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Simulating the human-building interaction: Development and validation of an agent-based model of office occupant behaviors

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ABSTRACT

This paper develops and validates an agent-based model (ABM) of occupant behavior using data from a one-year field study in a medium-sized, air-conditioned office building. The full ABM is presented in detail using a standard protocol for describing this type of model. Simulated occupant "agents" in the full ABM behave according to Perceptual Control Theory, taking the most immediate, unconstrained adaptive behaviors as needed to maintain their current thermal sensation within a reference range of seasonally acceptable sensations. ABM validation assigns simulated agents the personal characteristics and environmental context of real office occupants in the field study; executes the model; and compares the model's ability to predict observed fan, heater, and window use to the predictive abilities of several other behavior modeling options. The predictive performance of the full ABM compares favorably to that of the other modeling options on both the individual and aggregate outcome levels. The full ABM also appears capable of reproducing more familiar regression relationships between behavior and the local thermal environment. The paper concludes with a discussion of the model's current limitations and possibilities for future development.

1. Introduction

Long-term field observations of building occupants broadly support Humphrey's hypothesis that *"If a change in the thermal environment occurs, such as to produce discomfort, people react in ways which tend to restore their comfort"* [1]. Indeed, occupant adaptations are seen to contribute to both thermal comfort and energy use outcomes [2,3].

To account for occupants' adaptive behaviors as part of the building design and operation processes, several behavior models have been developed over the last decade for integration with whole building energy simulations. The most prominent of these models are regression-based, describing the group-level probability of a given behavior in terms of thermal stimuli like indoor and outdoor temperature [4]. The regression-based models are commonly calibrated to data from cellular offices in naturally ventilated buildings in Europe, and focus most often on window opening.

Examples of existing regression-based models are found in the study of Nicol [4], which introduces the concept of simulating multiple behaviors stochastically using generalized linear models; the study of Rijal et al. [5], which calculates the probability of a window opening in terms of operative indoor and outdoor air temperatures after a +/-2K deadband around "comfort temperature" has been breached (the "Humphreys algorithm"), and which also suggests the incorporation of "active" and "passive" window users; the study of Yun and Steemers [6], which fits sub-models of window opening probability for occupant arrival, intermediate, and departure periods, with indoor temperature and previous window state as predictor variables; and the studies of Haldi and Robinson [7,8], in which the authors find occupant behavior to be better described by internal than external temperature, and develop sub-models for window opening probability for arrival, intermediate, and departure times using Markov chains coupled with survival analysis.

In general, the regression-based models have the advantage of being simple to communicate and implement as part of building simulation routines. However, some issues arise with their use:

- The models typically only roughly account for inter-individual variability in behavior through the definition of "active" and "passive" occupant groups.

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- The models do not simulate multiple behaviors together or address behavioral sequencing.
- The models do not account for social influences/other constraints on behavior in non-private offices.
- Few models address the most immediate adaptive opportunities (clothing, personal fans/heaters) despite the substantial use of these behaviors when available [9].
- The extensibility of these models to air-conditioned buildings in climates with greater seasonal variability is not well established.

It has recently been suggested that some of the above points could be addressed by the development of Agent-Based Models (ABMs) of occupant behavior [10]. ABMs represent individuals as autonomous "agents" with personal attributes and behavioral possibilities, as well as rules for interacting with other agents and their surrounding environment [11]; group-level behaviors then emerge from the adaptive behaviors of individual agents. In the context of building occupant behavior, ABMs continue a conceptual progression of existing modeling approaches as shown in Fig. 1.

A few existing studies have attempted to develop ABMs of building occupants' behavioral adaptations. For example, Andrews et al. [12] coupled an ABM of daily office occupant lighting use with the RADIANCE software, basing agent decisions on the Belief-Desire-Intention (BDI) software model. Azar and Menassa [13] modeled interactions between office occupant agents of different energy consumption habits as they relate to whole building energy use. Lee and Malkawi [14] used an agent-based model to explore how a single hypothetical commercial building occupant might adapt to changing thermal conditions in a manner that optimizes thermal comfort or energy savings, with five adaptations considered in the modeling approach.

In the residential context, Chen et al. [15] developed an agent-based model of individual resident energy consumption behavior to explore the effect of peer network structure on energy saving behavior in residential buildings. The authors used individual electricity consumption data collected from 45 occupants over 46 days to calibrate initial individual energy use distributions and social network weights, and found that tighter and more robust associations between network members are more important than network size in influencing energy savings behavior. Kashif et al. [16] used a daily activity survey to build an agent-based model of reactive and deliberative thermal behavior profiles for a family in France, incorporating perceptual, psychological, and social behavioral drivers in the developed model. Multiple agent-based models have also been developed to simulate residential water use [17,18].

The above studies suggest the promise of using an agent-based approach to represent individual occupants' adaptive behaviors as part of building simulation; however, the studies also reveal two consistent shortcomings:

- ABM descriptions are not presented in a standard manner that is clear and complete. Key details about the modeling assumptions, source of agent behavior rules, etc. are often missing, making it difficult for other researchers to interpret, reproduce, and build upon the given model.
- A general approach to ABM validation is not provided; the studies do not validate outputs from developed models against long-term field data on behavior.

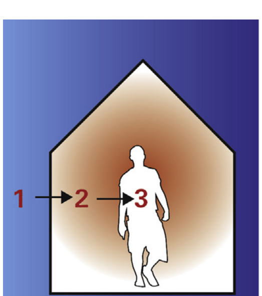


Fig. 1. Conceptual progression in behavior modeling approaches.

With these shortcomings in mind, this paper presents the development and validation of a novel ABM of thermally adaptive office occupant behavior in a way that is clear to other researchers and useful to future behavior model-building efforts. The paper builds towards two primary outcomes: 1.) A comprehensive ABM of office occupant behavior that reflects key findings on personal comfort and environmental adaptation in the field, and which is presented using a standard description protocol, and 2.) A validation of the developed ABM against long-term field data on behavior and comparison of its predictive performance to that of multiple other behavior modeling approaches.

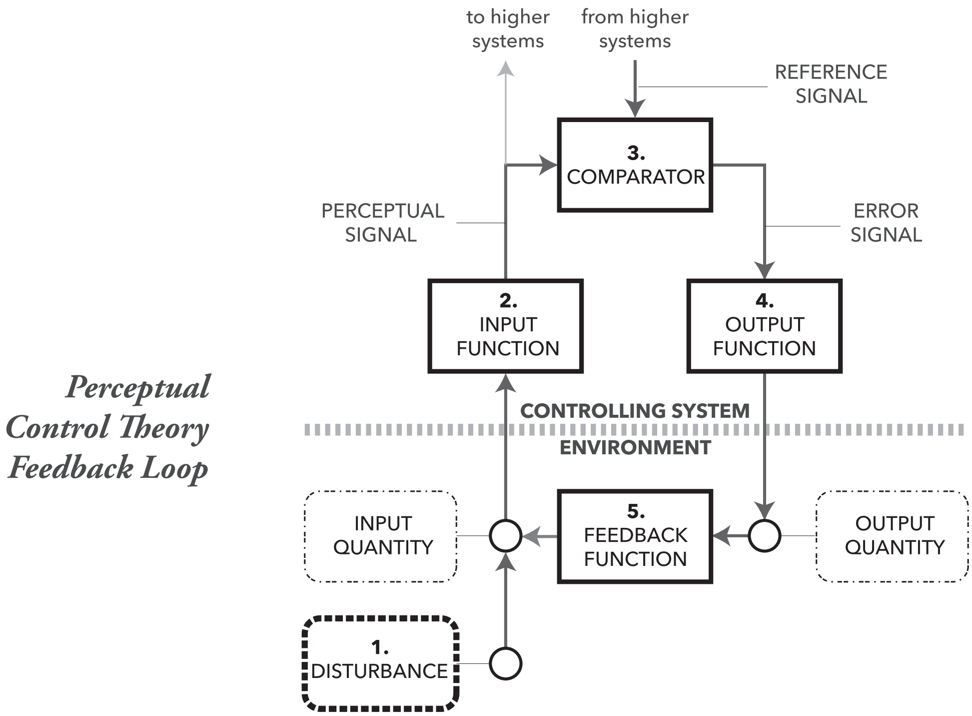
2. Methods

2.1. Field study

Development and validation of this paper's agent-based occupant behavior model draws from longitudinal field comfort and behavior data collected by the authors [19]. Here, key aspects of the field study, conducted between July 2012 and July 2013 in the Friends Center medium-sized office building in Philadelphia, PA, are reviewed:

- **Subject sample.** From an initial sample of 45 occupants who completed a background survey that asked about personal characteristics, typical occupancy periods (arrival/departure times), general thermal comfort, and behavioral control opportunities in the office, a final sample of 24 occupants was selected for participation in the full study. The final sample includes occupants of all office types (private/semi-private/open), from all floors of the building, with varying control opportunities that include the use of windows ($N=10$) and personal heaters/fans ($N = 4$ and $N = 5$, respectively).
- **Daily surveys.** For two weeks in each season, the occupant sample completed an online survey three times daily (shortly after arrival; late morning; late afternoon). The survey included questions about recent occupancy; work flow/productivity; thermal comfort; thermal sensation, acceptability, and preference; and recent behavioral opportunities and actions. At the end of two weeks, a final retrospective survey asked about occupancy, thermal comfort, and behavior over the past two weeks of surveying.
- **Environmental measurements.** Across the full year of the study, data loggers measured the local thermal environment continuously. Local ambient temperature was logged for all occupants, either through HOBO loggers (Onset, Bourne, MA) at their desks (5 min interval) or through nearby thermostat readings (15 min interval). Relative humidity was measured at the desks of half the occupant sample (5 min); globe temperature was measured at one perimeter and core desk on each floor (5 min); and air velocity was measured at one desk on each floor (5 min).
- **Behavior measurements.** Personal fan and heater use were logged at 15-min intervals using WattsUp? power meters (EED, Denver, CO). Window use was monitored using HOBO state loggers.

The Results section summarizes field study findings with the greatest significance to behavior model development.



ITEM	REQUIREMENT (*for each simulation time step)	REALIZATION APPROACH
1.	*A calculation of non-behavior related changes in the local thermal environment (i.e. due to outdoor temperature dynamics, general patterns of occupancy in the space).*	Using whole building energy simulation tools (i.e. *EnergyPlus, esp-R*), calculate ambient/radiant temperatures and relative humidity for an agent's thermal zone in the building.
2.	*A routine that determines how an agent perceives the current thermal conditions.*	Using the thermal sensation probability distributions in Langevin et al [26], sample an agent's current thermal sensation given its Predicted Mean Vote (where PMV = f(local environment, personal variables), see Fanger [27]).
3.	*A routine that determines whether the agent's current thermal perception is within a reference range of acceptable thermal perceptions .*	Compare agent's current thermal sensation to a seasonally acceptable range of sensations sampled using the acceptability distributions in Langevin et al [26] to determine a comfort state ("cool", "warm", or "comfortable").
4.	*A routine that determines which (if any) behavioral adaptations are chosen to move an agent's current thermal perception back towards the acceptable range.*	If uncomfortable, choose available behavior that comes first on user-defined action/action reversal hierarchy and is unconstrained (i.e. by mgmt., other occupants).
5.	*A definition of how a given behavioral action affects the local thermal environment if taken.*	Incorporate effects of any behavior into PMV inputs for next time step (i.e. fan use increases air velocity, heater use affects temperature, etc.)

Fig. 2. Perceptual Control Theory as it applies to simulation of thermally adaptive occupant behaviors.

2.2. General modeling approach

Occupant agent behavior rules are approached in this paper through the theoretical framework of Perceptual Control Theory (PCT),[1] which states: "behavior is the control of perception" [20]. Under PCT, behavior is not regarded as the response to a catalyzing stimulus, but as the by-product of a negative feedback loop in which an organism acts to bring some perceived state of the world into line with a reference perception, despite environmental disturbances.

Fig. 2 presents the general PCT schematic and suggests how each of its items can be translated to an agent-based simulation of building occupant behavior. Here, thermal sensation is treated as the perception under control in the PCT framework; behavior is then required when one's thermal perception is outside of a reference thermal acceptability range, with "warm" behavior required when the occupant's current sensation is *warmer than* his or her *warmest acceptable sensation*, and "cold" behavior required when a current sensation is *colder than* the occupant's *coldest acceptable sensation*. The behavioral option chosen to manage these

[1] PCT is also referenced in Schweiker and Shukuya [23] as a potential theoretical basis for occupant behavior models, and is implicit in Humphrey's algorithm [5,24].

cases of discomfort is conceived of as that which is most immediately accessible and unconstrained (i.e. by management, others in the space).

