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Citation to Publisher Version: Andrews, Clinton J., Senick, Jennifer & Wener, Richard. (2012). Incorporating occupant perceptions and behavior into BIM. In S. Mallory-Hill, W Preiser, C. Watson (Eds.), *Enhancing Building Performance* (234-246). Oxford, UK: Blackwell Publishing Ltd. https://www.wiley.com/en-us/Enhancing+Building+Performance-p-9780470657591.

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20 Incorporating Occupant Perceptions and Behavior into BIM

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20.1 Introduction

Building information management (BIM) systems that incorporate simulation modeling can pre-test how alternative building designs will perform. A current weakness of most such simulation models, however, is that they ignore the wide variability in occupant preferences and behaviors. It is typical to design for the average occupant, or to meet minimal code requirements, and to assume that occupants are passive objects that merely emit heat, consume energy and water, and require certain indoor environmental conditions.

This chapter introduces a simulation-modeling framework that highlights the occupant's influence on building performance and seeks to provide a basis for prospectively assessing the user's experience. The model has been calibrated and validated using post-occupancy survey data from an office/classroom building located in the North Eastern United States. An application to lighting design in a similar, nearby building with green features shows that the model successfully predicts some, but not all, relevant aspects of building performance. This comparison of modeling and empirical results provides an opportunity to reflect on the potential as well as the limits of modeling, and on the value of dialogue between the BIM and building performance evaluation (BPE) communities.

Post-occupancy evaluation (POE) often characterizes occupant perceptions and behaviors, and uses these data to assess how well the facility meets the criteria and goals identified in the planning, programming, and design phases. As such, it is an important element of BPE that integrates evaluation throughout the life cycle of the building (see Chapter 2). Often missing from BPE is attention to the flip side of the environment-behavior equation – the impact of user behavior on the building performance. How does the daily

Enhancing Building Performance, First Edition. Edited by Shauna Mallory-Hill, Wolfgang F. E. Preiser and Chris Watson.

activity of building users (occupants and building managers) affect the building's performance with respect to energy efficiency, water usage, and indoor air quality? This may be especially relevant for green buildings, which explicitly pursue superior performance on these measures.

20.2 BIM and the design process

Good design depends in part upon exploring a wide range of design possibilities and engaging closely with future users of the product, and good design tools should help with both objectives. Simulation modeling is an effective way to accomplish rapid, cost-effective prototyping and engagement. A successor to computer-aided design (CAD), BIM aspires to represent digitally the physical and functional features needed to develop and document building designs. Much as BPE can play a role at every stage of a building's life cycle (see Chapter 2), the cutting edge of practice merges design-oriented BIM with operations-oriented building management system (BMS) tools.

BIM is finding increased use for analysis and simulation; and BIM applications now support walk-through visualizations, heating-ventilating-air-conditioning (HVAC) system design, energy performance estimation, lighting design, and assessment of safety/security issues such as evacuation. BIM simulations, however, are deficient in providing representations of occupants and operators as active participants in the operation of their buildings who want a variety of outcomes, behave in heterogeneous ways, and exhibit bounded rationality. These elements belong in the simulation because they affect the relative performance of alternative building designs. Estimates of likely user satisfaction are also desirable outputs of design simulations.

20.3 Linking BPE and BIM

At the early stages of a building's life cycle, BPE results from other relevant buildings can be used to guide design practice (see Chapter 2) or, as advocated in this chapter, provide an evidence base for developing simulation models that can assist the design process. Modeling requires data, and the empirical requirements for simulating user behavior toward lighting or temperature control in buildings are significant. POE-based observations about user behavior, and occupants' likes and dislikes, add nuance and suggest testable theories about the basis of user behavior. BPE, which combines POE and engineering measures of performance, controlled experiments, and field studies, provides a way to connect individual behaviors to building-wide outcomes.

