Degrees of desire: Household preferences are key determinants of indoor temperatures in Phoenix

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INTRODUCTION

Heat mitigation and adaptation strategies are generally focused on outdoor thermal conditions, yet in the developed world, heat-related discomfort, injuries, and death often occur due to indoor heat exposure within private residences. Previous studies characterizing the indoor residential thermal environment mainly examine its relationship to physical factors, such as outdoor temperature, radiation, and building construction (e.g. material, orientation, window placement). Yet little attention has been paid to social and behavioral factors that may account for significant variance in indoor conditions within and between households, including access to and use of cooling resources, constraints on these resources, thermal preference, and demographic variables.

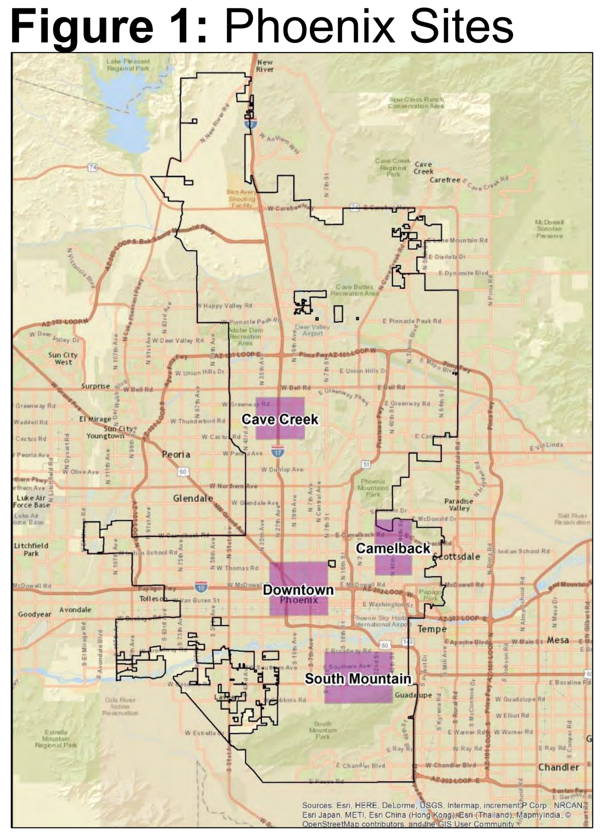
MATERIALS AND METHODS

3HEAT Project:
3HEAT is an NSF-supported interdisciplinary collaboration between researchers at Arizona State University, Georgia Tech, and University of Michigan (NSF SES-1520803).

Phoenix heat survey:
Using stratified random sampling, we conducted 163 door-to-door surveys in the summer of 2016 asking Phoenix residents about:

1. *Access to and use of cooling resources*
2. *Constraints on cooling resources*
3. *Thermal preference*
4. *Demographics*

Figure 1: Phoenix Sites

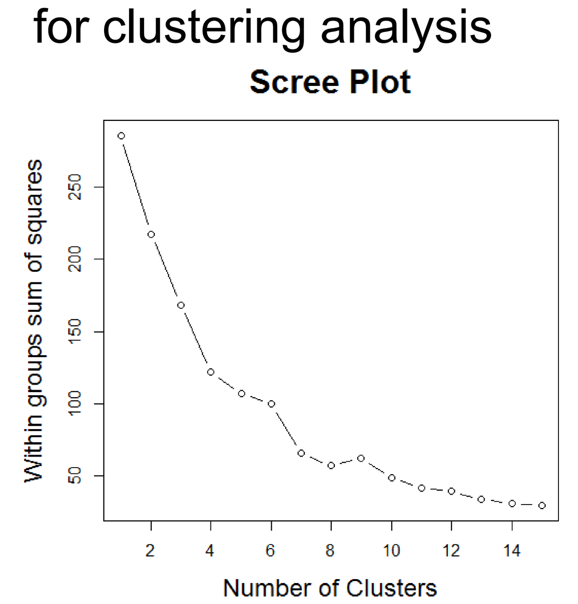


Temperature observations:
In a subset of 46 households, we continuously monitored indoor temperature and humidity for four weeks (8/21/16 – 9/19/16).

