# *Quantified Cognitive Empathy* Improves Sustainable Design


IRIS DESIGN LAB

PI: Erin MacDonald

Co-PIs: Maria Yang (MIT)
John Duchi (Stanford)
W. Ross Morrow (Former PI) (Ford)

Graduate Students: Mike Erikson, Ping Du
Undergraduate Student: Kelley Gomez
Postdoctoral Researcher: Le Chen

Design
Mechanical Engineering
Stanford


Scan this code to see a Mix of our work.

***Quantified Cognitive Empathy*** **allows us to include human-centered design in mathematical models of products *and* statistically test hypotheses in test vs. control experiments.**

**By injecting perspective-taking into models, we can represent how people will prefer and react to cognitively complex product purchase, use, and involvement decisions.**

**Decisions about sustainable products and technologies are cognitively-complex decisions. People need to weigh distant concerns along with everyday concerns during product interactions.**

## Consideration, Design and Energy Policy (#1334764) with Former PI W. Ross Morrow

### Motivation

Creating a sustainable vehicle fleet is necessary to maintain the global ecosystem. Engineering a vehicle is a multidisciplinary process that includes engineers, politicians, and marketers.

Current marketing models are incomplete in that they do not represent consideration behaviors. Consideration is a non-compensatory decision process in which a deficit in a particular product feature cannot be compensated by outstanding performance in another. For example, a consumer may exclude any vehicles that are over-budget, regardless of the attractiveness of other features. The figure below illustrates an example of consider-then-choose being applied to a vehicle.

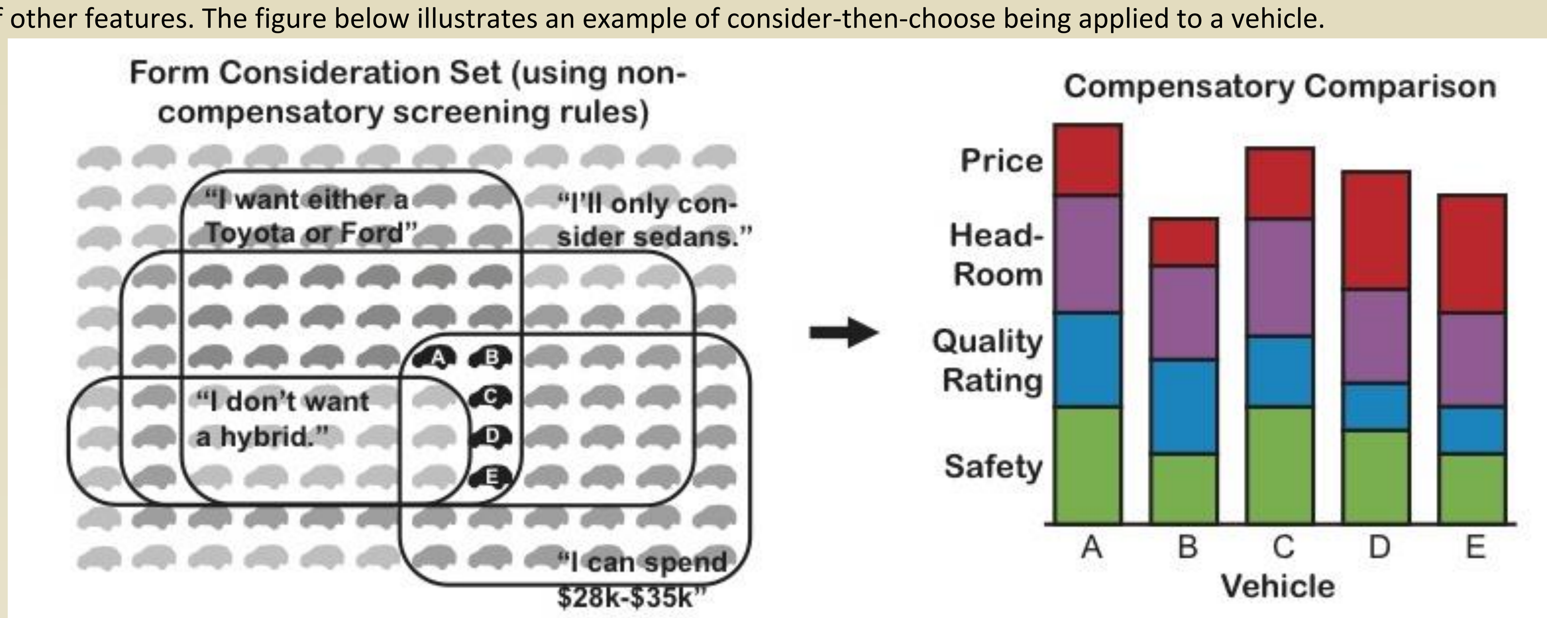


Figure 1: Illustration of consider-then-choose process for new vehicle purchase. Screening rules eliminate all but 5 vehicles (in black, A-E).

