63	13	24
Healthy Consumer	18		57	14	29
Traditional Consumer	7		33	0	67

TABLE IV
BEHAVIORAL OPTIONS AND THEIR RATINGS

Option/Attribute	**Service rec'd**	**Env. impact**	**Effort**	**Discomfort**	**Cost**
If too dark…					
Do nothing	High	Low	Low	High	Low
Adjust window blinds	Low	Low	High	Low	Low
Switch lights on	Low	High (-)	Medium	Low	High (-)
If too bright…					
Do nothing	Low	Low	Low	High	Low
Adjust window blinds	Low	Low	High	Low	Low
Switch lights off	Low	High (+)	Medium	Low	High (+)

proportions suggest that the survey does not measure pure intrinsically held values but also captures the effects of social norms; in other words, the labels overstate the strength of the stated value sets.

Occupants' preferences for illumination also vary. Table III summarizes responses from occupants included in the calibration sample. Occupants were placed in a closed room, and illumination levels were varied from 0 lx to 1000 lx, as measured by a handheld meter. Each occupant specified on their survey instrument which illumination level they preferred. An illumination level of 300 lx $+/-$ 100 lx was considered the normal range.

Potential occupant actions in response to changed lighting conditions are summarized in Table IV. Note an asymmetry: when switching lights *off*, there is a high *beneficial* impact on the environment and cost.

One final occupant characteristic is the influence of subjective norms, determined by answers to two survey questions based on widely used wording in [27]. This characteristic is operationalized by increasing the environmental impact category weight as the occupant assigns greater influence to the opinions of other occupants. In the calibration sample, the average response is 6/10 ("a little influenced") for all occupant

TABLE V
COMPARISON OF CALIBRATION AND VALIDATION CASES

Case/Attributes	Calibration case (100 runs)	Validation case (100 runs)	Percent Difference
Average daily effectiveness (% of time light levels meet targets)	1.22	1.37	11.9%
Average daily occupant dissatisfaction (0 = satisfied, 1 = dissatisfied)	0.83	0.81	-2.7%*
Average daily electricity cost per occupant ($)	0.205	0.201	-1.6%*
Average daily electricity use per occupant (kWh)	2.18	2.14	-1.6%*
Average daily effort per occupant (# actions)	8.3	7.6	-7.9%*
Average daily discomfort per occupant (% of time light is too dark or bright)	14.0	13.7	-2.1%*

* Difference between means is significant at the 95% confidence level.

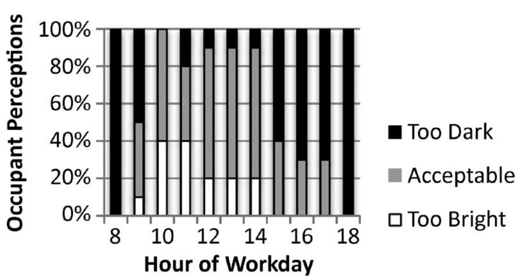

Fig. 7. Acceptability of illumination (validation run).

types, except for good citizens, who average 8/10 (“somewhat influenced”).

B. Model Validation

The model described in the previous section was calibrated using the site and design characteristics of a real building, along with half the respondents to the occupant survey. The validation effort uses the same building's site and design characteristics, along with the survey results for the remaining half of the responding occupants. Because the focus of the model is on occupant behavior, this validation strategy is reasonable.

The model includes stochastic elements and path-dependent behavior; hence, it is necessary to perform repeated model runs and compare the mean performance of the calibration and validation cases. Table V shows summary usability statistics for 100 24-h simulations of the calibration and validation cases, as well as the average percent difference between the cases.

Fig. 7 shows the percentage of occupants who perceive illumination levels to be acceptable, very bright, or very dark for each hour of the day in a validation run. The pattern is similar (but not identical) in the calibration run. As both modeling runs suggest, this building has usability problems, particularly with regard to the ability of occupants to set lighting levels that they individually prefer.