Figure 2: HOBO UX100-011 Temperature & Relative Humidity Sensor

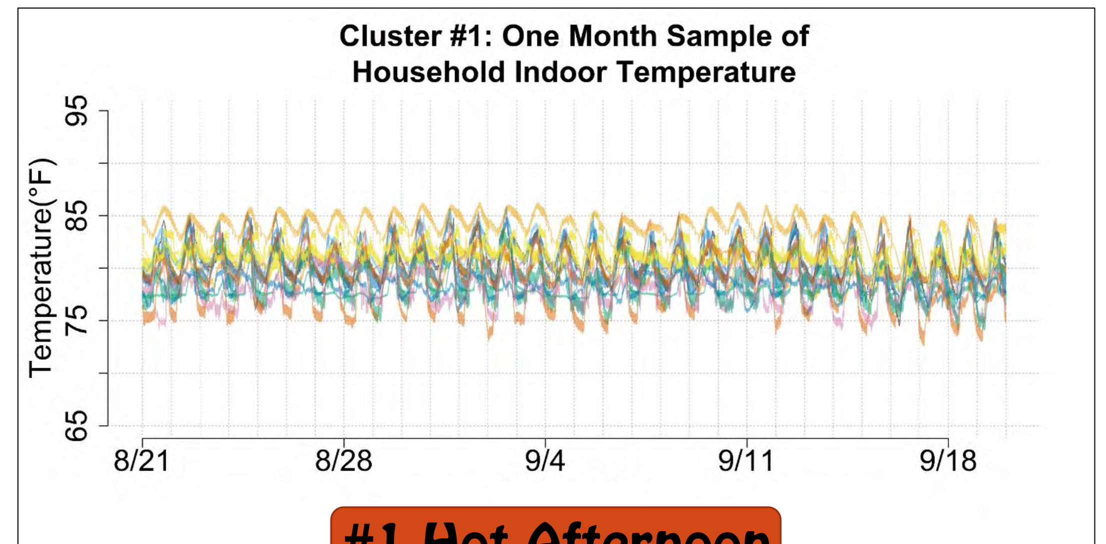
Cluster Analysis:
We clustered households based on seven metrics describing the five-minute indoor temperature observations: mean, range, variance, and autocorrelation at four time steps (1, 6, 12, 24h). The clustering procedure used four principal components that explained 90% of the variance in the original data set and a k-means nonhierarchical clustering algorithm. We selected a solution with five clusters based on visual examination of a scree plot.

