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TELEPATHIC PRODUCT DESIGN FOR WATER CONSERVATION

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Abstract

Can a product that reads the user's mind behave more efficiently and eventually train the user to conserve? Here, as a first step to answering this big question, we present a design method for telepathic products applied to the case study of a kitchen faucet. The case study is used to illustrate the different steps of the design method: (A) Build cognitive empathy and define cognitive styles; (B) Define design requirements, articulate variables that will control performance, understand limitations and design physical product; (C) Design the machine learning algorithm, inputs, and outputs; and (D) Integration and refinement. This work-in-progress report highlights the intricacies of applying adaptive machine-learning behavior to physical products performance in the "real world" rather than to a website or device such as a smart phone. Interesting findings include that automatic response, typically associated with websites and phones, is not possible with plumbing as water cannot be instantly at the right temperature; and that cognitive styles indeed manifest in dish washing observations, with distinctly different styles in terms of patience, temperature sensitivity, and laziness.

Keywords: Human behaviour in design, Ecodesign, User centred design, Case study, Design methods

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1 INTRODUCTION

This paper presents a design method for morphing the physical behaviour of products based on mental behaviour of users, applying the method to a faucet design case study with the motivation of reducing water use. The new approach rests at the intersection of user behaviour, product physicality, and artificial intelligence. Smart products, such as the Nest thermostat (Nest, 2016) may learn about a user's preferences, but they do not know how the user thinks. While such products are able to predict what a user may want over time, their accuracy is limited by the fact that they assume that all users have the same underlying manner of interacting with the world. This paper presents insights on how people use products differently due to different "cognitive styles," and this can possible save water. The paper reports on the development of the design method and implementation of the case study, both still in-progress.

The design method uses machine learning (ML) algorithms to guide faucet response to user behaviour. This approach is based on past success in the field of marketing research, where such an ML algorithm served-up website advertisements based on a viewer's cognitive style, or behavioural-binning. When the ads were "morphed" to match behaviour style, click-through on advertisements increased by 245% over traditional ads (Urban et al., 2014). Cookies that collected link-clicks on other pages provided the data used for the morphing behaviour. Applying information about the user learned elsewhere (via cookies, in this case) to tailor a target design interaction is a new approach to affordance design.

The design vision, explored only in a faucet design here, is a "telepathic" home water system where all tap outlets (kitchen, vanities, shower, bath) have empathy for how its users think. The faucet anticipates their needs and performance preferences (see Figure 1). For the impulsive but picky five-year-old, it stays on longer to encourage a thorough hand washing, while waiting until the water is the perfect temperature before coming to full flow. For the busy parent with free but dirty hands, it will know to immediately turn on at full force to allow for quick hand washing, even if the water is still cold. The goal is to provide appropriate flow, temperature, and on/off behaviour for dish-cleaning, vegetable-rinsing, hand-washing, and pot-filling without user input. Over time, the behaviour of the water system trains user behaviour towards conservation.

