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Social and behavioral determinants of indoor temperatures in air-conditioned homes

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ABSTRACT

The causes and consequences of indoor heat exposure are receiving growing attention as global temperature rises and people seek respite from the heat in indoor spaces. In this study, we measured indoor temperatures of 46 air-conditioned residences in Phoenix, Arizona, United States. Temperatures were collected concurrently at 5-min intervals from August 21 to September 19, 2016. Indoor temperatures exhibited significant heterogeneity across all residences, ranging from 16.5 to 37.2 °C with a mean (SD) of 26.4 °C (2.2 °C). On average, the 5-min indoor temperatures were moderately correlated with outdoor temperature (r = 0.421), although individual household correlations were highly variable, ranging from r = -0.244 to r = 0.924. Households were grouped into six clusters using K-means based on 19 temperature metrics. We tested for differences in demographic, behavior, and infrastructure indicators between those six clusters based on responses to a social survey. Nearly half the variance in preferred thermostat setting was explained by cluster (R^2 = 0.455, p < .001). For the most part, measures of air-conditioning use, limitations on air-conditioning use, and household resources (e.g., income) did not vary significantly by cluster. The same was true for heat-related health and comfort outcomes. Two households that did not pay their own electric bill were by far the coldest homes (average temperature of 20.0 °C). We conclude that indoor temperature preference may supersede concerns related to the cost of using air-conditioning and that resource-constrained households may be sacrificing other necessities to keep their homes comfortable.

1. Introduction

Extreme heat and its human impacts are the subject of considerable focus in the contemporary meteorology, public health, and urban planning communities. This focus is warranted because exposure to extreme heat is hazardous to human health, particularly during prolonged heat events [1,2]. In extreme cases, public health emergencies are declared, as in the 2010 Ahmedabad, India heat wave that led to more than 1300 excess deaths [3], the nine-day European heat wave of 2003 that resulted in 70,000 deaths in multiple countries [4], and the Chicago heat wave of 1995 that resulted in approximately 700 deaths [5,6].

The urban heat island effect unevenly intensifies heat in many cities through spatial variations in urban form and types of anthropogenic activities [7,8]. In many cities, neighborhoods with lower socioeconomic status and higher percentages of ethnic minorities tend to experience a higher burden of heat due to systemic social inequalities that have led to residential neighborhoods with lower vegetation density and a larger footprint of impervious surfaces than wealthier, whiter neighborhoods [9–11].

Virtually all studies related to heat, health, and social equity have measured only outdoor temperatures. Yet a significant portion of exposure for many people may not be associated with outdoor conditions, as people in the developed world spend, on average, 87% of their

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time indoors (69% of which is in a residence) [12,13]. Research shows that the indoor thermal environment plays a key role in individual heat exposure and heat-related discomfort, injury, or death. Quinn et al. [14] simulated indoor conditions in New York City homes under prolonged heat wave conditions and found that projected air temperatures inside many homes, particularly those of lower-income residents, were above safe thresholds for extended periods. Walikewitz et al. [15] observed that summertime temperatures in Berlin, Germany homes exceeded thresholds for heat stress 35% of the time.

Most jurisdictions do not systematically collect information about the location of heat-related injury but data suggest a strong influence of the indoor environment on the risk of heat-related illness and death in locations where such information is available. In New York City, over 80% of heat strokes occur due to indoor exposure [16]. During the 2003 nine-day extreme heat wave in Europe, over 50% of fatalities in France occurred indoors, not including deaths that occurred after hospitalization, which may include exposure that began indoors [17]. Between 2011 and 2018, in Maricopa County Arizona—which encompasses the greater Phoenix area—approximately 40% of heat-related deaths were assigned a hospital code that indicated the initial place of injury for heat-related illness occurred indoors [18].

Despite data suggesting the importance of the indoor residential thermal environment as a driver of heat exposure and health risks, our understanding of why indoor temperatures vary among residences remains incomplete. This is particularly true for *in situ* observations in occupied homes. In 2005, Wright et al. [19] pointed out the "little published field data on internal summer temperatures" and over a decade later Quinn and Shaman [20] noted that "little monitoring has been conducted on temperature and humidity inside homes despite the fact that these conditions may be relevant to health outcomes." A major challenge in characterizing the indoor environment is the significant between-home variations in temperature and humidity measurements. Indoor observations of two adjacent buildings recorded at the same time can exhibit significantly different temperature conditions [14,19,21]. As such, predicting indoor temperature requires obtaining a more generalized perspective on indoor thermal conditions across a city by identifying variables or groups of variables that modify or correlate with indoor temperatures.

Research that identifies variables related to indoor temperatures has primarily focused on physical factors that alter the incoming and outgoing energy within a building, such as outdoor temperature and radiation, construction material, wall and roof insulation, and window properties [22–25]. For example, certain building materials (e.g., brick versus asphalt siding [26]) retain heat more readily and building insulation and window thermal properties (e.g., single-pane vs. double-pane) make a significant difference in the internal heat gain of a building [27].

Others have found that much of the variation in indoor temperature is due to occupant behavior and adaptation strategies (e.g., preferred indoor temperature; hours spent at home; type, use, affordability, and setting control of mechanical cooling devices; opening and closing windows and window shades, etc.) [28]. Recently, using sensors to detect opening/closing of windows and occupancy Tsoulou et al. [29] found that occupant behavior played a major role in modifying the indoor environment among a sample of primarily window air-conditioned homes in New Jersey. Several studies over the past 15 years have called for more research of this type that would help fill a critical gap in our understanding of exposure and vulnerability to extreme heat inside homes [14,19,21,26,30].

Among behavioral factors, the use of air-conditioning (hereafter referred to as AC) is often considered a highly effective strategy to reduce indoor heat exposure and protect against ill health effects [31–34]. In heat-health and heat vulnerability literature, this protective factor is usually measured by indicators of the *presence* of AC, derived from administrative parcel and housing data. Presence of AC has been linked to socioeconomic inequalities, where people in the USA that are members of an ethnic minority are less likely to have an AC unit in their home [35,36]. However, little is known about AC *use* among homes that have AC units. Socioeconomic circumstances may constrain or completely prohibit AC use in homes where an AC unit is present because of the cost of electricity or AC maintenance, or other reasons, such as medical or environmental concerns. Survey data from Phoenix, Arizona suggest that AC use may be a continuous, rather than a binary variable. In two social survey instruments measuring heat vulnerability in Phoenix, the Phoenix Area Social Survey (PASS) and Community Assessment for Public Health Emergency Response (CASPER), about half the residents who reported using AC to cool their homes also report being too hot in their home at some point in the summer [37,38]. Clearly, variables other than *presence* of AC are shaping residential indoor temperatures and residents' experiences and health risks.

This study examined residential indoor temperatures in the hot, semi-arid city of Phoenix, Arizona. We included only homes that reported using AC in the summer to explore similarities and differences across homes that are typically described as protected from negative heat impacts in the literature. To address the gaps in our understanding of indoor residential temperatures, our objectives were to:

1. Quantify indoor temperatures and variability in individual homes among a sample of air-conditioned homes.
2. Determine if and how indoor temperatures vary between households.
3. Identify social characteristics and AC related behaviors of residents that may explain any differences in temperatures between households.
4. Identify heat-related health and well-being outcomes of residents that may be explained by differences in indoor household temperatures.

2. Materials and methods

2.1. Study area

All data used in this analysis were collected during the summer of 2016 in the City of Phoenix, Arizona. Phoenix is a semi-arid desert city in the Southwestern United States. The City of Phoenix proper has a population of 1.6 million, 42% of whom identify as Hispanic or Latino [39]. The summer of 2016 saw temperatures as high as 47.8 °C with average high temperatures of 40 °C June–September (data accessed through NOAA xmACIS2 platform: https://xmacis.rcc-acis.org/). AC is abundant in the region: 95% of residences in Maricopa County (which encompasses Phoenix) have central AC [40]. Here, central AC refers to any cooling system which makes use of forced-air equipment (ducts, vents, etc.) to distribute cool air throughout the building. In 2016, 154 people in Maricopa County died due to heat-related illness, 60 of whom were indoors when the initial injury occurred [18].

