

A Novel Methodology for Longitudinal Studies of Home Thermal Comfort Perception and Behavior

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ABSTRACT

Human-building interactions significantly influence building energy consumption and affect peak energy demand. For example, heating and cooling contribute 46% of daily peak residential energy demand. Grid-interactive efficient buildings (GEBs) can potentially increase energy-demand flexibility and accelerate the adoption of renewables. However, traditional demand response (DR) programs focused on shedding peak loads disregard the human-building interactions leading to occupant thermal frustration. Specifically, they do not model occupants' ability to override thermostat controls, nor how indoor environmental conditions and socio-cultural factors affect the timing and magnitude of overrides. Studies have found 20% of occupants override thermostat setpoints during DR events longer than 6 hours yet lack detail about the motivation that might guide more successful efforts. Balancing energy-demand flexibility with occupant thermal comfort requires understanding dynamic occupant behavior, the underlying psychophysiological drivers, in the context of homes.

This paper presents methods for scalable longitudinal studies of residential occupant behavior dynamics to inform the development of psychophysiological occupant-centric building models. Smart sensors were installed to measure local environmental conditions in 20 homes in two regions of the United States. Just-in-time ecological momentary assessments (EMAs) provided qualitative data on occupant thermal comfort and local environmental conditions not captured in Internet-of-Things (IoT) based studies or existing datasets. Participant interviews provided insight into environmental attitudes, mental models, and the role of economics in comfort and behavior, which in turn may affect thermostat interactions. Based on these data, interventions in the next phase of the study will collect data and monitor occupant behavior during simulated DR events.

Introduction/Background

Accelerating the adoption of renewable energy on the electric grid is an essential strategy for mitigating climate change. However, some of the most common and bountiful renewable energy sources, such as wind and solar, are more variable, less reliable, and uncontrollable compared to their fossil-fuel-based counterparts (Denholm et al. 2014). Although, renewable energy has the potential to meet energy demand, there is often both a temporal and geographical mismatch between the generation of such renewables (supply) and electrical load (demand) (Gao et al. 2022) most famously illustrated by the California Independent System Operator (CAISO) “duck” curve (California ISO 2016); the energy demand in the late-afternoon/evening ramps up while the generation of solar energy during this time diminishes. These challenges pose

substantial barriers in widespread adoption of renewables, which are further exacerbated by projected growth in total and peak electric demand (IEA 2022) as industries continue to electrify systems (Hale et al. 2018).

The building industry in particular presents great challenges and opportunities as 75% of U.S. electricity is consumed within buildings (EIA 2019) and it is estimated that heating and cooling account for up to 46% of daily peak residential energy demand nationally (Neukomm, Nubbe, and Fares 2019). There is also a large push within the industry to replace fossil-fuel-based heating systems, like gas-fired furnaces, to heat pumps powered by electricity, which gets cleaner as the grid incorporates more renewables (IEA 2021). That shift will increase the total electric demand on the grid and requires transitioning from meeting a highly variable demand by tightly controlling supply, to a model that incorporates greater variability in supply by controlling the time and magnitude of demand. That means making buildings—including homes—more efficient and responsive to the needs of the grid, so-called Grid-interactive Efficient Buildings (GEBs) (Neukomm, Nubbe, and Fares 2019). Existing policy, programs, and technology, such as Demand Response (DR) programs, seek to reduce peak electric demand and increase building-grid load flexibility but do not always achieve their goals. State-of-the-art grid-service programs see up to 30% of customers overriding controls (Navigant 2017), exceeding the 75% commitment required by regulations. This prompts stiff penalties; US utilities paid ~\$13 million USD in penalties in 2010-11 for DR shortcomings, including \$2M/year in the PJM interconnection regional transmission area in the mid-Atlantic and eastern mid-west region alone. (“PJM - Capacity Market (RPM)” n.d.).

A home’s ability to provide grid services, such as load shedding and shifting, depends significantly on the dynamic feedback response of the building and its occupants. Building occupants’ choices and behavior drive a significant portion of total building energy consumption, a substantial body of research seeks to understand the mechanisms driving human-building interactions and quantify their effect. Prior studies estimate occupants impact building energy consumption by 2 kWh/day-occupant (Selvacanaby and Judd 2017). Designing programs and controls for *effective* grid-services requires an integrated model of the grid-building-HVAC system-and occupants.

The integrated dynamics of heat pumps and occupant behavior over time remain a knowledge gap despite the availability of grid control and dynamic building energy models. The concepts of occupant thermal comfort (ASHRAE 55 2017; de Dear and Brager 1998) are well established, and a vast amount of data on occupant thermal comfort, perception, and behavior are available (Dong et al. 2021). However, previous longitudinal studies have primarily focused on commercial buildings, especially workplaces (Humphreys, Nicol, and Raja 2007; Rijal et al. 2007; Yun and Steemers 2008; Herkel, Knapp, and Pfafferoth 2008; Langevin 2019; Jayathissa et al. 2020). Unlike homes, buildings of this type include many people in one space, operate primarily during weekdays, do not have personal control systems, and depend on complex HVAC systems installed and operated by professionals. And as such, they do not test or measure, building or occupant responses to *active* HVAC controls. On the other hand, longitudinal studies analyzing changing temperature preferences and environmental, psychological, and interpersonal influences in residential buildings are scarce. Data sets of temperature and override dynamics in homes equipped with smart thermostats exist (ecobee 2019), but do not explicitly measure or explain how occupant comfort changes over time nor the underlying states that drive behavior and actions, such as human physiology, social cognition, and decision making. Moreover, the human comfort implications of providing heating and cooling with electric heat-pumps rather

than conventional fossil-fuel based HVAC systems (e.g., boiler, furnace, etc.) have not been widely studied or well understood.