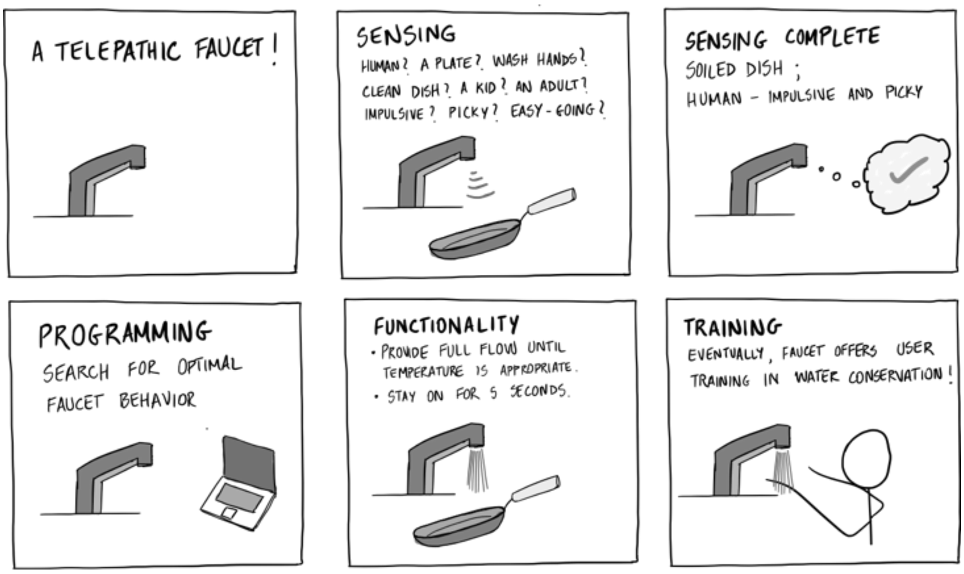

Figure 1. An example of how a telepathic faucet might work

2 RELATED WORK

Water conservation, user behaviour, and design affordances: This paper is inspired by the work of Srivastava and Shu (2013), who studied Old Mennonite lead users to rethink how water interactions at home could be designed to encourage conservation. Additionally, these authors created a faucet experiment that involved a washing exercise to understand how people used water. Through analysis of the lead users and the faucet experiment, the authors concluded that discretizing water in measurable units would probably help people use less water at home. Their paper also provides an excellent review of affordances, or different ways of interacting with a product. It discusses pro-environmental behaviour and existing approaches for changing user behaviours to be more pro-environmental. For the sake of brevity, these excellent literature reviews will not be repeated here.

Cognitive Styles: The way people think influences how they interact with the world around them, including how they interact with products. People have different styles for processing information and interacting, broadly termed cognitive style. Some common classifications of these styles are visual/verbal and analytical/instinctive or holistic (Riding and Rayner, 1998). While recent work has claimed that using cognitive styles to tailor learning approaches is ineffectual, the idea of styles has proven useful elsewhere. Researchers such as Nesbitt (2004) have found partial cultural explanations for cognitive styles. Novak and Hoffman (2009) found cognitive style classification to be task-dependent, meaning people call-up different cognitive styles for different tasks. The research at-hand combines cognitive style and task to tailor product behaviour. Typically, when cognitive styles are discussed in the context of design, it is within the framework of inclusive or universal design. Universal design (Story et al., 1998), asserts that designers should strive to design a product such that the largest number of people can use it, for example, making straightforward design improvements for handicap accessibility or illiteracy. Within the design world of hard goods, this approach leads to designs that have affordances (Maier and Fadel, 2009) such that use is inclusive and adaptable. But the goal of universal design is distinct from the proposed research, as it strives to reach a single design configuration to be used by all. Here, the single design adapts or morphs into different modes to match interaction style, which are hypothesized to be driven by different cognitive styles and tasks.

3 DESIGN METHOD

Our design method is described in Figure 2. The first part, **Part A – Build cognitive empathy, define cognitive styles,** involves understanding users and the task they are performing to uncover related cognitive attributes. Users are observed, surveyed, and interviewed. **Part B – Define design requirements, articulate variables that will control performance, understand limitations, design product** describes that the designer must understand the limitations of the product performance – not all aspects of performance are real-time adaptable. Using information from Part A, the designer can define how the product will be controlled, using what variables. In **Part C – Design ML algorithm, inputs, outputs**, the designer will choose an appropriate ML algorithm for the design problem, and define the inputs to the algorithm, how users will be grouped by their behaviours, and how product performance will change over time. Once all components of the design are defined, they will be integrated and tested with users and subsequently refined in **Part D – Integration and refinement**.

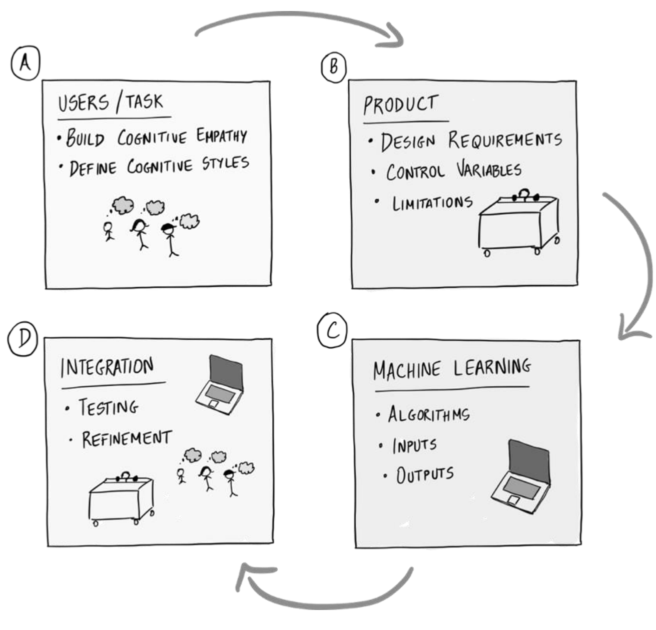

Figure 2. A general method to design a resource-sensitive product that morphs its behaviour to users' cognitive styles

4 CASE STUDY

Faucets represent 19% of total water usage in a household, as shown in Figure 3 (DeOreo et al., 2011), yet have seen limited innovation that mainly focuses on convenience. Automatic faucets were introduced for hygiene and convenience reasons, but researchers found that they use more water than regular faucets (Gauler and Koeller, 2010). Designing faucets for water conservation remains an open area for innovation.

