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Publication Date

2020-10-15

DOI

10.1016/j.buildenv.2020.107129

Targeted occupant surveys: A novel method to effectively relate occupant feedback with environmental conditions

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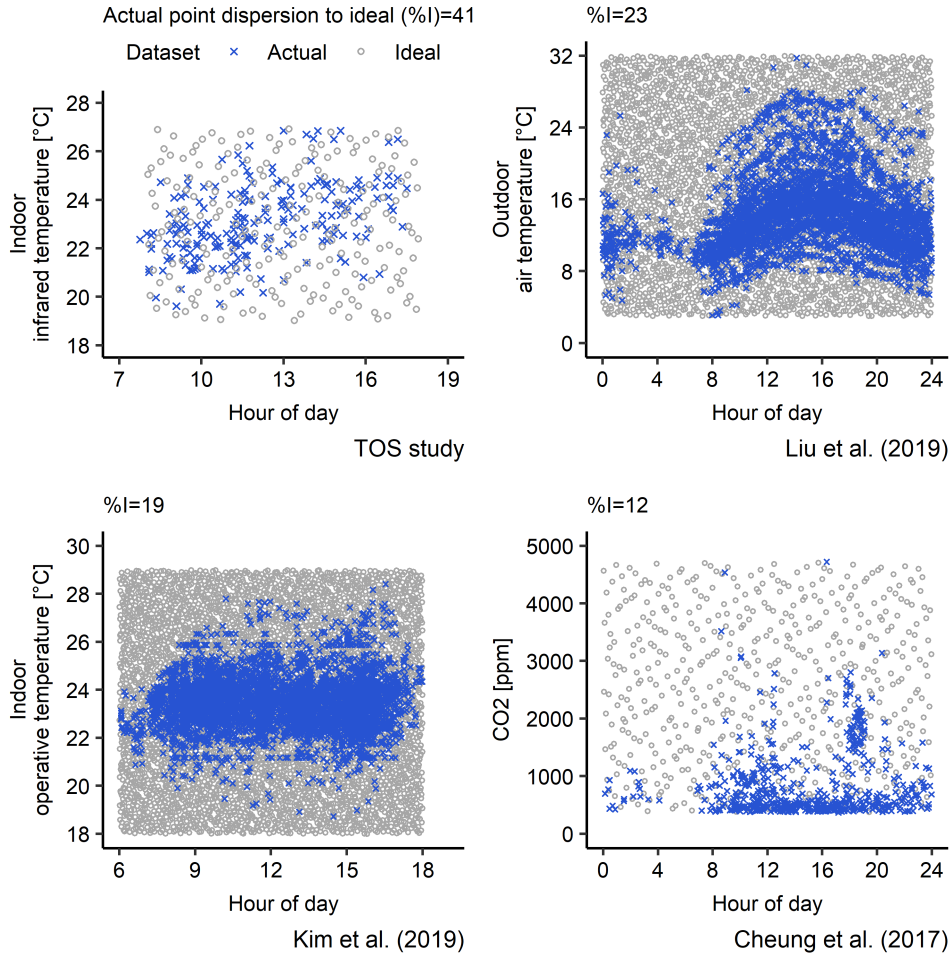
Highlights

- Developed survey platform to distribute "right-now" assessments based on targeted IEQ measurements.
- Conducted pilot study in a radiantly conditioned building to test survey platform.
- Pilot study shows collected dataset better approaches ideal point dispersion (41%) compared to other methods (23, 19, and 12%).
- New survey platform decreased occupant disturbance and data redundancy.

Abstract

Occupant satisfaction surveys are widely used in laboratory and field research studies of indoor environmental quality. Field studies pose several challenges because researchers usually have no control over the indoor environments experienced by building occupants, it is difficult to recruit and retain participants, and data collection methods can be cumbersome. With this in mind, we developed a survey platform that uses real-time feedback to send targeted occupant surveys (TOS) at specific indoor environmental conditions and stops sending survey requests when collected responses reach the maximum surveys required. We performed a pilot study of the TOS platform with occupants of a radiant heated and cooled building to target survey responses at 16 radiant slab surface (infrared) temperatures evenly distributed from 15 to 30 ˚C. We developed metrics and ideal datasets to compare the TOS platform against other occupant survey distribution methods. The results show that this novel method has a higher approximation to characteristics of an ideal dataset; 41% compared to 23%, 19%, and 12% of other datasets in previous field studies. Our TOS method minimizes the number of times occupants are surveyed and ensures a more complete and balanced dataset. This allows researchers to more efficiently and reliably collect subjective data for occupant satisfaction studies.

Graphical Abstract

Actual point dispersion to ideal (%I)=41

Dataset × Actual ○ Ideal

TOS study

%I=23

Liu et al. (2019)

%I=19

Kim et al. (2019)

%I=12

Cheung et al. (2017)

Keywords

Post occupancy evaluation, Ecological momentary assessment, Targeted occupant survey, Case study, Radiant system, Thermal comfort

1. Introduction

1.1. Literature review

Post-occupancy evaluation (POE) is a general approach to obtaining feedback about a building's performance during operation. POEs can include assessments for energy and water performance, indoor environmental quality (IEQ), and occupant comfort, satisfaction, and productivity. If defined and used properly, they provide a wealth of information to help researchers and other stakeholders identify building features and characteristics that function as intended and areas that need improvement (Leaman, Stevenson, and Bordass 2010). They also provide diagnostic information for building managers and owners to identify specific problems, and feedback for designers to improve future buildings (Preiser 1995).

Occupant surveys are one method often used in POEs to evaluate occupant comfort and satisfaction with the built environment (Humphreys 1976; P. Li, Froese, and Brager 2018). There are two main types of occupant surveys; general and comprehensive assessments, and 'right-now' surveys that are known in other research fields as ecological momentary assessments (Shiffman, Stone, and Hufford 2008). General POE surveys are designed to gather an overall description of the building, assess occupants' long-term satisfaction and comfort, and collect occupant characteristics (Schiller et al. 1988; Frontczak et al. 2012) . In contrast, the right-now surveys are designed to provide a snapshot of how occupants perceive their indoor environment at the moment in time they are completing the survey e.g. 'Right now I feel …', 'Right now I prefer …', etc (Benton, Bauman, and Fountain 1990). Right-now surveys are typically coupled with IEQ measurements, such as temperature, air velocity, sound pressure level, illuminance, and CO_2 concentration. However, there are several obstacles to reliably gathering the contemporaneous IEQ measurements necessary for robust analyses of paired subjective and objective data.

Researchers have employed different methods to distribute occupant surveys and simultaneously monitor environmental conditions in buildings. Administering surveys traditionally involved labor-intensive distribution of paper-based format, but in recent years has advanced to the use of computer software (Newsham and Tiller 1997; Zagreus et al. 2004) with some optimized for use on mobile devices (Parkinson, Candido, and de Dear 2012). Today, web-based tools like SurveyMonkey™, Qualtrics™, and Google Forms™ have reduced the technological barriers to create, distribute, and analyze digital surveys (Finley 2019; Qualtrics 2014; Google 2019). Aside from the distribution method, the content of IEQ surveys has been through many iterations. The Center for the Built Environment's (CBE) Occupant Survey developed in 2000 is currently the most widely used standardized IEQ survey method (Zagreus et al. 2004; Frontczak et al. 2012; CBE 2019; Graham, Parkinson, and Schiavon 2020). Other widely used survey methods are Building Use Studies Ltd's PROBE, Overall Liking Score, and Building Occupants Survey System Australia (Cohen et al. 2001; Levermore 1994; Candido et al. 2016; Dykes and Baird 2013).