The present study addresses these gaps by collecting longitudinal data about human-in-the-loop (HuIL) performance of home heating and cooling systems. Our team developed a methodology to conduct longitudinal occupant thermal comfort studies in residential buildings based on smart thermostats and other smart devices, as well as wearable smart watches for occupants, and tested it in two different climates across the USA. This project seeks to enable the design of new control algorithms that offer grid services, such as load shedding and shifting by delivering a dataset that is useful to grid service aggregators to design new programs, incorporate new technology, and improve controls for the breadth of equipment, homes, climates, and occupants on the market today. This paper presents that design and methodology for a scalable, longitudinal study of residential occupant behavior dynamics to inform the development of psychophysiological occupant-centric building models.

Study Design & Methodology

The following sections detail the study methods for recruiting participants and conducting field work to document the participating homes, install a system of wireless sensors, and on-board the participants.

Recruiting Participants

To study the interaction of humans, heat pumps and homes, and to develop individualized dynamic models of occupant thermal comfort and behavior, the team designed detailed procedures to recruit and screen participants. The multi-year timeline of this longitudinal study requires ongoing commitment from participants, and recruiting presents the first point of contact to build an ongoing and productive research relationship with the study participants. The research team relied on its extensive professional network of contacts with engineering, architecture, and mechanical, electrical, and plumbing (MEP) design firms, contractors and manufacturers, non-profit organizations, and governmental organizations to recruit study participants. Through social media platforms, mailers, and direct outreach, interested applicants were directed to the main project website. From there, they could learn more about the study, the requirements of participating, and the research team, and apply to participate by filling out a brief, online screening survey. Based on responses to the screening survey, the research team invited those who met the basic study inclusion criteria to participate in a screening phone call to answer additional follow-up questions and complete the informed consent process with potential participants. Those who fit the inclusion criteria and provided informed consent were then enrolled in the study.

The inclusion/exclusion criteria for participating in the study were based on a mix of research design and technical limitations of the study. The target population focuses on homeowners occupying single-family, detached (SFD) homes, which comprise 70% of the US housing stock (EIA 2015), multifamily homes were excluded from the study to reduce the modeling complexity and subsequent uncertainties. All participating homes have central forced-air heating and cooling systems. Although the study focuses on heat pumps, the scarcity of those systems in some areas presents a substantial barrier to recruiting. The team determined that homes with furnaces could be operated to emulate a heat pump, broadening the pool, but homes with radiant heating systems, such as electric-resistance baseboards, were excluded as they do

not supply heat through convection. Homes with de-centralized forced-air systems, such as ductless heat pumps, were also excluded from the study, as these systems generally cannot be centrally controlled. Additionally, many decentralized HVAC systems communicate with the thermostat through proprietary controls, precluding the use of internet-connected “smart” thermostat provided as part of the study (see “System Installation” below), so as a technical matter, all homes in which HVAC systems rely on proprietary controls were excluded. In other words, homes were not excluded based on the type of existing thermostat (i.e., manual, programmable, or “smart”/internet-connected), rather if an ecobee thermostat *could* be installed given the existing wiring infrastructure. Prior to the installation of a new thermostat for participation in this study the study population included a mix of existing thermostat types with 50% of homes having programmable thermostats, 45% having “smart” or internet-connected thermostats, and 5% having manual thermostats. Although the variation across homes means participants previously interacted with a variety of thermostats, all the interaction behavior in this study is the same through a smart thermostat and the home assistant phone app. After applying these exclusion criteria, 20 households with 41 total participants in the greater Boston and Denver metropolitan areas are currently enrolled. This sample is not meant to be representative of US homes or occupants and will not be used to characterize a population. Instead, these data will enable development of individual models across that population. Additionally, this pilot study enables the research team to assess the methods for data collection and model development before scaling to larger study populations.

Field Work: Documentation, Installation, and On-boarding

The research team visited each participating home to document the size, layout, and construction; audit the energy consuming features; install sensors and IoT devices to conduct the study; and on-board the participants. The procedures for these site visits are described and explained in detail in the subsequent sections.

Home Documentation and Energy Audit

The study includes developing building performance models of each home to effectively characterize operating building thermal dynamics and response, and to simulate and test HVAC interventions prior to deploying them in participating homes. As such, the research team collected data during the site visit to develop these digital twins.