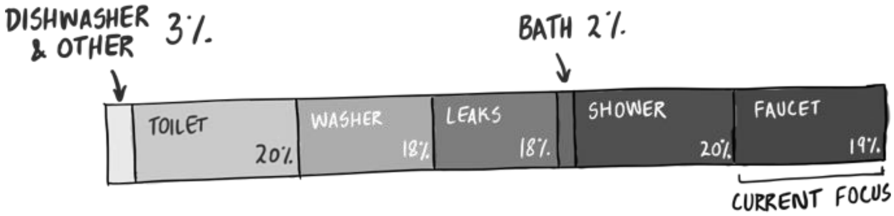

Figure 3. Average water usage in a household (Aquacraft, 2016)

4.1 Design Part A: Build Cognitive Empathy with Faucet Users

The design method requires the assumption that different cognitive styles result in different faucet-use-styles. Exploring this assumption for faucets requires understanding the cognitive attributes that govern faucet use behaviours (Figure 2A). Although there are a number of different interactions with kitchen sinks, washing dishes is the most complex and water-intensive. This is the focus of the empathy-building observations.

4.1.1 Dishwashing Observations

In order to build empathy with people using a kitchen sink, we observed fifteen people washing dishes on regular household kitchen faucets (not our prototype). In order to cover a diverse sample set, participants represented a wide age range (19-50 years of age), encompassing both genders, multiple geographies (USA and India), varying dishwashing experience (0 to 10+ years), and varying familiarity with the faucet/sink used. All participants were provided one spoon, fork, bowl, plate and pot to wash, using dishwashing soap and an optional scrubber. A few participants washed unsoiled dishes, i.e. dishes that were not visibly dirty. For the others, the dishes and utensils were deliberately soiled with a sticky paste. We observed duration of entire wash time, periods of water on/off, and user activity at each stage of washing, as shown in Figure 4.

After washing observations, participants explained why they made certain decision choices during the dishwashing process, such as, "why did you choose the hot water setting to unsoil the dishes?" or "why did you use your hands instead of the scrubber for the plate?" This set of questions complemented general questions regarding such as "how long have you been washing dishes?" or "how much do you care about water conservation?"

4.1.2 Observation Analysis

The observations served to categorize dishwashing activity into four stages—Preparation, Unsoiling, Soaping, and Rinsing. All 15 participants in the experiment completed each of these stages, either in series or parallel. Preparation represents the user briefly wetting their hands and dishes, as well as soaping the scrubber. Unsoiling represents the removal of stains from the dishes using hands or a scrubber. In some cases, participants combined unsoiling with the Soaping stage, in which soap is spread on the dish. Rinsing uses water to remove the soap and any remaining dirt.

Figure 4 represents these different stages. Water use varied by stage and participant. All participants turned the faucet on in the preparation and rinsing stages. However, water use in the unsoiling and soaping stages depended on the participant. For approximately equally soiled dishes, the dishwashing time ranged from 3 minutes to 5.5 minutes.

Rinsing and soaping together accounted for 50% or more of the dishwashing duration, while preparation was typically 5-10% and unsoiling (when applicable) was 20-30%. Another observation was that in the latter dishwashing stages, the participant's hands were primarily in contact with the dishes, and we noted less adjustment to temperature and flow of the faucet, suggesting that having a precise temperature was important for hand contact but not necessarily for dish contact.