User behavior in buildings can be simulated using prescriptive, correlational, or rule-based models. The approach that is most widespread reduces human behavior to a fixed set of performance targets: 300 lux for the illumination level, 20°C for the indoor air temperature, 40°C for the domestic hot water temperature, and so on. Elaborate engineering calculations build deterministically on these assumptions. This approach fits well with prescriptive design processes that aim at targets, and it limits models to well-known algorithms based on physical principles of optics and energy and mass transfer. It entirely misses, however, the possibility that some users might not prefer the standard performance levels, and that their behavior might influence the building's performance.

Correlational approaches link occupant characteristics through multivariate regression analysis, for example, to predicted water or energy consumption. This approach fits well with standard tools of empirical research such as surveys and objective measurements of building system operation, but it has limited explanatory power in novel situations such as when simulating the behavioral response to a new design, or considering the implications of differentiated behavioral responses rather than central tendencies.

A third approach is rule-based, specifying simple behavioral rules that occupants are likely to follow as they interact with building systems. It is implemented here in an agent-based modeling framework. Its strengths are that it makes use of both qualitative and quantitative data, allows for heterogeneous preferences and behaviors, relates individual-level behaviors to emergent, system-level performance, and is forward looking instead of historically based. Weaknesses include validation challenges due to its many degrees of freedom, and its unfamiliarity to many in both the BIM and BPE communities.

20.4 Simulating behavior

There are both conceptual and practical issues to be addressed in developing an agent-based model of occupant behavior in buildings.

The most challenging conceptual issue is the need for a single, coherent theory of occupant behavior to implement in the data collection and model. An economic approach assumes that external factors, such as prices, lead to specific behaviors, whereas a psychological approach places greater emphasis on internal factors, such as beliefs and attitudes, which influence behavior. Computer science, on the other hand, focuses on the procedural steps that lead to enactment of a specific behavior. Since this research seeks to use observational and POE-derived data to inform model building, it requires a theoretical synthesis (see Figure 20.1).

The utilitarian framework of microeconomics already has close counterparts in psychology and decision science that start with a premise of informed self-motivation. Ajzen's (1985) *Theory of Planned Behavior* (TBP) proposes a causal chain that links beliefs about behaviors, social norms, and ability to control one's environment, to attitudes, intentions, and actions. TPB has been operationalized in a vast array of survey instruments that give it empirical

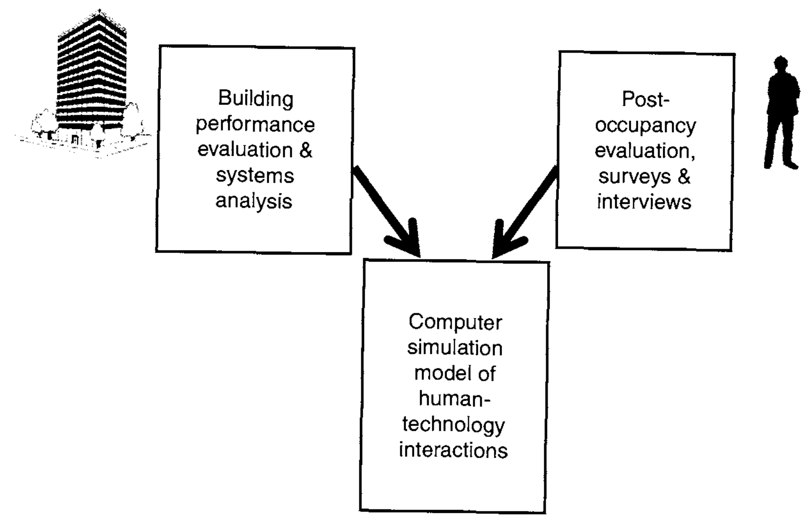

Figure 20.1 From fieldwork to modeling.

relevance and make it a plausible basis for predicting goal-directed behaviors to maintain occupant comfort at minimal cost. Schwartz' (1977) Norm Activation Theory provides a useful bridge from self-enhancing to self-transcendent beliefs, attitudes, and behaviors, and it can be adapted to consider environmental values, beliefs, and norms that might influence energy and water conserving behaviors by building occupants.