The Fig. 2 schematic serves as a conceptual core for the full occupant behavior ABM that constitutes the first primary outcome of this paper. The full ABM is presented in the Results section using the ODD (Overview, Design concepts, and Details) protocol devised by Grimm et al. [21] to standardize published descriptions of ABMs. First developed in 2006, the ODD protocol has since been updated based on a review of its use across three years [22]. The most up-to-date ODD version used in this paper consists of the following ABM description elements: 1.) Purpose; 2.) Entities, state variables, and scales; 3.) Process overview and scheduling; 4.) Design concepts; 5.) Initialization; 6.) Input data, and; 7.) Submodels.

2.3. Model validation procedure

Given the full ABM and its standardized description, ABM validation constitutes a second primary outcome of this paper. Validation of the full ABM involves assigning simulated agents the personal and environmental characteristics of real occupants in the Friends Center field study; executing the ABM; and comparing simulated agent behaviors against measured behaviors for the field occupant during the simulated time period. The validation procedure focuses on personal fan, heater, and window use outcomes because high-resolution measurements are available for these behaviors across the longitudinal study period.

Agent variables (further detailed in the Results) are set to a corresponding Friends Center occupant's data for the validation as follows:

- ***Control availabilities*** are set based on the occupant's indication of control possibilities on the initial background survey.
- ***Thermal acceptability ranges*** are set seasonally based on the acceptability limits most frequently reported by the occupant across the two-week daily surveying run for each season.
- ***Daily occupancy*** is set based on the daily arrival/lunch/departure times,[2] walkabouts, and periods of significant absence reported by the occupant.
- ***Morning metabolic rates*** are set based on the commute method typically reported by the occupant, with reference to ASHRAE Std. 55 [25].
- ***Morning clothing levels*** are set based on the clothing reported by the occupant on the morning survey for each simulated day, based on the clothing checklist in ASHRAE Std. 55 [25].
- ***Local thermal environment*** is updated with the datalogger and/or thermostat measurements for the occupant at every simulation time step.

For each season of the Friends Center study, at least one week of occupant fan, heater, and window use data are selected for validation purposes, during times when corresponding occupancy information is available from daily survey responses. In total, a single simulation run encompasses four and a half Friends Center work weeks:

- August 6th – August 10th, 2012
- October 31st – November 9th, 2012
- February 4th – February 8th, 2013
- April 15th – April 19th, 2013

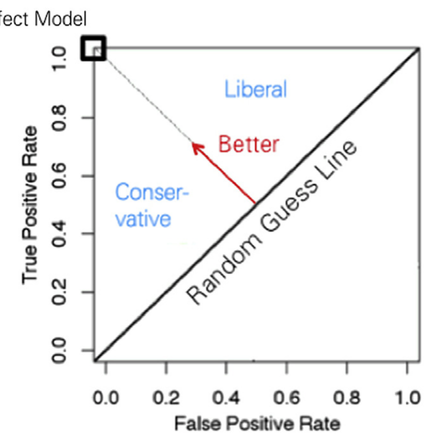


Fig. 3. Interpretation of the Receiver Operating Characteristic (ROC) space.

Because the full ABM includes stochastic elements, its predictive performance is evaluated after 20 repeated simulations of the above time periods.[3] Drawing from the validation approach of Haldi and Robinson [7], predictive performance is assessed on the level of both individual and aggregate outcomes. At the individual outcome level, each simulated outcome is classified as either: a truly positive outcome (TP); a falsely positive outcome (FP); a truly negative outcome (TN); or a falsely negative outcome (FN). From these classifications, the following metrics are calculated:

- **True Positive Rate** (TPR) = TP/(TP + FN);
- **False Positive Rate** (FPR) = FP/(FP + TN);
- **Specificity** (SPC) = 1- FPR = TN/(FP + TN)
- **Balanced Accuracy** (BA) = (TPR + SPC)/2

The model's True Positive Rate can be plotted against its False Positive Rate in the Receiver-Operating Characteristic (ROC) space [28]. As diagrammed in Fig. 3, the ROC space allows a graphical assessment of how well the full ABM predicts individual outcomes compared to an ideal model (upper left corner, TPR = 1; FPR = 0) and a random guess model (on the diagonal line). Models yielding points that fall towards the far left side of the ROC space are considered "conservative", making positive classifications only with strong evidence and yielding lower true positive rates; models yielding points that fall towards the upper right hand side of the ROC space are "liberal", making positive classifications with weak evidence and yielding higher true positive rates, but at the expense of higher false positive rates as well. As noted in Fawcett [29], performance towards the left ("conservative") side of the ROC space is more desirable for modeled phenomena with large numbers of negative instances, when it is advantageous for a model to be better at identifying likely positives than at identifying likely negatives. Occupant behavior tends to represent such a phenomenon – particularly in air-conditioned office settings, where there is less need to adapt to wide temperature variations and building management may restrict certain behaviors.

On the level of aggregate behavior outcomes, simulated and observed daily trends in group-level behavior frequencies are

[2] Note that since fans are often turned on upon office arrival, fan use WattsUp? measurements could be used as a check against the reported daily arrival time for occupants with this measurement available.

[3] 20 runs were deemed enough to generate a full range of simulated behavior outcomes while remaining manageable in terms of computational time. We arrived at this conclusion after running the simulation 5, 10, 20, 50, and 100 times and observing little change in the range of results above 20 runs.

plotted by season and compared qualitatively.[4] Quantitative assessment of aggregate predictive performance then calculates the coefficient of determination (R^2) and Root Mean Square Error (RMSE) between simulated and observed aggregate behavior outcomes at each time step (see Ref. [30]).

A final qualitative measure of the full ABM's predictive performance examines its ability to reproduce *stylized facts*, described by Rand and Rust [31] as "general concepts of a complex system derived from the knowledge of subject matter experts". Stylized facts for the three behaviors examined can be stated as follows:

- Personal fan and window use probability *increases* as indoor temperature *increases.*
- Personal heater use probability *decreases* as indoor temperature *increases.*

These assumed relationships can be verified with the Friends Center validation data by regressing observed behavior states on corresponding measurements of indoor operative temperature.

To place the validation of the full ABM into context, the predictive performances of several alternative behavior modeling approaches are also evaluated as above and compared to that of the full ABM approach. The full set of modeling options follows:

1. **Random Guess.** Agent behavior is determined by a coin toss.
2. **Logistic Regression (Aggregate-level Friends Center data).** Agent behavior is determined by a logistic regression model, fit to *group-level* behavior data collected in the Friends Center during the periods of daily surveying.
3. **Logistic Regression (Individual-level Friends Center data).** Same as # 2, but with logistic regressions fit to behavior data for *each individual occupant* separately.
4. **Humphreys Algorithm.** Agent behavior is determined using the group-level regression fit in #2 in the Humphreys behavior algorithm of Rijal et al. [5].[5]
5. **Haldi Regressions.** Agent behavior is determined by group-level logistic regressions fit in Haldi et al. [8] for naturally ventilated buildings in the summer (only fans and windows).
6. **ABM (Standard Acceptability).** Agent behavior is determined as in Fig. 2, but agents are all assigned the standard thermal acceptability range (-1 ("Slightly Cool") to $+1$ ("Slightly Warm")).
7. **ABM (Standard Clo/Met).** Agent behavior is determined as in Fig. 2, but agents cannot modify clothing from seasonal standards (0.5 Clo spring/summer; 1.0 Clo fall/winter), and have constant standard activity level (Met) of 1.1 (i.e., based on ASHRAE Std. 55 Clo/Met assumptions [25]).
8. **ABM (Reversed Behavior Order).** Agent behavior is determined as in Fig. 2, but agents are assumed to undertake the least accessible, most constrained behaviors first (windows/thermostats) and the most accessible, least constrained behavior last (clothing), with fans/heaters in between.
9. **ABM (Full).** Agent behavior is determined as in Fig. 2, using realistic thermal acceptability ranges; accounting for realistic clothing/Met dynamics; and assuming a realistic behavior hierarchy for air-conditioned occupants, where the most immediate/unconstrained behavior comes first (clothing); the least immediate/most constrained behaviors come last (windows/thermostats); and fans/heaters come in between.

Each of the modeling options is simulated in MATLAB, with individual agents and agent groupings implemented using Structure Arrays.

3. Results

3.1. Full ABM description

3.1.1. Relevant field observations

Certain aspects of the full ABM described below reflect key findings on occupant thermal comfort and adaptive behavior from the Friends Center field study, as well as related findings from the existing behavior literature. Field observations with the greatest significance to model construction are reviewed here:

- **Thermal acceptability and comfort:** Normalizing an occupant's thermal sensation to his or her personal range of acceptable sensations may effectively account for inter-individual variations in thermal comfort and associated adaptive behaviors. In the Friends Center study, there is a significantly negative linear relationship between thermal comfort votes and the degree to which occupants' sensations fall outside their reported acceptable ranges (linear regression $R^2 = 0.44$, vs. $R^2 = 0.19$ if a standard acceptable range ("Slt. Cool" to "Slt. Warm") is assumed, p value of difference <0.001).[6] Occupants' thermal acceptability ranges change most substantially on a seasonal basis.
- **Behavioral preference and sequencing**: Friends Center occupants tend to exercise the most immediate thermal adaptations with some regularity when available (clothing; fans; heaters), and less immediate adaptations infrequently (thermostats; windows).[7] Datalogger information shows that personal heaters tend to be turned on first in late morning (around 10:30 AM), in contrast to first use of fans and windows, which peaks in the early morning (8:30–9:30 AM). Window use rarely occurs before a fan adjustment for the limited number of Friends Center occupants with both these control options (5% of the time).[8]
- **Behavioral constraints:** Occupants generally do not wear clothing less than 0.3 Clo or greater than 1.3 Clo. For window use, a small peak is seen at an outdoor temperature around 24 °C, suggesting that occupants constrain window opening when warmer outdoor air is anticipated to make discomfort worse.[9] In the Friends Center background survey, several occupants indicate certain available controls are not allowed, or that use of some controls must be checked with others; these responses suggest contextual constraints on behavior.
- **The role of clothing and activity level:** Clothing change is significant for Friends Center occupants both within and between days, but is more prevalent for the latter (about 50% of the time between days vs. about 20% within a day).[10] Activity levels are significantly higher on occupants' morning surveys due to each occupant's preceding morning commute. This condition

[4] Mean daily behavior frequencies are calculated for each season by averaging the total number of occupants using a given behavior at each time step across all the time steps simulated for that season.

[5] The algorithm checks whether current operative temperature is within 2K of the comfort temperature (see Ref. [32]); if outside this 2K deadband, warm/cool behavior is predicted probabilistically using a logistic regression equation with operative indoor temperature and outdoor temperature as predictors.

[6] Humphreys and Hancock [33] similarly suggest the possibility of normalizing thermal sensations to personal preferences in the description of thermal comfort.

[7] Consistent with findings for air-conditioned buildings in Ref. [9]. Doors and drinks are both used significantly, but occupants frequently indicate non-thermal reasons for these behaviors.

[8] This suggests a different control sequencing in air-conditioned vs. naturally ventilated buildings, where window use has been suggested to occur before the use of fans (see Refs. [34,8]).

[9] As suggested in previous naturally ventilated building studies (i.e. [34,8]).

[10] Consistent with previous findings in Haldi et al. [8].