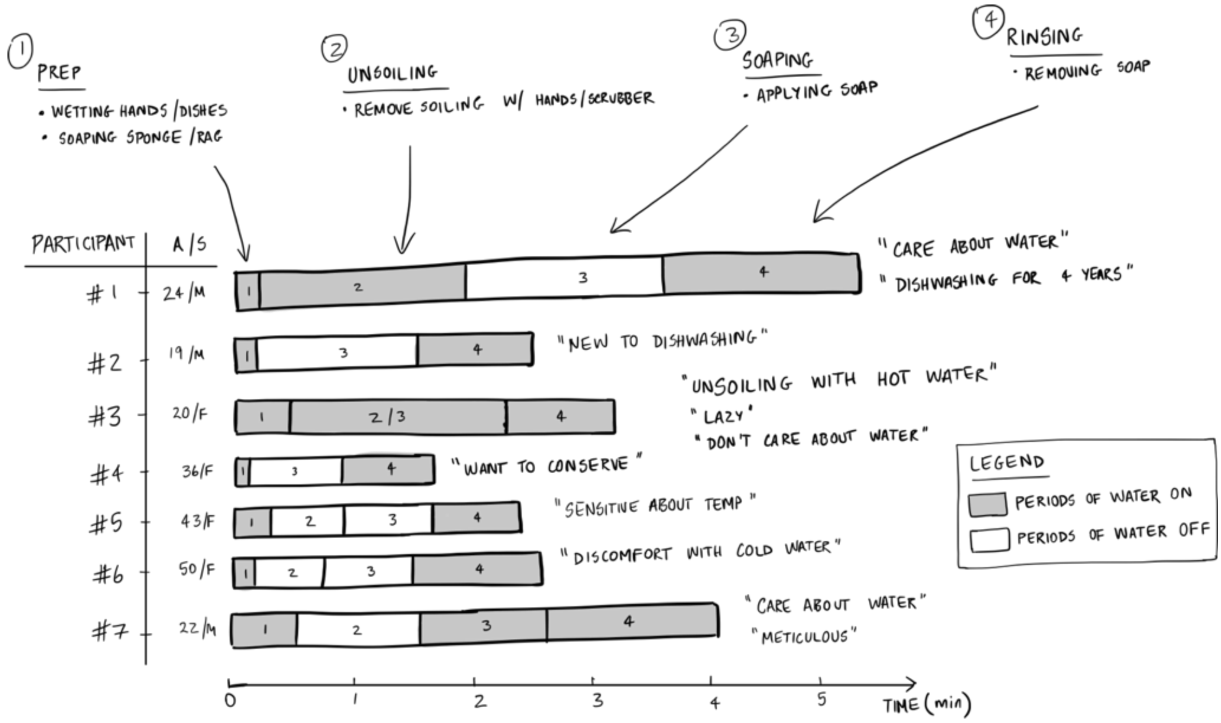

Figure 4. Data collected from the dishwashing experiment. The four stages of dishwashing are listed at the top. Participant information is on the left. Bar length represents duration of each stage

During the interviews, a few common themes emerged that guided participants' explanations of their behaviours; patience, sensitivity to temperature, resource conservation and laziness.

Participants suggested that their patience, or impatience, was directly proportional to faucet flow rate. For example, participant #3 explained that she increased the faucet flow rate to speed unsoiling and rinsing. Sensitivity to temperature represents the pickiness of a user, narrowing the band of preferred water temperatures, despite the fact that hotter water helps unsoil and rinse dishes better. Participant #5 said that she turned off the water in the middle stages of dishwashing since her water heater was not working and the she did not want to come into contact with the cold water. Also, when users mentioned that they cared about resource conservation, they typically used a slower flow rate and lower temperature. For example, participant numbers 1, 4 and 7 deliberately reduced the faucet flow and temperature in order to conserve water and energy.

Lastly, the interviews suggested laziness as a metric for number of adjustments to the faucet. For example, participant number 3 stated that they left the water running during all dishwashing stages since they were too “lazy to turn it off.” However, participant number 7 mentioned that they wanted to be meticulous about the dishwashing process and used water only where necessary. While we had initially hypothesized that dishwashing experience would be a factor that affected a participant’s faucet settings, the collected data did not provide any conclusions in this regard.

4.1.3 Define case-specific cognitive styles

Of the four cognitive attributes described in the last section, laziness was not included as one of the parameters to assess cognitive style. This was because the designed faucet was made to incorporate user adjustments and would do a better job catering to specific user adjustment needs automatically by recording the changes.

Therefore, this experiment uncovered cognitive style parameters to bin users’ faucet behaviours based on three scores — their impatience, temperature sensitivity and empathy for the environment. Figure 5 summarizes our hypotheses on how these parameters affect flow rate and temperature preferences. For a group of users with similar scores on these three parameters, the combination of these parameters would manifest itself as a region of preferred flow rates and temperatures in the Figure 5 plot.

While our research applies these learnings to a kitchen faucet in the short-term, it is interesting to note that these parameters can actually guide water usage behaviour on any product in the household, such as a shower, or hand washing sink. Thus, these insights may have larger implications on sustainability in the household.
Lastly, a broader observation is that one does not need to study many users in order to begin uncovering governing cognitive parameters that impact their use of a product. This research studied fifteen participants from two cultures and seems sufficient to create useful bins for the ML algorithm.