Detailed spot measurements have historically been performed using different design iterations of mobile carts and stationary sensor kits (Benton, Bauman, and Fountain 1990;

Heinzerling et al. 2013; Newsham and Tiller 1997; Chiang et al. 2001; Lai et al. 2009; Ncube and Riffat 2012). A subject would complete a right-now survey while the researcher measured their immediate indoor environment. This process is time-consuming and expensive since assessments are normally done using only one or two of the expensive sensor arrays. Improvements in measurement technologies have led to sensors becoming inexpensive, increasingly accurate, easy-to-use, smaller, and more portable. This sensor revolution has driven the development of continuous IEQ monitoring systems designed to be permanently distributed throughout an indoor environment (Brager, Paliaga, and de Dear 2004; Goto et al. 2007; Cheung et al. 2017; de Dear, Kim, and Parkinson 2018; Kim et al. 2019; Liu et al. 2019; Parkinson, Parkinson, and de Dear 2019).

1.2. Motivation and objectives

Collecting subjective data relied on repeated right-now surveys based on a schedule, time intervals, or manual triggers. These survey distribution methods lack a mechanism for feedback and can result in responses during environmental conditions that do not add new information to the set of measurements e.g. responses were previously collected within the same study or external studies. If environmental conditions are oversampled or the research objectives are not to verify the outcomes of previous studies then subjects are unnecessarily disturbed in such cases, leading to survey fatigue (Porter, Whitcomb, and Weitzer 2004) and unbalanced or incomplete datasets.

Given these challenges and shortcomings of methods currently used in field studies, there is a need for more advanced and robust survey methods to collect occupant responses for research studies. Important design characteristics of such a tool are: 1) ability for storage and retrieval of completed occupant responses along with specific environmental conditions the moment the survey was completed, and 2) ability to distribute occupant surveys at specific environmental conditions or throughout the researcher-defined region of interest depending on researchers' study objectives while avoiding clustering of data. We define the "region of interest" as the range of environmental conditions that researchers are interested in surveying. Meeting the two design characteristics listed above necessitates the use of continuous real-time IEQ measurements. It also requires a tracking system for distribution details, target conditions, and recording when surveys are sent and completed. As such, the primary objectives of this research are:

1. develop an online platform that incorporates these characteristics to administer right-now surveys based on specific IEQ measurements,

2. conduct a pilot study of the survey platform using occupants of an office building.

2. Methods

2.1. Targeted occupant survey

2.1.1. System overview

The targeted occupant survey (TOS) platform runs on any local or remote computer with an internet connection. Figure 1 is a schematic representation of the main components of a

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TOS study. There are three key parameter sets for configuration by the researcher or other survey designer: occupant, survey distribution, and physical measurement parameters. The TOS platform uses these parameters to define when and whom to send the occupant surveys. The occupant list contains the relevant participant information, including email addresses, personalized survey links, and identification number of the assigned IEQ sensor. The survey distribution parameter controls when occupant survey requests should be sent to participants e.g. during office hours only. In addition, the researcher can implement a sampling method for survey distribution based on the number of eligible participants. The sampling method can be defined by time of day / day of week, the number of survey requests, or participant responses. If no sampling method is defined, the TOS platform distributes the occupant survey to all eligible participants. Another key input among the distribution parameter is the maximum allotted surveys per participant per target IEQ bin. The TOS platform stops sending additional survey requests to a participant for the specific target IEQ bin when the maximum number of surveys for that condition has been met. The TOS platform would be performing as designed if the collected surveys match the defined maximum surveys input. The physical measurement parameter controls any transformations performed on incoming sensor data. The actual sensor reading, along with any transformation, can be defined to trigger survey requests. For example, raw data can be used to define a new metric such as the ramp/drift rate for the previous hour or the maximum/minimum temperature of the last 15 minutes. These flexible parameters offer a significant advantage to using TOS for field studies of occupant satisfaction.
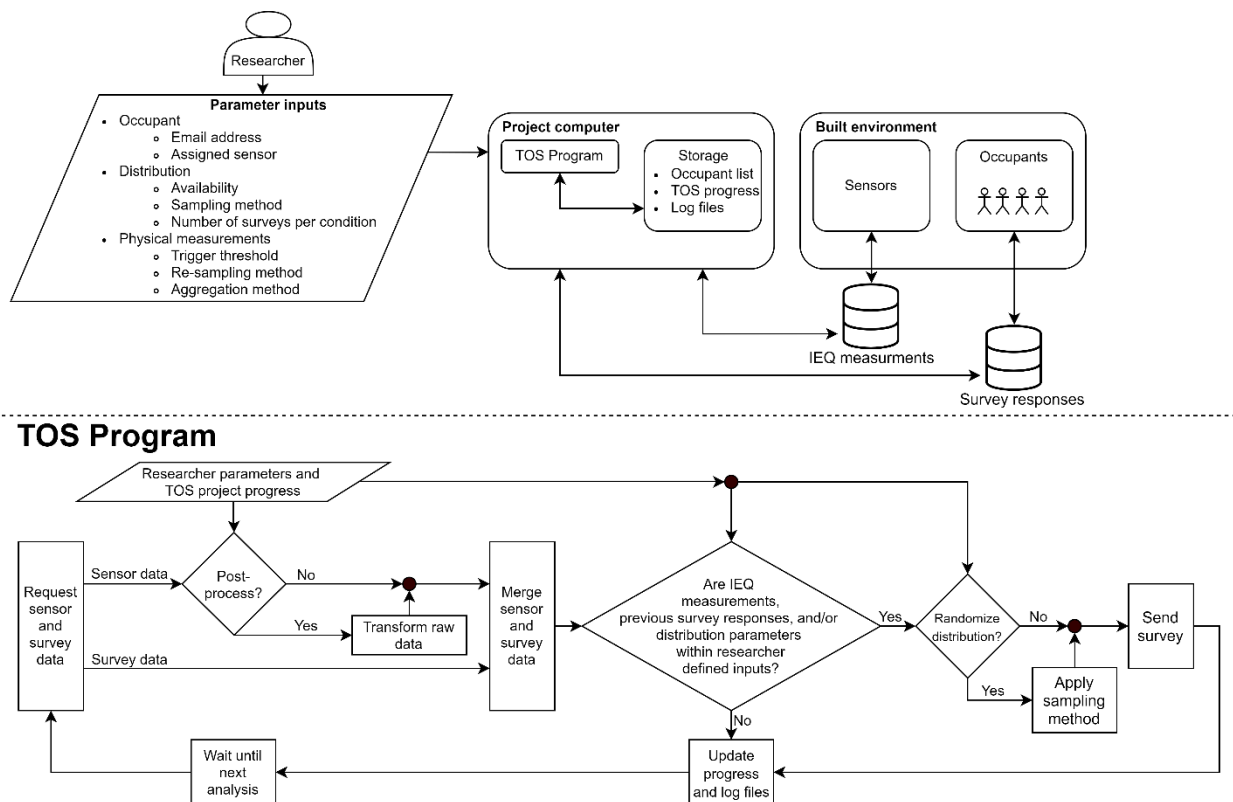

Figure 1: Targeted occupant survey (TOS) platform overview. The top schematic shows a high-level overview of how TOS projects are setup while the bottom schematic shows the TOS program flow.

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2.1.2. Software program environment

The TOS platform is written in Python (Python 2018, version 3.6.8) (Kuhlman 2012). We used pandas and NumPy to manage and analyze time-series data (pandas 2019; NumPy 2019). Data analysis for the pilot study was done in R Statistical Software (The R Foundation 2019, version 3.6.1) with the tidyverse package (Wickham et al. 2019). Links to the source code for the TOS platform, helper programs, and analysis can be found in the supplementary material.