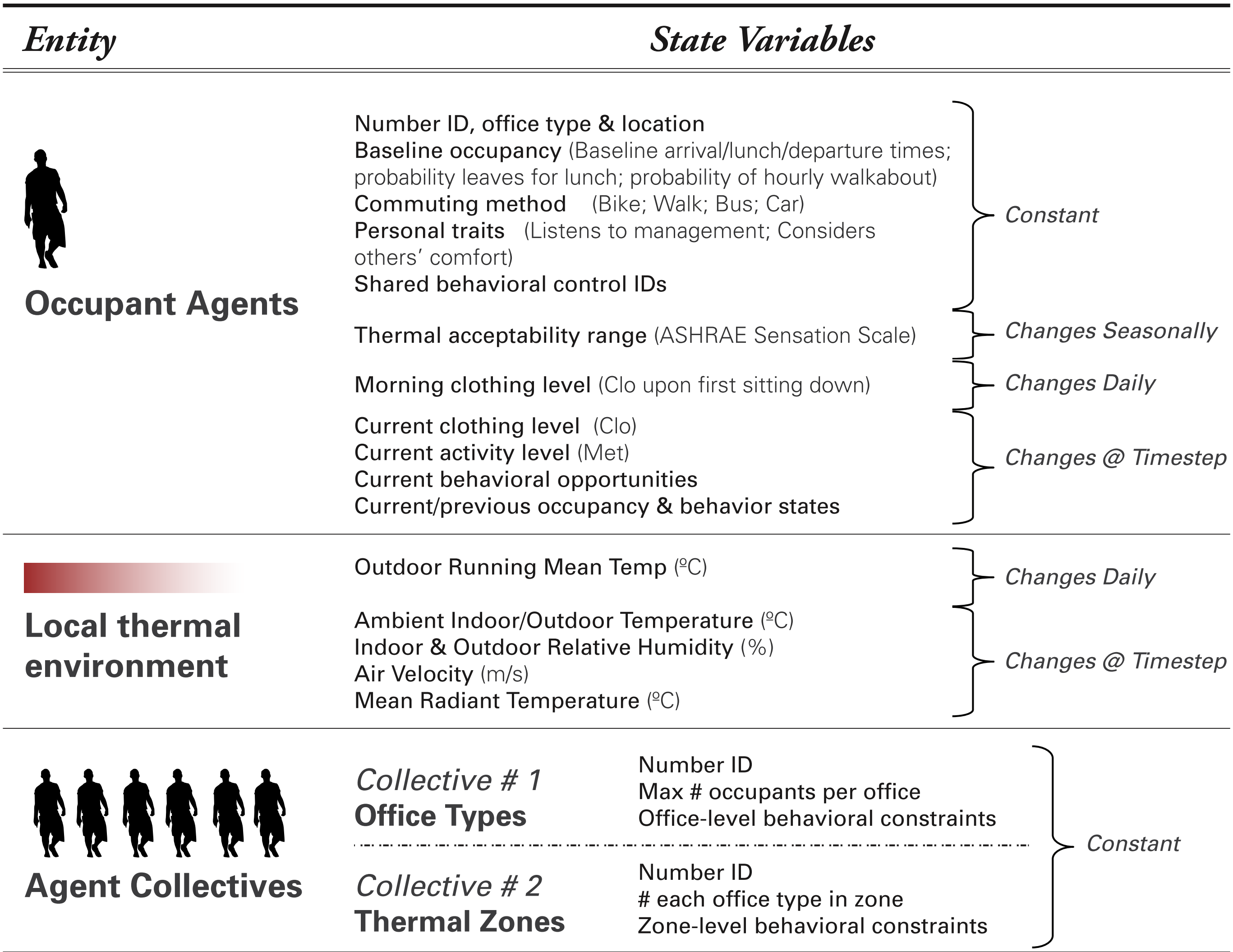


Fig. 4. Outline of entities and state variables in full ABM.

possibly explains the peak in first fan and window usage upon arrival (the occupant is warm), as well as the lag in first heater usage (the occupant cools off by late morning).

The following section details the agent-based occupant behavior model that was informed by the above observations.

3.1.2. ODD outline of full ABM

1. **Purpose:** The model is used to predict the thermal comfort and related adaptive behaviors of individual office building occupants over time, from which zone-level behavior trends can be constructed for use in whole building energy simulation. The current model implementation considers the following thermally adaptive behaviors:
   - Clothing adjustment
   - Personal fans on/off
   - Personal heaters on/off
   - Thermostat up/middle/down
   - Windows open/closed

Note: occupant use of warm/cool drinks, doors, and blinds are not currently implemented under the assumption that these behaviors are not primarily thermally driven.

2. **Entities, state variables, and scale**: See Fig. 4 for an outline of entities and state variables. The scale of the model is a single office building, with no further spatial resolution. One time step in the model currently represents fifteen minutes; it is generally expected that users would simulate a full period of one year or less.
3. **Process overview and scheduling**: See Fig. 5.
4. **Design Elements**
   a) **Basic Principles**: Agent behavior in the model is founded on Perceptual Control Theory (PCT), with thermal sensation as the perception under control in the PCT framework, as described in the Methods.
   b) **Emergence**: Both the thermal comfort and behavior of agents in the model constitute emergent outcomes, varying in complex ways according to the dynamics of one's local thermal environment, occupancy patterns, and the acceptability of various thermal sensations in each season.
   c) **Adaptation**: Agents adapt aspects of their thermal environment and clothing in order to maintain a thermal sensation that is within a reference acceptable range. For each time step that the agent's sensation is outside of this reference range (representing discomfort), the agent chooses and executes an adaptive action, monitors the feedback of the action on its comfort level, and acts again if still uncomfortable. Currently, this

process is iterated up to four times per time step, reflecting the field-observed possibility of an overlap in behavior sequencing, with multiple behaviors taken within a short time window.

Note: uncertainty in the Langevin et al. sensation/acceptability models is not currently accounted for in the agent sensing scheme. Ultimately, the standard errors attached to these models' coefficient estimates are small because the models are based on large numbers of occupant field responses from the ASHRAE RP-884 database. The models have also been developed using a Bayesian approach to parameter estimation, allowing parameter coefficient estimates and their standard errors to be updated in the future as

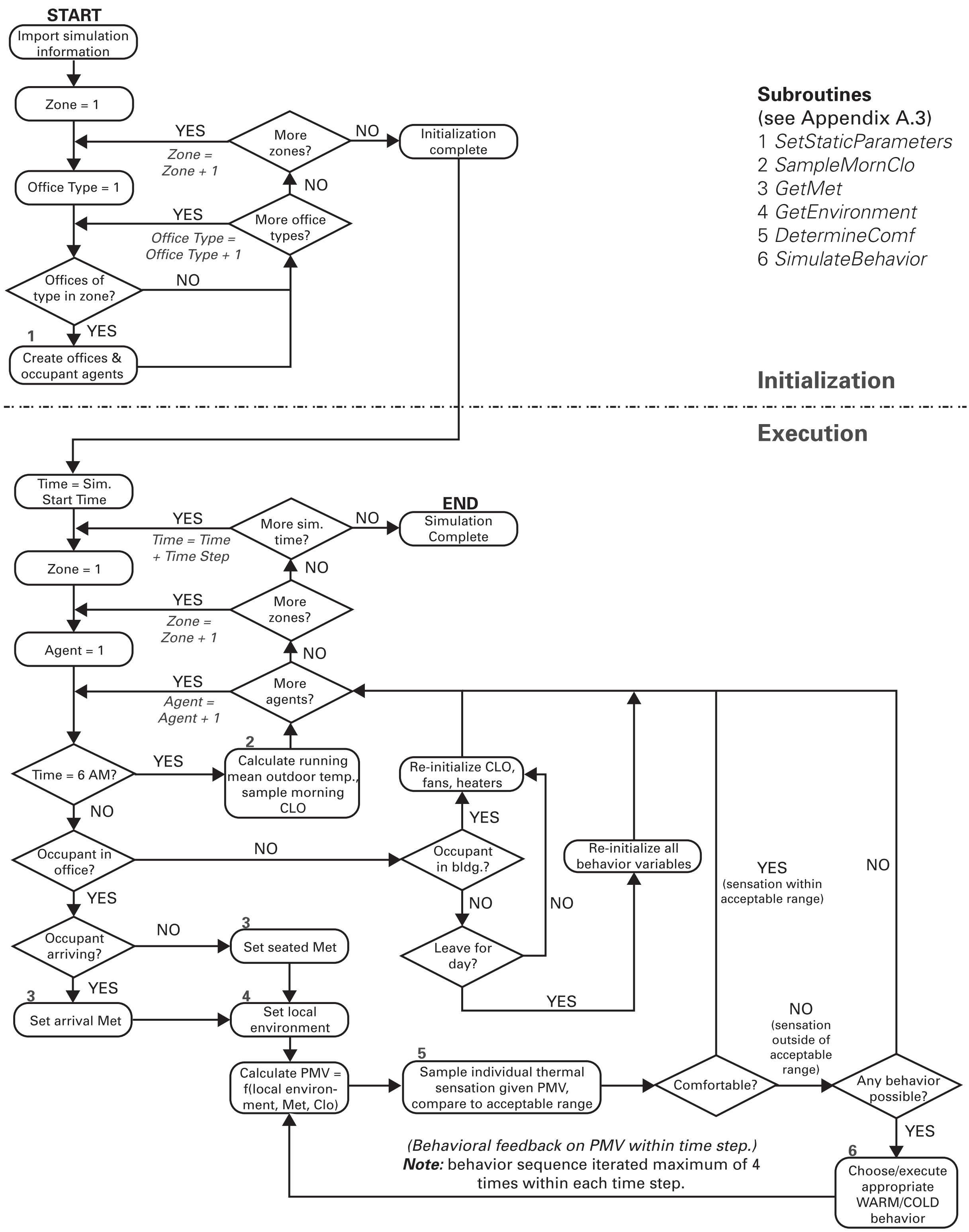


Fig. 5. Simulation process flow chart. Sub-routines of various process elements are numbered on the chart, with their names given at top right – each sub-routine is further detailed in the Appendix.

more sensation/acceptability response data are collected. The reader is referred to Langevin et al. [26] for more details.

d) **Objectives**: The agents' primary objective is to keep its thermal sensation within a personal seasonally acceptable range of sensations. In choosing behavioral actions to meet this objective, the agent adheres to a hierarchy of adaptive possibilities and constraints. In the current full ABM setup, the agent checks to see if previous adaptations can be reversed; if not, the agent chooses the most immediate and unconstrained adaptations first (clothing, then fans/heaters) and moves on to less immediate options if still uncomfortable (thermostats, windows). Current constraints on behavior come from its state (i.e. reasonable office clothing limits) as well as its context (i.e. management or social restrictions).
e) **Learning**: Agents in the model do not currently change adaptive traits over time through learning.
f) **Prediction**: Agents do not open windows when the action is predicted to make warm discomfort worse (in the simulation, when the daily outdoor running mean temperature [35] is greater than the indoor operative temperature).
g) **Sensing**: Agents translate information about their local thermal environment and personal characteristics into a thermal sensation at a given simulation time step using the Predicted Mean Vote (PMV) model [27], which calculates a group-level thermal sensation as a function of ambient air temperature, relative humidity, air velocity, mean radiant temperature, clothing level, and metabolic rate. Here, the group-level PMV outcome is translated to an individual thermal sensation by sampling from the individual sensation probability distributions of Langevin et al. [26]. The agent's individual sensation is then compared to an acceptable sensation range to determine behavioral outcomes, as described above. Agent acceptability ranges are sampled separately for each season at the beginning of the simulation using the individual acceptability distributions in Langevin et al. [26] (see the Appendix for more details and a test of the acceptability sampling scheme).
h) **Interaction**: Agents in shared private offices and in open offices may have user-defined social constraints on certain behaviors. When considering a socially constrained behavior, the agent checks whether use of the given control leads to discomfort for greater than 50% of the other agents sharing it (control sharing is set at the beginning of the simulation). If so, the behavior is removed as an option for that time step.
i) **Stochasticity**: During model initialization, an agent's commuting type, personal traits, occupancy, thermal acceptability ranges (by season), and initial morning clothing level are modeled stochastically, as indicated in Table 1 below. During the simulation run period, an agent's thermal sensations are modeled stochastically using the individual thermal sensation probability distributions of Langevin et al. [26], as described in the "Sensing" section above. The reader is referred to the Appendix for details about relevant simulation subroutines; again, the Appendix includes a test of the scheme used to sample agent thermal acceptability ranges from the acceptability distributions of Langevin et al. [26].
j) **Collectives**: Collectives include agent office types and thermal zones, as was outlined earlier in Fig. 4. An agent's behavioral opportunities and associated contextual constraints are initialized based on the type of office and zone it occupies.
k) **Observation**: For model verification, individual agents and their state variables were tracked at each time step to ensure that the variables were changing in an expected way, and that the processes determining agent comfort and behavior were running as intended. For model validation, at each time step: simulated and observed individual behavior states were tracked for use in calculating model predictive metrics; group-level behavior statistics were calculated for use in time series plots; and simulated and observed individual behavior outcomes were tracked alongside corresponding indoor and outdoor temperatures, for use in stylized facts plots.