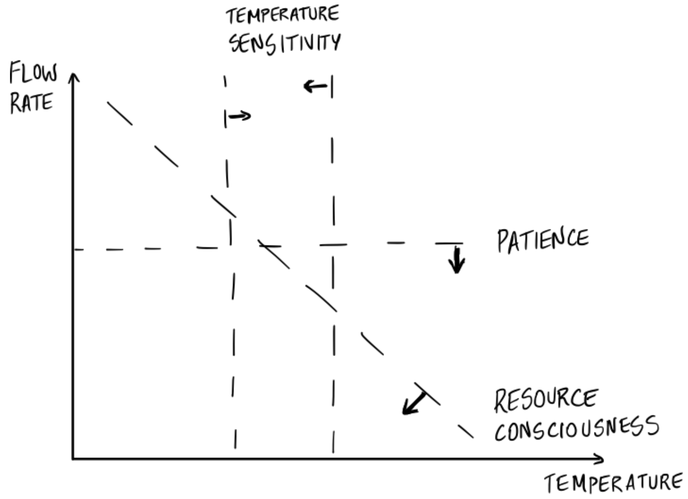

Figure 5. Observed correlation between temperature / flow rate and cognitive style parameters. The arrows represent the correlation with flow rate and/or temperature

4.2 Design Part B: Define the design requirements, understand physical limitations

This section discusses the design process, build, and operation of the case study faucet prototype. Designing and building the faucet required modifying an existing faucet and plumbing system so that it could be paired with an ML algorithm. This section first describes the design requirements used to build the product, then explains how the faucet works and finally, examines the mapping between faucet valve openings to the range of water temperatures and flow rates that the faucet can provide (physical limitations).

4.2.1 Design requirements

The faucet includes functional, aesthetic and convenience-related requirements.
Functional: temperature and flow must be controlled electronically to enable ML algorithms to automate faucet performance. A large range of flow rates and temperatures allow for a variety of use-cases, including hand washing and dishwashing. "Instant-heating" is important so that the faucet is not judged as malfunctioning when in automatic mode—if the user needs to wait for hot water, they may think the algorithm is not working. Manually adjustable temperature and flow, on top of electronic ML algorithm-offered temperature and flow, allow the algorithm to gather user feedback on optimal performance and refine its prediction of user preferences.
Aesthetic: An appearance as similar as possible to a regular household faucet provides familiarity to users. During testing of the prototype faucet, we desire that user behaviour be as realistic as possible.
Convenience: A free-standing and mobile unit for testing in the lab and in homes. Must be operated without hook-up to drain. Electronics and sensors must be attached to water-resistant areas.

4.2.2 Design Description

Figure 6 shows an image of the completed and operational prototype faucet, without sensors. A number of off-the-shelf items were purchased, assembled and customized to meet the design requirements. A laundry sink cabinet was attached to a Delta Vessona 2-handle kitchen faucet. A deep laundry sink and a tall faucet were chosen so that the product could be used for dish washing as well as hand washing. A plastic enclosure was built to cover the electronics under the faucet knobs. Furniture casters were installed at the bottom of the cabinet for mobility. Figure 6 also shows a simplified schematic of the faucet. The water supply line entering the laboratory branches into two, with one branch being heated

by an instant water heater. Both branches flow through valves before entering the sink. The valves have inserts for probes, where the inserted type-K thermocouples read the water temperature entering the sink through both the cold and hot lines. At the top of the faucet, a gear train connects a servo motor and knob valve on each side. When the servo motor rotates, the faucet knob opens to an angle prescribed by the servo motor, and scales through the gear train. The servo motor mechanism provides the initial flow rate and temperature for the user. For manually adjustability, two potentiometers are used as fake knobs. As the user rotates a potentiometer knob, the Arduino communicates this to the servo motor, which opens or closes the knob valve corresponding to the adjustment. The Arduino is powered externally by a 12V wall wart.
Note that the design of the system of sensors that will determine the task being performed and the specific user performing the task is still to be addressed.