### Outcomes

This grant has supported two peer-reviewed papers [1][2], two working papers [3][4], and one workshop. These papers have confirmed that modeling considerations can impact designs by

1) Improving predictive accuracy
2) Enhancing profitability
3) Introducing realistic feature diversity

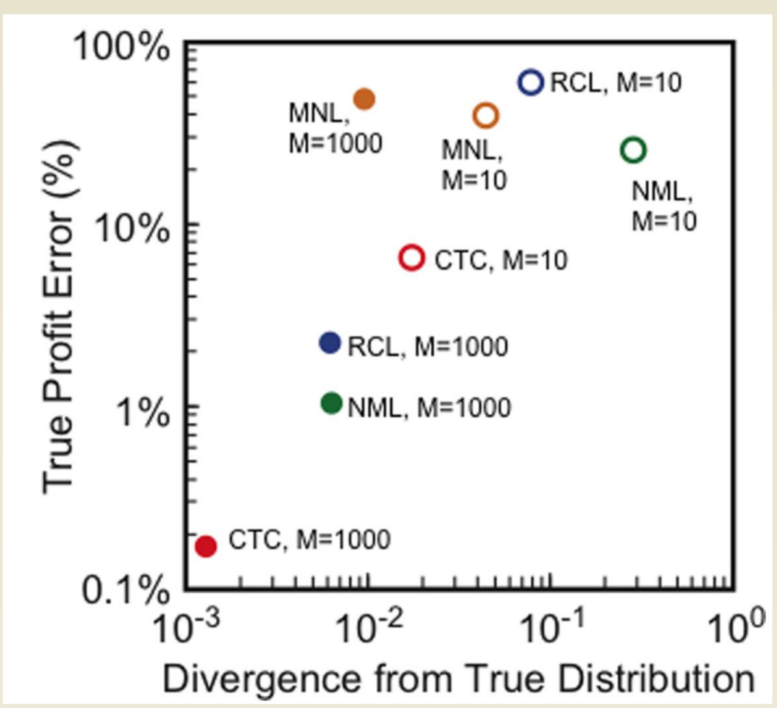


Figure 2. Profit error vs. KLD for each model, averaged over trials. Complete recovery of ideal profit yields 0% error, while zero profit yields 100% error.

**Should Optimal Designers Worry About Consideration? [1]**

A simulation with market-based synthetic data compares consider-then-choose (CTC) models and compensatory models in a vehicle design process. The compensatory models included are: multinomial logit (MNL), nested multinomial logit (NML), and random coefficients logit (RCL).

The paper concludes that:

- Modeling consideration is worthwhile even though compensatory models can approximate consideration
- Consideration has high accuracy in both predictive power and profitability

(see the figure to the right, large market size M=1000, and small market size M =10)

**Market-System Design with Consider-Then-Choose Models [2]**

Including consideration models in optimization is difficult due to discontinuities at feature cut-offs. This research provides three treatments to this numerical challenge: complementarity constraints, smoothing functions, and genetic algorithms. To guide the choice of numerical tools for future design optimization practices, the paper documents insight performance evaluations of these methods in optimality, feasibility, and computation burden.

**Complex Choice Behaviors and Transportation Energy Policy Conference**

Scan here to see spreadsheets of resources recommended by workshop attendees.

43 leaders from academia, government, and industry met for three days to discuss the future of behavior modeling in transportation research and policy. The attendees identified the following needs:

- Improved communication between model stakeholders
- Standard model verification methods
- Increased attention to foreign economies.

The conference resulted in a working manuscript available upon request [3].


Figure 3. Word diagram of participant survey responses.

## EAGER: Using Learning Algorithms to Morph Product Behavior for Specific Task Contexts and Cognitive Styles of Users (#1548234), with Co-PI John Duchi

### Motivation

Smart products use automated, sensor-guided behavior to learn user interaction patterns and then self-program. Users have installed the smart Nest Thermostat in their homes to successfully reduce energy consumption. But a smart product has limitations: it does not know one user's personality from another; and cannot understand that different users want different design configurations in the same circumstance.