Computer scientists have developed the Belief-Desire-Intention (BDI) framework to characterize the process of human decision-making (Rao and Georgeff, 1998). In the variant of the framework used here, autonomous agents follow five procedural steps in making behavioral decisions: establishing beliefs, desires, and intentions, developing plans, and deciding to carry out a particular plan of action. This synthesis uses empirical evidence on values and beliefs regarding behavior, norms, and control to calibrate the processors in the BDI framework. Occupant agents in the model deliberate on benefits to self (service provided), benefits to others (green innovation encouraged), costs to self (effort, discomfort, utility bills), and costs to others (pollution) using weights based on survey data.

Programming and validation are major practical challenges that appear when implementing an agent-based model of occupant behavior. Unless a programmer is willing to replicate the complex building-science algorithms included in the typical BIM simulation tool, then the programmer has to hot-link a standalone occupant behavior model to the BIM tool. Agent-based models are typically under-constrained, having many more degrees of freedom than data points. Many modelers settle for 'verification' rather than full-scale calibration and validation.

20.5 Metrics

Decision support systems work best when they evaluate decisions against formal metrics. BPE includes objective and subjective metrics: measures obtained using engineering instruments including occupancy sensors, electric meters, water meters, light meters, and IAQ sampling; and measures obtained using social scientific instruments including questionnaires, interviews, focus groups and observations. See Chapter 18 for additional discussion of this topic.

Metrics used here include building-wide performance as affected by human behavior (normalized energy use, water use, IAQ), and measures of occupant satisfaction (comfort, effort, cost). The vocabulary of 'usability' ties these elements together. Usability has dimensions of effectiveness, efficiency and satisfaction that are measured in specific contexts. Effectiveness is measured here as the percentage of time a building system achieves its target performance level, such as a temperature setpoint or workplane illuminance standard. Efficiency is measured as the resources required to deliver thermal comfort or illumination, including natural resources such as energy and human resources such as occupant effort. Satisfaction is measured here as occupants' expressed satisfaction on a survey scale.

20.6 Illustrative simulation model

Lighting design is the decision domain targeted by the model of occupant behavior described in this chapter (see Figure 20.2). The model functions as a design simulator: the user specifies a set of lighting design choices and the model simulates how occupants interact with the building's features on a set of usability metrics (see Figure 20.3). Interested users of the model may also explore how different assumptions about site conditions, lighting technology characteristics, occupant locations within the building, and the distribution of occupant characteristics affects building-wide lighting system performance.

The model greatly simplifies reality by representing the building as a stylized five-zone space with exterior glazing facing North, South, East, and West, respectively, as well as an interior zone. Ten software agents that can be programmed to have different characteristics represent the occupants of the building. The model was calibrated and validated on a building in the northeastern United States, as described in Andrews et al. (2011).

As an example for this discussion, model parameters have been based on conditions found in another nearby building. This 2005 LEED Platinum commercial office building has just over 7000 m^2 (76 000 square feet) of leasable space on four floors, divided among multiple tenants. The tenant spaces offer spectacular views through large windows covering 50 percent of

<u>Set up simulation</u>

- 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)

↓

<u>Perform simulation</u>

- 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

Figure 20.2 Programming steps in the simulation model.

the façade. Glazing on the south façade is protected from the summer sun by overhangs. Private offices have locally controlled lighting and blinds, whereas cubicles and common areas have lighting on timers.

A POE has provided additional context and nuance to the modeled conclusions, plus suggestions to improve the extent to which the model can serve as a decision-making tool. One of the tenant spaces studied provides illustrative insights.

This tenant occupies approximately 465 m^2 (5000 sq. ft) of space on a middle floor. Its employees greatly appreciate the natural light afforded by windows on three sides (South, West, and North). General satisfaction with lighting is high, although some occupants experience more natural daylight than others.