2.2. Participants

We recruited participants living in Phoenix to participate in a multi-week indoor, outdoor, and personal data collection effort. We selected the participants from a larger sample of Phoenix households that had taken a survey as part of the 3HEAT Project. The 3HEAT Project is an interdisciplinary collaboration between researchers at Arizona State University, the Georgia Institute of Technology, and the University of Michigan, which investigates the social, environmental, and technological adaptations that affect health outcomes due to independent or coupled heat and power failure events. A major component of the 3HEAT project involved administering surveys in person to 163 Phoenix residents in four study sites. Households selected for survey sampling in each neighborhood were stratified by two criteria: household income (by Census block group according to the 2014 5-year American Community Survey) and building types (masonry or non-masonry) that were representative of their proportion of occurrences in Phoenix. In our sample, homes with masonry construction were generally made with concrete blocks finished with stucco, while non-masonry homes were made with wood frames and dry wall.

Survey data collection primarily occurred between May and August 2016. The survey was administered by an interviewer to one adult (at least 18 years of age) who was at home when the interviewer visited. The survey, which took on average 20 min to complete, contained questions about residents' experiences and perception of heat, limitations on cooling resources, thermal comfort and preference, AC usage in their homes, and demographic information. The minimum response rate (RR1) was 30.4% [41]. The study protocol was reviewed and approved by the Institutional Review Board at Arizona State University (study number 2831).

The data used in this article were collected from 46 individuals in the larger sample who agreed to participate in the subsequent multi-week data collection effort. Sampling for this phase of the project was purposive to maximize demographic variability. These participants ranged in age from 22 to 81, with a median age of 48. They predominantly identified as White (65%), Hispanic (26%), and Native American (11%). 59% of the participants identified as female and 41% identified as male. The household income for each of the participants ranged from below $20,000 to above $200,000, with a median of $60,000–$80,000. Most participants owned their home (80%). Compared to US Census ACS responses for the City of Phoenix, our sample underrepresents young adults, people that identify as Hispanic, and overrepresents older adults, females, and homeowners. The residences in our sample were comprised of single family, free standing buildings (70%) and low-rise multi-family buildings (30%). Based on parcel data from the City of Phoenix [42], 40% of the residences were built with masonry building materials and the remaining 60% were built with non-masonry materials. All but one household used central AC to cool their home during the summer and the household without central AC used window AC.

2.3. Indoor temperature monitoring

We used calibrated Onset Corporation HOBO Temperature/Relative Humidity 2.5% Data Loggers (UX100-011) to monitor the residential temperatures of 46 Phoenix households concurrently from August 21 to September 19, 2016, for a total of 30 days. One sensor in each household sampled air temperature and humidity at 5-min intervals; in total, we collected 397,440 observations of each variable. This manuscript exclusively examines the air temperature observations. The sensors were placed indoors in the room in which residents said they spent most of their waking hours. They were placed about 1.5 m above ground and away from AC vents, waste heat sources, and direct sunlight in a location that was amenable to the resident. As a result, in most cases, the sensor was located in the participants' living room or great room.

2.4. Temperature metric selection

Initial visual investigation of the time series plots of temperatures for each of the 46 households revealed distinct intra-household differences across the 4-week study period, as well as shared patterns among multiple households. Such differences were not initially anticipated because all homes reported using AC to cool their homes in the summer, which we expected to homogenize indoor conditions. To further understand the heterogeneity within and between individual homes, we used exploratory methods. Specifically, we selected temperature metrics that we determined were likely to explain some aspect of the patterns we observed and used these metrics to quantitatively cluster households into distinct groups. The metrics we selected were intended to be representative of recurring patterns we visually identified but were not necessarily a comprehensive set of all the possible metrics that may explain the data. In total, we calculated 19 different metrics from the 5-min indoor temperature observations to measure intra- and inter-household differences.

First, for each households' 5-min temperature observations, the mean and median were calculated to represent central tendency. Extreme temperatures were measured by calculating the mean of the daily maximum and daily minimum, where daily was defined as 00:00 MST to 23:59 MST. The mean of the daily minimum and maximums, rather than the minimums and maximums of all observations, were used because some households had single days with large extremes that were not representative of the extremes for the rest of the study period. While a single day of extreme heat exposure can be hazardous to the residents' health, our intention was to capture recurring patterns for the purposes of clustering. Several metrics were used to account for variation in indoor temperatures, including variance, the mean of the daily range (daily maximum minus the daily minimum), and the variances of the daily maximums and minimums.

It was also evident that the consistency of hourly and daily patterns varied considerably across households. To capture the observed (in) consistency, we calculated autocorrelation at various time lags. Prior to analysis, we detrended autocorrelation values because, in some cases, trends that spanned a large portion of the 4-week study period overrode the sub-daily patterns. It is our assessment that these trends were either related to a strong association with outdoor temperature change or an apparent regime shift in AC use—where it appears the residents made a decision to change their thermostat settings, though data concerning those decisions were not systematically collected to confirm our assessment. We de-trended the data using Seasonal and Trend decomposition using Loess (STL) with a periodic "seasonal" component of one 24-h period and trend calculated using loess smoothing with a window of 1.5 days [43] (see Supplementary Fig. 1 for an example). Autocorrelations were then calculated for the de-trended observations at 1-hr, 6-hr, 12-hr, 18-hr, and 24-hr time lags, and for the seasonal data at 1-hr, 6-hr, and 12-hr lags. The 1-hr autocorrelations were selected to detect differences among households in how smoothly the temperatures changed throughout the day. The 6-hr and 18-hr autocorrelations were selected to capture sub-daily patterns where homes consistently had two or more clear peaks and troughs within one day. The 12-hr autocorrelations detected diurnal signals where the home was clearly warmer in the afternoon and cooler at night. The 24-hr autocorrelation detected how similar the patterns were from day to day.

Lastly, it was apparent in some homes that indoor temperatures were partially related to outdoor temperature. Previous research has demonstrated such an association with outdoor temperatures, although the strength and magnitude is variable and prior studies have largely not accounted for the moderating effects of AC (e.g., [14,19]). We used two metrics to quantify this relationship: Pearson product-moment correlation of indoor temperature with outdoor temperature and the slope coefficient of an ordinary least squares (OLS) regression of 5-min indoor temperature on 5-min outdoor temperature. The correlation of indoor and outdoor temperatures indicated the strength of the relationship, while the slope indicated the magnitude of effect (i.e., the magnitude of indoor temperature change per 1 °C of outdoor temperature change). Outdoor temperature observations were obtained from Sky Harbor International Airport, a first order weather station located within the urban core of the City of Phoenix maintained by the National Weather Service.

2.5. Survey measures and building characteristics

In total, 33 survey and building variables were selected for analysis (Table 1). We used 20 variables from the 3HEAT survey that we hypothesized would modify each household's indoor thermal environment via the direct or indirect influence of those variables on AC use in the home (full survey questions and responses, see Supplementary Table 1). Since all 46 households reported using some form of AC to cool their home in the summer, AC (non-)use was considered the predominant potential influence on indoor temperature. Thus, the survey variables

Table 1
Survey variables and building characteristics derived from the 3HEAT survey (n = 46) and the City of Phoenix parcel database, including response scales to abbreviated versions of the questions. M = mean; SD = standard deviation.