2.1.3. Survey service

The TOS platform can interface with any survey service that supports the download and use of data within the Python environment. We used Qualtrics Survey Software for the pilot study (Qualtrics 2014). Qualtrics uses a REST API to request survey information (Fielding et al. 2017) for subsequent download and analysis of responses. The questionnaire used in the pilot study is described in 2.2.2, and the full questionnaire can be found in Appendix A.

2.1.4. IEQ measurements

The TOS platform was designed to be sensor-agnostic and supports any device that can leverage a Python environment for code execution. The IEQ measurement collection program, referred to as the polling program, is an independent module that polls each sensor and transmits data to storage for later use. We developed and tested two acquisition systems, and plan to support more in the near future. The first acquisition system uses a simple data structure in Javascript Object Notation (JSON) format stored on the project computer. The second system uses an open-source database called simple Measurement and Actuation Profile (sMAP) (Dawson-Haggerty et al. 2010). We chose to use sMAP since it uses REST API for data retrieval for both TOS and post-processing, and also provides long-term storage solution. Appendix B contains more details about the data acquisition systems we tested.

2.2. Pilot study

We tested the TOS platform in a pilot study conducted in the David Brower Center (DBC) building in Berkeley, CA from October 20 through December 10, 2019. Berkeley has a Köppen Csb climate zone (California climate zone 3, ASHRAE climate zone 3C) characterized by dry, warm summers and mild winters. UC Berkeley's Committee for the Protection of Human Subjects approved the IRB protocol (IRB-2011-04-3163).

This pilot study is one example of a use-case scenario for the TOS platform. We designed the parameter sets above to give researchers extensive control over the data collection process. The key advantage of the TOS platform is that researchers define specific environmental conditions to trigger survey requests based on their particular study objectives and research questions. This increases the probability that more of the collected survey responses will contribute to answering their research questions.

2.2.1. Building characteristics

The DBC building is a 4-story mixed-use building with a floor area of 3,900 m² (42,000 ft²) for multiple tenants and a total of approximately 150 occupants (Raftery, Duarte, and Dawe 2018). The heating, ventilation, and air-conditioning (HVAC) system includes a thermally activated building (TABS) radiant system for the primary heating and cooling in

the office spaces (Babiak, Olesen, and Petras 2009). A 100% outside air underfloor air distribution (UFAD) system and natural ventilation through operable windows provide fresh air. The TABS radiant system uses a control strategy developed by Raftery et al. (2017) where the extreme thermal conditions of the zone from the previous day are used to adjust the slab setpoint for the next day.

2.2.2.Subjects and questionnaires

We recruited eight occupants from the DBC building to respond to three surveys for our pilot study. The first survey was used to gather a general description of the built environment, occupant characteristics, the long-term satisfaction and comfort, and invitation to our pilot study. The second survey asked information about personal characteristics (i.e. sex, age, height weight), use of personal comfort devices, temperature sensitivity, method of commute, work desk location, and email address. The third questionnaire was a right-now survey of 11-questions that took about a minute, on average, to complete. We used this survey in conjunction with the TOS program. The goal of the right-now survey was to characterize whole-body thermal comfort (thermal sensation, thermal acceptability, and thermal preference) and self-reported well-being (ability to concentrate, level of sleepiness, and perceived productivity) when subjects completed the survey. We used a continuous scale with 7-points (the ASHRAE scale: -3 - cold; 0 - neutral; +3 - hot) to evaluate subjects' thermal sensation (ASHRAE 2017). For thermal acceptability, subjects marked their responses on a continuous scale with 7-points ranging from clearly not acceptable (-3) to just unacceptable (-0.1), and from just acceptable (+0.1) to clearly acceptable (+3); subjects were required to distinguish between acceptable and unacceptable. Subjects were asked to rate their thermal preference by selecting if they prefer to be cooler, warmer, or no change. Self-reported productivity questions used a 5-point discrete scale. We also asked subjects about their level of activity in the past 15-20 minutes, clothing ensemble, and their use of fans and windows. The complete right-now survey can be found in Appendix A. Data were anonymized and made publicly available.

2.2.3.IEQ measurements

We built a small IEQ measurement system to monitor indoor dry-bulb temperature, relative humidity, operative temperature, and surface (infrared) temperature. We placed one sensor kit on each subjects' desk to measure their immediate environmental conditions but did not assess the difference in measurements due to the position of the sensor due to limited placement options. Figure 2 shows the stand-alone sensor kit and positioned on a subject's desk in the case study building. We used Senseware nodes to create a mesh network, and a central Senseware gateway device to transmit data to both the Senseware database and our sMAP archiver (Senseware 2019). Table 1 reports specifications of the sensors use in the kit while Appendix C contains more details about the sensors and the calibration method.

Table 1: Custom IEQ measurement system's sensors specifications.

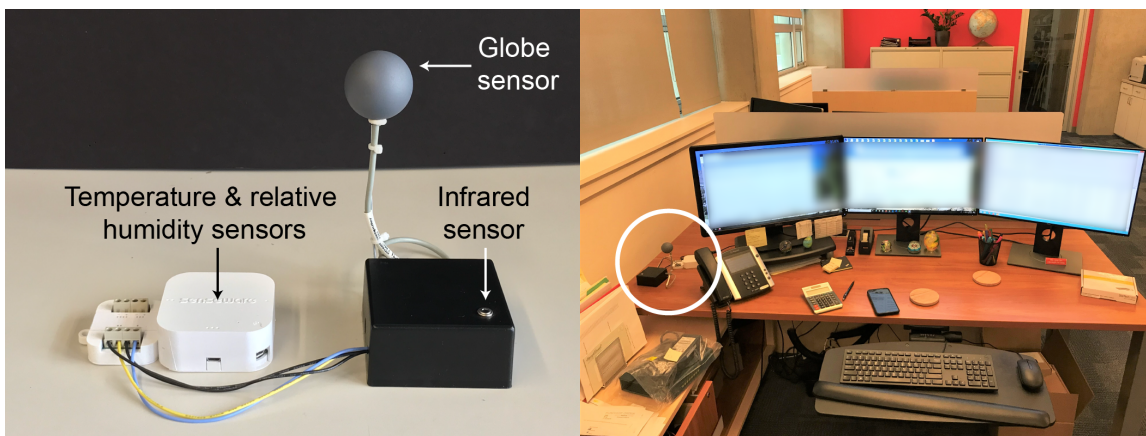| Measurement	Manufacturer and model	Uncertainty	Additional comments
Dry-bulb temperature	Senseware node	0.3 ˚C	-
Relative humidity	Senseware node	2%	-
Operative temperature	HOBOware TMC1-HD	0.25 ˚C	2 min response time
Infrared temperature	Melexis MLX90614	0.5 ˚C	90˚ field of view

Figure 2: Small custom-made sensor kit used in our pilot study. We placed one sensor kit on the subject's desk as shown within white circle of the bottom image. The sensor kit measured dry-bulb air, operative, and infrared temperature and relative humidity.

In addition to the sensor measurements, we collected three different temperatures; zone radiant slab, zone dry-bulb as measured through the thermostat, and outdoor air. The radiant slab and thermostat temperatures are part of the building's energy management system. We compared its measurements with calibrated sensors and found no meaningful difference between the two. We downloaded outdoor air temperature from a nearby weather station (*www.wunderground.com*). Since the building's HVAC system switched between heating and cooling, we grouped temperature measurements by HVAC mode. Measured data are publicly available with collected survey responses.