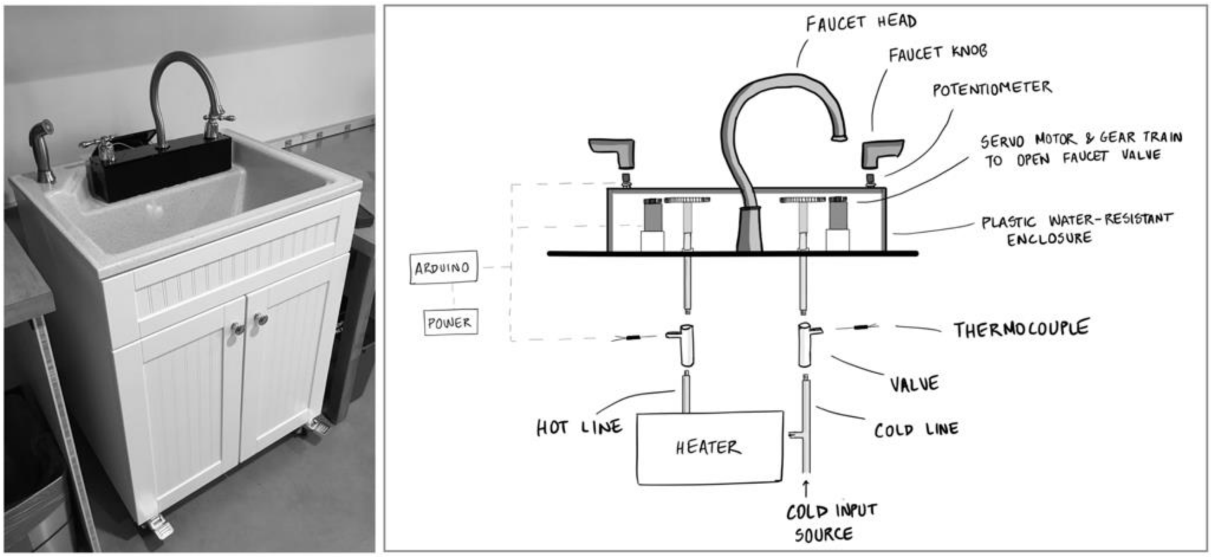

Figure 6. Image (left) of the prototype faucet. Schematic (right) of the faucet's components

4.2.3 Physical limitations

One of our design requirements was to have full electronic control of the flow rate and temperature provided to a faucet user. In order to accomplish this, it was necessary to calibrate our faucet, i.e. map the angle of servo motor angle opening to the flow and temperature output.

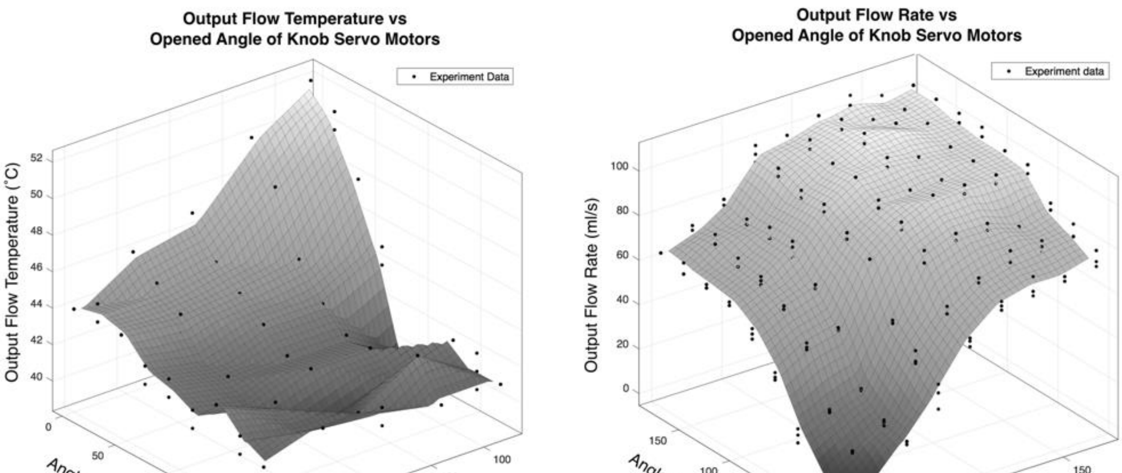

Figure 7. Measured output temperature and flow rate mapped to angles opened on the servo motors connected to the faucet knobs/valves

For this mapping, the hot and cold servo motors were opened to different angles (h and c respectively) to measure the temperature, T and flow rate output, f. Temperature was measured using a thermocouple probe placed at the faucet outlet. Flow rate was measured by measuring the volume of water output over a given time. Surface plots through the observed points were made through MATLAB and show the mapping in Figure 7. The corresponding equations are shown below. Thus, we were able to understand what temperature and flow the user was being provided through the faucet at any angles on the faucet knobs, thereby providing full electronic control.