Survey Question	Scale	*M*	*SD*
How air conditioning is used			
Use central air conditioning	0 (No) or 1 (Yes)	0.98	0.15
Use window air conditioning	0 (No) or 1 (Yes)	0.15	0.36
Program thermostat	0 (No) or 1 (Yes)	0.34	0.48
% of time air conditioning is on	0–100%	0.92	0.22
Time of use	0 (No) or 1 (Yes)	0.52	0.51
Limitations on air conditioning use			
Cost of electricity	4-point scale from 1 (Not at all limiting) to 4 (Very Limiting)	2.55	1.02
Cost of repairs	4-point scale from 1 (Not at all limiting) to 4 (Very Limiting)	2.14	1.17
Concerns about noise levels	4-point scale from 1 (Not at all limiting) to 4 (Very Limiting)	1.52	0.9
Concerns about causing a blackout	4-point scale from 1 (Not at all limiting) to 4 (Very Limiting)	1.89	1.08
Environmental concerns	4-point scale from 1 (Not at all limiting) to 4 (Very Limiting)	2.2	1.05
Medical concerns	4-point scale from 1 (Not at all limiting) to 4 (Very Limiting)	1.75	1.04
Pay own electric bill	0 (No) or 1 (Yes)	0.96	0.21
Set and preferred temperature			
Set temperature when awake at home	Open-ended numeric (°C)	26.01	1.48
Set temperature when asleep at home	Open-ended numeric (°C)	25.43	1.93
Ideal temperature	Open-ended numeric (°C)	24.92	1.7
Too hot temperature	Open-ended numeric (°C)	27.66	2.06
Household resources			
Own home	0 (No) or 1 (Yes)	0.78	0.42
Have enough food to eat	4-point scale from 1 (Often we don't have enough to eat) to 4 (We always have enough to eat and the kinds of food we want)	3.85	0.36
Household Income	11-point scale in $20,000 increments from 1 (below $20,000) to 11 ($200,000 and above)	4.35	2.63
Struggle to afford essentials	4-point scale from 0 (Never) to 3 (Often)	1.61	0.77
Heat Outcome			
Individual			
How often too hot in home	5-point scale from 1 (Never) to 5 (Very Often)	2.59	1.11
Left home because too hot	0 (No) or 1 (Yes)	0.35	0.48
Experienced heat illness	3-point scale from 0 (No), 1 (Yes, once), 2 (Yes, more than once)	0.59	0.83
Heat illness occurred in home	0 (No) or 1 (Yes)	0.11	0.31
Sought medical attention for heat illness	0 (No) or 1 (Yes)	0.07	0.25
Household			
Experienced heat illness	3-point scale from 0 (No), 1 (Yes, one person), 2 (Yes, more than one person)	0.65	0.85
Sought medical attention for heat illness	0 (No) or 1 (Yes)	0.09	0.28
Building characteristics			
Construction year	Numeric	1968.26	21.57
Building Size	Numeric (m^2)	143.52	59.26
Single family building (free-standing)	0 (No) or 1 (Yes)	0.7	0.47
Masonry construction (vs. non-masonry)	0 (No) or 1 (Yes)	0.43	0.5

**Note:* "Time of use" refers to participation in utility programs where cost of electricity varies during the day, usually most expensive during afternoon hours when electricity demand is highest. Household income currency is in United States dollars.

included questions from four categories: "How AC is used", "Limitations on central AC use", "Set and preferred temperature", and "Household resources." We postulated that the influence of household resources on AC use could be both direct (e.g., contributing to a household's ability to pay for electricity required to use AC and repair or replace faulty equipment) and indirect (e.g., ability to modify the quality of housing infrastructure, including insulation, AC efficiency, and other factors).

An additional seven heat-related health and comfort outcome variables from the 3HEAT survey were also selected ("Heat outcome"), including self-reported individual and household experience with heat illness and how often residents reported being too hot in their home. Finally, four variables related to the physical structure of the homes in the sample ("Building characteristics") were derived from the City of Phoenix parcel database: construction year, square footage, masonry vs. non-masonry construction material, and single family vs. multifamily building structure.

Some 3HEAT survey responses were incomplete. In total, there were 34 cases of missing data out of a possible 1380 responses (30 questions x 46 respondents). Two households were not given the option in the survey to respond to the questions asking about their limitations on AC use due to intentional skip patterns in the survey, accounting for 10 cases of missing data. One household only used window AC; the other household indicated their apartment complex had a chiller to cool the residence, which we recoded as having central air conditioning for subsequent analyses. Responses to the limitations questions were left as missing in the analysis for those two households. In the remaining 24 cases, we applied multiple imputation by fully conditional specification using predictive mean matching with 10 iterations [44]. To ensure imputed observations maintained the same relationship with dependent variables as the observed data, all independent and dependent variables previously selected for analysis from the 46 households were used in the imputation, including survey variables, building characteristics, cluster, temperature metrics, and temperature metric component scores [45].

2.6. Analysis

Our primary analyses consisted of cluster analysis and ANOVA. Given the lack of residential indoor temperature monitoring research, analytical techniques used in this article are largely exploratory and intended to broaden understanding of the nature of summertime indoor temperatures, particularly in households that report using AC. All analyses were conducted using R software (version 3.5.1).

First, a two-stage clustering technique was used to classify households into distinct groups, based on the 19 temperature metrics we calculated. Since many of the temperature metrics were highly correlated, with Pearson product moment correlation coefficients ranging from $r = -0.82$ to $r = 0.99$ (Supplementary Table 2), we used principal component analysis (PCA) with varimax rotation to reduce the data into uncorrelated components. The resulting component scores for each household were extracted and used as inputs in a K-means clustering algorithm, using Euclidean distances [46]. The algorithm was iterated 50 times before selecting the solution with the minimum within sum of squares. K-means clustering was selected over other clustering methods because it does not assume a hierarchical structure between the households' temperature observations, and we had no theoretical reason to believe there would be any hierarchical structure. Significant differences in responses to survey and building variables between clusters were assessed with a permutational one-way analysis of variance (ANOVA) using Euclidean distances, which is a robust, non-parametric technique [47]. Multinomial logistic regression would also be a suitable technique for data of the type we collected, but a larger sample size would have been needed for reasonable statistical power.

3. Results

3.1. Descriptive statistics for households and study sample

We observed high variability in indoor temperature metrics between, and in many cases within, study households (Fig. 1; Supplementary Table 2). Across the entire study period, the average indoor temperature in participating households was 26.4 °C, which was approximately 6 °C lower than the average outdoor temperature recorded during the same time period (32.1 °C), as measured at Sky Harbor airport. Indoor temperatures ranged from 16.5 to 37.2 °C, whereas outdoor temperatures ranged from 21.0 °C to 42.0 °C. The standard deviation for indoor temperatures (2.2 °C) was half of the standard deviation of outdoor temperatures (4.3 °C). Across all households in the sample, 5-min indoor temperatures increased by an average of 1.1 °C for every 10 °C change in 5-min outdoor temperatures.

3.2. Clustering households based on indoor temperature observations

3.2.1. Principal component analysis of temperature metrics

We clustered households based on principal components of the 19 indoor temperature metrics derived from the original observations. The Kaiser criterion of eigenvalues greater than 1.0, a clear break in the scree plot of components, and parallel analysis [48] all suggested retaining four components in the analysis. These four components together explained 84% of the variance of the original 19 metrics (Table 2).

The first component, which accounted for 23% of the variance, loaded strongly on metrics related to autocorrelation at 1-, 12-, and 24-h lags as well as the correlation between indoor and outdoor temperature. Households with high scores on this component generally have a high degree of predictability in indoor temperatures both from hour to hour and from day to day, where previous temperatures are strong predictors of future temperatures. These households tend to have more positive 24-h and 1-h autocorrelation, more negative 12-h autocorrelation, and large positive correlations with outdoor temperatures, indicating a strong diurnal cycle. For easier interpretation, this component was termed Predictability. The second component, which we termed Variability, accounted for 22% of the variance. Households with high scores on the second component have relatively variable temperatures. Average temperatures and average maximum and minimum temperatures load highly on the third component (accounting for 21% of the variance). Households with high scores on this component tend to have higher indoor temperatures, thus this component was termed Averages. The fourth component (Single Peak) loaded highly on metrics related to autocorrelation at 6- and 18-h autocorrelations and accounted for 18%