Table 1
Initialization of agent state variables.

State variable	Initial value[a]
Number ID	Assigned as agent is created
Office type	"
Office location	"
Typical occupancy information	Sampled from user-defined occupancy schedules/parameters.[b]
Commuting method	Sampled from user-defined commuter distribution
Personal traits	Sampled from user-defined personal traits distribution
Thermal acceptability ranges	Seasonal ranges sampled from thermal acceptability probability distributions in Langevin et al [26]. [c]
Morning clothing level	Sampled from user-defined morning clothing lognormal distribution for starting season of simulation (constrained to $0.3 \le Clo \le 1.3$)
Current clothing level	Set to morning clothing level
Current activity level	Set based on commute method, using ASH Std. 55 [25] Met values
Current behavior opportunities	Set based on office type & zone restrictions
Current behavior states	All set to zero (off/closed)

[a] Default values are provided for user-defined distributions; initial values could also be based upon field survey data for a given building being simulated, if available.
[b] Daily occupant arrival/lunch/departure times are sampled from a normal distribution around baseline arrival/lunch/departure times (default std. dev. = 8 min.)
[c] Langevin et al. [26] report acceptability distributions only for summer and winter seasons - in the current model, the summer distribution is used to represent spring, and the winter distribution used to represent fall.

5. **Initialization**: Users define the number of occupants per each of nine office types (classified as basement/non-basement; perimeter/core; private/semi-private/open) and the number of each office type per zone. The user can also impose any office or zone-level behavioral constraints (default values are otherwise provided). Together, this information guides the agent initialization process, as diagrammed earlier in Fig. 5 – also see Table 1 for more details on initialization.
6. **External input data**: The model does not require external input data to represent changes in the local thermal environment over time; these changes would be calculated via a coupled building energy simulation routine (see Discussion).
7. **Subroutines**: see the Appendix.

3.2. Full ABM validation

To validate the full ABM as described in the Methods, an agent's variables were set to corresponding field measurements for a Friends Center occupant; the model was executed 20 times; and the model's resulting predictive performance was compared to that of several other behavior modeling options.

Table 2 summarizes quantitative validation results for the full ABM and all other modeling options tested. In general, the Table shows that on both the individual and aggregate outcome levels:

- The predictive performance of the full ABM is comparable to or better than that of the individually-fit Friends Center regression

Table 2
Summary of individual-level and aggregate-level prediction metrics for all modeling options.

Model	Fans					Heaters					Windows				
	Individual Predictions			Aggregate Predictions		Individual Predictions			Aggregate Predictions		Individual Predictions			Aggregate Predictions	
	TPR	FPR	BA	R^2	RMSE	TPR	FPR	BA	R^2	RMSE	TPR	FPR	BA	R2	RMSE
Random Guess	0.50	0.50	0.50	0.23	1.00	0.51	0.50	0.50	0.12	0.94	0.51	0.50	0.50	0.00	3.46
Log.Reg. (Agg.)	0.41	0.26	0.58	0.53	0.64	0.26	0.18	0.54	0.19	0.55	0.05	0.02	0.51	0.06	0.59
Log.Reg. (Indiv.)	0.58	0.18	0.70	0.62	0.58	0.46	0.12	0.67	0.38	0.47	0.09	0.02	0.54	0.14	0.58
Humphreys	0.11	0.01	0.55	0.16	1.08	0.39	0.16	0.61	0.08	0.78	0.14	0.01	0.56	0.43	0.49
Haldi	0.09	0.05	0.52	0.34	1.03	–	–	–	–	–	0.39	0.34	0.53	0.02	2.42
ABM (Std. Prefs.)	0.12	0.04	0.54	0.51	0.99	0.10	0.03	0.53	0.37	0.63	0.09	0.04	0.52	0.34	0.50
ABM(Std. Clo/Met)	0.59	0.28	0.66	0.45	0.74	0.67	0.38	0.64	0.27	0.81	0.40	0.25	0.58	0.00	1.82
ABM (Rev. Order)	0.60	0.20	0.70	0.61	0.59	0.78	0.33	0.72	0.43	0.73	0.71	0.19	0.76	0.32	1.62
ABM (Full)	0.56	0.18	0.69	0.61	0.59	0.48	0.15	0.67	0.43	0.46	0.52	0.07	0.72	0.64	0.57

*TPR = True Pos. Rate; FPR = False Pos. Rate; BA = Balanced Accuracy; RMSE = Root Mean Sq. Error.

model, and consistently better than that of the group-fit Friends Center regression model.

- The predictive performance of the full ABM is also generally better than that of existing regression-based behavior models fit to naturally ventilated data, which tend to either under or over-predict fan and window use.
- Relative to the full ABM, two alternate ABMs with standard agent clothing/metabolic rate settings and a reversed behavior action sequence tend to overpredict behavior, while a third alternate ABM with standard agent acceptability ranges tends to underpredict behavior.

These results are elaborated upon in the following sub-sections.

3.2.1. Quality of individual predictions

Fig. 6 plots the outcome of each tested model in the ROC space. From this and the associated "Individual Predictions" statistics in Table 2, it is clear that the full ABM performs favorably relative to the regression-based modeling options for all three behaviors considered. For fan use, the full ABM achieves a balanced accuracy close to that for the logistic regression model fit to each individual Friends Center occupant (69% vs. 70%); for heater and window use, the balanced accuracy of the full ABM is equal to or higher than that of the individually fit logistic regressions (67% vs. 67% and 72% vs. 54%, respectively). The full ABM also performs substantially better than the group-level logistic regression model for the Friends Center in all cases, without being tuned to the outcome data (as both of the Friends Center regression models are).

Behavior models based on the regressions of Haldi et al. [8] tend to under-predict fan use (low true positive rate of 9%), and over-predict window use (high false positive rate of 34%). This result suggests that the apparent preference for window opening over fans in the naturally ventilated offices of the Haldi study does not apply to the air-conditioned context and sub-tropical climate of the Friends Center. The other regression-based modeling option tested from the existing literature – the Humphreys algorithm – under-predicts both fan and window use (with true positive rates of 11% and 14%, respectively); ultimately, the cool environment of the Friends Center rarely reaches above the high indoor temperature threshold that prompts fan/window use in this modeling scheme.

Relative to the full ABM, the three other ABM options tested either under or over-predict behavior outcomes. In the version of the ABM where clothing and metabolic rate are fixed, for example, high true positive rates are achieved for fan and heater prediction (59% and 67%, respectively), but at the expense of higher false positive rates (28% and 38%), indicating that failure to consider realistic occupant clothing and metabolic rate dynamics leads to over-prediction of behavioral interactions. Conversely, when agents are assigned standard acceptability ranges, the model tends to under-predict behavior, as evidenced by the low true positive rates for this ABM scenario (~10% across behaviors). The third ABM version, which assumes a reversed ordering of behaviors, yields balanced accuracy outcomes comparable to or better than that of the full ABM (70–76%); however, this ABM more than doubles the false positive rates of the full ABM for heaters and windows (33% and 19%), indicating a tendency to over-predict these behaviors.

3.2.2. Quality of aggregate predictions

Fig. 7 shows that the full ABM effectively reproduces qualitative trends in aggregate behavior across the seasons. Note that the Figure shows only results for simulated seasons where the given behavior is expected to have the greatest intensity; aggregate prediction statistics for all four simulated seasons and modeling options are indicated in Table 2. Examining the R^2 and RMSE values in Table 2, it is evident that on the aggregate level, the predictive performance of the full ABM is comparable to or better than that of the individually-fit Friends Center regression models, and consistently better than that of the group-fit Friends Center regression models. Aggregate predictive performance for the full ABM is also generally better than that of the two regression-based models from the existing literature, though the Humphreys model yields a lower RMSE value for window use, owing to its tendency to predict closed windows - the typical window state in the field data.

On the aggregate level of prediction, the three alternative ABM options show the same tendencies to over and under-predict behavior as they did on the individual level, generally yielding lower R^2 values and higher RMSE values than for the full ABM. RMSE values are particularly high for the fixed clothing/metabolic rate ABM across all behaviors and for the reversed order ABM for heaters and windows, as these two ABM versions continue to over-predict behavior outcomes on the aggregate level.

3.2.3. Reproduction of stylized facts

The final validation exercise examined how well each of the four ABM options was able to reconstruct the commonly reported logistic regression relationships between behavior probabilities and indoor operative temperature, where the baseline regression relationships are derived from the Friends Center field data for the simulation run period.

Results are shown in the regression plots of Fig. 8. From the Figure, it appears that regressions fit to outputs of the full ABM closely track each of the baseline curves; regressions fit to the other three versions of the ABM often deviate substantially from these baselines. In particular, the ABM with fixed agent clothing and metabolic rates tends to over-predict the probabilities of all three behaviors; the ABM with standard agent acceptability ranges under-

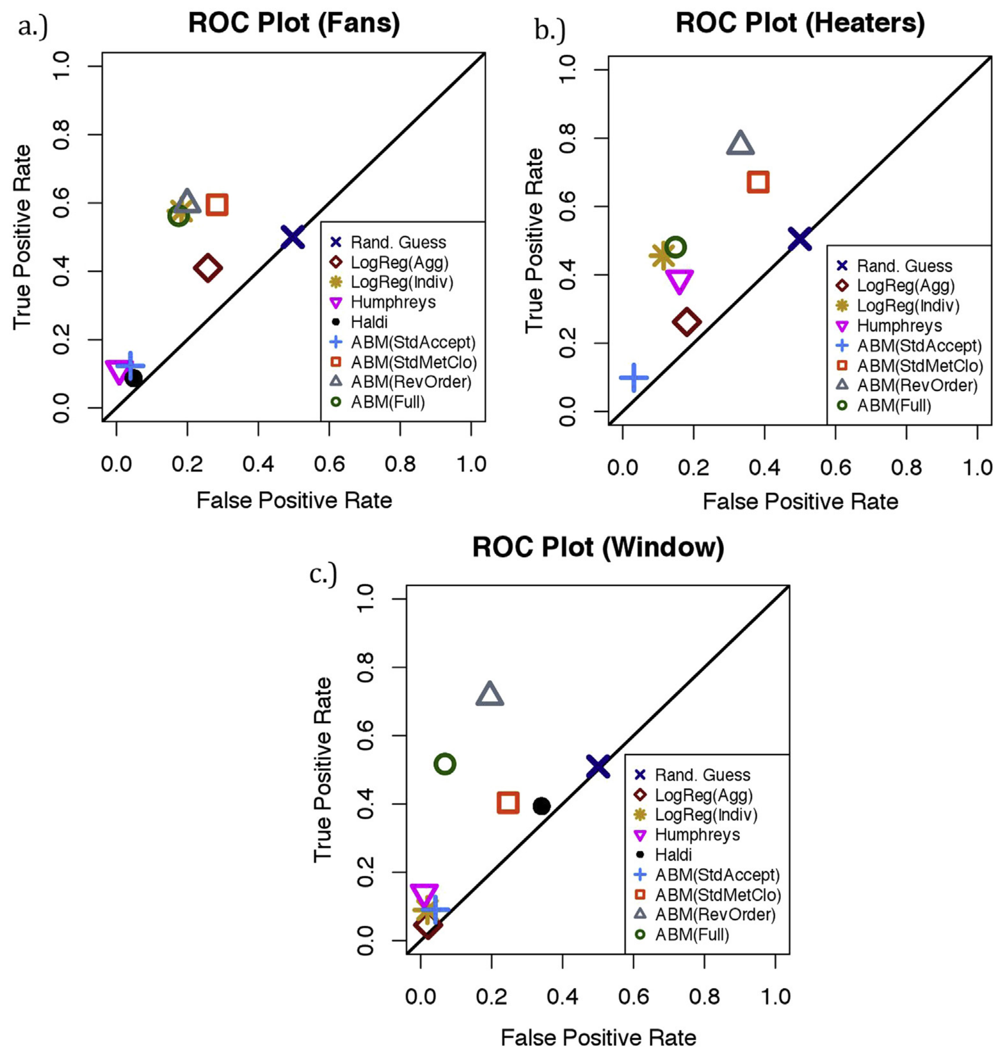


Fig. 6. Individual-level prediction metrics in the Receiver-Operating Characteristic (ROC) space for a.) Fans, b.) Heaters, and c.) Windows, where the diagonal represents a Random Guess model.

predicts fan/heater use probabilities and the probability of window use at higher indoor temperatures; and the ABM with a reversed behavior order over-predicts heater and window use probabilities, performing comparably to the full ABM in predicting fan use probability. Similar results are observed when behavior probability is related to outdoor temperature (see Appendix Fig. A.5)

4. Discussion

4.1. General comments

By adopting the individual occupant as the basic unit of behavior simulation in buildings, the developed ABM attempts to directly consider the real mechanisms behind behavioral actions at the individual level, placing thermal perception, comfort, and behavioral action under one simulation umbrella. Under this approach, key determinants of individual-level differences in behavior frequencies (and associated zone and building-level differences) are accounted for explicitly in the model construction and execution, improving the model's generality. Here, it is noted that the ABM does not use field-calibrated relationships between behavior outcomes and environmental stimuli to generate its predictions, as is commonly done in the existing behavior modeling literature. Instead, the model's predictive performance depends on the realism with which its agents' attributes are specified (i.e. morning clothing, metabolic rate values); the accuracy with which agent thermal comfort levels can be determined from general comfort probability distributions (see Ref. [26]); and the strength of the theoretical foundation on which its agents' behavior rules are based.