Using field measurements, the team sketched a site plan with building footprint and developed exterior elevations of all facades. We noted nearby trees and buildings with the potential to shade the building, located them on the site plan and estimated heights using a clinometer and tape measure. The dimensions and constructions of windows, doors, and other exterior features were documented on the elevation drawings. The research team used the RoomScan LiDAR iPad application (“RoomScan LiDAR” 2021) to create interior floor plans of each home. Using this application, the research team could rapidly generate digital floorplans while on-site, manually spot-verify dimensions, and then document additional features and installed sensors directly on the generated floorplan while still in the field. The team then translated this set of drawings: floor plans, site plan, and elevations, into 3D models used for analysis and subsequently, building performance simulation.

In addition to building geometry, the research team documented building envelope materials and assemblies and estimated material properties from in-situ field measurements. This included noting window and glazing constructions such as window type, frame material, number

of panes, and presence of any coatings. The team determined the presence of coatings, or films, by holding a lighter next to the window and observing the number and color of flame reflections, Figure 1, left. Four reflections indicate a double-pane window: one reflection from each glazing surface. A deviation in color between reflections can indicate the presence of a coating on that surface. Additionally, the Visible Light Transmittance (VLT) of each window type was estimated using a color-calibrated illuminance meter, as seen in Figure 1, center. We took five spot measurements of daylight transmitted through the window at the indoor surface, followed immediately by five measurements in the same locations but of the total daylight incident on the outside surface of the window. The VLT was calculated as the ratio of interior illuminance (transmitted light) to exterior illuminance (incident light), and the International Glazing Database (IGDB) (LBNL 2019) was used to identify a probable glass type. This type allowed us to estimate the Solar Heat Gain Coefficient (SHGC) of each window, which was then used as an input in the building performance model.

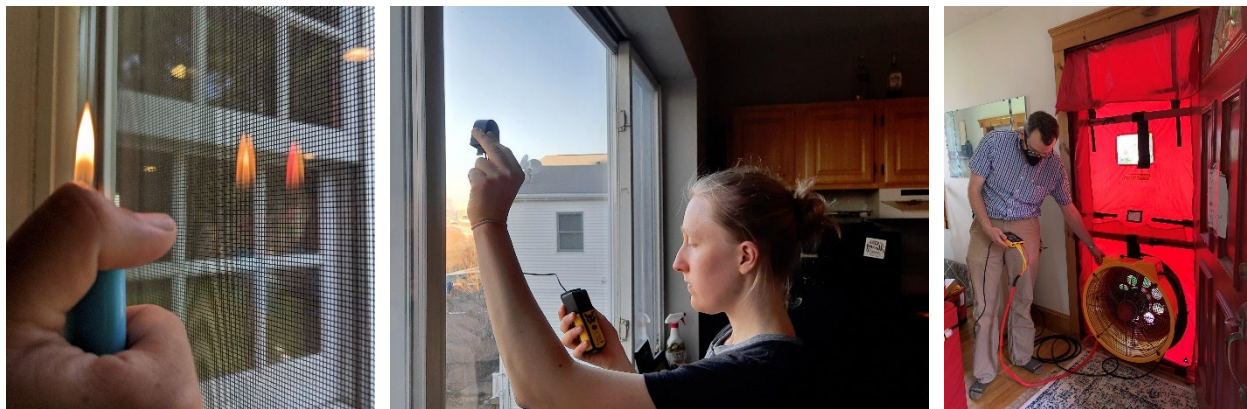


Figure 1. Determining number of panes and estimating presence of coatings with lighter (left). Estimating VLT with color-calibrated light meter (center). Conducting subtractive, multi-point blower door test (right).

Many methods for directly measuring the in-situ R-value of building envelope assemblies have been developed, most commonly using heat flow meters or infrared thermography. A variation of the air-surface temperature ratio—or thermometric—method was selected in this case as a rapid way to estimate in-situ R-values of exterior walls without the need for heat flux sensors (Lu and Memari 2022). Indoor (T_{in}) and outdoor (T_{out}) ambient air temperature were measured with radiation-shielded air temperature sensors of high accuracy (error $< \pm 0.2^{\circ}\text{C}$). Indoor surface temperatures (T_{wall}) were read as the area-weighted average using a FLIR ONE Pro thermal imager, adjusted for wall surface emissivity. From these measurements, heat flow through the assembly can be calculated as in the equation below.

$$Q = \frac{T_{in} - T_{wall}}{R_{IAF}}$$

Where Q is heat flow ($\text{BTU}/(\text{h}\cdot\text{ft}^2)$), T_{in} is indoor ambient air temperature ($^{\circ}\text{F}$), T_{wall} is indoor surface temperature of the exterior wall ($^{\circ}\text{F}$), and R_{IAF} is the empirically derived indoor air film R-value ($\text{BTU}/(\text{h}\cdot\text{ft}^2\cdot^{\circ}\text{F})$). The R-value of the exterior wall can then be calculated as in the equation below.

$$R_{wall} = \frac{T_{in} - T_{out}}{Q}$$

Where R_{wall} is the R-value of the exterior wall (BTU/(h·ft²·°F)) and T_{out} is the outdoor ambient air temperature.