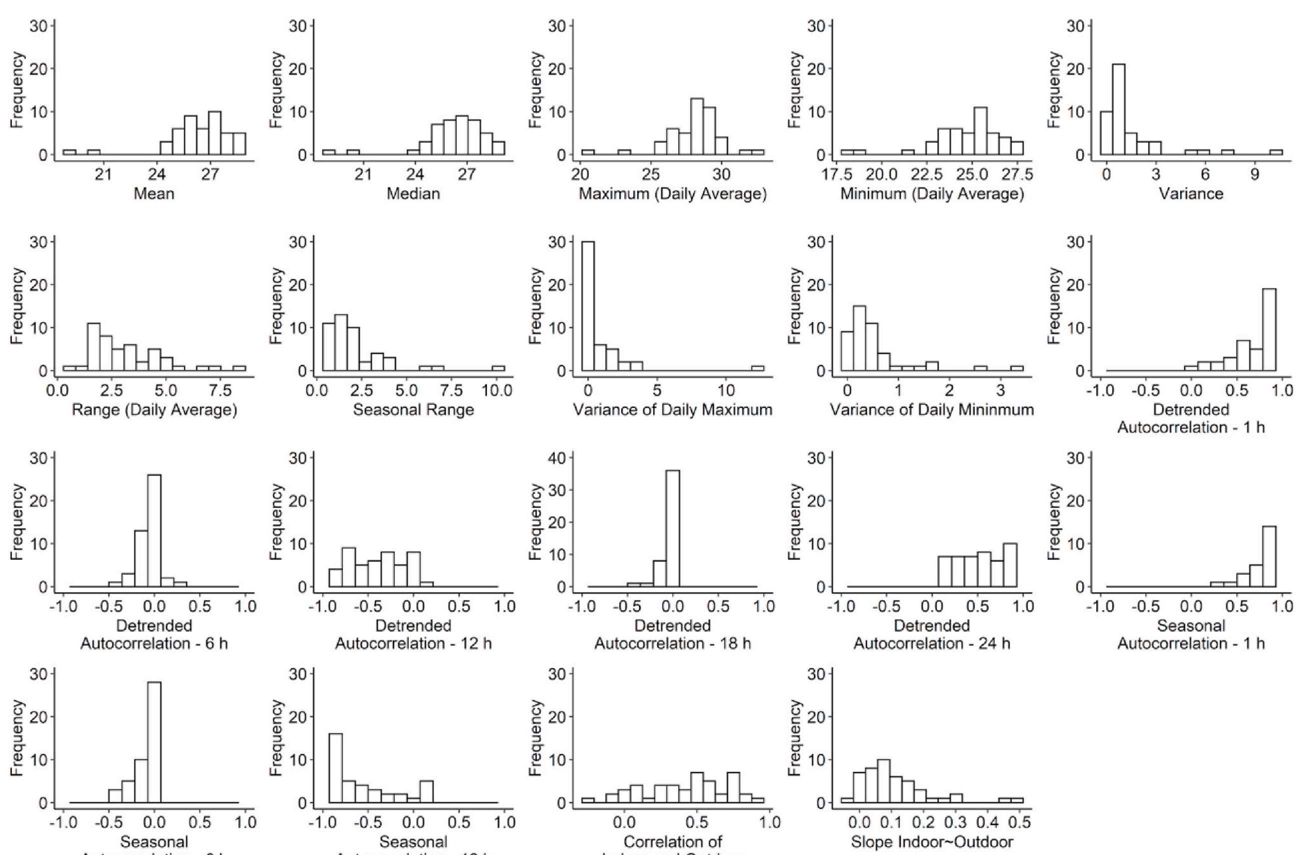

Fig. 1. Distribution of each indoor temperature metric by household (n = 46). Units are in °C where applicable.

Table 2
Rotated component (RC) loadings for the PCA of indoor temperature variables.

Rotated component loadings				
	RC1: Predictability	RC2: Variability	RC3: Averages	RC4: Single Peak
Correlation of Indoor and Outdoor	**0.88**	0.08	0.23	0.16
Detrended Autocorrelation - 1 h	**0.86**	0.15	−0.10	−0.07
Detrended Autocorrelation - 24 h	**0.85**	0.12	0.37	−0.16
Seasonal Autocorrelation - 1 h	**0.84**	0.08	−0.09	0.10
Detrended Autocorrelation - 12 h	**−0.76**	−0.08	−0.25	−0.53
Variance	0.15	**0.97**	−0.02	0.07
Range (Daily Average)	0.04	**0.92**	0.04	0.03
Seasonal Range	0.31	**0.89**	0.15	−0.12
Variance of Daily Maximum	−0.07	**0.75**	−0.16	−0.10
Slope Indoor ~ Outdoor	**0.60**	**0.69**	0.14	0.21
Variance of Daily Minimum	0.08	**0.52**	−0.09	0.37
Mean	0.07	−0.01	**0.99**	−0.04
Median	0.08	−0.05	**0.99**	−0.02
Maximum (Daily Average)	0.11	0.42	**0.89**	−0.05
Minimum (Daily Average)	0.08	−0.37	**0.87**	−0.07
Detrended Autocorrelation - 18 h	−0.11	0.06	0.02	**0.92**
Seasonal Autocorrelation - 6 h	0.12	−0.05	0.04	**0.91**
Detrended Autocorrelation - 6 h	0.04	0.05	−0.19	**0.80**
Seasonal Autocorrelation - 12 h	−0.58	−0.02	0.07	**−0.73**
Eigenvalue	4.41	4.25	3.90	3.43
Cumulative Variance	0.23	0.46	0.66	0.84

Note: Loadings > 0.5 are bolded.

of the variance. Households with high, positive scores tend to have one clear high temperature and low temperature occurring at a consistent time from day to day (e.g., early morning low temperature, and late afternoon high temperature), while households with negative scores tend to have multiple, consistently-timed, peaks in temperature throughout the day. For better illustration, example plots of homes that loaded highly on each component are available in Supplementary Fig. 2.

3.2.2. K-means clustering results

The scree plot of the within sum of squares values from the K-means clustering algorithm with component scores as inputs weakly suggested a five or six-cluster solution. Visual examination of 5-min indoor temperature observations plotted by cluster supported the selection of six clusters over a five-cluster solution. Each cluster has distinct patterns that differentiate it from the other clusters visually (Fig. 2A–F) and numerically (Table 3). Individual household temperature plots are also viewable in Supplementary Fig. 3.

Clusters are ordered from highest number of households to lowest, with the majority of households (36 of 46) falling into Clusters 1–3. For easier reference, each of the clusters was assigned a descriptive name based on its differentiating characteristics. Cluster 1 is characterized by comparatively high predictability as shown by the highly positive rotated component 1 (RC1) score, thus we have termed it High Predictability. Cluster 2 does not have any obvious distinguishing features except that it does not have any extreme variables in any of the metrics we used, so we called it Moderate. Cluster 3 scored highly negatively on RC1 (Predictability), so we called it Low Predictability. Cluster 4 scored most negatively on RC4, differentiating it as the cluster with multiple peaks within one day, so it is called Multiple Peaks. Cluster 5 is most strongly related to outdoor temperatures (average $r = 0.62$) and includes some of the highest means, maximums, and variances, scoring highly on both RC2 (Variability) and RC3 (Average), so we termed it Hot Extremes. Although Cluster 5 scored more highly on predictability than Cluster 1, the other features of Cluster 5 were so predominant that we chose to name Cluster 5 after those features instead and reserve High Predictability for Cluster 1. Cluster 6 is mostly distinguished by its low temperatures (mean of 19.9 °C compared to the overall sample mean of 26.4 °C), so we called it Cold.

3.3. Relating clusters to survey variables

Each cluster of households derived from the temperature metrics exhibited unique characteristics based on the survey variables and there were significant contrasts for some survey variables between clusters (Table 4).

3.3.1. Descriptive summaries of survey questions by cluster

Cluster 1 (High Predictability) (n = 15), had the largest number of homes in the sample, all but one of which were owned by the residents. Aside from Cluster 6 (Cold), these households were the least likely to be too hot in their home and the least likely to leave their home because they were too hot. Households in this cluster also had relatively low incidence of heat-related illness, though one household did report experiencing heat-related illness inside their home. The mean recorded temperature inside these homes was 1.8 °C above the residents' ideal temperature, but only 0.4 °C below the residents' too hot temperature—the lowest difference of any cluster. Residents of these homes reported relatively low limitations to central AC use.