The full ABM – which assigns occupant agents realistic dynamics in clothing, metabolic rate, and thermal acceptability as well as a behavior choice hierarchy drawn from field observations – provides favorable predictive performance when compared to regression-based behavior modeling approaches. For both individual and aggregated behavior outcomes, the full ABM performs as good as or better than a logistic regression model of behavior separately calibrated for each occupant in the Friends Center field study; and substantially better than a logistic regression model of behavior calibrated to grouped occupant data from the Friends Center. In the case of the former regression approach, the incorporation of individual behavior differences clearly improves the quality of predictions over the group-level regression; yet, it is cumbersome to fit separate regression curves for all the individuals or individual types in a building in order to predict the building's behavior outcomes. Moreover, such curves do not accommodate the consideration of situational factors not present in their calibration (i.e. introduction of alternative behavioral options, new behavior constraints, etc.).

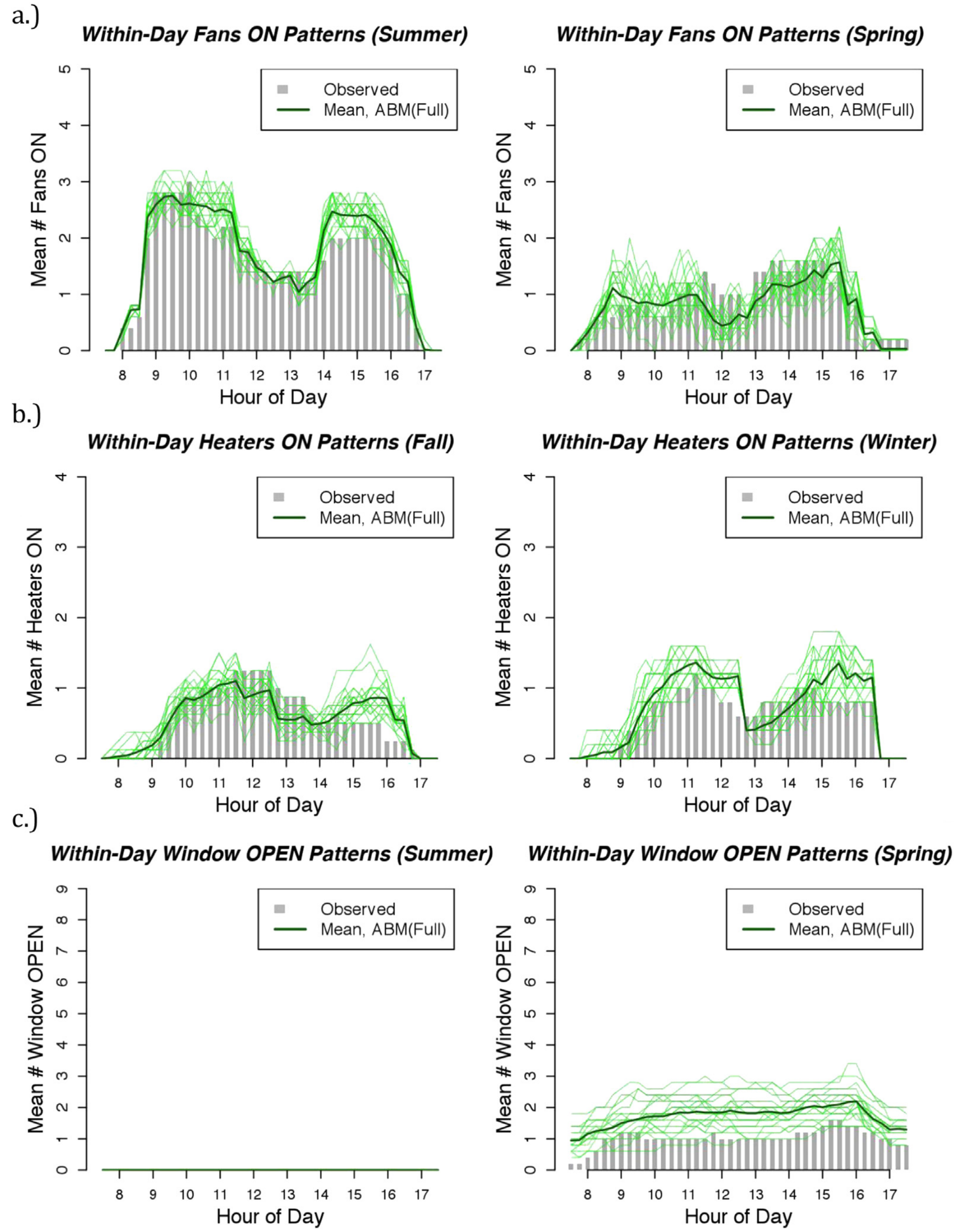


Fig. 7. Comparison of observed and simulated average daily trends in aggregate fan (a), heater (b), and window (c) behavior for each season, using the full ABM. Note: window opening is not observed or predicted in summer; lighter lines represent individual simulation runs for the full ABM.

By offering predictive capabilities comparable to those of the individually fit regressions without relying on curve fitting, the full ABM presents a viable platform for considering important inter-individual differences in behavior while also remaining flexible to the introduction of behaviorally significant changes in the building context. Furthermore, the full ABM appears capable of accurately reproducing the familiar group-level relationships between behavior outcomes and indoor/outdoor temperature for a given office context (see Fig. 8); these simple curves may be easier for architects, engineers, and policymakers to understand as part of building design guidelines. Finally, the predictive performance of the ABM would likely have been improved by the availability of higher-resolution occupancy data from loggers (vs. surveys); such logger data yield a more accurate and granular understanding of daily office arrival and departure events, which are highly influential in determining subsequent behavior trajectories.

In the model validation procedure, running alternate versions of the full ABM reveals the model's sensitivity to changes in key parameters and assumptions. In one case, assigning each agent a standard acceptability range ("Slightly Cool" to "Slightly Warm") results in the *under-prediction* of behavioral outcomes. In this case, it seems the thermal environment of the Friends Center generally satisfied this standard acceptability range, obviating the simulated need for behavior. Overall, the poor predictive performance of this ABM version suggests that a standard acceptability range should not be assumed across all occupants for the purpose of behavior modeling.

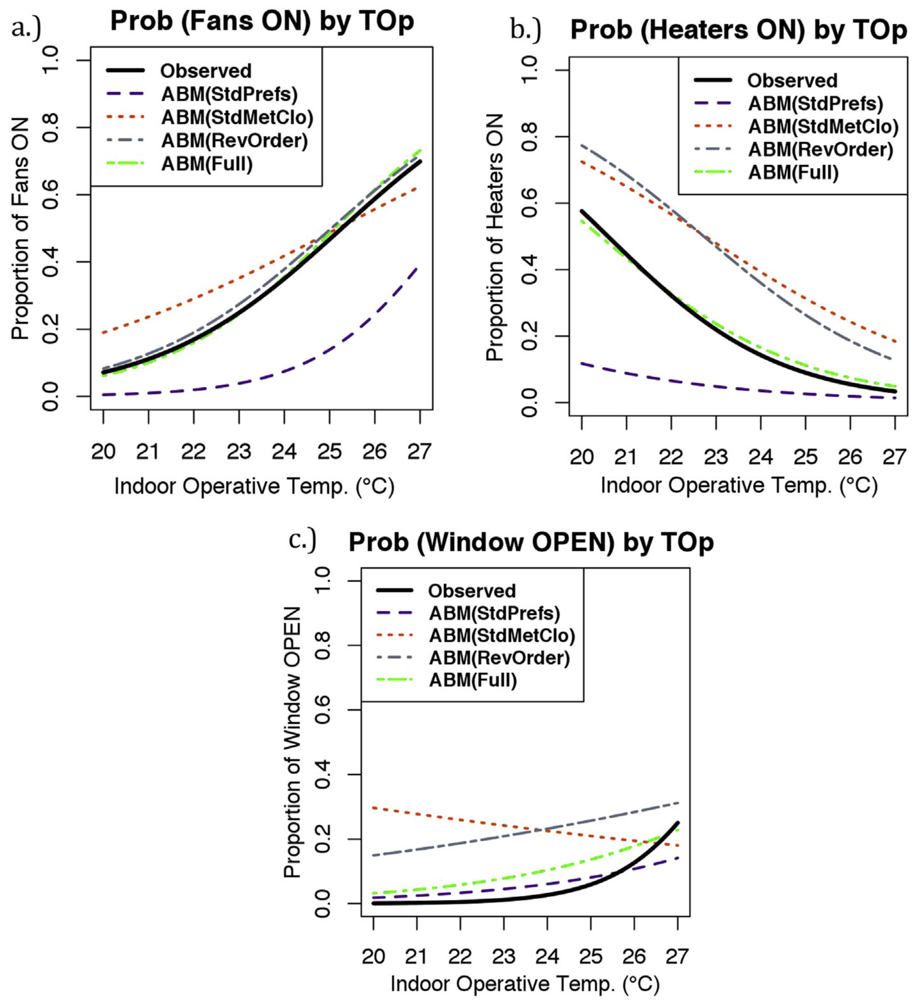


Fig. 8. Friends Center logistic regression trends in fan (a), heater (b), and window (c) behavior probability vs. regression trends fit to simulated behavior data generated with four ABM options and indoor operative temp. (TOp) predictor.

By contrast, a second case that fixes agents' clothing and activity levels at standard values results in the *over-prediction* of fan and heater behavior. This outcome reinforces the importance of clothing and activity level dynamics to thermal comfort and behavior prediction: as modeled, early clothing adjustments appear effective enough to reduce the need for heater use year-round and fan use in colder seasons (when there are layers to remove when warm); at the same time, elevated metabolic rates upon first arrival at the office make warm discomfort more likely, encouraging fan use and discouraging heater use.

A final ABM version reverses the expected order of behavior in the agent model, yielding comparable predictive ability to the full ABM for fan use, but tending to over-predict heater and window use. Overprediction of heater use in the reversed order ABM likely results from this model's swapping of clothing and thermostat adjustments in the sequence of behaviors taken when “too cool”: as modeled, thermostat set point adjustments have less impact on cold discomfort than do clothing adjustments, often requiring that agents also turn a heater on to warm up in the reversed order scenario.

The over-prediction of window use in the reversed order ABM provides further evidence that air-conditioned occupants probably choose other behaviors (clothing, fans) before opening a window. However, the model's high true positive rate for window use (71%) suggests its assumed first priority for window opening may be valid for at least some occupant cases in an air-conditioned building. Ultimately, window use was infrequent in the current field study, and more long-term data from office buildings with frequent window opening are needed to place the current window validation results into context. More generally, such future studies must continue to focus on the issue of behavior hierarchy and its measurement in the field, ensuring that occupant preferences for certain behavioral actions over others in a given context are accurately represented as part of future occupant behavior models.