To validate the in-situ R-value of exterior wall assemblies through infrared thermography methods, building envelope assemblies were documented to calculate assembly R-values based on assumed constructions. The overall thickness of each assembly was measured or estimated, and the interior and exterior materials noted, along with the age of the home and any other features that may hint at the assembly.

The team conducted multi-point blower door tests (Figure 1, right) to measure and locate air infiltration through the building envelope following industry standards (ASTM E1827 2017; ASTM E0779 2019). The team slightly modified the standard by sealing supply and return ducts to isolate the measurements of air infiltration to the building envelope. The research team conducted both pressurization and depressurization tests and averaged the results, except in one home, where the team elected to conduct only a pressurization test for health and safety reasons. For both pressurization and depressurization tests, the team took ten air flow measurements (in CFM) at pressure differences across the building envelope of 20 Pa, 30 Pa, 40 Pa, and 50 Pa. From these measurements of air flow (CFM) and pressure difference (Pa), the team developed air leakage curves and calculated effective leakage area. The team determined stack and wind coefficients on the geometry and air leakage distribution of the building and input these parameters into the building performance models.

Additionally, the team studied the design of and photographed the nameplates on HVAC equipment to document the capacities and efficiencies of existing mechanical equipment to model HVAC systems in the building simulation.

System Installation

This two-year study of *homes* and their *occupants* necessitates the use of non-intrusive smart devices and mobile applications for data collection and subsequent interventions (simulated DR events). For this reason, the research team deployed a system of smart devices that are readily available on the market and designed for non-expert users.

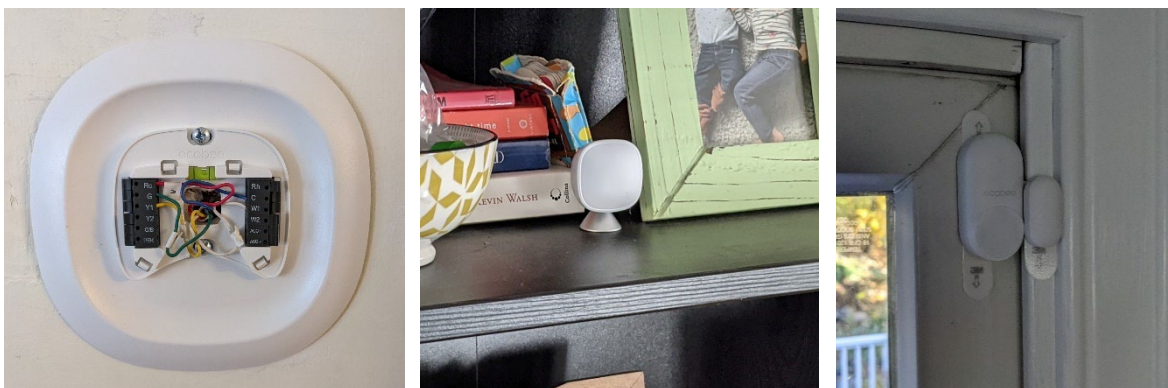


Figure 2. Ecobee smart thermostat wiring (left). Ecobee occupancy and remote temperature sensor (center). Ecobee window and door contact sensor (right).

The team decided to collect study data using IoT devices and smart sensors based on their ability to continuously and unobtrusively monitor conditions, to provide near-real-time reporting without additional site visits. We identified five IoT devices and sensors, Table 1, to collect primary and secondary HVAC system run-time, occupancy, and local environmental conditions such as ambient air temperature and relative humidity.

We replaced all existing thermostats in the participating homes with ecobee smart thermostats (Figure 2, left). In addition to controlling the HVAC system remotely, these thermostats report data on HVAC mode, system run time, ambient air temperature, relative humidity, and occupancy. Of the participating homes, 70% are single zone with one thermostat while 30% are multi-zone with two or more thermostats. We selected the ecobee smart sensors for detecting occupancy and measuring temperature (Figure 2, center) in many locations around the home, and monitoring when and for how long occupants opened windows and doors (Figure 2, right) for natural ventilation or heating/cooling. The number of smart sensors we installed in each home varied based on the size of the home (number of rooms, number of floors, total square footage, etc.) and how many windows and doors the occupants opened and how often. We also selected and installed BN-Link/Tuya smart plugs to monitor usage of secondary heating and cooling systems such as portable heaters and fans.

Table 1. IoT devices installed in participating homes (n = 20)

Smart Device	Mfr & model	Comm. Protocol	No. Installed	Sensor	Data Collected
Thermostat ¹	ecobee EB-STATE5-01	Wi-Fi	27	HVAC Mode	Heat/Cool/Auto
				System run time	Minutes
				Air temp	°F
				RH	%
				Occupancy (PIR)	Detected
SmartSensor – Occupancy ²	ecobee EBERS41	915 MHz	157	Occupancy (PIR)	Detected
				Air temp	°F
SmartSensor – Window/Door ³	ecobee EBDWC01	915 MHz	102	Windows/doors	Open/Close
Plug Load ⁴	BN-Link/Tuya	Wi-Fi	26	Voltage	Volts
				Current	Amps
				Power	Watts