In addition to having moderate indoor temperatures, households in Cluster 2 (Moderate) (n = 12), were also near the sample averages with respect to many survey variables save a few notable exceptions. This cluster had the second highest percentage of households participating in a program that adjusts the price of electricity cost based on time of use (67%) and the second highest overall limitations on AC use (average of 2.22 on a 4-point scale from 1, Not at all limiting, to 4, Very Limiting).

Cluster 3 (Low Predictability) (n = 9) was the only cluster in which all respondents reported using central AC 100% of the time during the summer to cool their home. Yet it was also one of the clusters with the highest occurrences of heat outcomes, including heat-related illness (occurred once, on average, in each household), leaving the home in the summer because it was too hot inside (78%), heat-related illness occurring inside their home (22%), and seeking medical attention for heat-related illness (33%). This cluster also reported the highest overall limitations on AC use (average of 2.30 on a 4-point scale from 1, Not at all limiting, to 4, Very Limiting) and home ownership was among the lowest of the clusters at 67%.

Cluster 4 (Multiple Peaks) (n = 4) had a high proportion of households that reported having and using a programmable thermostat (3 out of the 4), which may explain some of the "Multiple Peak" phenomena in

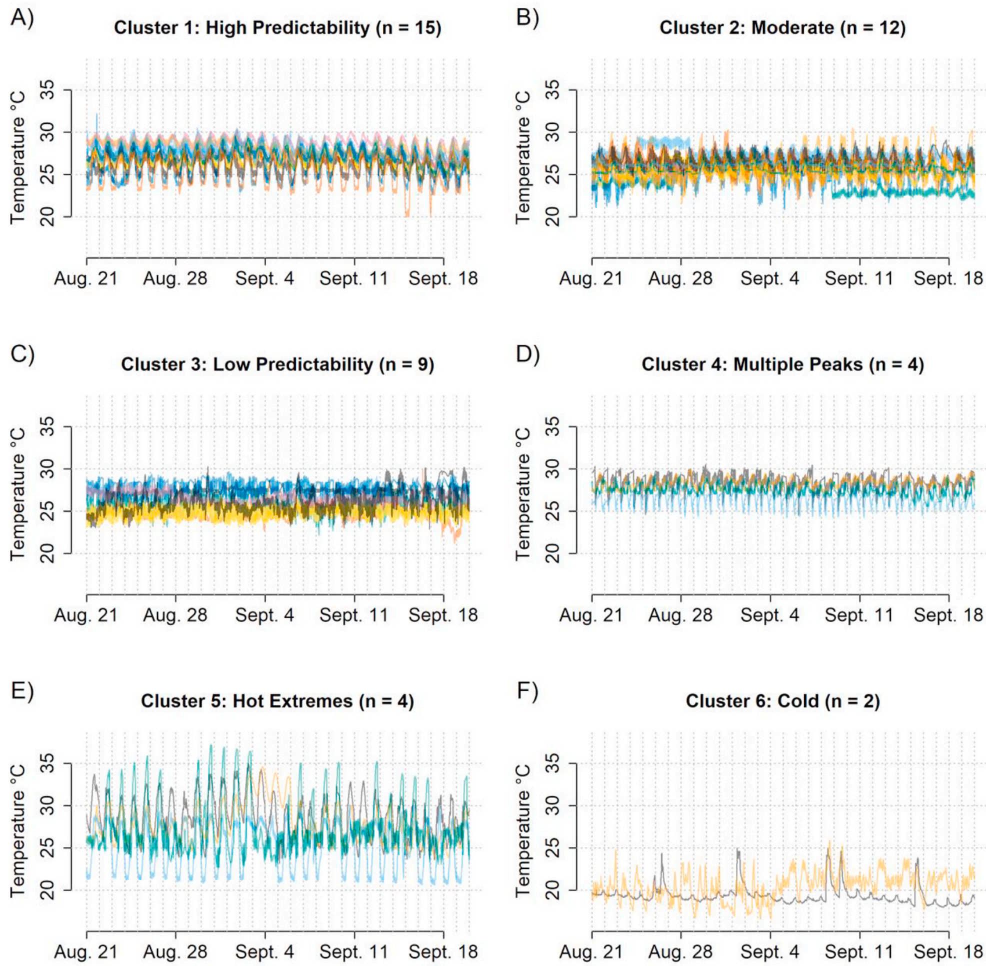

Fig. 2. (A–F): Five-minute indoor temperature observations plotted over the four-week study period (August 21, 2016–September 19, 2016) by cluster assignment. In each plot, individual households' temperatures are plotted with different color lines. Vertical gridlines are plotted at 12:00 a.m. for each day. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

this cluster. The peaks and troughs in each household did not necessarily occur at the same time across households, perhaps illustrating that temperature preference throughout the day is not universal. Household resources were much higher in this cluster than in others, with 100% home ownership and the highest household income (mean $80,000-$100,000 USD per year). Members of this cluster were among the least likely to leave their home because they were too hot and had the lowest incidence of individual heat-related illness, although the one individual reporting heat-related illness indicated that the illness had occurred inside their home.

Cluster 5 (Hot Extremes) (n = 4), reported the lowest limitations on using central AC (average of 1.67 on a 4-point scale from 1, Not at all limiting, to 4, Very Limiting), in spite of high temperatures that were on average 2.6 °C above the residents' ideal temperature (the highest difference of any cluster). Respondents in this cluster were the most likely to report being too hot in their home and struggle to afford essentials and the least likely to have enough food to eat. This cluster includes a couple unique cases that may in part explain some of the discontinuity when assessing this cluster in the aggregate. One household only used window AC and reported 'always' being too hot in their home and leaving their home because it was too hot. This household was also the only household in this cluster to not own their home and reported a household income of less than $20,000 (see household AS428 in Supplementary Fig. 3). In contrast, this cluster also includes a home that reports a household income of $160,000–180,000 that uses a programmable thermostat with a large difference in temperatures (daily average range of 7.5°C—see household AS418 in Supplementary Fig. 3). Both households have similar enough temperature patterns to be clustered together, but are likely very different in their ability to modify the indoor environment to their liking.

The two households in Cluster 6 (Cold) households (n = 2) were the coldest homes. The residents of these households reported the lowest preferred temperatures of the sample and the observed temperatures were well below their reported preference. These households were also among the lowest income earners in our sample, with annual household income levels below $40,000, and both households were renting in multifamily apartment complexes with relatively small living space (average 67.1 m^2). Aside from a preference for lower temperatures, these households also did not directly pay their own electric bill. Instead, electricity was included in their fixed monthly rental payment. While renting may be considered an indirect limitation on AC use (due to reduced ability to modify the home's infrastructure), it is clear in this case that with a well-functioning AC unit, small spaces to cool, and no variable costs tied to electricity use, the two households in this cluster appeared unrestricted in their AC use. This cluster includes the household that indicated their building used a chiller rather than central AC, which disqualified them from answering many central AC related questions. As a result, it is unknown if they had control over their thermostat. However, we sampled four other households from the same apartment complex in the initial survey (prior to temperature data collection) and they all indicated they had control over their thermostat, had central air conditioning, and did not pay their own electric bill. As

Table 3
Means of temperature metrics (°C) and varimax rotated component scores by cluster. Temperature metrics are organized under the component on which they loaded most highly, and in order of highest to lowest loading metric for the respective component.