Figure 3: Scree plot used for clustering analysis

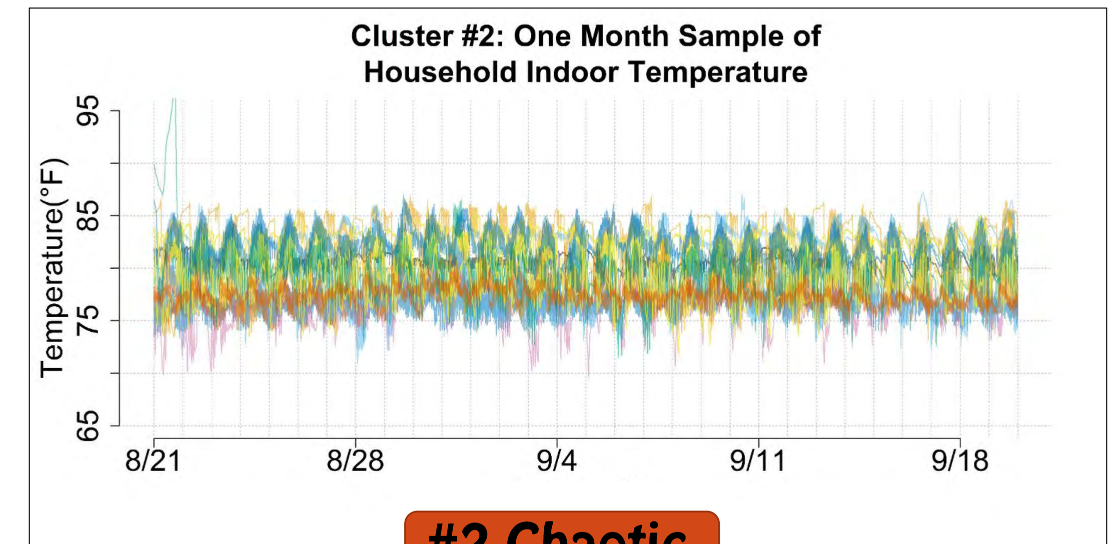


Hypothesis: Survey variables related to access to, use, and constraints on cooling resources will explain indoor temperature profiles.