2.2.4. TOS input parameters

We configured the TOS to administer surveys on weekdays from 8:00 to 18:00, with each subject receiving a maximum of three surveys per day at least two hours apart. Based on a 15-minute iteration interval, the TOS polls sensors and identifies eligible subjects to receive survey requests. A subject is eligible if the environmental conditions are at the defined IEQ measurement targets within the region of interest, the subject has not exceeded the maximum number of completed surveys per IEQ measurement target and/or the maximum number of surveys per day, the current time is within the specified range for survey distribution, and the interval time between subsequent surveys is greater than what is defined.

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For the IEQ measurement targets, we defined 16 binned radiant slab surface temperatures measured from the infrared sensor in the kit at which survey requests were sent to subjects. We also defined a maximum number of surveys collected per target temperature for each subject; four for each infrared target bin except for bins 23, 24, and 25 °C where only two surveys were collected. Furthermore, we implemented a sampling method where the probability of sending a survey to an eligible subject decreased linearly with each survey they completed. That is, they had a 100%, 67%, 33%, 0% probability of receiving a survey request if the subject had completed 0, 1, 2, and 3 surveys that day, respectively. This sampling method helped avoid multiple surveys completed within one day at the same target infrared temperature. We anticipated the number of survey requests sent and, by extension, the number of completed surveys to be higher at the beginning of the distribution timeframe than later in the day. We instructed subjects to reply to the last survey request they received if multiple unanswered requests accumulated.

2.2.5. TOS performance

We developed a new metric, D_K, to measure the points' proximity to other points within the TOS platform's dataset as well as the datasets from other studies we used for comparison. The metric can be used to evaluate the clustering of data points. If the resulting D_K is low, it indicates that many survey responses were collected at similar environmental conditions which may be undesirable. To derive the metric, D_K, we first calculated the Euclidean distance between each point n and its K nearest points, averaged the K distances to get one value per point ($\bar{d}_K$), and found the median among the N calculated $\bar{d}_K$ to get one value per dataset (D_K). We use the median because the distributions of the target measurements might be different for each dataset. Equation 1 shows the calculation for D_K for any dataset.

$$\bar{d}_K^n = \frac{\sum_{k=1}^{K} \sqrt{\sum_{i=1}^{I} \left(q_{ni} - p_{ki}\right)^2}}{K}, \quad 1 \leq n \leq N \qquad \text{Equation 1.1}$$

$$D_K = median\left(\bar{d}_K^n\right), \quad 1 \leq n \leq N \qquad \text{Equation 1.2}$$

Where I is the number of dimensions in the Euclidean space, q_n is the current point and p_k is one of the K nearest points. We used two dimensions in our analysis - target IEQ measurement and time at which the subject took the right-now survey - and chose five total nearest points to find D_5. We found that the rate of change between D_k and D_{k+1} for $k \geq 5$ is fairly constant for the datasets evaluated in this study. We chose time as one of the dimensions because the current TOS version does not allow researchers to set multiple IEQ measurement targets; this limitation is addressed in Section 5. We also calculated the

variance of each dimension and in conjunction with the D_5 metric, quantified the dispersion, or spread, in a dataset.

We calculated the two metrics for the dataset collected in our pilot study and thermal comfort datasets from Liu et al. (2019), Kim et al. (2019), and Cheung et al. (2017). Liu et al. (2019) collected environmental parameters, occupant behavior, physiological measurements, and occupant thermal satisfaction responses from 14 subjects for 2-4 weeks to develop personal comfort models. Subjects in this field study completed right-now surveys at their own discretion but researchers required 12 surveys per day, with incentives to complete more. Kim et al. (2019) collected environmental parameters, occupant behavior, and occupant thermal satisfaction responses from 37 subjects for 12 weeks to study the use of personal comfort systems. Researchers sent email invitations to complete right-now surveys three times a day. Subjects completed the survey during their available time after the request was sent. Cheung et al. (2017) collected dry-bulb temperature, relative humidity, and carbon dioxide concentration, as well as thermal and air quality acceptability responses from 15 subjects for seven consecutive days. The researchers requested subjects complete a survey on their smartphone after each significant change in environmental conditions i.e. transitions between outdoor and indoor environments.

To accompany these field measurements, we created ideal datasets for each field study with the assumption that the number of points were evenly distributed throughout the regions of interest which is consistent with each study's research objectives. Collecting evenly distributed occupant responses within the region of interest is just one-use case for the TOS platform. Researchers can also use the TOS platform to survey occupants at only extreme or very specific environmental conditions (e.g. every time a fan is first used and when it is turned off) while ignoring the rest. The ideal datasets were generated using Halton sequences (Halton 1960), a quasi-random sampling method with applications in Monte Carlo simulations. The region of interest for the datasets are: in our pilot study, time between 8:00 and 18:00 and radiant slab surface temperatures between 19 and 27 °C; in Liu et al. (2019), time between 0:00 and 23:59 and hourly mean outdoor air temperature between 3 and 32 °C; in Kim et al. (2019), time between 6:00 and 18:00 and indoor operative temperature between 18 and 29 °C and; in Cheung et al. (2017), time between 0:00 and 23:59 and carbon dioxide concentration between 370 and 4720 ppm. The temperature or concentration range corresponds to the observed minimum and maximum in each dataset, and the time range corresponds to the building occupancy hours in our pilot study and in Kim et al. (2019). For Liu et al. (2019) and Cheung et al. (2017), we considered all 24 hours because subjects were able to take surveys at their discretion with no time restrictions.

In practice, achieving the characteristics of an ideal dataset is a challenge because:

1. subjects may not take the survey immediately following the request, or may complete the survey at another target IEQ measurement that falls outside the region of interest;

2. researchers do not have control over the environment that subjects are exposed to during field studies, so there is a higher likelihood to survey subjects at average conditions than more extreme conditions; and

3. given that there is no control over the environment, subjects may never experience the conditions depicted in the ideal dataset.

The ideal datasets provide a measure of how effectively the data collection methods sampled the respective region of interest. The hypothesis is that the TOS platform will collect more occupant survey responses sampled from within the region of interest with the available survey requests.

3. Results

The results are split into two sections. First, we analyze the TOS performance, quantify its collected data distribution with the ideal counterpart, and compare its data distribution to other datasets collected in other studies. Second, we present the subjective and IEQ measurement data collected during the pilot study.

3.1. TOS Performance

A summary of the TOS statistics during the pilot study are shown in Table 2. The TOS platform sent 329 survey requests, with subjects completing 216 surveys at a response rate of 66%. Subjects evaluated their whole-body thermal comfort and well-being at the moment they completed the survey rather than when the survey request was sent. Thus, subjects only completed one survey in cases where multiple unanswered survey requests had accumulated. The average number of completed surveys per subject was closely aligned with the defined maximum number of surveys, with the exception of the 23 and 24 °C bins due to an issue in the TOS programming. The issue prevented proper parsing of timestamps to determine when survey requests were sent and surveys completed. This resulted in surveys requests being sent to subjects that violated the minimum time interval between survey requests. After fixing the issue, the TOS platform sent survey requests at an average time interval of 215 minutes; well above our minimum. It also administered surveys within our defined distribution hours and days of the week after fixing the issue. The number of surveys across the target temperature range shows that more extreme indoor temperatures were rarely experienced in the building.

Table 2: Comparison between our input maximum number of surveys per target temperature per occupant and total survey requests sent and survey completed. TOS is designed to stop sending survey requests to a participant at a particular bin when the bin's maximum allotted survey threshold is reached. TOS is performing well when the maximum allotted surveys match the actual completed surveys collected per participant per bin.