	Cluster 1: High Predictability (n = 15)	Cluster 2: Moderate (n = 12)	Cluster 3: Low Predictability (n = 9)	Cluster 4: Multiple Peaks (n = 4)	Cluster 5: Hot Extremes (n = 4)	Cluster 6: Cold (n = 2)
RC1: Predictability Scores	**4.080**	**−0.761**	**−7.046**	**−1.999**	**6.380**	**−3.092**
Correlation of Indoor and Outdoor	0.682	0.410	0.006	0.340	0.623	0.165
Detrended Autocorrelation - 1 h	0.862	0.655	0.419	0.726	0.926	0.867
Seasonal Autocorrelation - 1 h	0.947	0.865	0.622	0.814	0.940	0.923
Detrended Autocorrelation - 24 h	0.736	0.433	0.221	0.660	0.743	0.162
Detrended Autocorrelation - 12 h	−0.693	−0.386	−0.084	−0.039	−0.648	−0.129
RC2: Variability Scores	**−0.090**	**−1.104**	**−2.960**	**−1.822**	**12.070**	**0.122**
Variance	1.031	1.062	0.559	0.542	7.425	1.871
Range (Daily Average)	2.843	2.793	2.742	2.874	6.813	3.108
Seasonal Range	2.185	1.544	1.097	2.263	6.641	1.235
Variance of Daily Maximum	0.393	0.804	0.455	0.113	4.437	2.577
Slope Indoor ~ Outdoor	0.152	0.082	0.000	0.056	0.381	0.049
Variance of Daily Minimum	0.426	0.506	0.303	0.160	1.757	0.863
RC3: Averages Scores	**2.216**	**−1.343**	**−1.192**	**2.914**	**2.658**	**−14.337**
Mean	27.121	25.855	26.208	27.753	27.277	19.884
Median	27.121	25.738	26.187	27.755	27.075	19.810
Maximum (Daily Average)	28.583	27.228	27.497	29.015	30.921	21.680
Minimum (Daily Average)	25.740	24.435	24.755	26.141	24.108	18.573
RC4: Single Peak Scores	**2.054**	**0.600**	**−1.939**	**−8.153**	**2.226**	**1.577**
Detrended Autocorrelation - 18 h	−0.025	−0.046	−0.028	−0.256	−0.030	−0.049
Seasonal Autocorrelation - 6 h	−0.032	−0.071	−0.130	−0.350	−0.086	−0.074
Detrended Autocorrelation - 6 h	−0.025	−0.041	−0.086	−0.286	−0.022	0.054
Seasonal Autocorrelation - 12 h	−0.895	−0.722	−0.229	−0.072	−0.784	−0.785

such, we believe it is most likely the respondent with missing data did have control over their thermostat.

3.3.2. *Permutational ANOVA results*

Of the 31 survey and building variables, eight were significantly different ($p < .05$) between clusters. With α = 0.95, we would have expected only one or two variables to be related to the clusters by random chance. Cluster explained significant variation among four survey questions related to thermostat set temperature and preferred temperature (R^2 values ranging from 0.359 to 0.525). Of the thermostat questions, set temperature when awake ($R^2 = 0.525, p = .002$) and ideal temperature ($R^2 = 0.455$, $p = .001$) varied the most by cluster. Among those variables, Cluster 4 (Multiple Peaks) and Cluster 6 (Cold) have the highest and lowest average set and preferred temperatures, respectively.

None of the questions related to AC use or limitations on AC use were significantly different between clusters, except for whether residents paid their own electric bill. As previously discussed, this was driven by the two households in Cluster 6 (Cold) not paying their electric bill. Thus, cluster completely explains the variation in ‘pay electric bill’ ($R^2 = 1.000$, $p = .002$) in our sample.

Of the household resource variables, only home ownership varied significantly by cluster ($R^2 = 0.242$, $p = .044$). At the extremes, no households in Cluster 6 (Cold) owned their homes and all households in Cluster 4 (Multiple Peaks) owned their homes. Household income did not vary significantly by cluster ($R^2 = 0.108$, $p = .436$). A sensitivity analysis revealed similar patterns at other scales of income and of income controlled by household size.

Heat outcomes do not appear to be well-explained by cluster. Cluster 3 (Low Predictability) was the only cluster in which households report seeking medical attention after experiencing heat-related illness (three out of the nine households), a response which was significantly explained by cluster ($R^2 = 0.287, p = .048$). However, incidence of heat-related illness, being too hot inside one’s home, and leaving home after becoming too hot did not vary significantly by cluster.

Among the building characteristics variables, only square footage varied significantly by cluster ($R^2 = 0.316, p = .004$). Homes in Cluster 6 (Cold) were the smallest by a wide margin, averaging 67.1 m^2. Four other clusters were close to the sample average of 143.5 m^2, and Cluster 4 (Multiple Peaks) had the largest homes (averaging 233.8 m^2).

4. Discussion

We analyzed residential indoor temperatures of 46 homes with AC in Phoenix, Arizona and examined relationships of these temperature observations with household survey data. As it becomes increasingly evident that the indoor environment plays a major role in understanding human heat exposure and associated risks, our work contributes to the growing body of research investigating the patterns and drivers of indoor temperatures using observational data. We quantified the variability between and within households and related that variability to both the characteristics of the people living in the households, and the heat-related health impacts they may have experienced as a result of the indoor temperatures. Though high variability existed between the households, we found some shared patterns that allowed us to cluster households into six distinct temperature profiles. Cluster was strongly related to thermostat set and preferred temperature, and was also

Table 4
Variables selected for analysis were taken from the 3HEAT survey (n = 46) and City of Phoenix parcel database. Abbreviated versions of the questions are shown along with the response scale, means, and standard deviations by cluster. The results of permutational ANOVA using Euclidean distances show which variables were significantly different by cluster.