### Objectives

Create a design method that uses behavior-predicting morphing algorithms to design generative, customized product behavior that responds to how people think, termed cognitive style, and the tasks they are performing. Demonstrate the method on a test-case, creating a "telepathic" product, a kitchen faucet.

| | Tasks | Calculations |
|---|---|---|
| **Calibration** Prior to in vivo morphing ~200 test subjects | 1. Measure cognitive styles & task preferences to establish segments. | 1. Assign users to a cognitive-style segment. |
| | 2. Observe users w/ **sensors**, collect data on each segment. | 2. **Calibrate** model to infer user's segment from sensor data. |
| **Operation** In vivo faucet General population | 1. Observe a user w/sensors. Use model to **infer user's latent cognitive style** segment. | 1. Calculate user's cognitive style probabilities for each latent segment. |
| **Exploration** / **Exploitation** | 2. Observe user's manual **feedback** (temperature, flow, timing). **Update** model for each segment and design behavior. | 1. Index value for each segment X design combination after the $n^{th}$ use. |
| | 3. **Design** to best product **behavior** using latent segment probabilities and indices. | 3. (Near-) optimal assignment of a morph to the $n^{th}$ use to balance exploration and exploitation. |

Figure 4. Overview of the generative design approach: calibration study and in vivo behavior morphing.

### Test-Case

The "telepathic" **kitchen faucet** is expected to

- Identify separate users
- Infer their cognitive styles from their usage behavior
- Identify the task at hand
- Supplies the desired product behavior, in terms of flow rate, temperature, and auto on/off sensitivity

....and, most importantly, conserve water.

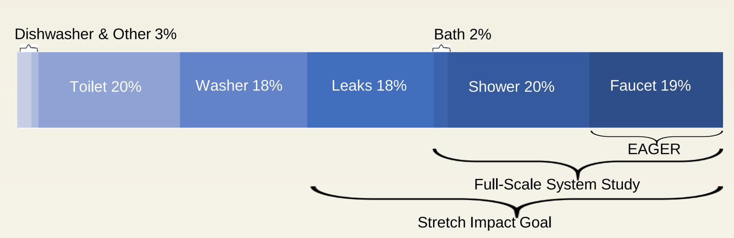


Figure 6. Water conservation goals.

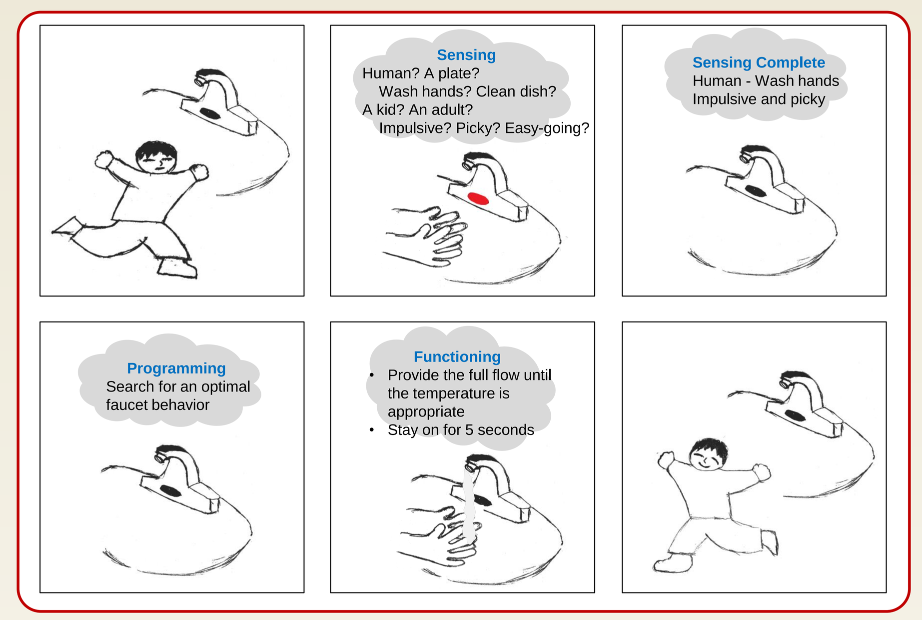


Figure 5. An example of how the "telepathic" faucet works.