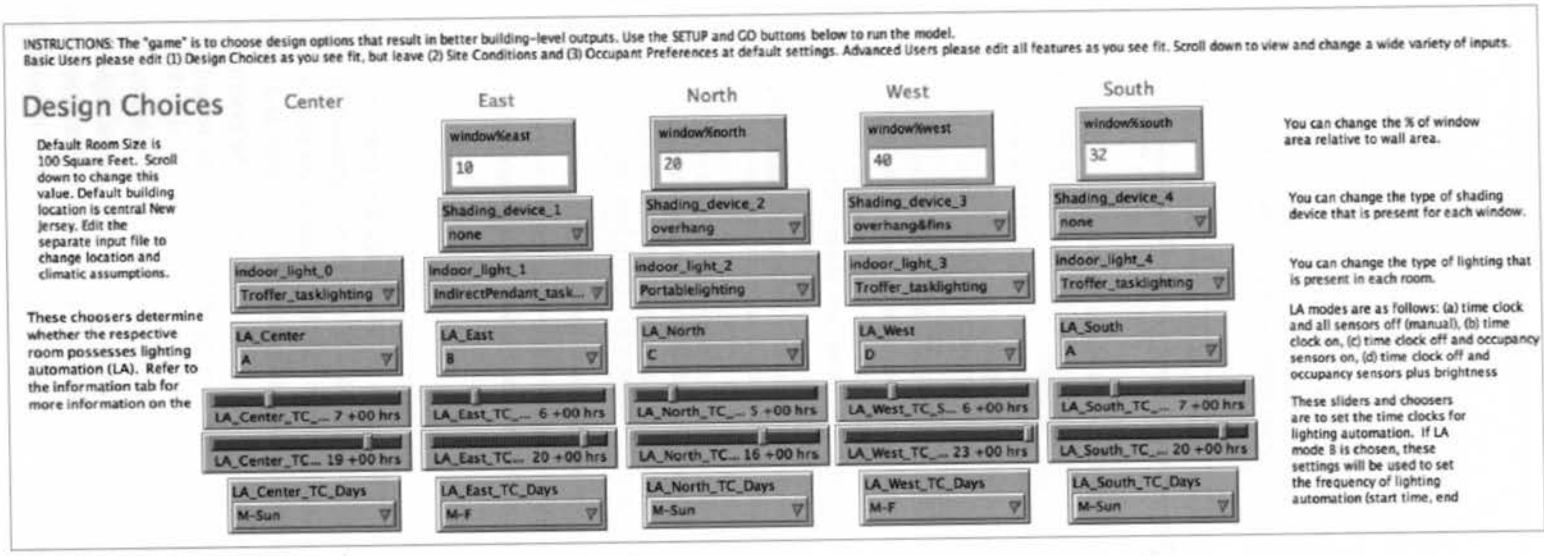

Figure 20.3 Lighting design model design choice and output screens.