$$T(h,c) = \frac{K\left(\frac{h_{min}}{h}-1\right)+T_H-T_S}{(A_f-h)^2}c^2 + \frac{2\left[K\left(\frac{h_{min}}{h}-1\right)+T_H-T_S\right]}{(A_f+h)}c + \left[K\left(\frac{h_{min}}{h}-1\right)+T_H-T_S\right], \tag{1}$$

with $K = \frac{(T_H-44^{\circ}C)\cdot 180^{\circ}}{180^{\circ}-h_{min}}$, when $h > h_{min}$ and $c \leq A_f - h$,

$T(h,c) = T_C$ when $h \leq h_{min}$, and

$T(h,c) = T_S$ when $c \geq A_f - h$.

Here, T_C = Temperature of the cold supply line = 26°C, T_H = Maximum temperature attainable in faucet = 52°C, T_S = Temperature at maximum flow = 42°C, h_{min} = Angle of hot valve at which heater starts working = 90°, and A_f = Sum of angles where maximum flow is achieved = 225°.

$f(h,c) = 0.8 \cdot f_{max} \cdot \frac{(h+c)}{180^{\circ}}$ when $h + c \leq 225^{\circ}$, and (2)

$f(h,c) = f_{max}$ when $h + c > 225^{\circ}$.

Here, f_{max} = Maximum flow rate attainable in faucet = 100ml/s.

4.3 Design Part C: Design ML algorithm, inputs, outputs

In part B of our design method, we described the three internal cognitive attributes that govern user faucet behaviour. These attributes provide information for our faucet prototype to **initialize** faucet settings for new users based on their personality type. In Part C of the method, we propose to collect a user's quantified scores on impatience, sensitivity and empathy. The method for this collection is not yet determined, though it could be through a survey (see Figure 8). An unsupervised learning clustering algorithm would then cluster these users into cognitive bins. An example would be to use k-means clustering, where $\{x^{(1)}, \ldots, x^{(m)}\}$ is a training set where $x^{(i)} \in \mathbb{R}^3$ where each $x^{(i)}$ is a vector containing a user's scores on the cognitive parameters. A k-means clustering method would minimize the below distortion function, where μ represents a cluster centroid (Ng, 2016).

$$J(c, \mu) = \sum_{i=1}^{m} ||x^{(i)} - \mu_{c^{(i)}}||^2 \tag{3}$$

A more accurate initialization will be conducted through pilot study, where a set of users is provided a variety of flow rates and temperatures conducted for a variety of at-sink tasks, here we focus on dishwashing as an example. At each setting provided to the user, we would gauge their "happiness" with the setting, i.e. ask whether they would like to change the faucet setting, or not. In order to eliminate the bias in user responses due to the previous water setting provided to them, we will randomize the order in which they receive each setting. This turns into a binary classification problem with input features of flow rate and temperature, and target output of user happiness. A supervised learning algorithm for nonlinear binary classification such as kernelized support vector machines (SVM) would be able to roughly provide the preferred faucet settings for each bin, and can program the faucet to prove each bin its "preferred" initialization, thereby minimizing adjustment time, inconvenience, and water. The kernelized SVM method (Ng, 2016) would minimize the function below for training set $\{x^{(1)}, \ldots, x^{(m)}\}$ where $x^{(i)} \in \mathbb{R}^2$ where each $x^{(i)}$ is a vector containing one flow rate and one temperature. Each $x^{(i)}$ has a corresponding "happiness" label $y^{(i)} \in \{1, -1\}$ that represents whether the user was happy with the faucet setting.

$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} \varphi(y^{(i)}\theta^T \emptyset(x^{(i)}))$, where (4)

$\varphi_{hinge}(z) = \max\{1 - z, 0\}$ and $\emptyset(x)$ is a feature mapping such that $K(x,z) = \varphi(x)^{\mathrm{T}}\varphi(z)$

Since a faucet is typically an adjustable product, where a user is able to adjust temperature and flow rate settings per task and during operation, our design method needs to learn how a user would adjust or **tune** the aforementioned initialization to their needs. Here, a reinforcement learning algorithm (Duchi, 2016) would incorporate user adjustments as an added feature with temperature and flow rate, and record the modified setting for the user the next time around. Over time, the faucet would be tuned through user adjustments and accurately learn the preferences for each user.
Still to-be-addressed is expanding the ML algorithm's decisions to identify tasks beyond dish-washing, such as hand-washing and pot-filling. This will require input from the sensor system, which, again, is yet to be designed.