4.2. Relation to whole building energy simulation

The full ABM is structured for integration with whole building energy simulation programs. The exchange requires reading in zone-level environmental information from the energy simulation at each time step; determining aggregated behavior outcomes via the behavior model; and using these outcomes to modify relevant input schedules in the energy simulation for the next time step. This exchange has been implemented in a Human And Building Interaction Toolkit (HABIT) that couples the full ABM in MATLAB with EnergyPlus via the Building Controls Virtual Test Bed (BCVTB). Currently, HABIT runs are configured via a simple Excel file (for more details, see Langevin et al. [36]). The program has initially been tested on a 300 occupant, medium-sized EnergyPlus office model, with a single run covering one simulated month taking about 6 min to complete. While reducing this run time presents a key challenge going forward, it is noted that the above ABM scheme could be easily adapted to alternate programming languages and co-simulation setups where necessary to improve run time performance.

4.3. Model limitations

Development and validation of the full ABM relies on field data from a mid-sized, air-conditioned office building; accordingly, the applicability of the model is currently limited to this type of field setting. In particular, while it is believed that the basic rules for agent behavior could be successfully extended to other building types, it is not known whether certain assumptions of the current model setup, such as that regarding the sequencing of actions, apply across different built contexts. In naturally ventilated office buildings, for example, the increased propensity to open windows may suggest that this behavior is generally taken before the use of fans, perhaps because window use is more acceptable and viable in these buildings, which tend to be situated in moderate climates. Future work should thus attempt to repeat the ABM development and validation procedure reported in this paper on similar field data collected from offices of different cultures, climates and conditioning strategies, again placing a particular focus on the issue of behavior hierarchy and its accurate representation in the behavior model.

Another possible limitation of the full ABM is its basic handling of behavioral constraints, which may require further development with supporting field data. Personal constraints relating to one's values and/or controls knowledge, for example, are not yet applied in the execution of the full ABM, as it is not clear from the field data whether or how these constraints actually operate on behavior, despite their suggested importance in previous ABM studies (i.e, Andrews et al. [12]); indeed, such constraints may already be built into occupants' reported thermal acceptability ranges. Moreover, the social constraints currently addressed by the model may require stronger representation in smaller-scale office settings, where people are physically closer to one another. Future work should thus closely examine the significance and operation of plausible constraints on behavioral action in offices of varying scales to determine whether adding complexity to the full ABM in this area is warranted.

Finally, the full ABM does not consider behavioral adaptations that previous research and the authors' own field study suggest do not originate for primarily thermal reasons, including: consumption of warm/cold drinks; opening/closing doors/blinds; and turning on/off lights. While the validation results above indicate the current ABM yields acceptable predictive performance without considering non-thermal behaviors, such behaviors may nevertheless influence thermal comfort outcomes, and some are also significant in their own right from an energy use perspective (i.e. lighting behavior).

Accordingly, future work should seek to incorporate non-thermally driven behaviors into the current ABM when such behaviors are determined to have important effects on comfort and/or energy use. It is envisioned, for example, that lighting and blind use could be folded into the PCT-based agent behavior algorithm by replacing thermal sensation with visual sensation as the perception of focus. This sensation could be represented by an appropriate physical variable like illuminance, which would then be compared to an individual's acceptable range of lighting levels to determine the need for lighting/blind adaptations. Alternatively, zone-level changes in lighting/blind state could be accounted for alongside individual thermal adaptations by sampling from existing regression models of aggregate light/blind use probability available in the literature (i.e. [37–39]). This approach may also be useful in considering behaviors like warm/cold drink consumption, which previous studies and our own field study have shown are not easily tied to a single driver (see Refs. [8,36]).

5. Conclusion

This paper has used thermal comfort and behavior data from a one-year field study in a mid-sized office building to develop and validate an agent-based model (ABM) of building occupants' thermally adaptive behaviors. Using a standard protocol for describing ABMs, the full ABM was presented in detail, including the underlying rules for occupant agent actions and their theoretical basis in Perceptual Control Theory. Validation of the full ABM assigned simulated agents the personal characteristics and environmental context of real office occupants in the case study; executed the model; and compared model's resulting predictive performance to that of several other behavior modeling options. The predictive performance of the full ABM compares favorably to that of the other modeling options tested, on both the individual and aggregate outcome levels. It is hoped that future studies can build from the reported ABM and its underlying field data in advancing more comprehensive and flexible simulations of the adaptive interactions between human occupants and their surrounding built environments.

Acknowledgments

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Appendix

A.1 ODD point 7: description of sub-routines used in the full ABM

a) *SetStaticParameters:* This subroutine initializes an agent's state variables. Of particular interest is the approach used to sample agent's thermal acceptability ranges for warm and cool seasons on the seven point ASHRAE scale. This thermal acceptability sampling scheme draws from the acceptability distributions reported in Langevin et al. [26]; it is diagrammed in Fig. A.1.
b) *SampleMornClo*: This subroutine predicts an agent's clothing level at the beginning of each simulated day (when they first sit down at their desk to begin work). Subsequent clothing adjustments for the day move up/down from this morning reference value, which must be in range $0.3 \leq \text{Clo} \leq 1.3$ (typical for office). In the routine, an agent's morning clothing is predicted using the following regression:

$$\log(MornClo(d)) = \beta_0 + \beta_1 T_{out,6am} + \beta_2 Wpref + \beta_3 MornClo(d-1) + \varepsilon \quad (1)$$

where

MornClo(d) = The agent's morning clothing on the current day *d*.
MornClo(d-1) = The agent's morning clothing on the previous day.
$T_{out,6AM}$ = Outdoor air temperature (°C) on the current day at 6 AM.
Wpref = A dummy variable indicating whether the median of the occupant's thermal acceptability range is warmer than “Neutral”.
ε = Error term, $\sim N(0, RMSE_{model})$. The RMSE value fit from Friends Center data is 0.24.

The parameter values fit from Friends Center data (with standard errors in parentheses) are:

$[\beta_{0...3}\ (\sigma_{0...3})] = [-0.91\ (0.038)\ -0.01\ (0.001)\ 0.14\ (0.022)\ 0.71\ (0.049)]$

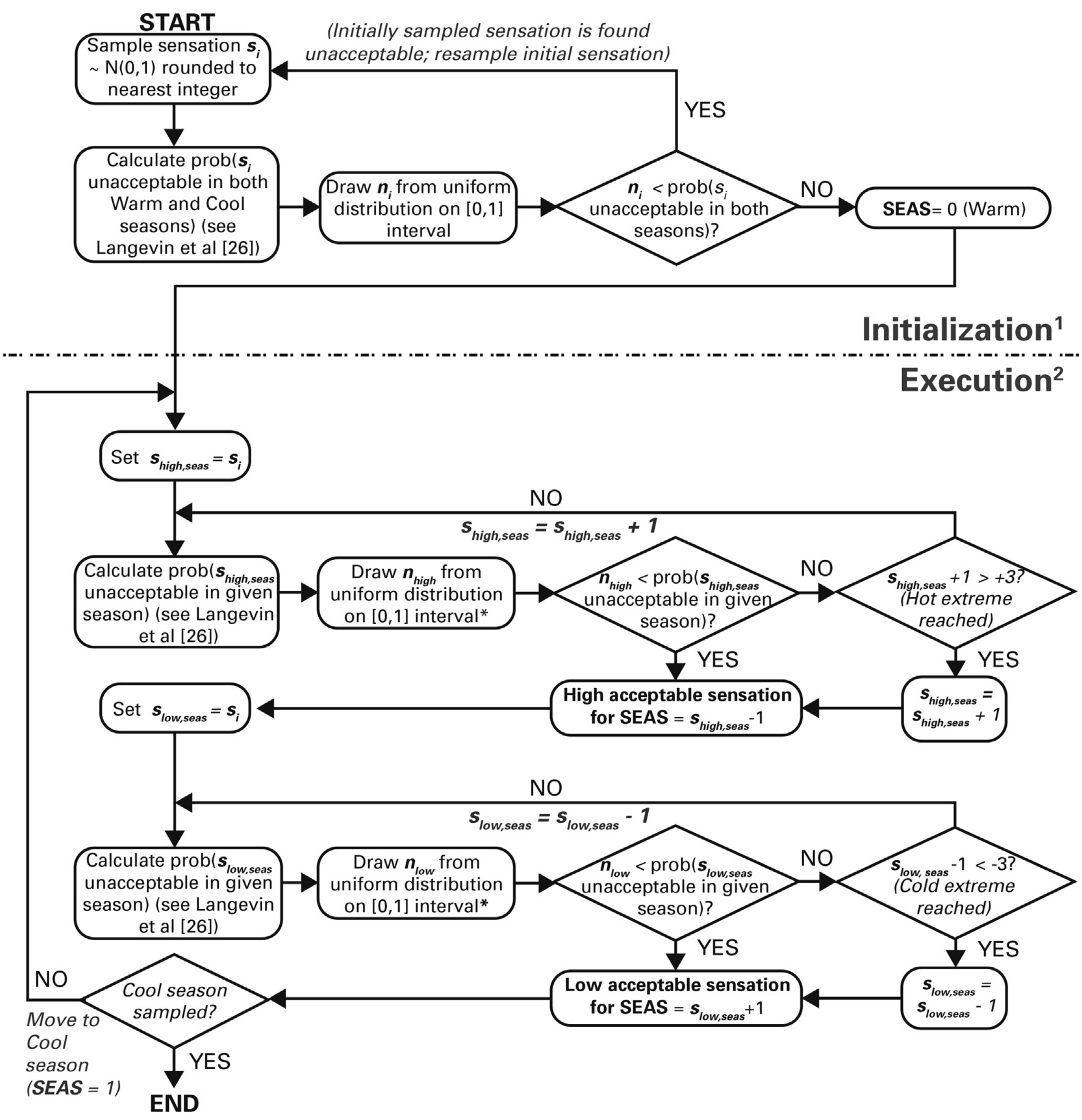
Table A.1
Activity scenarios and associated MET values.

Scenario	MET value
Agent arrived from outside bldg. (commute)	Based on commute method: 3.4 (Bike); 3.0 (Walk); 2.2 (Drive Car); 2.1 (Public Transit)
Agent arrived from outside bldg. (lunch break)	1.7 (leisurely walk)
Agent arrived from other part of bldg.	1.7 (leisurely walk)
Agent has been working at desk	1.1 (seated, typing) + (lagged MET - 1.1)[1]

1 Lagged MET = $a(1-r)^x$, where a = initial MET value upon arrival at office, r = exponential decay rate, and x = time unit. In the current setup, an elevated arrival MET has a halflife of 8 min (in line with Goto et al. [40]; this means an arrival MET continues to influence MET values for ~30 min

c) *GetMet:* This subroutine determines the agent's current metabolic rate based on its activity in the previous time step. Table A.1 details the various activity scenarios and the metabolic rates they yield in this subroutine.

d) *GetEnvironment*: This subroutine updates the four environmental parameters needed to calculate an agent's PMV. In doing so, it incorporates any baseline changes in the environment with environmental feedback from behavior in the previous time step (see Table A.2). Baseline environmental information would be provided at each time step via a coupled building energy simulation routine.



1 Initialization: Determine starting sensation that is acceptable summer and winter; set starting season. Initial sensation sampled from ~N(0,1) distribution to ensure high likelihood that it is found acceptable.
2 Execution: Move outward in each direction from starting sensation until unacceptable sensation is found (determine "cold"/"warm" limits for given season). ***Note:*** For given agent, sequence of random uniform draws are identical for each season. Only unacceptable probabilities change across seasons.

Fig. A.1. Flow diagram of acceptability sampling scheme in the SETSTATICPARAMETERS subroutine. Note fall and winter are considered "Cool" seasons and summer/spring considered "Warm" seasons.

e) *DetermineComf:* This subroutine determines the agent's general thermal comfort using the algorithm diagrammed in Fig. A.2, which draws upon the thermal sensation distributions reported in Langevin et al. [26].