Survey Question	Mean (Standard Deviation)						Permutational ANOVA of cluster membership	
	Cluster 1: High Predictability) (n = 15)	Cluster 2: Moderate (n = 12)	Cluster 3: Low Predictability (n = 9)	Cluster 4: Multiple Peaks (n = 4)	Cluster 5: Hot Extremes (n = 4)	Cluster 6: Cold (n = 2)	Psuedo-R^2	*P*
How air conditioning is used								
Use central air conditioning	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)	0.75 (0.50)	1.00 (0.00)	0.233	0.203
Use window air conditioning	0.00 (0.00)	0.17 (0.39)	0.33 (0.50)	0.00 (0.00)	0.50 (0.58)	0.00 (0.00)	0.214	0.065
Program thermostat	0.33 (0.49)	0.17 (0.39)	0.33 (0.50)	0.75 (0.50)	0.67 (0.58)	0.00 (NA)	0.149	0.250
% of time central air conditioning is on	0.87 (0.28)	0.96 (0.14)	1.00 (0.00)	0.72 (0.36)	1.00 (0.00)	1.00 (NA)	0.150	0.250
Time of use	0.53 (0.52)	0.67 (0.49)	0.56 (0.53)	0.50 (0.58)	0.25 (0.50)	0.00 (0.00)	0.096	0.530
Limitations on central air conditioning use								
Cost of electricity	2.47 (1.13)	2.67 (0.78)	2.78 (1.20)	2.50 (0.58)	2.33 (1.53)	1.00 (NA)	0.073	0.750
Cost of repair	1.80 (1.15)	2.58 (1.24)	2.00 (1.22)	2.50 (0.58)	2.33 (1.53)	1.00 (NA)	0.105	0.521
Noise concerns	1.33 (0.62)	2.00 (1.13)	1.56 (1.13)	1.25 (0.50)	1.00 (0.00)	1.00 (NA)	0.134	0.332
Blackout concerns	1.73 (1.10)	1.83 (1.03)	2.11 (1.27)	2.00 (0.82)	1.33 (0.58)	4.00 (NA)	0.124	0.397
Environmental concerns	2.00 (1.07)	2.50 (1.17)	2.11 (0.78)	2.25 (0.96)	2.00 (1.73)	3.00 (NA)	0.053	0.858
Medical concerns	1.73 (1.03)	1.75 (1.06)	2.00 (1.32)	2.00 (0.82)	1.00 (0.00)	1.00 (NA)	0.066	0.783
Pay own electric bill	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)	0.00 (0.00)	1.000	0.002**
Set and preferred temperature								
Set temperature when awake at home	25.89 (1.09)	26.16 (0.93)	25.86 (1.42)	27.78 (0.78)	26.11 (0.56)	20.00 (NA)	0.525	0.002**
Set temperature when asleep at home	25.26 (1.82)	25.51 (1.07)	26.24 (1.66)	26.95 (1.32)	23.33 (2.78)	20.00 (NA)	0.364	0.006**
Ideal temperature	25.37 (0.96)	24.40 (1.15)	25.06 (1.72)	26.81 (1.83)	24.73 (1.73)	20.55 (0.78)	0.455	0.001***
Too hot temperature	27.70 (1.69)	27.22 (1.71)	27.65 (1.35)	30.55 (1.92)	27.92 (2.88)	23.61 (0.40)	0.359	0.004**
Mean - Ideal temperature	1.75 (1.14)	1.46 (1.44)	1.15 (1.48)	0.95 (2.07)	2.56 (2.90)	−0.67 (0.01)	0.150	0.226
Mean - Too Hot temperature	−0.58 (1.80)	−1.37 (2.14)	−1.45 (1.26)	−2.80 (1.80)	−0.64 (3.30)	−3.73 (0.40)	0.168	0.189
Household resources								
Own home	0.93 (0.26)	0.75 (0.45)	0.67 (0.50)	1.00 (0.00)	0.75 (0.50)	0.00 (0.00)	0.242	0.044*
Have enough food to eat	3.87 (0.35)	3.83 (0.39)	3.89 (0.33)	4.00 (0.00)	3.50 (0.58)	4.00 (0.00)	0.109	0.423
Household Income	4.07 (2.71)	4.17 (2.21)	4.44 (2.19)	5.75 (1.50)	5.75 (4.99)	1.50 (0.71)	0.108	0.436
Struggle to afford essentials	1.53 (0.74)	1.67 (0.78)	1.67 (0.71)	1.25 (0.50)	2.00 (1.41)	1.50 (0.71)	0.048	0.856
Heat outcome								
Individual								
How often too hot in home	2.40 (0.74)	2.67 (1.23)	2.67 (1.12)	2.75 (0.50)	3.50 (1.91)	1.00 (0.00)	0.166	0.179
Left home because too hot	0.20 (0.41)	0.33 (0.49)	0.78 (0.44)	0.25 (0.50)	0.25 (0.50)	0.00 (0.00)	0.222	0.063
Experienced heat illness	0.33 (0.72)	0.58 (0.90)	1.00 (0.87)	0.25 (0.50)	0.75 (0.96)	1.00 (1.41)	0.109	0.446
Heat illness occurred in home	0.07 (0.26)	0.08 (0.29)	0.22 (0.44)	0.25 (0.50)	0.00 (0.00)	0.00 (0.00)	0.068	0.736
Sought medical attention for heat illness	0.00 (0.00)	0.00 (0.00)	0.33 (0.50)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.287	0.048*
Household								
Experienced heat illness	0.33 (0.72)	0.58 (0.90)	1.00 (0.87)	1.00 (0.82)	0.75 (0.96)	1.00 (1.41)	0.106	0.472

(continued on next page)

Table 4 (*continued*)

Survey Question	Mean (Standard Deviation)						Permutational ANOVA of cluster membership	
	Cluster 1: High Predictability) (n = 15)	Cluster 2: Moderate (n = 12)	Cluster 3: Low Predictability (n = 9)	Cluster 4: Multiple Peaks (n = 4)	Cluster 5: Hot Extremes (n = 4)	Cluster 6: Cold (n = 2)	Psuedo-R^2	P
Sought medical attention for heat illness	0.00 (0.00)	0.08 (0.29)	0.33 (0.50)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.201	0.112
Building characteristics								
Construction year	1970.93 (21.13)	1966.92 (20.35)	1967.22 (25.60)	1981.00 (24.39)	1950.00 (17.91)	1972.00 (0.00)	0.103	0.471
Building Size	150.35 (55.92)	127.02 (61.68)	139.52 (39.70)	233.81 (37.77)	124.35 (41.69)	67.08 (20.76)	0.316	0.004**
Single family building (free-standing)	0.80 (0.41)	0.50 (0.52)	0.67 (0.50)	1.00 (0.00)	1.00 (0.00)	0.00 (0.00)	0.240	0.062
Masonry construction (vs. non-masonry)	0.40 (0.51)	0.33 (0.49)	0.44 (0.53)	0.50 (0.58)	0.50 (0.58)	1.00 (0.00)	0.072	0.728

Note: "Time of use" refers to participation in utility programs where cost of electricity varies during the day, usually most expensive during afternoon hours when electricity demand is highest. Household income currency is in United States dollars. *$p \leq .05$, **$p \leq .01$, ***$p \leq .001$ indicate significant differences exist between clusters based on permutational ANOVA.

associated with home ownership and seeking medical attention for heat-related illness. We did not observe strong relationships between cluster and many other commonly cited risk factors in the environmental health and hazards literature (e.g., household income), and other measures of heat-health outcomes. We hypothesize that resource-constrained households may be prioritizing AC over other necessities because Phoenix is dangerously hot for most of the summer. An unusual situation existed in two households that were apparently completely unconstrained in AC use because they do not pay their own electric bill (Cluster 6 (Cold)) were by far the coldest homes in our sample.

4.1. Variability of indoor temperatures

A critical finding from this work is that even among a sample of air-conditioned homes (all but one of which used central AC), indoor temperatures were considerably heterogeneous. Heterogeneity of temperatures is a common finding in indoor residential temperature studies; however, we are among the first to investigate only homes that use AC. Tsoulou et al. [29] also observed considerably variable temperatures among a sample of air-conditioned residences, but homes in that study were primarily cooled via window air conditioners, which are likely not as effective at homogenizing temperatures as central AC. The heterogeneity in our sample was present among most of the temperature metrics that we used, including measures of central tendency, variability, and autocorrelation.

Autocorrelation proved to be a key variable in differentiating household temperatures and identifying sub-daily patterns, which were clearly observed in the clustering output. Homes with strongly negative 12-h autocorrelations exhibited obvious, consistent diurnal patterns. These were homes such as those in Cluster 5 (Hot Extremes) and Cluster 1 (High Predictability). Homes with relatively low 1-h autocorrelations were generally highly inconsistent, with more disordered appearing time series plots (such as those of Cluster 3 (Low Predictability)). To the best of our knowledge, no other indoor temperature research has investigated autocorrelation. Additionally, we noticed that in some cases, daily patterns would remain the same, but at some point in data collection, the mean temperature around which those patterns occurred would change. In some cases, this shift happened more gradually (likely a strong association with outdoor temperatures), while in other cases this shift happened abruptly (resident likely adjusted the thermostat to a different temperature). Even among homes with programmable thermostats, residents may often select a temperature they prefer and leave the thermostat at that temperature for long periods of time [49], which we believe is most likely what drove these abrupt shifts in temperature regimes. Without further data, such as a longitudinal survey or interview responses, it is unclear what motivations are driving the decision to change indoor temperatures over longer time periods in the manner we observed.

Similar to other studies, we found that indoor temperature and outdoor temperature were correlated. However, the strength of associations varied considerably between homes in our sample. Correlations ranged from −0.244 to 0.924, with a mean (SD) correlation of 0.421 (0.286). Slope coefficients ranged from −0.043 to 0.486, with a mean (SD) of 0.111 (0.113). Most other studies only report the indoor/outdoor correlation as an aggregate (rather than within-home as we have done), so we can only compare our average correlation, which is relatively low compared to previous work. Among a sample of 327 dwellings in New York City, Tamerius et al. [21] found indoor and outdoor temperatures were correlated ($r = 0.68$) during the summertime (AC presence was unknown). Garcia et al. [50] analyzed indoor/outdoor temperature relationships of homes in three U.S. states and found the correlations were quite different depending on geographic location ($r = 0.717$ in New Jersey, $r = 0.444$ in Texas, and $r = 0.639$ in California). Of the three states, Texas reported the highest percentage of homes using AC (60%) and had the most similar correlation with outdoor temperatures to the average of our Phoenix sample. Outdoor temperatures in Texas were also the most similar to outdoor temperatures in Phoenix during our study period. The low correlation, likely a result of high AC use, is important to consider when deciding how to appropriately address indoor heat exposure, especially in cities with high outdoor temperatures and high AC saturation like Phoenix. Other studies have shown that indoor temperature can be predicted by outdoor temperatures with high accuracy using more complex models and knowledge of building materials, however, these studies typically use data from homes with little to no AC or, when AC use is unknown, from geographic areas that generally have lower AC use [14,51,52].