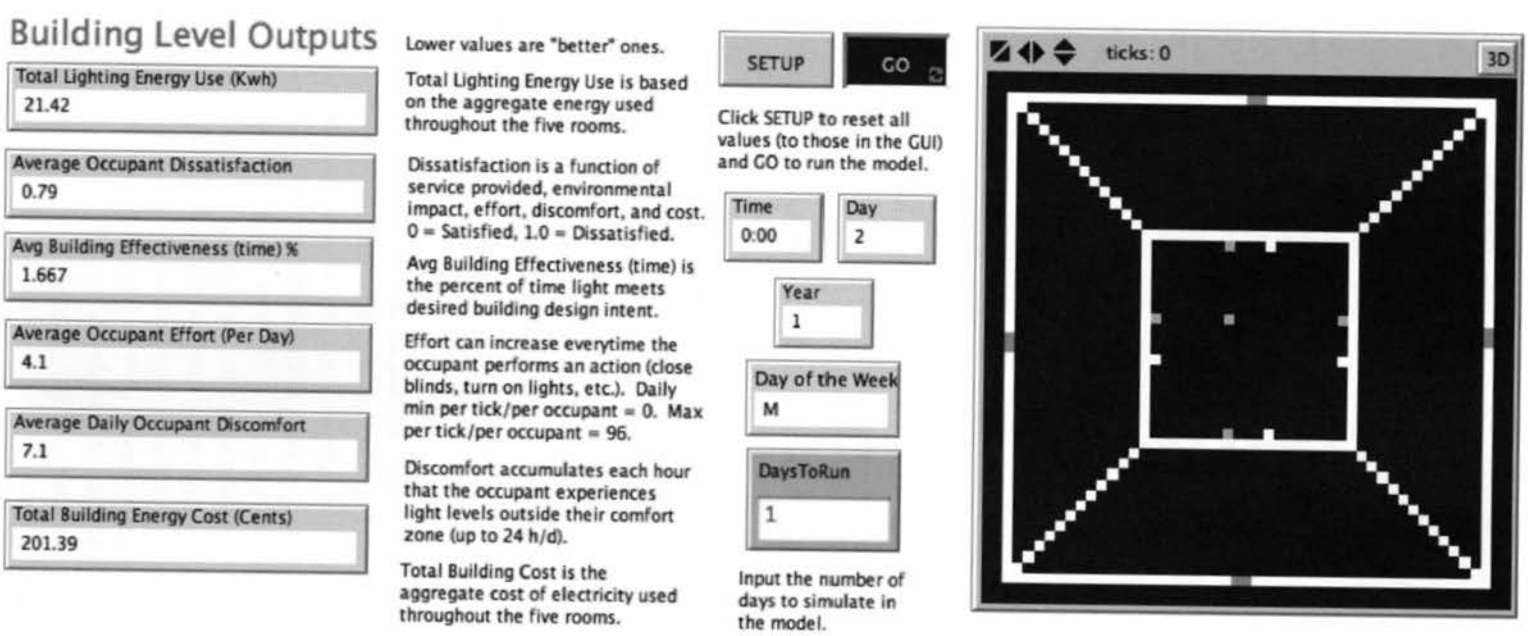

Figure 20.3 (*Continued*).

Table 20.1 Modeling results for lighting performance in tenant space.

	A. Private Offices (base case)	B. Cubicles (base case)	C. Cubicles (more automation)	D. Cubicles (more local control)
Glazing Orientation	West	North, some south & interior	North, some south & interior	North, some south & interior
Floor area (sq. ft)	1250	3750	3750	3750
Lighting	Indirect Pendant	Indirect Pendant	Indirect Pendant	Task lights
Automation	Manual	Time clock	Occupancy & brightness sensors	Manual
Effectiveness	57%	95%	84%	90%
Efficiency				
Lighting energy use (kWh/SF-yr)	6.2	2.2	2.3	6.4
Occupant effort (ordinal)	1129	0	0	37
Satisfaction				
Dissatisfaction (ordinal)	3	2	2	5
Discomfort (ordinal)	12	3	4	1

NB: Mean values for 20 simulations of each case are shown. All differences in values shown are significant at the 95 percent level.

Private offices and a conference room line the west side of the space. Cubicles with high partitions occupy the large, central space up to the north curtain wall, and they rely on overhead lighting, although one row appears to receive substantial natural light. There is no local control over the overhead lights, which are on a timer. Some always stay on and double as 'night lights'. The tenant controls the remaining lights in the private offices and conference room.

Table 20.1 shows results from a model of this space. Column A summarizes results for the private office spaces along the west side of the building. Column B shows results for the main cubicle area facing north. The modeled usability metrics are quite different for these two areas: effectiveness is higher in the cubicle areas than in the private offices; efficiency is better in the cubicle areas; and dissatisfaction is lower in the cubicle areas. The modeled discomfort metric also suggests that the cubicle areas, with their largely Northern exposure, are more comfortable than the west-facing private offices that inherently suffer from afternoon glare. This result derives from a premise that fundamentals (window orientation and scale) trump subtler factors such as controllability. The model's agent-based decision-making algorithm does not currently assign intrinsic utility to designs that give users greater control (or a nicer view or a larger, private space), instead, it only recognizes the instrumental value of greater controllability in better tailoring environmental conditions to individual preferences.