A.2 Test of thermal acceptability scheme

Behavior model validation results for the "Standard Acceptability" ABM reveal that simulated behavior outcomes

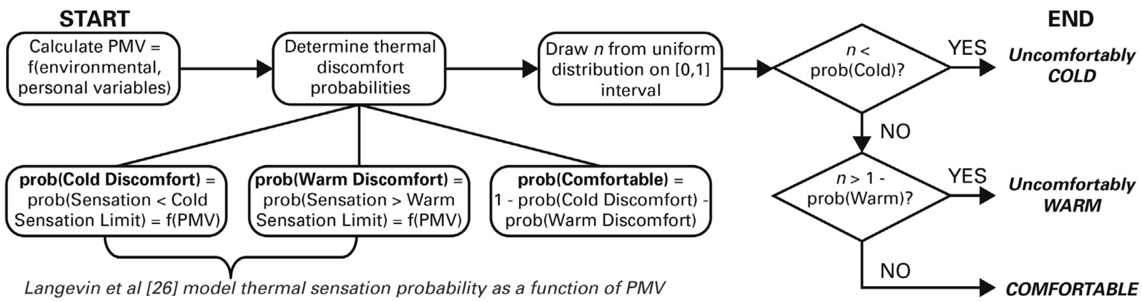


Fig. A.2. Flow diagram of GETCOMF subroutine for determining an agent's thermal comfort level.

f) *SimulateBehavior*: If the *DetermineComf* routine indicates that the agent is uncomfortable, this subroutine establishes the behavioral action taken to regain comfort (if any). The process unfolds as diagrammed in Fig. A.3. Note in the Figure that the user defines both "action" and "action reversal" hierarchies, which determine the order in which available behaviors are taken and/or reversed. Note as well that when a given behavioral action is needed and physically possible in the office context, its ultimate availability depends on whether it passes a series of constraint checks.

are highly sensitive to agent acceptability ranges. While agents were assigned the surveyed acceptability ranges of corresponding field occupants in the ABM validation, in practice these survey data will not be available for each simulated agent and agent acceptability ranges will need to be sampled using the scheme in Fig. A.1. Accordingly, it is important to verify that the Fig. A.1 acceptability sampling scheme yields reasonable results.

Fig. A.4 tests the ability of the acceptability sampling scheme to reproduce the thermal acceptability distributions for air-

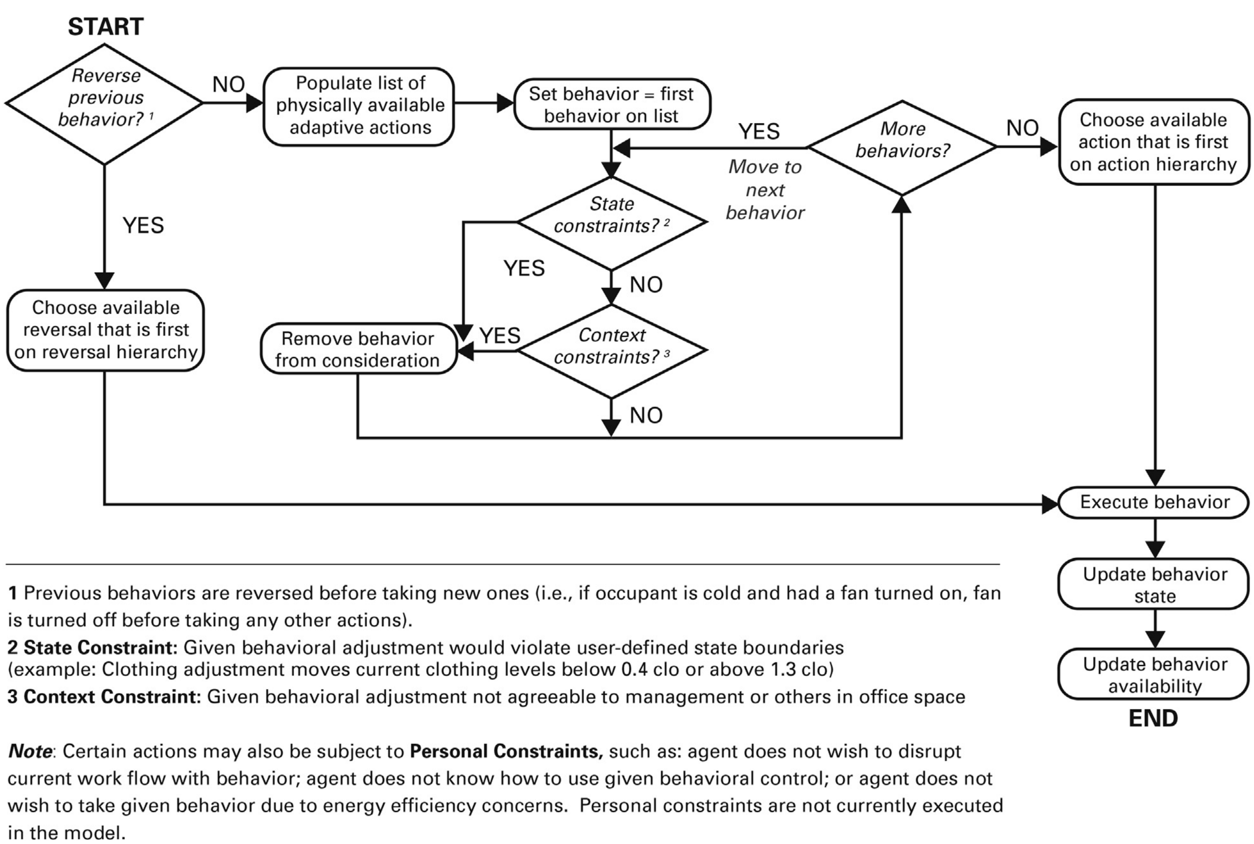


Fig. A.3. Flow diagram of SIMULATEBEHAVIOR subroutine for determining an agent's behavioral action when uncomfortable.

conditioned (HVAC) occupants published in Langevin et al. [26]. The test used to generate Fig. A.4 involves four steps:

1. Sample summer/winter acceptability ranges for each of N occupant agents using the scheme from Fig. A.1.
2. Using each agent's sampled acceptability ranges, determine which of the seven ASHRAE sensations the agent finds unacceptable in summer and winter; code unacceptable sensations as “0” and acceptable sensations as “1”.

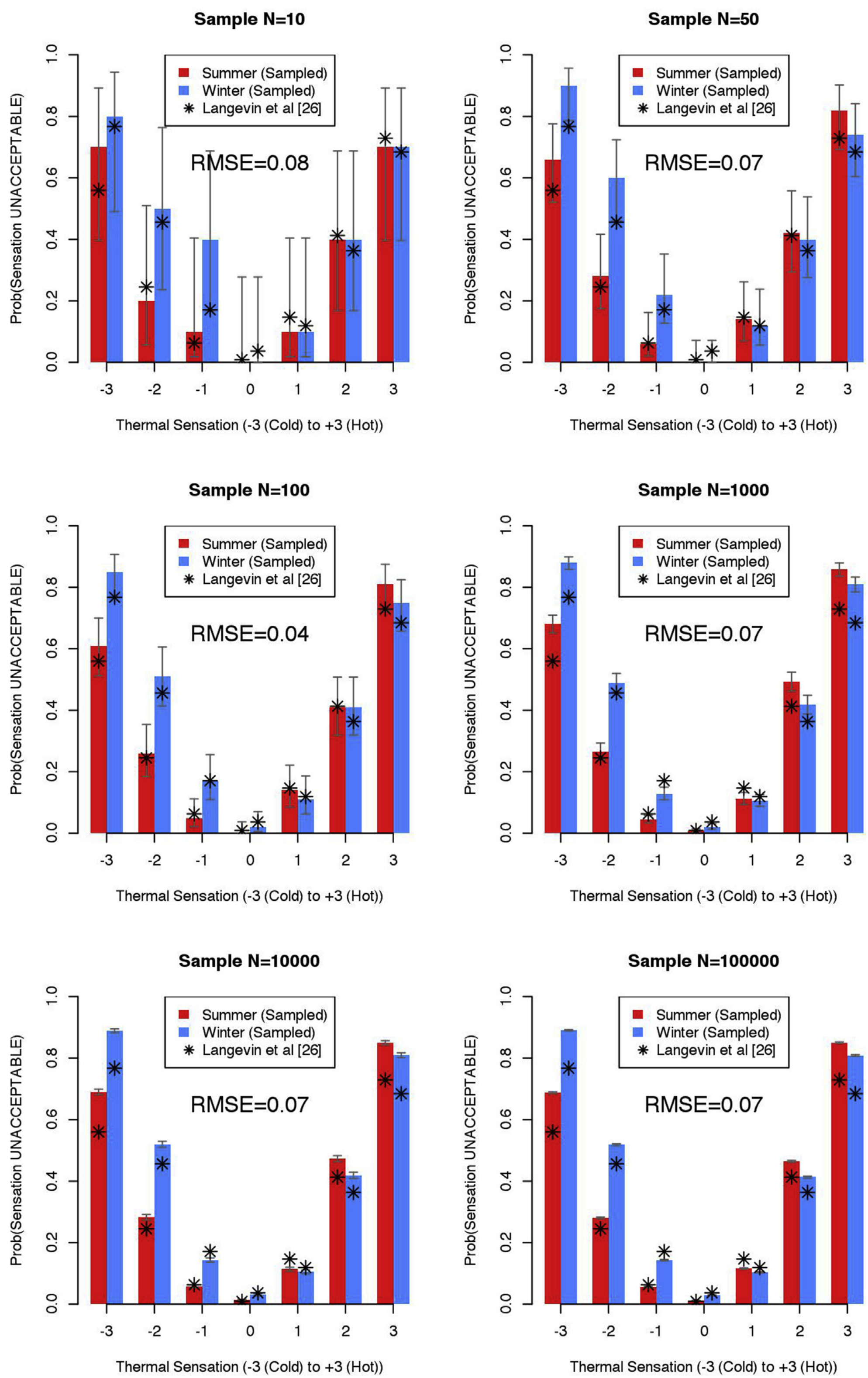


Fig. A.4. Sampled group acceptability fractions vs. modeled acceptability probabilities in Langevin et al. [26] for different numbers of sampled occupant agents. 95% Wilson binomial confidence interval shown on each sampled acceptability fraction; RMSE = Root Mean Square Error.

Table A.2
Adaptive behaviors, their hierarchy, potential constraints, and feedback in the full ABM.

Behavior	COOLS?	WARMS?	ORDER[1]	CONSTRAINTS[2]		LOCAL/ZONE LEVEL FEEDBACK		
			(Act; Reverse)	State[3]	Context[4]	Description	Δ_{local}	Δ_{zone}
Minor CLO adjust.*(roll sleeves up)*	■		1; 3	■	■	Changes Clo	−0.08Clo	–
Major CLO adjust.*(add/remove sweater)*	■	■	2; 2	■	■	Changes Clo	+/− 0.3 Clo	–
Turn on heater		■	3; 1		■	Changes air temp.	+2 °C	+1200 W equip.(max)[5]
Turn on fan	■		3; 1		■	Changes air velocity	+0.75 m/s	–
Thermostat up/mid/down	■	■	4; 4		■	Changes air temp.	–	+/− 1.00 °C set point[6]
Open window	■		4; 4	■	■	Changes temp./humidity/air velocity	+0.25 m/s	+25 x design infil. (max)[7]

1 The sequencing of thermostat vs. window actions (both 4th in the above ordering) is determined by a coin toss.
2 Additional personal constraints (i.e. concern for energy) are possible, but not implemented in current model due to lack of supporting field data.
3 *Clothing* may not be adjusted below 0.4 (lowest typical trousers ensemble # 1 in ASH Std. 55 [25] assuming light pants) or above 1.3 (highest ensemble in ASH. Std. 55 [25]); *Windows* are not opened when Running Mean Outdoor Temp. > Indoor Operative Temp.
4 Context constraints may come from a.) building or office management restrictions on behavior or b.) conflicting comfort states of other occupants.
5 Watts can be converted to convective/radiant zone heat gain via whole building energy simulation; for model validation work, only the local feedback component is represented (+2 °C ambient air temp. when heater is on, with mean radiant temp. = ambient air temp.).
6 For model validation work, no zone level ambient temperature change due to a thermostat adjustment is represented - it assumed some of this change would be captured by measured HOBO/BMS temperature readings near each occupant's desk.
7 For model validation work, no zone level temp./humidity/air velocity changes are represented.