## References & Collaborations


[1] Long, M., and Morrow, W.R., 2015. "Should Optimal Designers Worry About Consideration?" *Journal of Mechanical Design*, 137(7), p. 071410.

[2] Morrow, W.R., Long, M., and MacDonald, E.F., 2014. "Market-System Design Optimization With Consider-Then-Choose Models." *Journal of Mechanical Design* 136(3) p. 031003.

[3] Erickson, M.A., Morrow, W.R., MacDonald, E.F., Bordley, R.F., Chernicoff, W., Greene, D.L., Helfand, G., Katsikopolous, K., Keefe, R., Michalek, J., Papalambros, P., Pickrell, D., Samaras, C., Swait, J., and Walker, J., Working paper. "A Review of Current Transportation Modeling Methods and Recommendations for Improvements."

[4] Long, M., Morrow, W.R., and MacDonald, E.F., Working paper. "Consideration and Product Portfolio Strategy."

[5] Macal, C.M., Graziano D.J., and Ozik J., 2014. "Modeling Solar PV Adoption: A Social-Behavioral Agent-Based Framework." *Energy Market Predictions: Papers from the 2014 AAAI Fall Symposium*. Arlington, VA: Argonne National Laboratory.

[6] MacDonald, E.F. and Yang, M., 2014. "Collaborative Research: Modelling the Interrelated Impact of Design Decisions, Industry Adoption Incentives, and Government Policies on Solar Market Penetration." Stanford University, Massachusetts Institute of Technology.

[7] SolarCity, 2015. *Preliminary Design Proposal*. San Jose, CA: Corey Lehman.

[8] California Solar Initiative, 2015. *CSI Working Data Set* [Data file]. Retrieved from californiasolarstatistics.ca.gov/data_downloads.


## Collaborative Research: Modelling the Interrelated Impact of Design Decisions, Industry Adoption Incentives, and Government Policies on Solar Panel Market Penetration (#1363167), with Co-PI Maria Yang

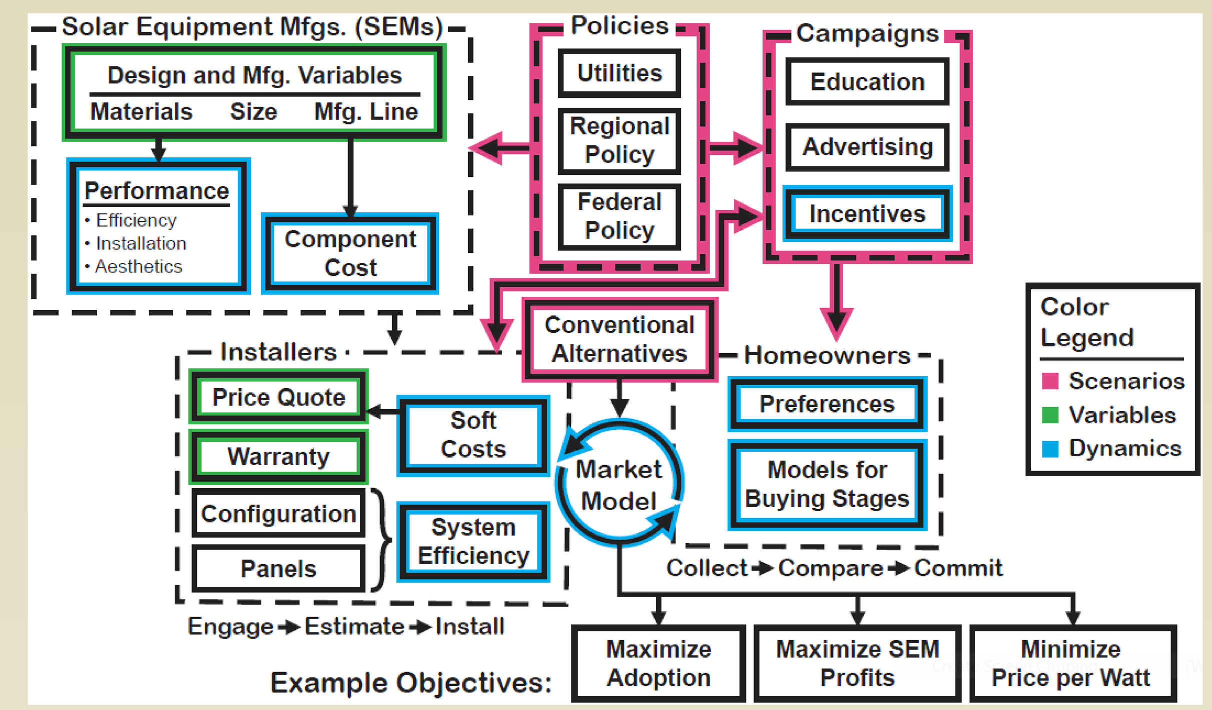


Figure 7. System model.