Radiant slab surface (infrared) temperature target [°C]	Maximum allotted surveys[1]	Total survey requests sent	Total surveys completed[2]	Average surveys completed per subject[3]

15	4 | 32	0	0	0
16	4 | 32	0	0	0
17	4 | 32	0	0	0
18	4 | 32	0	0	0
19	4 | 32	0	0	0
20	4 | 32	23	5 | 1	0.63
21	4 | 32	64	22 | 1	2.75
22	4 | 32	63	37 | 12	4.62
23	2 | 16	64	42 | 13	5.25
24	2 | 16	57	32 | 10	4
25	2 | 16	44	21 | 7	2.62
26	4 | 32	9	6 | 1	0.75
27	4 | 32	5	4 | 2	0.5
28	4 | 32	0	0	0
29	4 | 32	0	0	0
30	4 | 32	0	0	0
Total	58 | 464	329	169 | 47	21.13

1. Categorized as: per subject | total for all subjects
2. Categorized as: at workplace | not at workplace
3. Average only includes responses where subjects were at workplace

The goal of the TOS platform in this study is to minimize data clusters by more evenly distributing responses across various conditions with minimal redundancy. Figure 3 shows visualizations of point dispersion of measurements from the datasets for A) our pilot study, B) Liu et al. (2019), C) Kim et al. (2019), and D) Cheung et al. (2017) in the top row, along with their respective ideal dataset in the bottom row. Table 3 shows the calculated values for the metrics D_5 and variances for each dataset. The higher the variance, the larger the spread in the data, suggesting greater sampling of that dimension. The desired outcome is for metric values to be close or identical to the ideal values. By dividing the actual metric by its ideal counterpart, we could quantify the percentage of ideal (*%I*). The higher the *%I*, the closer the metric approaches the ideal. The *%I* shows that our pilot study with the TOS platform is closer to the ideal dataset – 41% compared to 23%, 19% and 12%. Also, the variance in y (target measurement) is further apart from its respective ideal in other studies when compared to our pilot study. These results suggest that the TOS platform can accomplish the desired objective of better data representation.

Table 3: Calculated values of data dispersion metrics for each of four actual datasets and their ideal counterpart along with percentage of ideal (%I).

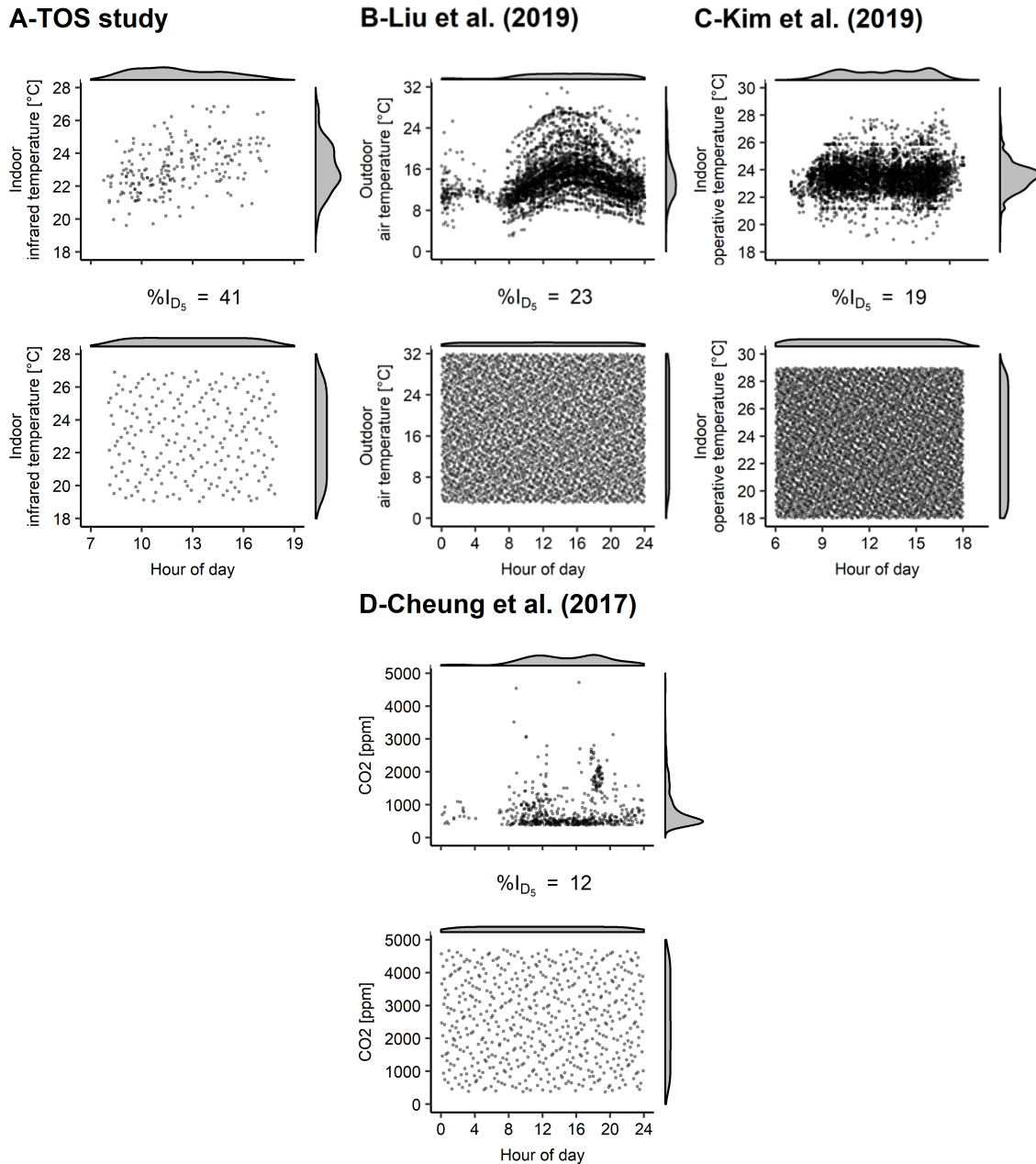|	TOS pilot study			Liu et al. (2019)			Kim et al. (2019)			Cheung et al. (2017)		
Survey distribution method	TOS			Subject's discretion with hourly text reminders			Email requests three times a day			Subject's discretion after environmental changes		
Region of interest	8:00-18:00 and 19-27 ˚C			0:00-23:59 and 3-32 ˚C			6:00-18:00 and 18-29 ˚C			0:00-23:59 and 370-4720 ppm		
Target IEQ measurement	Radiant slab surface temperature			Hourly mean outdoor air temperature			Indoor operative temperature			Carbon dioxide concentration		
	Actual	Ideal	%I	Actual	Ideal	%I	Actual	Ideal	%I	Actual	Ideal	%I
Variance in x	6.51	8.32	78	27.26	47.99	57	7.81	11.99	65	22.35	47.85	47
Variance in y	2.14	5.35	40	18.42	70.06	26	1.22	10.08	12	382,999	1,576,440	24
D_5	0.175	0.431	41	0.049	0.215	23	0.006	0.031	19	39.8	334.7	12

Figure 3: Visualization of point dispersion in actual datasets for A) our pilot study, B) Liu et al. (2019), C) Kim et al. (2019), and D) Cheung et al. (2017) in the top row and the their respective ideal dataset in the bottom row. Ideal datasets contain the same number of points as its respective actual dataset; A) N=169, B) N=3585, C) N=4655, and D) N=550.