4.2. Determinants and covariates of indoor temperature patterns

We identified six distinct clusters of households that shared similar temperature profiles during the study period. In a study by [53], K-means clustering was also employed for indoor temperature during the cold (heating) season. Their clustering algorithm, which used only mean and standard deviation, also resulted in six clusters, with the majority of homes falling into three of the six clusters—a similar result to this study. However, we found that other metrics besides mean and standard deviation played an important role in distinguishing the clusters. Many households in our sample had very similar means, but their temperature profiles were quite different. The heterogeneity of temperatures between households and the variety of temperature profiles between clusters indicate that presence of AC alone does not necessarily result in similarly cooled homes.

In general, the clusters were not well explained by social survey data related to household resources, AC use, and self-reported limitations on AC use, with two notable exceptions: home ownership and paying the electric bill. Of particular note, household income did not statistically significantly explain variations in cluster ($R^2 = 0.108$, $p = .436$). Similarly, Tamerius et al. [21] did not find income to be a significant predictor of indoor temperature during warm (cooling season) conditions, although their study did not have access to AC data. Our findings, and those of Tamerius et al. [21], are contrary to previous work that shows income is a significant contributing factor to indoor temperatures under cold (heating season) conditions [54,55]. In the outdoor environment, income is well-established as a strong predictor of outdoor summertime temperatures (largely due to the positive correlation with income and vegetation density), particularly in the southwest United States, where the topic has been studied extensively [9,56]. Thus, while we might expect income to play a role in the indoor environment as well, it does not appear to do so in our sample. Instead, cluster was well explained by set and preferred temperature variables, including household's set temperature when they were awake ($R^2 = 0.525$, $p = .002$), set temperature when they were asleep ($R^2 = 0.380$, $p = .01$), ideal temperature ($R^2 = 0.455$, $p = .001$), and temperature at which they became too hot inside ($R^2 = 0.359$, $p = .004$). Arguably, the set and preferred temperature variables are the most proximate to AC use, which we have postulated is the primary influence on indoor temperature in our sample.

The finding that temperature preference and comfort were clearly related to cluster while the relationships to other household resources were less clear, suggests that these temperature thresholds may supersede other concerns when deciding how to allocate household resources. The Residential Energy Consumption Survey (RECS) issued by the U.S. Energy Information Administration found that 20% of U.S. households reduce or go without food and medicine in order to pay energy bills [57]. We believe households in our sample may have made similar tradeoffs. During summertime in Phoenix, where temperatures are dangerously high for much of the year, the use of AC is essential for well-being and safety. Thus, residents may prioritize AC above other needs, and suffer the loss of other essential necessities. We did include survey measures that are intended to capture households financial well-being more generally (e.g., struggling to afford essentials, having enough food to eat), but we think future research needs to consider how financial well-being changes in relation to varying energy costs. While we did not see ample evidence of households' avoiding AC use altogether, a future study with a larger sample of resource-constrained households may find such patterns.

We did, however, see evidence of households using AC in abundance in the two households in Cluster 6 (Cold) that did not pay their own electric bill. These households were arguably completely unconstrained in their AC use, and had mean temperatures, on average, below their reported ideal temperatures. Among households that paid their own electric bill who told us they had no trouble affording essentials, there was still evidence of some restraint in the use of AC (presumably related to cost) as the mean temperatures were above ideal temperatures on average for all clusters except for Cluster 6. Our sample demonstrates that the relationship between income, temperature, and preference is not clear-cut, and the way energy cost factors into that relationship is important to consider.

Heat-related health outcomes were inconsistently related to cluster. Cluster only significantly explained whether residents sought medical attention for heat-related illness ($R^2 = 0.287$, $p = .048$). Cluster 1 (High Predictability) and Cluster 3 (Low Predictability) shared generally similar temperature metrics, except for metrics related to 'Predictability', yet households in each cluster reported different experiences with heat-related health outcomes. For example, Cluster 3 reported the highest percentage (78%) of respondents who left their home at some point in the summer because it was too hot, whereas only 20% in Cluster 1 reported the same. Cluster 3 also had the higher percentage of people experiencing heat illness in their home: 22% vs. 7% in Cluster 1. It seems possible that predictability/consistency of indoor temperatures may have some relationship to thermal comfort. Cluster 3 has the lowest values for 1-h autocorrelations, indicating an unpredictable shift in temperatures throughout the day, while Cluster 1 has some of the highest 1-h autocorrelations. Additionally, of all the clusters, Cluster 5 (Hot Extremes) would appear to be the most likely to experience heat-related health outcomes due to indoor conditions, yet this is not the case. No members of Cluster 5 ever experienced heat-related illness indoors and only one of the four households in Cluster 5 reported leaving their home because it was too hot. However, Cluster 5 did report the highest frequency of being too hot in their home, averaging between sometimes and often.

4.3. Study design and future research

This study uniquely focused only on homes that report using AC in the summer to cool their homes in a hot city. We have added geographic and climatic breadth to the literature by focusing on a hot city with high AC saturation. An accompanying social survey that collected both demographic data and data about how people use AC allowed us to shift the focus from physical building characteristics, to occupant characteristics and behaviors in understanding indoor residential temperatures. We collected temperature data at a high temporal resolution (5-min samples) which were recorded concurrently in each home for 4 weeks. High temporal resolution allowed us to elucidate sub-daily patterns that may be drivers of indoor thermal comfort, which would not have been possible with lower resolution observations.

This study was limited by several factors. First, we did not have sufficient occupancy data to indicate to what extent residents were exposed to the indoor temperatures we observed. However, national surveys have shown that people spend about 69% of their time at home [12], therefore, it is likely that our indoor measurements capture a significant portion of people's exposure. Additionally, while we asked residents to place the temperature sensor in the room in which they spent most of the waking hours, temperatures can vary significantly between rooms, so we may be missing some of the picture by using only one sensor. We also did not have any information on the age or quality of the residents' AC system or data related to the strength of insulation and efficiency of the building overall. Additionally, interpretability of our statistical tests is limited by the small sample size. We also did not measure any component of the radiant environment (i.e., short and longwave radiation) that has been shown to be an important determinant of thermal comfort both outdoors and indoors. Particularly in poorly insulated buildings, the radiant environment can vary significantly more than air temperature alone [58,59]. However, in our study, there was no significant correlation between indoor comfort (being too hot inside the home)—which should be reflective of the total thermal environment and not simply air temperature—and household income (a likely corollary to quality of building structure). We additionally did not control for confounding among the household features, and it is possible that negative confounding could be obscuring associations in our uncontrolled models.

5. Conclusion

Heat mortality statistics clearly indicate that the indoor residential environment plays a key role in influencing people's personal heat exposure during the summer. Phoenix, Arizona experiences dangerously hot summertime temperatures every year, where the most effective and widespread cooling strategy indoors is the use of AC. Our measurements of indoor temperatures in air-conditioned homes in Phoenix demonstrated that presence of AC alone did not homogenize temperatures. Using survey responses, we found that thermal preference, not limitations on AC use or income, was the strongest driver of indoor temperature profiles. Our findings indicate households that report difficulty affording essentials still find ways to keep their homes cool in the summer, suggesting that AC costs make it even more difficult to obtain medication, food, internet/phone connectivity, and other needs. Future work and policymakers should consider that lower-income households are likely burdened by heat, even if they are able to keep their indoor temperatures livable. We recommend future research into how people allocate their resources when prioritizing keeping a livable temperature inside their homes during dangerously hot summertime temperatures.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2020.107187.

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