### Motivation

Industry analysis assumes adoption is based primarily on a customer's decisions [5]. Current rhetoric does not account for installers as decision-making agents in the solar adoption process, despite the fact that installers are homeowners' primary link to the solar industry. Installers are homeowner's primary means of learning about solar power and frequently make all design decisions for the homeowner.

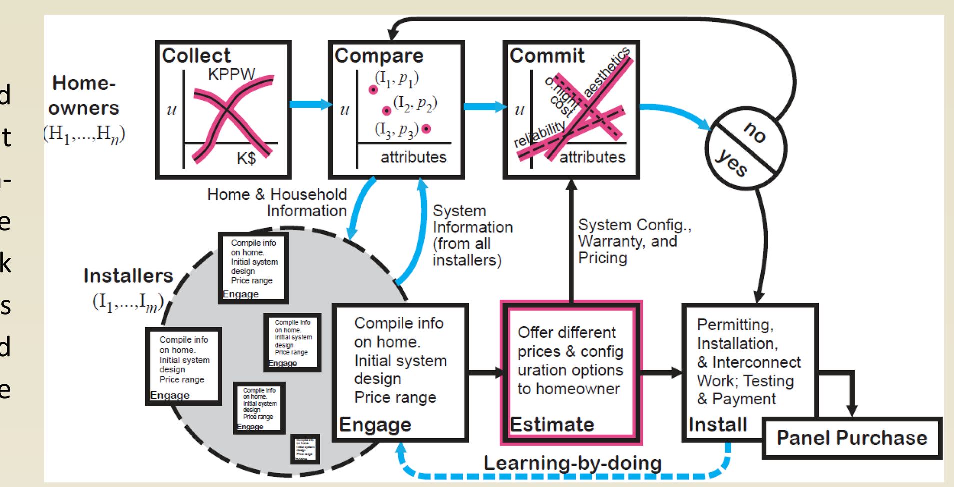


Figure 8 [6]. Individual three stage decision process that drive the interactions between Homeowners and Installers with regards to solar.

- Installers' and homeowners' decisions to work with each other affects the rate of adoption
- Rate of adoption can be measured by aggregating installed capacity of individual installers
- CA solar market is a unique case; it is largely based on economic factors
- Understand how external factors such as incentives and soft costs affect installed capacity


Figure 9 [7]: Estimated Cost of Solar System for small residential project in San Jose from Solar City.

### Current Work

Our lab is partnering with Maria Yang's Ideation Lab at MIT to analyze the two individual agents and their relationship, homeowners and installers, who make the primary decisions affecting the adoption of solar [6]. This relationship will then be incorporated into a larger system design model. The Stanford team focusing on the installer side, particularly in CA, and currently working on:

- Assessing how the installer presents the estimated price of solar and tracking how those costs change as the project progresses.
- Conducting installer and homeowner interviews in order to assess key decisions
- Gathering cost data from installers to detect "hidden" costs of solar
- Finalizing the utility function and partial weights for installers' decisions with project profit ($w_p$), estimated installation time ($w_t$), reputation ($w_r$), and estimated customer acquisition time being primary factors affecting installers' decision to work with a customer ( See Eq. (1))

**The utility function of installer j for customer i Uij:**

$$U_{ij}=w_p \times u_{p,ij}, + w_t \times u_{t,ij} + w_r \times u_{r,ij} + w_a \times u_{a,ij} \quad (1)$$

Where $w_k$ is the weight to satisfy: $\Sigma w_k=1$ for $k \epsilon K:\{p,t,r,a\}$ and $w_k$ , $U_{ij} \in [0,1]$

### Where we go from here

- Analyzing the California Solar Initiative "Currently Interconnected Dataset" to assess individual installers' capacity, average cost, and business growth [8]
  - will serve as one baseline for our agent based model
- Finalizing a parallel cost model for what installer must calculate and what homeowner sees
- Building the ABM using Repast Java to simulate how incentives, soft costs, and design decisions affect installers' installed capacity
  - Optimizing how the installer weighs these external factors and conveys them to the homeowner