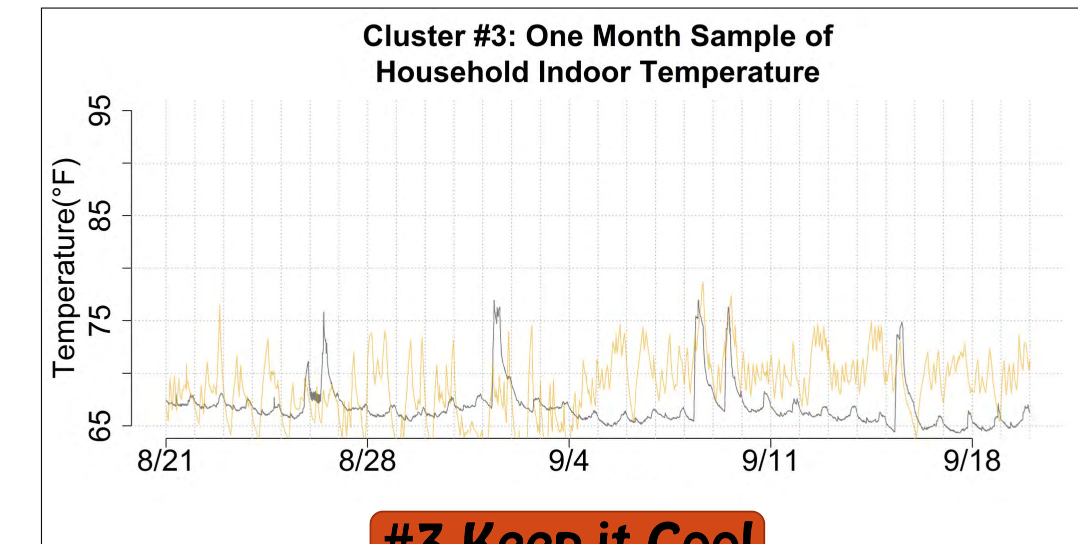
RESULTS



#1 Hot Afternoon



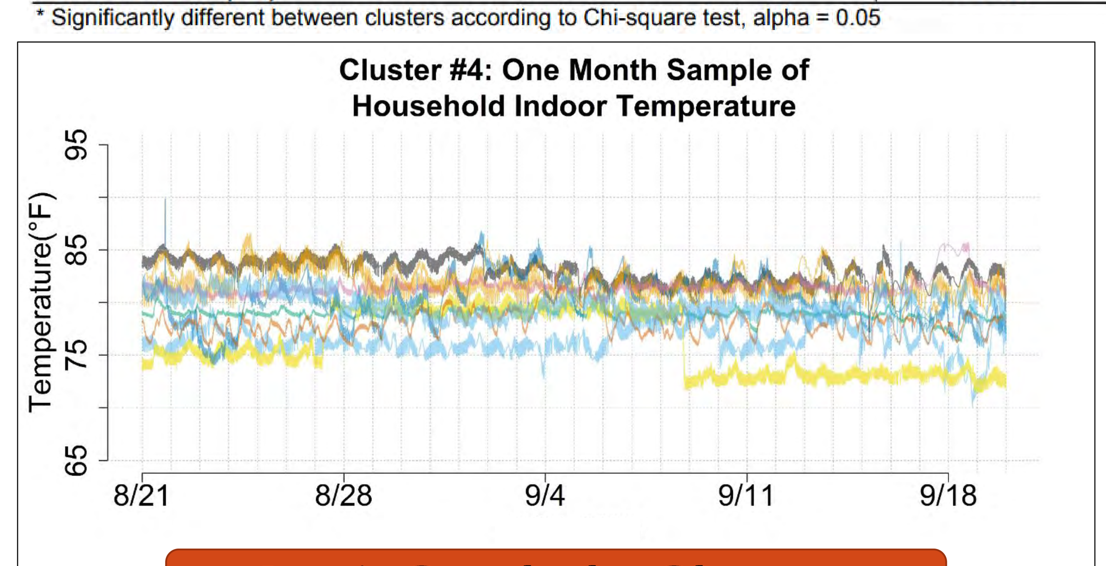
#2 Chaotic



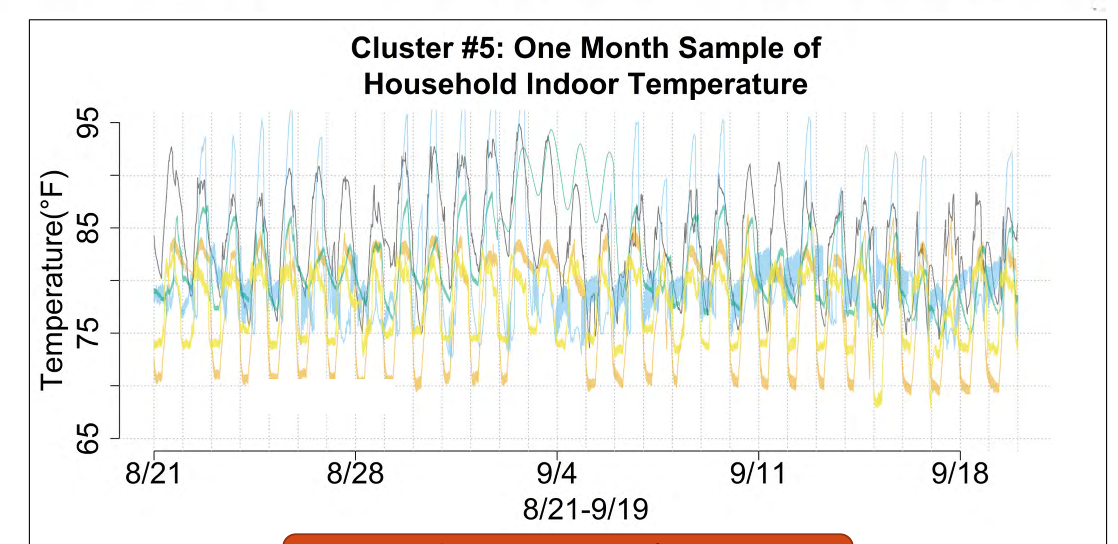
#3 Keep it Cool

	1. Hot Afternoon (n=15)	2. Chaotic (n=14)	3. Keep it Cool (n=2)	4. Don't Touch the Thermostat (n=10)	5. It Gets Hot in Here (n=5)	ALL (n=46)
* Renting (%)	7%	21%	100%	30%	0%	20%
* Cost of electricity limiting? (mode)	Somewhat	Somewhat	Not at all	Somewhat	Very	Somewhat
Do you program your thermostat?	40%	29%	0%	40%	60%	33%
* Participate in "time of use" program? (%)	73%	50%	0%	50%	20%	52%
* Are you ever too hot inside your home? (mode)	Sometimes	Sometimes	Never	Sometimes	Often	Sometimes
Have you ever left home because it was too hot?	40%	43%	0%	30%	20%	35%
Total combined household income? (median)	$60 - 80k	$40 - 60k	$20k	$60 - 80k	$20 - 40k	$60 - 80k
Non-white (%)	27%	57%	50%	10%	40%	35%

* Significantly different between clusters according to Chi-square test, alpha = 0.05