IoT Cloud Infrastructure

Recent advances in wireless communication have accelerated the adoption of residential Building Automation Systems (BAS) with several communication protocols available for cost-effective wireless sensors including: Zigbee, Bluetooth LE, Wi-Fi, Thread, and Z-wave. Home HVAC systems have varying degrees of sophistication with limited control points when compared to commercial building BAS and commissioning practices. On top of that, user

¹ <https://www.ecobee.com/en-us/smart-thermostats/smart-wifi-thermostat-with-voice-control/>

² <https://www.ecobee.com/en-us/accessories/smart-temperature-occupancy-sensor/>

³ <https://www.ecobee.com/en-us/accessories/smart-door-window-sensor/>

⁴ <https://cdn.shopify.com/s/files/1/0018/2521/0421/files/U133T.pdf?v=14915309573559959467>

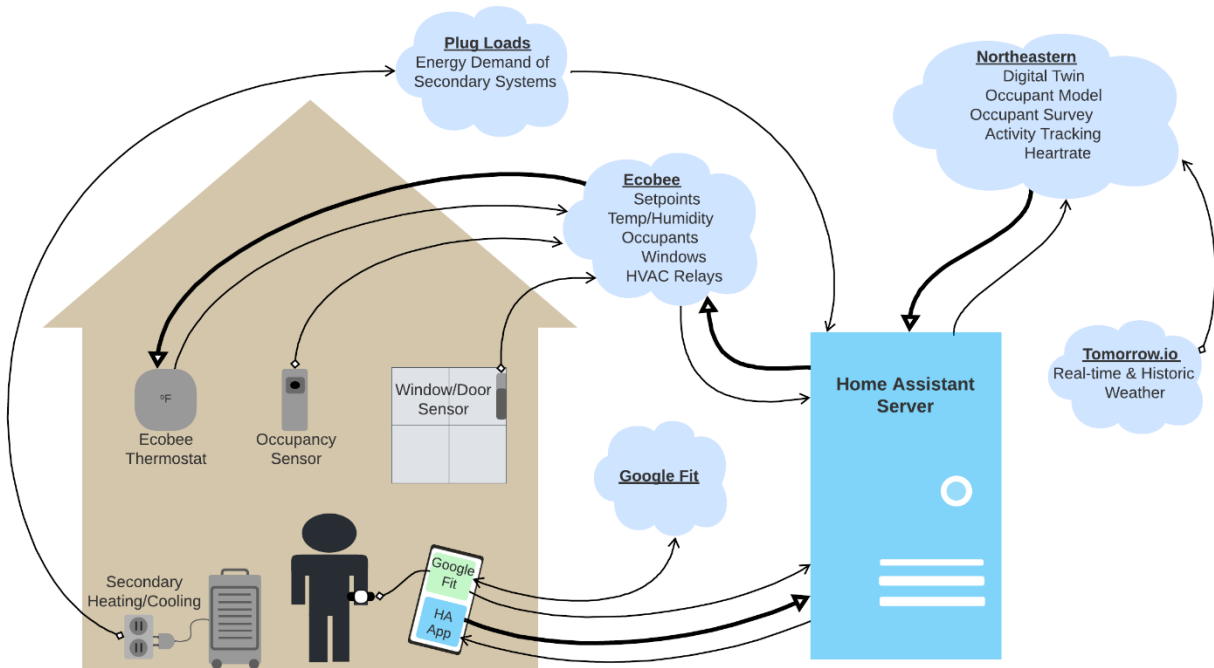


Figure 3. Integrated data collection schematic.

experience (UX) and functionality (UI) for residential BAS must be simple enough for lay users who may not necessarily understand the system they are trying to control. Currently, there are various open- and closed-source BAS and home energy management (HEMS) software solutions available e.g., (open source:) Home Assistant, OpenHAB, VOLTTRON, EasyIO by Johnson Controls, (closed-source:) Google Home, Apple HomeKit, Contorl4, SmartThings, and Wink. The team considered variabilities in communication protocols, system installation, and UX/UI and selected an open-source, technology-agnostic software platform that provides the necessary integrated real-time data gathering, monitoring, feedback, and control.

With these functions in mind, the team evaluated software platforms that satisfied our requirements for extendibility, scalability, and sufficient data-security. Based on these requirements four open-source software platforms were short listed for consideration: VOLTTRON (Haack et al. 2013), Foresee (Jin 2017), OpenHAB (Kreuzer 2016), and Home Assistant (Schoutsen 2014). A brief comparison between these software stacks is provided below in Table 2. VOLTTRON only allows IoT devices that communicate via ZeroMQ (pub-sub message bus) using either the BACnet or Modbus protocol. Although this is effective for commercial buildings, it is a significant limitation for single-family homes. In most smart home IoT devices, Wi-Fi, Bluetooth, or Zigbee are used for data communication. Apart from this, VOLTTRON also does not offer an out-of-the-box ready to deploy user interface that allows a non-expert audience to interact with the platform. To address these issues researchers at Oak Ridge National Lab (ORNL) attempted to use Home Assistant as a HEMS along with VOLTTRON (Zandi et al. 2019) as the optimization tool. This data integration process limits the extendibility of Home Assistant as it can support more than 24 entities (Schoutsen 2018) whereas VOLTTRON integration (to Home Assistant) is limited to 5 entities (climate, light, switch, and lock). Similarly, OpenHAB has significant integration limitations. For this reason, we selected the Home Assistant platform as it met the requirements of universal (web and mobile) UI/UX,