3.2. Subjective and IEQ measurements

During the pilot study, the observed minimum and maximum outdoor dry-bulb air temperature were 4 and 30 °C, respectively, leading the HVAC system to both heat and cool during the monitoring period. The HVAC system was in cooling mode for six consecutive days at the start of the study and one more day in the middle of November. Figure 4 shows (A) indoor and (B) outdoor temperature box-and-whisker plots grouped by

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HVAC mode. Figure 4 (A) only includes temperatures during the building occupancy hours (8:00-18:00) while (B) contains temperatures from all hours of the day. Measurements from both our sensor kits located on subjects' desks (workplace air) and from thermostats suggest that subjects experienced slightly cooler temperatures during heating mode than during cooling mode; 0.4 °C lower on average. As expected, the zones' radiant slab temperatures are 0.8 °C higher during heating mode on average when comparing the slab temperatures during cooling mode. The outdoor daily mean average was 9.2 °C higher in cooling mode than during heating mode. Overall, the building HVAC system maintained similar indoor temperatures during both heating and cooling modes. Therefore, we do not expect significant differences in subjects' satisfaction votes between modes.
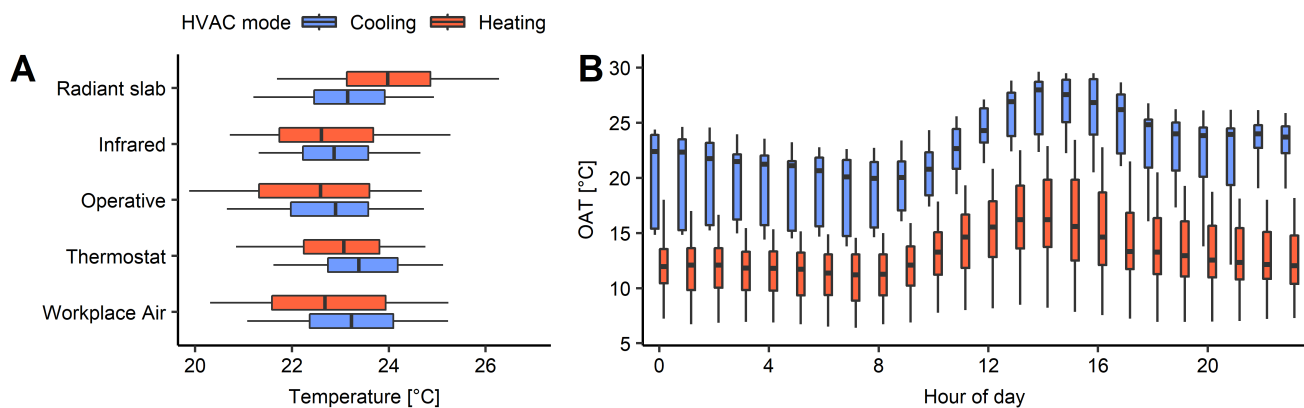

Figure 4: Box-and-whisker plots grouped by the building's heating, ventilation, and air-conditioning (HVAC) mode of A) various indoor temperatures collected through our sensor kits placed on subjects' desk and the building's energy management system and B) outdoor air temperature (OAT). The box represents the interquartile range (25th-75th percentiles) and the whiskers represent the 5th and 95th percentiles.

Figure 5 shows occupant thermal satisfaction results collected during our pilot study. Thermal preference is often the most useful discomfort parameter from a system controls perspective because subjects explicitly specify the corrective action for the HVAC system to improve their comfort. During the pilot study, 68% of responses voted "No change" to their thermal conditions, 15% voted "Cooler", and 17% voted "Warmer". The majority (82%) of "Warmer" responses occurred at temperatures below 22.5 °C. In contrast, there is no clear temperature threshold where subjects collectively responded with a preference for "Cooler" within the radiant slab surface temperatures measured during the study. The "Cooler" votes are scattered among the "No Change" votes.

Figure 5 (B) shows thermal acceptability votes across radiant slab surface temperatures, and acceptable and not acceptable votes as a percentage of total votes. Eighty one percent of responses were slightly to clearly acceptable thermal conditions at the time they completed the right-now surveys over an operative temperature range of 20.4 to 25.2 °C (5th and 95th percentiles respectively). This is slightly higher than the 80% goal of the ASHRAE thermal comfort standard (ASHRAE 2017). Comparing thermal acceptability to thermal preference, subjects were more lenient when responding to "Rate your acceptance of the current thermal environment." than to "Right now, you prefer." Occupants may willingly tolerate the current thermal environment even when their ideal

thermal conditions are not being met. The same results have been observed in other studies (Schiavon et al. 2017; Kim et al. 2019). This suggests that measures of thermal preference will lead to lower percentages of positive responses ("No change") than thermal acceptability questions (P. Li et al. 2019).

We also collected whole body thermal sensation votes, and Figure 5 (C) shows the relationship of subjects' thermal sensation votes across radiant slab surface temperatures. The majority of votes are within the central three thermal sensation points: slightly cool, neutral, and slightly warm. The complete dataset from this study, including all IEQ measurements and survey responses, is publicly available.
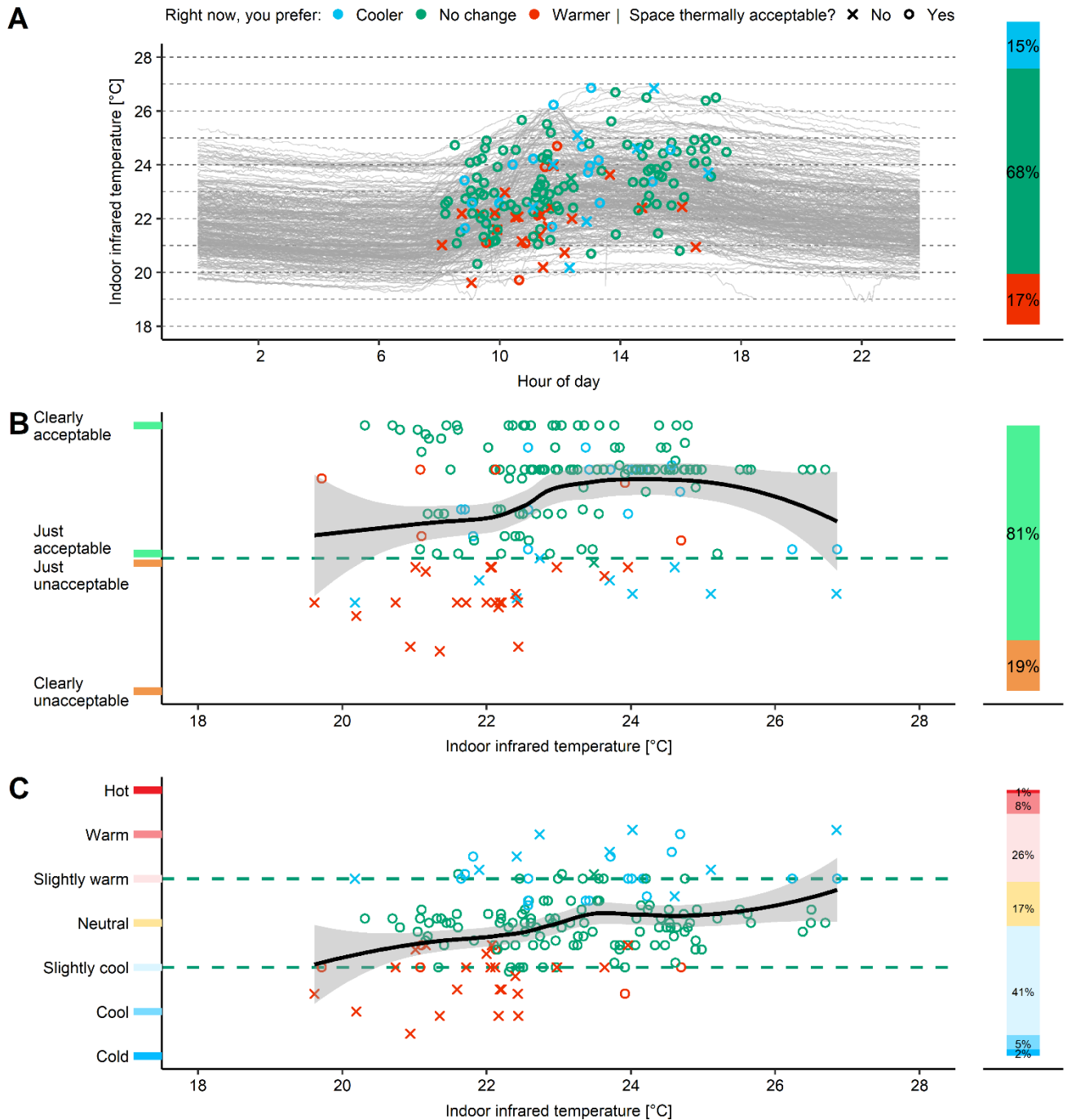
Figure 5: Occupant thermal satisfaction results from eight subjects in pilot study. Thermal A) preference, B) acceptability, and C) whole body sensation. Daily radiant slab surface measurements collected with our sensor kits on all subjects' workplaces and represented as gray lines in A). The solid black line in B) and C) is the local polynomial regression (LOESS) fit with 95% confidence interval in shaded area. Point color and shape in all scatter plots indicate thermal preference and acceptability votes, respectively.