Additional comparisons, not shown, confirm that the modeling stages of perception, cognition, deliberation, planning,

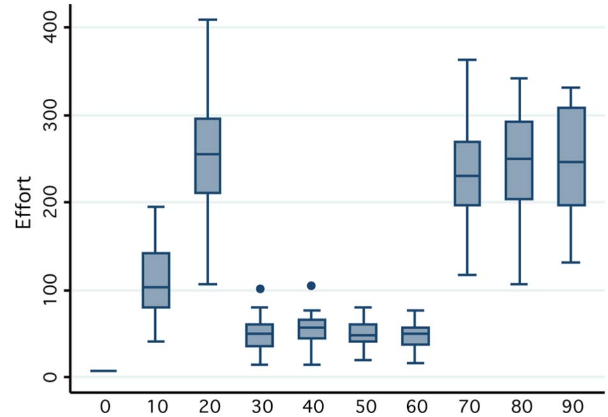

Fig. 8. How big should the windows be? Note that the window size was measured as the percentage of exterior wall that is glazed with windows, from 0% to 90%. Forty simulations were performed for each window %, holding fixed the lighting type (portable), window treatment (none), occupants' light sensitivity (dark), and preferences (traditional consumer) but varying the electricity price.

and decision making are performing as intended, providing face validity to the model.

The validation runs slightly differ from the calibration runs, as we might expect. The differences of means tests are significant at the 95% confidence level for all of the metrics shown in Table V, except for effectiveness. For two of the three usability metrics (efficiency and satisfaction), the cases are within 3% of one another, but for the effectiveness metric, they diverge by almost 12%, although nonsignificantly due to its high variance. Effort and discomfort diverge by smaller amounts. A part of the divergence is due to random differences between occupants in the two survey cohorts, chiefly with regard to illumination preferences. The remainder is attributable to the model. Nonetheless, this test indicates an acceptable level of validity, given the subjective nature of much of the occupant data.

V. RESULTS AND DISCUSSION

Following calibration and validation, we performed a series of simulations to illustrate how the model performs, gather insights into the interactions between design choices and occupant behavior, and show how we can prospectively assess usability. Selected results are summarized as follows.

Determining how big the windows in a building should be made is an important early design task. In a series of simulations that span the range from 0% to 90% of the exterior wall area in windows, bigger windows allow more use of daylighting, thereby saving energy and costs. However, windows that are very big cause significant discomfort and encourage occupants to expend greater efforts to adjust blinds and lights. This tradeoff suggests that an optimal window size is in the range of 30% of the wall area, a figure borne out in the literature [87]. Fig. 8 illustrates the link between window size and occupant effort.

The next step in daylighting design is to consider alternative window treatments, including overhangs, overhangs and fins, or no window treatment. A simple comparison of means across scenarios with different window treatments shows no significant differences in buildingwide performance that result.

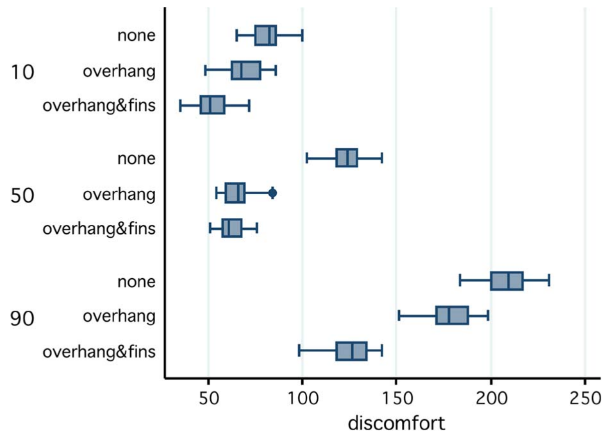

Fig. 9. Interactions between window size and window treatment. Note that 40 simulations were performed for each of the nine window %/window treatment combinations, holding fixed the lighting type (portable), occupants' light sensitivity (normal), and preferences (traditional consumer) but varying the electricity price. Window sizes are 10%, 50%, and 90% of the wall area. Window treatments include none, overhangs, and overhangs and fins.