continuous data collection, reliable long-term data storage, and automation workflows. New capabilities within Home Assistant can easily be implemented given the containerization-based, plug-n-play software architecture, component-based front-end, and active developer support. Some of the new and/or improved capabilities our team implemented in this current study include capturing user-interactions with the system, deploying thermal comfort surveys through actionable notifications, and developing real-time data visualization dashboards. These capabilities allow us to distinguish which user has interacted with the thermostat and push a notification to their mobile phone prompting them to take thermal comfort surveys in real time. With this approach, we can capture qualitative data on occupant thermal comfort and behavior in a variety of conditions over time. We are also able to observe occupants' responses to *active* HVAC controls, differentiating our approach from other recent studies (Jayathissa et al. 2019). Additionally, collecting this data on a single platform enables the research team to algorithmically conduct thermal comfort EMAs, completing the feedback loop of HuIL models for buildings.

We deployed Home Assistant with three core features in mind: minimal user learning effort, automated data gathering, and persistent data storage. Study participants needed an easy-to-use app that would let them control their thermostat, take thermal comfort surveys, and automatically send researchers data about their activity levels. Because the environmental, physiological, and IoT data reported by IoT sensors are updated at different frequencies, the developers of Home Assistant managed a consistent database schema (SQL) to make the automated data collection and persistent storage process easier.

Table 2. Comparison of VOLTTRON, Foresee, OpenHAB, and Home Assistant

	VOLTTRON	Foresee	OpenHAB	Home Assistant
Primary Function	Building-Grid Interactivity	HEMS	Smart Home Automation System	Smart Home Automation System with HEMS
BACnet & Modbus Support	Yes	No	Yes	Yes
IoT Data Comm. Protocol	ZeroMQ, PubSub	CAN bus	MQTT, CoAP, HTTP, WebSocket, PubSub	MQTT, HTTP, WebSocket, PubSub
IoT Network Comm. Protocol	No	No	TCP/IP, Wi-Fi, Bluetooth, Z-wave, ZigBee +	TCP/IP, Wi-Fi, Bluetooth, Z-wave, ZigBee ++
Cloud API Access	N/A	Yes	Yes	Yes
User Interfaces	Web Application	Web Application	Web & mobile Application	Web & mobile Application
Supports SQL or NoSQL databases	Yes	Yes	Yes	Yes
Guest-user Access Authorization	No	No	No	Yes
Authentication	Yes	Yes	No	Yes

Continuous data collection is necessary for capturing indoor temperature dynamics and occupancy patterns. These data will inform the building thermal dynamics and occupant comfort modelling. Figure 3 shows the integrated data collection system in each participating home.

Participant On-boarding

Before each site visit, the research team conducted a semi-structured interview with one participant from each household to provide input parameters for the building simulations and insight into household behaviors and underlying attitudes. Participants were asked to describe how they typically interact with their thermostat, and to explain their understanding of how it works. Questions about secondary heating and cooling systems, and general occupancy patterns within the home enable greater simulation fidelity. A series of questions elicited participant attitudes and background knowledge about environmental issues, affording the opportunity to explore any correlation between attitudes and action, as suggested by others' prior work. Sapcia and Considine (2014) and Enzler et al (2019) found environmental attitudes—more specifically environmental concern and consideration of future consequences—are negatively correlated to electricity use. Additionally, Volland (2017) found that individuals' propensity to trust is negatively correlated with residential energy demand while higher tolerances to risk are correlated with increased residential energy use. The team adapted questions from these previous studies into the participant interviews. These interviews consisted of 57 primary questions (with additional follow-up questions) in eight categories including occupant(s) demographics, home characteristics and use of secondary equipment, and attitudinal factors. In addition to the topics addressed in the interview, participants were also asked to complete a questionnaire on more sensitive information related to health conditions and demographic information, such as gender, height, weight, and household income – factors that affect thermal comfort and might influence interactions with the thermostat. Collectively, these qualitative data inform development of individual occupant behavioral models.