4. Discussion

4.1. TOS platform

Field studies of thermal comfort are necessary to verify results of human-subject laboratory tests or to gain new insights on occupant perception and behavior in real world settings. Because office workers are often time-poor, it can be challenging to recruit them for such studies. Furthermore, researchers usually do not have control over the occupants' indoor environment. These challenges often lead to field research methods that may not optimally collect subjective responses. The survey platform we developed is designed to address these methodological issues by performing targeted right-now surveys (TOS).

The goal of any TOS platform is to minimize disruptions to building occupants while maximizing the amount of useful data collected with right-now occupant satisfaction surveys. We achieved this by adding response feedback to the survey administering logic, a crucial element missing from existing solutions. Implementing a tracking system into the TOS platform allowed us to maintain records of when and at what target IEQ measurements the building occupants have completed right-now surveys. This is a significant improvement over current methods where researchers distribute surveys several times a day based on a schedule, manual triggers, or at participants' discretion. Although the intention may be to collect responses at different environmental conditions, the results in Table 3 and Figure 3 demonstrate the outcome is often far from ideal. The metric D_5, which is a measure of the points' proximity to other points in the same dataset, is much smaller in other studies without the use of the TOS platform which indicates a more clustered dataset. Our field study data approaches the characteristics of an ideal sample as demonstrated by the higher percentage to ideal metric (*I%*) across the different parameters. Although 41% is a long way from 100%, it is a marked improvement from what other field studies have achieved. Moreover, we don't know the upper limit to *I%* given the data collection limitations in Section 2.2.5. Nonetheless, this metric suggests that the TOS platform is successfully minimizing redundancy in the collected data, one of the key objectives of the platform.

Scheduled or manual triggering of surveys without feedback will inevitably lead to clusters of responses around the mean of the target IEQ measurement and fewer responses towards the extremes. These clustered measurements create unbalanced datasets that provide less usable information for the development of predictive models (D. Li, Menassa, and Kamat 2017; Cheung et al. 2017; Salamone et al. 2018; Kim et al. 2019; Liu et al. 2019). Avoiding clusters through the use of a TOS platform will lead to less participant disturbance and help limit associated costs of research subject participation. With the TOS platform, we defined 16 target radiant slab surface (infrared) temperatures with two or four maximum number of surveys per target temperature per subject. The TOS platform sent survey requests more frequently at the beginning of the study, but the frequency decreases as subjects completed them. We observed that the first conditions to reach the maximum allotted survey responses are those around the mean. As those allotments are fulfilled, the TOS platform will wait until extreme conditions are observed in the built environment. This functionality helps achieve the second key objective of reducing unnecessary participant

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involvement. These results show that the TOS platform functions as expected and achieved the desired goals.

Performing a controlled field study at that site with the same research objectives of our pilot study but without the use of the TOS platform would have allowed us to better assess the usefulness of the TOS platform. However, we were unable to perform this experiment due to time constraints and availability of participants. It is for this reason that we compared our pilot study to other field studies where the researchers' goal was to collect survey responses distributed throughout a region of interest. Nonetheless, we expect that experiments with and without the TOS platform would likely result in the same conclusions as our present study but with a different number of survey responses collected between the two experiments. Experiments without the TOS platform would have more responses because there is no feedback to guide survey requests towards the environmental conditions of interest. Researchers would therefore need to send more requests to increase the probability that the collected data will be useful to the research objective. In contrast, the feedback and storage of previous survey responses by the TOS platform will ensure that much of the collected data falls within the region of interest defined by the researcher while reducing the burden on the subject.

4.2. Subjective and IEQ measurements

We purposely selected a building with a radiant system to test the capabilities of the TOS platform to add to the body of literature on thermal comfort in radiant buildings (Karmann, Schiavon, and Bauman 2017). We aimed to collect survey responses at more extreme indoor temperatures to guide any modifications to the control sequences of the radiant system. The low number of recruited subjects meant we were unable to generalize our findings from the pilot study, but it was useful for testing our methods, and the dataset is publicly available for researchers to use in combination with other field study data (Duarte Roa, Schiavon, and Parkinson 2020). Nevertheless, we can make a few observations from the small dataset.

The average difference in the five indoor temperature measurements between the heating and cooling modes was 0.4 °C which is of little practical significance. It also demonstrates that the radiant system was able to maintain consistent indoor temperatures as the HVAC modes switched. In addition, the median infrared and dry-bulb temperature measured in the occupied zone by our sensor kits were 22.6 °C and 22.8 °C, respectively, indicating that there are negligible differences in air and mean radiant temperatures experienced by occupants in this building (Dawe et al. 2020). The subjective thermal satisfaction responses from the small number of subjects indicate that this radiant building exceeds the ASHRAE 80% acceptability criteria (Figure 5). These acceptability votes were cast at infrared temperatures ranging from 19.6 to 26.9 °C. Indicating we were able to receive votes at extreme conditions even though they did not happen often during our study period. A longer study period would have eventually fulfilled our defined maximum number of survey responses at mild target conditions forcing the TOS platform to only send survey requests at the extremes. The use of feedback to meet our input requirements is the key advantage of the TOS platform. In conclusion to our survey responses in our pilot study, the small

dataset does not suggest a thermal comfort advantage in this radiantly conditioned building when compared to all-air buildings (Karmann, Schiavon, and Bauman 2017).