#4 Don't Touch the Thermostat



#5 It Gets Hot in Here

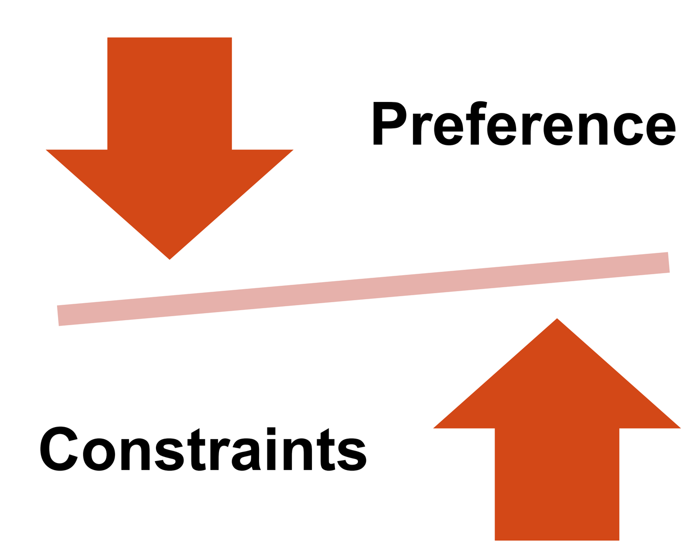
1. Hot Afternoon
   - High time of use participation
   - Most work full-time, some retired
   - Suffer in heat for savings?
2. Chaotic
   - Most affected by heat-related illness
   - Majority female, retired
   - Feel they can ask neighbors for help
3. Keep it Cool
   - Low income renters
   - Landlord pays electric bill
4. Don't Touch the Thermostat
   - Feel like they can't ask neighbors for help
   - Work outside more than other clusters
5. It Gets Hot in Here
   - Often too hot inside their home
   - Cost of electricity is very limiting

Spearman's Rank Bivariate Correlation Coefficients: Survey Questions and Indoor Temperature

Question		n	Mean	Maximum	Minimum	Standard deviation	Duration and severity above "too hot"
Ideal comfortable temperature [indoors]?	[open-ended numeric, degrees Fahrenheit] mean: 77.2, SD: 2.59	44	0.32*	0.35*	0.22	0	-0.35*
When it comes to air conditioning, the cost of electricity is…	[4] Very limiting (18%) [3] Somewhat limiting (39%) [2] Not too limiting (23%) [1] Not at all limiting (16%)	42	0.09	0.06	-0.06	0.31*	0
Household Income	[11 pt. scale] median: $60,000-80,000	38	0.05	-0.07	0.33*	-0.35*	-0.36*
Struggle to afford essentials?	[0] Never (55%) [1] Rarely (32%) [2] Sometimes (11%) [3] Often (2%)	44	-0.18	-0.08	-0.32*	0.31*	0.15
White	[1] yes (66%) [0] no (34%)	44	0.01	-0.23	0.2	-0.43**	0.14
Hispanic/Latino	[1] yes (27%) [0] no (73%)	44	0.05	0.2	-0.06	0.34*	-0.12

* p < 0.05, ** p < 0.01

Developing a framework for behavioral drivers of indoor temperature:



- We hypothesize that indoor residential temperature explained by behavioral factors is some combination of cooling constraints and temperature preference
- A highly constrained household is less likely to keep their home comfortable
- If a highly constrained household's home is comfortable, they are likely sacrificing on other essentials

CONCLUSION

Indoor temperatures in these 46 Phoenix households exhibit significant between-home variations. Nevertheless, some shared features in temperature profiles became apparent by using clustering techniques. Deeper understanding of the household-scale circumstances and behaviors clarifies drivers of indoor temperature variability not easily captured by simple demographic indicators. Reported ideal temperature, for instance, was the only survey question in our study that was significantly correlated with mean and maximum indoor temperature. In the hot summer climate of Phoenix, air conditioning may be valued more than other necessities, such that maintaining a temperature close to ideal is prioritized. Thus, we propose a framework for explaining indoor temperature variation due to behavioral factors (e.g. setting the thermostat) that acknowledges the balance between preference and constraints that residents must take into account.

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