During the site visit, each adult participant in the household was asked to install the Home Assistant application on their smartphone, and the research team set up Home Assistant user accounts for each participant to log-in to the app. The Home Assistant app is the single hub for participants; from their user account, they can interact with their thermostat to control the heating and cooling system and take brief, just-in-time thermal comfort surveys (Figure 4). We hypothesized that streamlining survey collection using personal smart devices would enable greater numbers of surveys and greater participation compared to other methods such as paper forms, emails, or webpages. Such methods have successfully been used within the health behavior field to understand real-time behavior in context (Spruijt-Metz et al. 2015) and similar efforts enable more effective surveys in buildings (Duarte Roa, Schiavon, and Parkinson 2020). The research team developed the back and front-end infrastructure to deploy brief surveys—also called Ecological Momentary Assessments or EMA (Shiffman, Stone, and Hufford 2008)—through the Home Assistant app. Using the Home Assistant platform, we can push targeted notifications to participants' mobile phones directing the user straight to the survey interface in Home Assistant, a separate dashboard from the thermostat interface. Deploying these EMAs directly from the Home Assistant platform integrates survey data directly with sensor data and offers additional benefits such as triggering survey prompts based on environmental conditions (e.g., indoor temperature above/below a certain threshold) or user behavior (e.g., adjusting the thermostat). For example, back-end automations in Home Assistant can trigger a notification prompting users to complete a survey when the indoor temperature goes beyond a certain

threshold or if a user opens/closes a window. Additionally, with the Home Assistant platform we can send survey notifications based on responses to previous survey questions. For example, if a participant indicates that they are “very dissatisfied” with the current temperature, this response can trigger another survey notification after a period of time asking if they have taken any adaptive measures to improve comfort such as changing clothing or moving to another, more comfortable, part of the house. Additionally, notifications are only sent if cellphone geo-fencing indicates a participant is home. Over the first six months of the study, we recorded over 2,600 total survey responses with a median response rate of 59% across all participants, indicating targeted occupant surveys enable efficient and reliable collection of thermal comfort data.

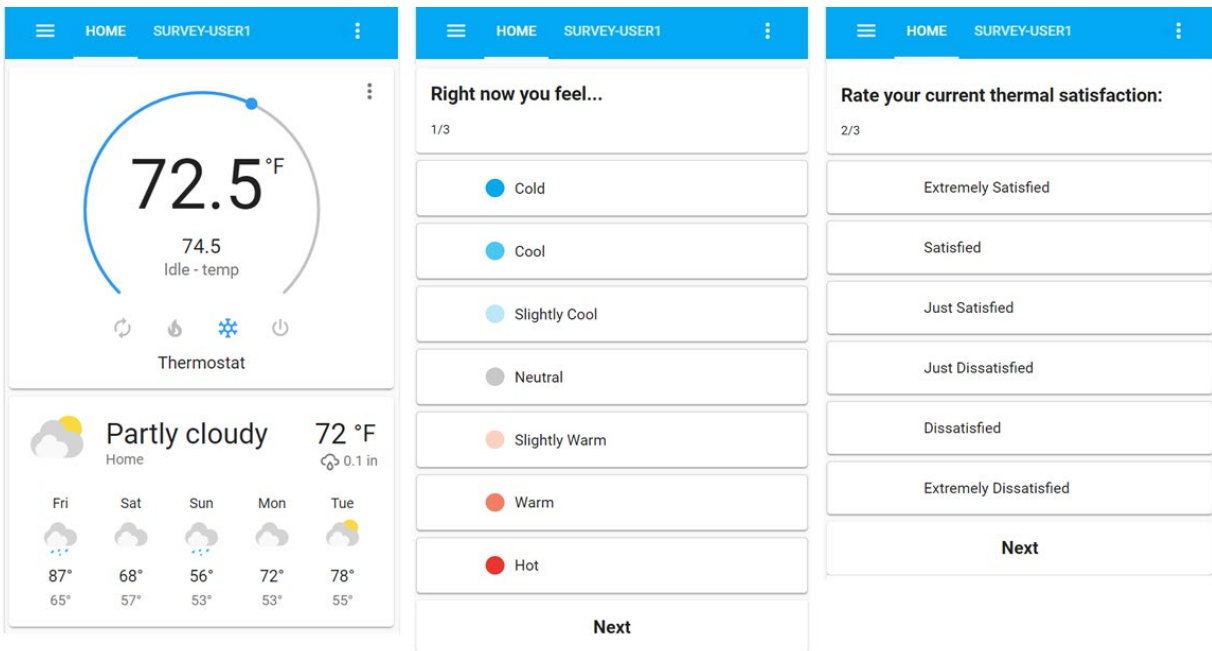


Figure 4. Home Assistant smartphone user interface.

Additionally, we provided smartwatches for up to two-adult participants in each household to wear for the duration of the study to collect heart rate and activity data. Given participants had a mix of mobile phones models, integration smartwatch data needed to work across popular mobile operating system (OS) users - Apple and Android. The research team selected the Google Fit application as it works with both major OS users and integrates easily with the Home Assistant platform. Since the introduction of OAuth 2.0 authentication standard—which occurred early in the study period—Google and Apple restricted sharing of sensitive health data to only applications whose only area of services is health related. While preserving user privacy, this change limits the availability of some data for research purposes, and the team is considering options to address this gap in the planned data stream.

