Poster Abstract: Homeowner Preference Elicitation - A Multi-Method Comparison

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ABSTRACT

Future smart homes are expected to satisfy homeowners by acting on their behalf through personalized adaptation to their preferences. It is important to understand how individuals' preferences vary, what occupants consider "ideal" and how they value tradeoffs between costs and benefits of home services. In this poster, we present three models of human preference capable of evaluating the utility of a home outcome and generating a unique, personalized score. Using these, a home energy management system (HEMS) can identify the outcome evaluated as best by homeowners. We discuss an online survey method, results, and comparison between three methods in terms of their preference prediction accuracy, time to complete, and participant usability.

1. INTRODUCTION

Homeowners' preferences vary across the population and change over time. Some occupants value a hot shower above all else; others may be willing to reduce the water temperature or shorten a shower occasionally to save money. With a deep understanding of occupant preferences, the HEMS can on the homeowner's behalf and simplify occupant engagement. **We believe this is necessary for mass-market acceptance of home automation.**

We studied methods for eliciting occupant preferences, with a focus on cases Which require insights about incommensurate multi-criterion tradeoffs between home air temperature, shower temperature and length, status of laundry and dishes, as well as financial and environmental costs. While machine learning algorithms can potentially predict desired appliance settings, acting on behalf of occupants in out-of-sample situations requires a preference-based behavioral model. Very little prior research exists on this topic, particularly with regards to multi-attribute decision problems (see [8] for a recent exception). Appliance scheduling, given a known utility function, has been studied [2, 9] but identifying that utility function is typically unaddressed. Therefore, we borrowed methods from other fields and explored their applicability to our challenge.

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2. METHODOLOGY

Three preference elicitation methods appeared potentially useful for our HEMS use case. For each, we conducted surveys using Amazon Mechanical Turk (AMT) to assess these methods. AMT provides a low-cost, high-volume subject pool, comparable to the University population typically used for academic research [1], for surveys and cognitive experiments online. While these demographics are not representative of the United States overall, they may be representative of potential "early adopters" of smart home technologies. For each method of interest, we surveyed 1,000 people.

2.1 Analytic Hierarchy Process (AHP)

Via pairwise comparisons using a pre-determined scale, AHP seeks users' input on decision-making within a structured hierarchy of goal, criteria, and alternatives as shown in Figure 1. Responses are used to calculate local and global priorities and rank the alternatives that cater to the overall objective, while satisfying different criteria [6, 7]. For our survey, each respondent was asked 45 questions to determine their operational preferences.

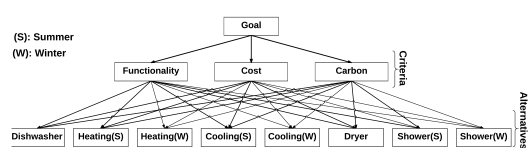

Figure 1: AHP hierarchy.

2.2 Discrete Choice Modeling (DCM)

In DCM, individuals must rank a finite set of alternatives from most to least desirable, within a series of choice situations. A hypothesized utility function's parameters can then be estimated. We used a procedure from [5] to fit respondents' preferences to the following utility model:

$$
\begin{aligned}
U_i = &\beta_{i,m}M + \beta_{i,c}C + d_{i,d}D + d_{i,l}L + \beta_{i,sl}S_l \\
&+ \beta_{i,st}S_t + \beta_{i,t}A_t^2 + \beta_{i,tn}I_{A_t<0}A_t^2 + \epsilon_i
\end{aligned}
\tag{1}
$$

where, for the home's planning horizon, M is operating cost, C is carbon emissions (environmental impact), D indicates if dishes are done when needed, L indicates if laundry is done when needed, S_l, S_t are shower length and temperature respectively, A_t is air temperature relative to the preferred set point, and I_{A_t} is one if air temperature is below the set point and zero otherwise.

	Best			Worst
Money	Average	Spend $2.50 Extra	Spend $2.50 Extra	Spend $2.50 Extra
Carbon	Average	Emit 20% more (about 12 lbs of CO_2)	Emit 20% more (about 12 lbs of CO_2)	Emit 20% more (about 12 lbs of CO_2)
Air Temperature	Ideal	2°F too warm	2°F too cold	Ideal
Shower	Half Length	Perfect	Perfect	Half Length
Dishes	Dirty	Clean	Clean	Clean
Laundry	Clean	Dirty	Dirty	Dirty

Figure 2: A DCM discrete choice ordering question.

2.3 Simple Multi-Attribute Rating Technique Exploiting Ranks (SMARTER)

SMARTER was developed to quickly create a decision model [3]. SMARTER avoids other processes' most cognitively difficult task of weighting attributes relative to each other. Rather than ask individuals enough questions to quantify how much attribute A is preferred to B, individuals simply rank the attributes, and weights are inferred. The authors claim "In short, when [surrogate] weights don't pick the best option, the one they do pick isn't too bad" [3]. SMARTER uses the utility form shown in (1). Participants were guided to define their own personal temperature sensitivity curve such as Figure 3. Similar methods explored other outcome variables. Finally, participants ranked home services, such as Figure 4, to indicate relative preferences.

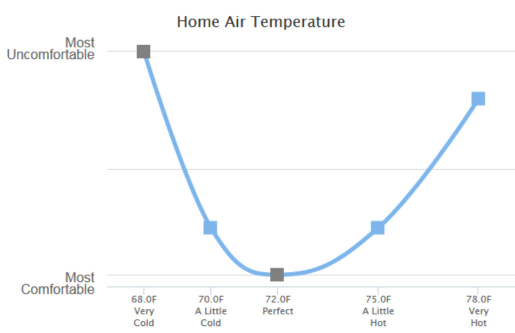

Figure 3: Temp sensitivity from SMARTER.

3. RESULTS

A longitudinal AMT survey of 250 randomly-selected participants was used to objectively measure each method's predictive ability. Table 1 shows the resulting predictive ability, time to complete the survey, and usability score as defined per the IBM "after-survey questionnaire" (ASQ) method [4]. Based on these results we found the SMARTER method most compelling for our use case.

Worst Daily Outcome		Best Daily Outcome
Too Cold	Shower Temperature	Perfect Temperature
Dirty Clothes (you wash what you need by hand)	Clothes that are Clean and Dry When You Need Them	Clean
Only 5 minutes	Shower Length	Average Length (20 minutes)
68°F During the Day	Comfortable Air Temperature in Your House	72°F During the Day
Dirty Dishes (you wash what you need by hand)	Dishes that are Clean When You Need Them	Clean
Emit 20% More Carbon (emit about 12 lbs more CO_2)	Lowering Your Environmental Impact	Emit an Average Amount
Spend $2.00 more	Saving Money	Spend an Average Amount

Figure 4: A preference ranking question from SMARTER survey.

Table 1: Preference elicitation method comparison

Method	Percent Correctly Predicted	Average Completion Time (min)	Ave. Usability Score* (1-7 scale)
AHP	49.0%	9.0	**2.48**
DCM	68.0%	5.7	2.57
SMARTER	**72.2%**	**5.5**	2.53

* lower scores are better

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