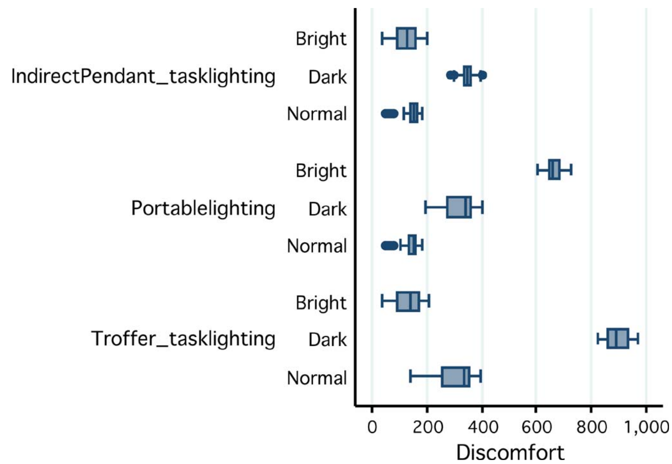

Fig. 10. Influence of light sensitivity on the lighting technology choice. Note that 1440 simulations were performed for each lighting technology, holding fixed the window % (50%) but varying the window treatment, occupants' light sensitivity and preferences, and electricity price.

However, a look at the window treatments that were applied to different window sizes shows that treatments affect performance. As Fig. 9 illustrates, the larger the window area is, the more the impact that the treatment has. Buildings with overhangs and fins that protect large window areas use more energy but cause less discomfort. Such buildings still use less energy (and achieve similar dissatisfaction levels) compared to buildings with small windows and no window treatments.

The final major step in lighting design is to select artificial lighting technologies that will be used in the building to supplement the daylight. One investigation of whether troffers, indirect pendants, or portable tasklights perform best shows that portable lighting consistently performs better than indirect pendants along key metrics; however, troffers show wide variation that prevents us from drawing conclusions. One possible explanation for the varied performance of troffers is the occupants' values systems. However, simulations that vary occupant values indicate that the different preferences of green activists, good citizens, healthy consumers, and traditional consumers do not explain the variation in troffers' performance.

Fig. 10 resolves the question, showing that occupants' varied light sensitivities drive the variation in the troffers' performance. Portable lighting tends to use less energy and is slightly less dissatisfying than indirect pendants or troffers across the range of light sensitivities, with one important exception. Occupants who prefer rooms to be darker than normal have trouble using troffers, because they are not locally adjustable. They frequently turn the lights on and off during the day in pursuit of greater comfort, which increases their levels of effort. The lights end up off most of the time, which saves energy and cost. The cost savings outweigh the increased effort and discomfort, paradoxically decreasing dissatisfaction.

The results suggest that the consideration of occupant behavior will, indeed, lead designers to different choices of lighting systems. The key is to bring the objective and subjective aspects of the lighting experience together within a common framework [89]. The simulations also show that it is possible and productive to model usability on a prospective basis. The usability of the model itself was shown to be adequate in a third-party evaluation [90]. Interested readers should download the model.[1]

VI. Conclusion

In this paper, we have shown that one attractive feature of this framework for assessing usability is that better data can yield better modeling. Future work should develop larger more robust databases about occupant sensitivities, preferences, and reported behaviors in a wider variety of contexts. These subjective data should be paired with monitoring protocols to collect objective data on occupant behavior and overall building performance. Such fieldwork will allow more complete calibration and validation of this framework and similar simulation models in the future.

It will also be valuable to learn how the behavioral model can be linked to other building system design tools, particularly HVAC and plumbing simulators. The agent-based implementation of the BDI framework should be robust enough to work with this full range of systems. Eventually, as the state of the art in BIM advances, it should be possible to perform more completely integrated assessments of whole-building designs. Such assessments should show us, prospectively, how well designs perform, given realistic occupant behavior.

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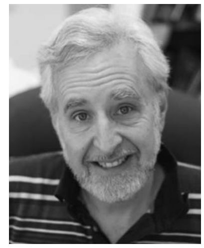

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