Discussion

Though richly-rewarding, field work to gather data from real buildings requires substantial time and effort. Even using the expedited field methods adopted here, documenting buildings’ dimensions, materials, and equipment requires a site visit, and demands the most time during that visit. The room-scanning tools described above expedite dimensioning compared to

other approaches and provide plans for validation and later use, but these tools require thorough understanding of limitations, especially sectional conditions like sloped ceilings and split-level stairs. On the other hand, methods for *in-situ* measurement of building *properties* remain difficult. For example, methods to estimate thermal conductance through opaque envelope assemblies rely on significant temperature differences and assumptions about conductance of air films, while instruments to directly measure these properties require significant time to achieve steady states for measurement. Documenting individual pieces of HVAC equipment may be as simple as photographing a nameplate, however, the operation and performance of the HVAC *system* may be difficult to discern. Even if perfect field data were collected, developing and calibrating building-performance models of existing buildings remains a laborious process. Even with detailed documentation and photographs, modelers may lack the overall context and conception necessary to make good choices and assumptions. Even with running models, quantifying uncertainty, identifying the source of differences, and implementing necessary adjustments demand time, expertise, and judgment. Simulation and calibration of models are areas of continuing effort in this project, and for refinement of these methods.



Figure 5. Real time dashboard of data collection in participating home. Thermostat heating/cooling, setpoint temperature, and remote temperature sensors (top). Remote occupancy sensors and cellphone geo-location (middle). EMA responses and total response rates (bottom).

Historically, detached residential HVAC was *sized*, but not necessarily *designed* to the same extent the systems in larger commercial buildings, and an existing residential HVAC system reflects perhaps decades of operation, maintenance, and changes carried out by a range of actors, including potentially homeowners or contractors with limited knowledge and expertise. The process of site visits and even cursory reviews of the early data revealed numerous problems in the participating homes, including failing to achieve comfort, excessive operating times, rapid cycling, inaccurate sensors, and even non-functioning equipment. Indeed, in every home in the study we found at least one aspect not performing as intended. Although beyond the scope of this study and recalling this is an instructive rather than representative sample, we believe these findings indicate possibly significant energy, economic, and comfort benefits by improving the in-service operation of existing residential buildings, perhaps akin to continuous commissioning.

The Home Assistant platform includes customizable dashboards (Figure 5) to visualize the integrated, real-time data collected from all twenty participating homes. Cellphone geo-fencing and location data augment the data from ecobee remote occupancy sensors. These passive infrareds (PIR) occupancy sensors, readily available on the market today, are known to have high rates of false-negative detection, meaning sensors falsely report no occupancy when, in fact, occupant(s) are present. The addition of the location data from the participants' phones, affords an alternative method for confirming participant (or their phone) presence in the house and will enable the development of more accurate *occupancy* schedules for building energy and occupant behavior modeling.

Conclusion

Existing datasets of occupant thermal comfort, perceptions, behavior dynamics, and building thermal dynamics are fragmented. The integrated data collection process adopted in this study yields a novel, feature-rich, time-series dataset incorporating continuous monitoring, feedback, and control of humans interacting with their homes under dynamic conditions. Additionally, qualitative data gathered through semi-structured participant interviews augment this time-series dataset and elicit environmental attitudes, future orientations, and understanding of HVAC systems, which may offer insight to occupant motivations, behavior, and energy consumption. This dataset, capturing the dynamic feedback response of buildings and their occupants, will enable the development of more effective controls for providing grid services.

This paper presents a method for scalable, longitudinal studies of dynamic occupant behavior in residential buildings. Twenty SFD homes with forced air heating and cooling systems in the greater Boston and Denver metropolitan areas are currently enrolled in this two-year longitudinal study. A system of IoT devices and sensors installed in each participating home were selected for their ability to continuously and un-intrusively monitor primary and secondary HVAC system run-time, occupancy, ambient air temperatures, and humidity. These IoT devices and readily available consumer-friendly open-source software enable the long-term, continuous data collection process, and make it extendable, scalable, and sufficiently secure. In addition to the real-time data collection, monitoring, feedback, and control through the chosen open-source home management software, HA, the research team has used this platform to deploy just-in-time thermal comfort surveys. This method of distributing surveys yielded over 2,600 survey responses across participants in the twenty homes enrolled with a median response rate of 59%. The research team developed procedures beyond industry-standard energy audits, to measure and document in-situ factors affecting building performance such as home size, layout, envelope construction, and HVAC system design.

These data will inform analysis and support building performance modeling to simulate and test possible HVAC interventions. Remote temperature sensors and just-in-time micro-surveys will enable more granular analysis of residential occupant thermal comfort dynamics and comparison to widely used steady state models. Preliminary data analysis shows large variations in temperatures across single-zone homes. Future analysis will calculate indoor temperature decay and growth curves to characterize home and system performance utilizing extensive sensor data and potentially correlate with home/system performance occupant thermal comfort. Additional analysis will look at the relationship between thermostat interactions (frequency of interactions, time to manual override, degree of manual override) with qualitative data from participant interviews providing rich information about socio-demographic and psychological factors. Phase two of the study will implement selected interventions in the controls of the participating homes and monitor the effects on humans and homes using surveys and sensors. Participant interviews provided insights into environmental attitudes, mental models, and the role of economics in comfort and behavior that augment the time-series data. Collectively, this novel, feature-rich, time-series dataset integrating human, HVAC equipment, and home performance will aid in the development of individual occupant behavior models, test multiple dimensions of potential grid-interactive efficient buildings, and advance understanding of human attitudes and behaviors when interacting with their homes.

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