Column C in Table 20.1 explores a hypothetical scenario in which occupants in the cubicle area cede further control over their environment to the building management system, which uses occupancy and brightness sensors to adjust lighting levels. The model predicts that using sensors (instead of a timer) diminishes occupant comfort and worsens effectiveness, while efficiency and overall satisfaction do not change very much. This plausible outcome may reflect the benefit of having an occupancy sensor that ensures that occupants who stay late do not find themselves in the dark.

Column D shows a hypothetical scenario that instead pushes the locus of control downward, allowing cubicle occupants to control local task lights manually. Compared to the base case, a manual, task-lighting strategy performs better on comfort and effectiveness, but worse on efficiency and overall satisfaction according to the model. Occupants who value comfort highly do well under this design, but those who dislike effort do poorly. Energy usage depends strongly on the likelihood that occupants turn off their lights when away from their desks.

Evidence from the field can help interpret and verify the modeling results. The fieldwork can also identify needed model extensions. The fieldwork forced the modeling team to improve the way it represented the occupant's tradeoff between comfort and effort in controlling lighting systems, as illustrated in the comparison of Scenarios B and D. During the fieldwork, several employees indicated a willingness to adjust blinds in order to achieve greater satisfaction by increasing natural daylight or reducing glare. While spectacular views were also mentioned as motivation for keeping blinds open, view appreciation is not yet a part of the model. On their visit, the field researchers were seated in the conference room with blinds open AND the overhead light on, in spite of sufficient daylight. On separate occasions, the receptionist and the office manager turned the light on upon entering the room by force of habit or out of politeness. Habitual behavior warrants attention in the modeling, because not all decisions are deliberative.

Box 20.1 Observations

1. Building Information Models (BIM) typically assume that occupants are passive objects who merely emit heat and consume energy and water.
2. Human perceptions and behavior belong in BIM because they influence building performance.
3. Additional behavioral data should be collected in field studies, but in more standardized formats that could allow aggregation of large data sets for model building.
4. A decision-support philosophy of model building is necessary here because models always differ from reality.

20.7 Conclusions: implications for emerging practice

Human perceptions and behavior belong in BIM because they influence building performance. People will make adjustments to increase comfort and satisfaction, such as adjusting thermostats, turning lights on or off, or open and closing shades and windows. By using POE data as input for the ways people respond to various configurations, BIM can include and better approximate how people will respond to system options, and hence, how their behavior will affect performance.

Only rarely can such simulation models be fully calibrated and validated in a traditional scientific sense, in part because qualitative insights are an important part of model building, hence verification is a more realistic goal. Use of a full-scale facility simulator might allow researchers to see the effects of exposing people to various configurations and situations (such as various options for lighting control) on behavior, satisfaction and energy use, which could serve as a test of the utility of BIM predictions. Additional behavioral data should be collected in field studies, too, but in more standardized formats that could allow aggregation of large data sets for model building.

A decision-support philosophy of model building is necessary here because models always differ from reality, and building design retains many irreducible elements. Nonetheless, if good design depends on rapid prototyping and close engagement with future users, this type of simulation model helps advance both of those objectives.

Better modeling results emerge when the algorithms incorporate both quantitative survey data and qualitative data drawn from interviews and walk-throughs, albeit at the cost of reducing the model's transparency. Occupant behavior has a predictable impact on building performance, and the building design influences occupant perceptions and the user experience, suggesting that future BIM systems should incorporate modeling of occupants.

Acknowledgements

The authors gratefully acknowledge research assistance from Daniel Yi and financial support from the National Science Foundation, US Green Building Council, and Liberty Property Trust.

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