5. Limitations and future work

The current version of the TOS platform allows researchers to use a single sensor to define target IEQ measurements. However, it does support the use of raw data points or a transformed metric like rate of change. It may be beneficial for future work to expand the functionality to include defining multiple target IEQ measurement types or multiple transformations of the same measurement type e.g. temperature rate of change at a specific temperature. We demonstrated that TOS performed well with one type of IEQ measurement target (indoor infrared temperature) and time, but it is uncertain how it will perform with the definition of multiple IEQ target types not including time. The joint probability distribution will change as multiple combinations of target IEQ measurement types are added. Thus, there should be an *a priori* understanding of the relationship between the proposed IEQ types in order to define effective target values. Nevertheless, the added functionality in the TOS platform would enable more effective data collection to study interaction effects (e.g. physiological signals with environment conditions Liu et al. (2019) or illuminance levels with indoor temperatures). The metric, D_K, can still be used to compare the actual collected dataset to an ideal as the Euclidean distance is generalizable to multiple dimensions.

The main challenge of deploying the TOS platform is the need for real-time IEQ measurements. This requires sensors within an internet connected network infrastructure. Companies generally do not grant access to corporate networks, so using ad-hoc local networks is recommended. Alternatively, existing sensors in the energy management system could be used even though they may differ from actual conditions experienced by building occupants due to their location and accuracy.

6. Conclusion

We developed the targeted occupant survey (TOS) platform to give researchers greater flexibility in distributing right-now occupant satisfaction surveys. The TOS platform provides control over many parameters that dictate the recipients and timing of survey requests. We established two design goals when developing the TOS platform for our field study: 1) minimize redundancy in the collected data, and 2) minimize disruptions to participants. These two goals are met by using feedback and a tracking system, which led to a more complete and balanced dataset, reduced respondent fatigue, and minimized survey time and costs. We created environment sensor kits and performed a pilot study with eight participants to test the TOS platform in a building with a radiant heating and cooling system located in a mild climate. We defined several infrared temperature target values at which to administer the right-now thermal comfort survey and collected an average of ~21 completed surveys from each subject over the study period. The results indicate that the TOS program achieved the two design goals. Our collected dataset better approached an ideal data point dispersion (41%) when compared to three other field study datasets (23%, 19%, and 12%). We found less redundancy in our dataset, thereby limiting unnecessary disturbances for participants. These advantages of the TOS platform over

current survey methods allow building stakeholders to quickly and effectively collect data necessary to answer research questions and evaluate indoor environmental quality.

7. Acknowledgement

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Appendix

A. Right-now survey used our pilot study

Targeted right-now survey

Are you currently at your workplace?

Yes   No

Have you been at or near your workspace for 15-20 minutes continuously?

Yes   No

Please select your predominate activity within the building during the last 15-20 minutes.

Sitting   Standing and light activities
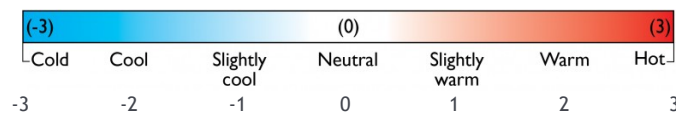
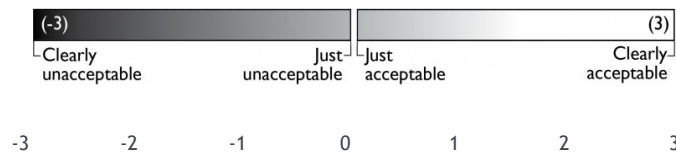Walking and climbing stairs   Jogging, running and others

Thermal environment for whole body

Rate your current whole-body thermal sensation

(-3)			(0)			(3)
Cold	Cool	Slightly cool	Neutral	Slightly warm	Warm	Hot
-3	-2	-1	0	1	2	3

Rate your acceptance of the current thermal environment (select a non- zero value)

(-3)			Just unacceptable	Just acceptable		Clearly acceptable
Clearly unacceptable						
-3	-2	-1	0	1	2	3

Right now, you would prefer to be:

Cooler   No change   Warmer

Are you using any type of air moving devices e.g. desk fans, ceiling fans, open window, etc right now?

Desk Fan

Ceiling Fan
Open Window
None

Please select your approximate clothing ensemble right now:

Naked
0   1   2   3   4   5   6   7   8

Right now, how do you feel?

I am **sleepy** ○ ○ ○ ○ ○   I am **alert**

It is **difficult** for me to concentrate ○ ○ ○ ○ ○   It is **easy** for me to concentrate

I do **not** feel **productive** ○ ○ ○ ○ ○   I feel **very productive**

B. Data acquisition systems tested

We tested two data acquisition methods. The first option uses simple data structure in Javascript Object Notation (JSON) format as illustrated in Figure B1. In this format, we require that each data entry contains a unique sensor ID along with the measured value, polling time in seconds from epoch (epoch is usually January 1, 1970, 00:00:00 (UTC)), description, and unit of measured value. Researchers can also assign additional information as metadata. If researchers select this option, the polling program will create a new file for each device used in the study every hour. The polling program then uses this file to append data entries up until the next hour. We define a device as a collection of sensors that are taking measurements from the same space. As an illustration, all of the sensors in a sensor kit can be considered as one device and each individual sensor is given a unique sensor ID to that device. The filename is then encoded with the date and hour it was created as well as with the device ID e.g <date>_<hour>_<device_id>.json. We found that this method allowed us to quickly find and retrieve data measurements for use within the TOS program.

The first option is beneficial for researchers who do not want to use external databases to store their data which may require subscription fees. This option is simple to setup and use. It avoids the increased complexity when using external databases. This polling program has the option to save the data on the local project computer. We also implemented a method to deploy multiple minicomputers like the Raspberry Pi to poll sensors attached to it and send data entries to a remote project computer over the internet.

```
{"sensor_id_1": {
    "value": 22.27,
    "reading_time": 1563483364.6483772,
    "description": "dry-bulb temperature",
    "unit": "degC",
    "location": "room A"
    },
{"sensor_id_n":
    "value": <float>,
    "reading_time": <float>,
    "description": <string>,
    "unit": <string>,
    }
```

Figure B1: Schematic of JSON data structure for sensor data measurement entries within the targeted right-now survey program.

The second option we implemented was using an open-source database for storing and accessing time-series data and actuating connected devices called simple Measurement and Actuation Profile (sMAP) developed by UC Berkeley's Electrical Engineering and Computer Sciences Department (Dawson-Haggerty et al. 2010). We used the second option in the TOS pilot study because we already have a central sMAP archiver that we used for our research group's field studies. We attached the same sensor point information and metadata when using sMAP as we described in our JSON example above. sMAP uses a REST API to retrieve data from our archiver using a unique data stream ID and a date interval. The REST API facilitates data imports into a Python environment for use within the TOS platform.

C. Sensor kit details

The dry-bulb temperature (0.3 °C accuracy) and relative humidity (2% accuracy) sensors were integrated into a Senseware node. We measured operative temperature using a small globe sensor, which has a HOBOware TMC1-HD temperature probe (0.25 °C accuracy and 2 min response rate) placed in the center of a 40 mm ping pong ball painted grey with 95% emissivity (Humphreys 1977). We used a Melexis MLX90614 sensor to measure infrared temperature (0.5 °C accuracy). This infrared sensor has a 90° field of view and it points directly to the ceiling surface which does most of the heat exchange for the radiant system. It was inevitable that we only capture the ceiling surface. The sensor's field of view may also capture window and monitor surfaces, but the sensor's sensitivity drops dramatically after 40° from its center reducing its impact on the reported average temperature. The infrared sensor also contains an optical filter that filters out most of the shortwave radiation (i.e. direct sunlight and lights). We calibrated the temperature probe sensors using a recirculating oil bath (PD7LR-20, Polyscience, U.S.). We also calibrated the infrared sensors using a thin metal pan coated with black matte paint submerged in the oil bath. We performed a four-point calibration from 15 to 30 °C for both sensor types.