4.4 Design Method Part D: Integration and refinement

The final part of our method for resource-sensitive design involves integrating the first three parts through conducting a large-scale testing study of ~200 users using the faucet for a variety of tasks. Comparing the water use from the testing study to regular water use would help quantitatively uncover how effective this design method is in saving water.
However, while the initializing and tuning method described in the previous section would only improve the faucets prediction of user preferences, its effectiveness would be limited by the setup of the problem. It is possible that there are other cognitive style features that we did not uncover through the dishwashing observations in Part A. The cognitive styles survey, or other assessment approach, may require additional information to make accurate predictions. Lastly, the faucet prototype itself may elicit different user behaviour than hypothesized due to form or function. In order to address these potential sources of error, refinement is important. This would involve revisiting each of the parts A, B and C and tweaking variables as necessary. Refinement is also important for the long-term project goal of training users in conservation. Understanding user behaviour holistically and iteratively would make the product more efficient in this regard.

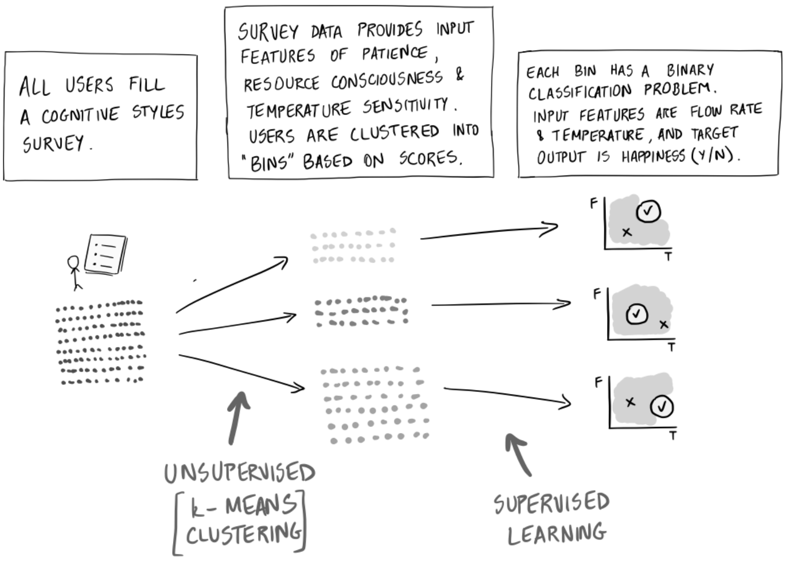

Figure 8. Integrating ML to initialize faucet settings based on user cognitive styles

5 CONCLUSION

This paper explored the design of a "telepathic" household faucet through the intersection of user behaviour, product physicality and machine learning (ML). The dishwashing experiment conducted found that user patience, temperature sensitivity and resource-consciousness were cognitive attributes that affect users' faucet setting preferences during dishwashing. We also designed and built a prototype that modified the physicality of traditional plumbing systems and faucets to incorporate electronic control of flow rate and temperature for ease of applying ML algorithms. Lastly, the insights were summarized in a design method framework to guide other resource-sensitive design.

One observation from the design process of this faucet, at the intersection of user behaviour and ML, was that it was important to include larger plumbing system considerations when designing the faucet, and not merely focus on the product itself. This opened an opportunity to explore how a plumbing system could be modified for ML algorithms. Upon closer examination of traditional household plumbing for a non-automatic faucet, we determined that it was easier to design the product at the faucet-knob level, rather than at the supply-line level for two reasons – the lack of customizability of traditional plumbing systems to incorporate electronics as well as to prevent contact of water and electronics. Therefore, faucet plumbing systems need to improve at a fundamental level to allow for fully integrated automatic faucets.

It is important to consider user reception of the telepathic faucet. For example, while users may be willing to wait for warm water out of a faucet they control manually, they might not be willing to wait for warm water the faucet is “supposed” to give it to them directly. They would not know if the faucet is malfunctioning or simply taking a while to warm up. We will gather similar user feedback regarding this in future research.

Next steps include conducting a large-scale experiment of ~200 participants using the design method to uncover how much water a kitchen faucet catering to user cognitive styles can actually save. We also must design the sensor network that will determine which user is using the faucet and the task they are performing. Finally, we will design and conduct experiments to attempt to change user behaviour and further conserve water.

Applying the insights to other household activities warrants further exploration. The presented design method has potential to conserve not only water, but other resources such as energy usage in a household.

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