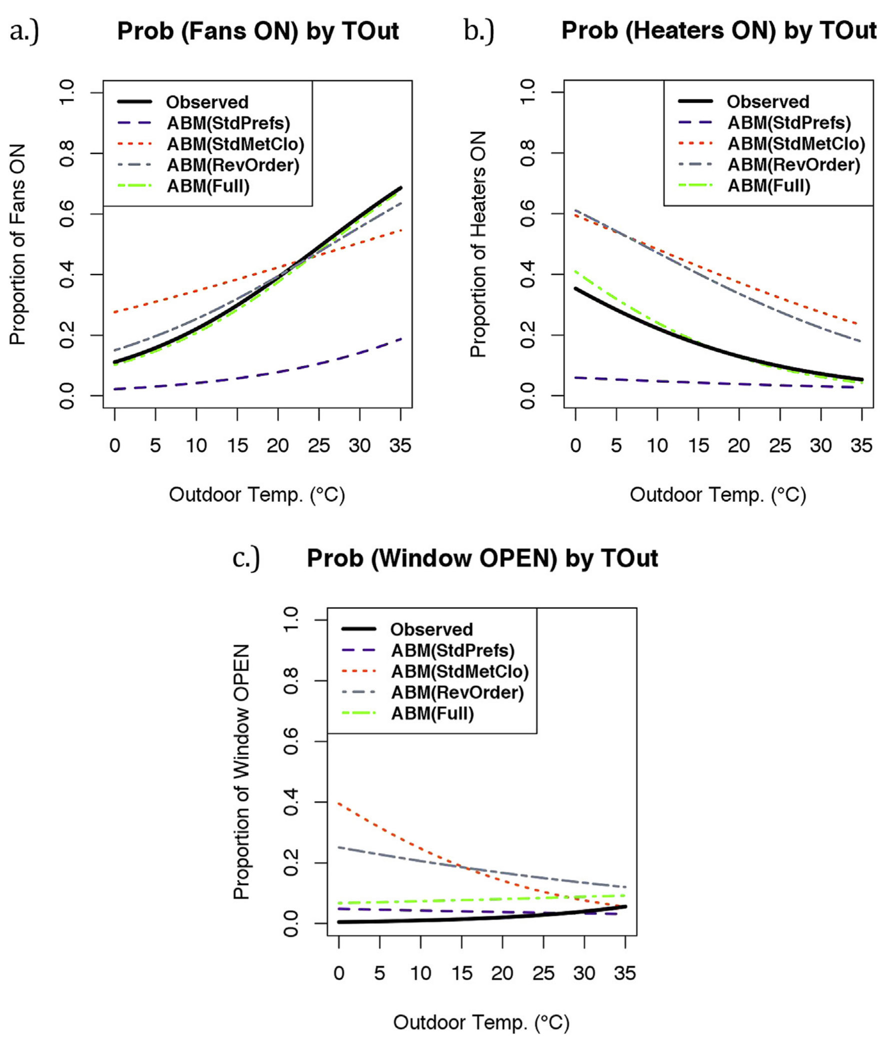


Fig. A.5. Friends Center derived logistic regression trends in fan (a), heater (b), and window (c) behavior probability vs. regression trends fit to simulated behavior data generated with four ABM options and outdoor temperature as predictor.

3. For each thermal sensation in each season, determine proportion of all agents finding the sensation unacceptable (i.e., determine proportion of "0" codes for each sensation across all agents by season).
4. Plot sampled unacceptable proportions for each sensation/season against the modeled probability that the given sensation is found seasonally unacceptable in HVAC buildings (from Langevin et al. [26] Table 10 and Figure 7).

In Fig. A.4, repeated runs of this procedure are used to generate six sub-plots representing different numbers (N) of simulated agents; in each plot, a 95% Wilson binomial confidence interval is shown around each sampled unacceptable fraction, and the Root Mean Square Error (RMSE) between sampled and modeled unacceptable fractions is indicated.

Qualitatively, the plots show a reasonable match between sampled and modeled unacceptable fractions, particularly above $N = 50$ sampled agents. Quantitatively, the confidence intervals around sampled unacceptable fractions at larger sample sizes ($N \geq 1000$) do not contain the modeled unacceptable fractions, revealing imperfections in the acceptability sampling scheme - particularly at the extreme ends of the thermal sensation range, where the scheme yields overly conservative estimates of thermal unacceptability. Nevertheless, RMSE values between sampled and modeled unacceptable fractions are less than 0.08 across all sample sizes, indicating a practically useful quantitative correspondence between sampled thermal unacceptability estimates and those of the Langevin et al. paper.

In Fig. A.4, sampled unacceptability estimates appear relatively stable between $N = 50$ and $N = 100{,}000$ agents; this suggests an ABM simulation that samples at least 50 agent acceptability ranges per building zone yields accurate enough estimates of the full distribution of thermal acceptability ranges in the building to use in behavior projections.[11]

A.3 Detailed behavior hierarchy, constraints, & feedback

Table A.2 presents all the behavioral possibilities implemented in the full ABM, their default hierarchy, potential constraints, and the way in which their feedback on the environment and personal characteristics is accounted for.

Note in the Table that major clothing and thermostat adjustments may either cool or warm the occupant, while other behaviors are assumed to operate in one direction. Moreover, certain behaviors like personal heaters are assumed to have local and zone-level feedback, while others like clothing and thermostat use are assumed to have feedback on just one of these levels.

A.4 Stylized facts plots for four ABMs: behavior vs. outdoor temperature. Please refer Fig. A.5.

[11] This requirement could be fulfilled in a single run if each zone of the building has at least 50 occupants; if not, multiple runs of the ABM would be needed (i.e., 10 occupants per zone * 5 model runs = 50 sampled acceptability ranges for the zone across the whole simulation).

References

[1] Humphreys MA. An adaptive approach to thermal comfort. In: Clements-Croome D, editor. Naturally ventilated buildings: buildings for the senses, economy and society. London, UK: E & FN Spon; 1997.
[2] Steemers K, Yun G. Household energy consumption: a study of the role of the occupants. Build Res Inf 2009;37(5–6):625–37.
[3] Hong T, Lin HW. Occupant behavior: impact on energy use of private offices. Berkeley: Lawrence Berkeley National Laboratory; 2013.
[4] Nicol JF. Characterizing occupant behavior in buildings: towards a stochastic model of occupant use of windows, lights, blinds, heaters, and fans. In: Seventh International IBPSA Conference. Rio de Janerio, BRA: International Building Performance Simulation Association; 2001 Aug 13–15. p. 1073–8.
[5] Rijal HB, Tuohy P, Humphreys MA, Nicol JF, Samuel A, Clarke J. Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. Energy Build 2007;39:823–36.
[6] Yun GY, Steemers K. Time-dependent occupant behaviour models of window control in summer. Energy Build 2008;43:1471–82.
[7] Haldi F, Robinson D. Interactions with window openings by office occupants. Build Environ 2009;44(12):2378–95.
[8] Haldi F, Robinson D. On the behaviour and adaptation of office occupants. Build Environ 2008;43(12):2163–77.
[9] International Facilities Management Association. Temperature wars: savings vs. comfort. Houston: International Facilities Management Association; 2009.
[10] Robinson D, Wilke U, Haldi F. Multi agent simulation of occupant's presence and behaviour. In: 12th Conference of International Building Performance Association. Sydney, AU: International Building Performance Association; 2011 Nov 14–16.
[11] Macal CM, North MJ. Tutorial on agent-based modelling and simulation. J Simul 2010;4:151–62.
[12] Andrews CJ, Yi D, Krogmann U, Senick JA, Wener RE. Designing buildings for real occupants: an agent-based approach. IEEE Trans Syst Man Cybern Part A – Syst Humans 2011;41(6):1077–91.
[13] Azar E, Menassa C. Agent-based modeling of occupants and their impact on energy use in commercial buildings. J Comput Civ Eng 2012;26(4):506–18.
[14] Lee YS, Malkawi AM. Simulating multiple occupant behaviors in buildings: an agent-based modeling approach. Energy Build 2014;69:407–16.
[15] Chen J, Taylor JE, Wei HH. Modeling building occupant network energy consumption decision-making: the interplay between network structure and conservation. Energy Build 2012;47:515–24.
[16] Kashif A, Binh Le X, Dugdale J, Ploix S. Agent based framework to simulate inhabitants' behaviour in domestic settings for energy management. In: 3rd International Conference on Agents and Artificial Intelligence. Rome, ITA: INSTICC; 2011 Jan 28–30.
[17] Linkola L, Andrews CJ, Schuetze T. An agent-based model of household water use. Water 2013;5(3):1082–100.
[18] Chu J, Wang C, Chen J, Wang H. Agent-based residential water use behavior simulation and policy implications: a case study in Beijing city. Water Resour Manag 2009;23(15):3267–95.
[19] Langevin J, Wen J, Gurian PL. Tracking long-term occupant IEQ outcomes: a longitudinal survey tool. In: IAQ 2013. Vancouver, CAN: ASHRAE; 2013 Oct 15–18.
[20] Powers WT. Behavior: the control of perception. New Canaan, CT: Benchmark; 1973.
[21] Grimm V, et al. A standard protocol for describing individual-based and agent-based models. Ecol Model 2006;198:115–26.
[22] Grimm V, Berger U, DeAngelis D, Polhill G, Giske J, Railsback S. The ODD protocol: a review and first update. Ecol Model 2010;221(23):2760–8.
[23] Schweiker M, Shukuya M. Comparison of theoretical and statistical models of air-conditioning-unit usage behaviour in a residential setting under Japanese climatic conditions. Build Environ 2009;44(10):2137–49.
[24] Rijal HB, Tuohy PG, Humphreys MA, Nicol F, Samuel AA. An algorithm to represent occupant use of windows and fans including situation-specific motivations and constraints. Build Simul 2011;4(2):117–34.
[25] American Society of Heating, Refrigeration, and Air-Conditioning Engineers. Standard 55–2010: thermal environmental conditions for human occupancy. Atlanta, GA: American Society of Heating, Refrigeration, and Air-Conditioning Engineers; 2010.
[26] Langevin J, Wen J, Gurian PL. Modeling thermal comfort holistically: Bayesian estimation of thermal sensation, acceptability, and preference distributions for office building occupants. Build Environ 2013;69:206–26.
[27] Fanger PO. Thermal comfort: analysis and applications in environmental engineering. Copenhagen: Danish Technical Press; 1970.
[28] Metz CE. Basic principles of ROC analysis. Seminars Nucl Med 1978;8(4):283–98.
[29] Fawcett T. Introduction to ROC analysis. Pattern Recognit Lett 2006;27:861–74.
[30] Montomery DC, Jennings CL, Kulahci M. Introduction to time series analysis. Hoboken, NJ: Wiley; 2008.
[31] Rand WM, Rust RT. Agent-based modeling in marketing: guidelines for rigor. Int J Res Mark 2011:181–93.
[32] European Committee for Standardization. Indoor environmental input parameters for design and assessment of energy performance in buildings: addressing indoor air quality, thermal environment, lighting and acoustics. Brussels: European Committee for Standardization; 2007.
[33] Humphreys MA, Hancock M. Do people like to feel 'neutral'?: exploring the variation of the desired thermal sensation on the ASHRAE scale. Energy Build 2007;39(7):867–74.
[34] Rijal HB, Tuohy P, Humphreys MA, Nicol JF, Samuel A, Raja IA, et al. Development of adaptive algorithms for the operation of windows, fans and doors to predict thermal comfort and energy use in Pakistani buildings. ASHRAE Trans 2008;114(2):555–73.

[35] Chartered Institution of Building Services Engineers. Guide A: environmental design. London: Chartered Institution of Building Services Engineers; 2006.
[36] Langevin J, Gurian PL, Wen J. Including occupants in building performance simulation: integration of an agent-based occupant behavior algorithm with EnergyPlus. In: ASHRAE/IBPSA-USA 2014 Simulation Conference. Atlanta, GA: ASHRAE/IBPSA; 2014 Sep 10–12.
[37] Haldi F, Robinson D. Adaptive actions on shading devices in response to local visual stimuli. J Build Perform Simul 2010;3(2):135–53.
[38] Hunt DRG. Predicting artificial lighting use – a method based upon observed patterns of behavior. Light Res Technol 1980;12(1):7–14.
[39] Reinhart CF. Lightswitch 2002: a model for manual control of electric lighting and blinds. Sol Energy 2004;77(1):15–28.
[40] Goto T, Toftum J, de Dear R, Fanger PO. Thermal sensation and thermophysiological responses to metabolic step-changes. Int J Biometeorology 2006;50(5):323–32.