Enabling Bottom-up Research to Increase Access to the Benefits of Smart Systems

Neal Patwari
Professor, School of Engineering and Applied Science
Washington University in St. Louis

Abstract -- We propose that internet-of-things (IoT) and smart devices can enable individuals to conduct randomized controlled trials on themselves, which we refer to as *self-science*, to answer questions that are individualized and relevant to them and their communities. This paper addresses the challenges in this bottom-up approach to scientific research.

I. Introduction

Human subject research traditionally takes a top-down approach, with the researcher deciding on the research question, designing the experiment, recruiting the subjects[1] who then do what they are told, collecting and analyzing the data, and testing the hypothesis. The subjects may or may not learn from the results, and if they do, it often has no direct benefit to them. The top-down approach fundamentally biases research questions to those relevant to those with power in the academy, typically with less racial, gender, age, health status, ability, and class diversity than the community as a whole.

This proposal explores what changes when a bottom-up approach is taken. In this approach, an individual wants to answer a question about themselves. They formulate the hypothesis and identify how to set and measure the independent and dependent variables. A smart system is set to randomize the independent variable and measure the dependent variable. The system runs for a set period of time, and at the end, reports the evidence, the decision, and the statistical significance.

Several questions may be amenable to such a bottom-up approach. For example, a person may want to know if having a blue light gradually turn on in the morning helps them wake up happier in the morning, or having background noise playing helps them fall asleep faster. Or, a person may want to

[1] Although the term “participant” has been proposed to replace “subject”, fundamentally the individual’s place in the experiment remains largely as a person who is subject to an interaction, and not as a participant in the experimental design; as such we intentionally use “subject” here.

know if use of a particular app on a certain day helps them smoke less on that day. A person may want to know if a blood-pressure medication actually reduces their blood pressure. While simply “trying” the light, noise, app, or medication on a certain day, or a few days, might give them some data, a randomized (or even blind) controlled trial on themselves over many days would introduce less selection bias and lead to a more robust conclusion about how they can improve their own life. While the results might not generalize to others, the purpose is to learn how to make a personal decision.

The key motivation for such an approach comes from users themselves. For example, the *quantified self* movement helps thousands of individuals form communities with others interested in similar aspects of how to increase their health and athletic performance, using data collected from personal devices and sensors [2]. As another example, patients diagnosed with chronic diseases often spend significant time switching medications before finding one that works for them. Medical literature addresses formalized “n-of-1” studies which involve one patient and more than one treatment [3]. Finally, many IoT devices are marketed as helping people not simply monitor their health, but also to learn how improve their health, for example the beddit sleep monitor promises you can “learn why you sleep well and why not” [1]. However, recommendations from IoT device software are at best only loosely based on scientific research, as little medical research is conducted using such IoT devices.

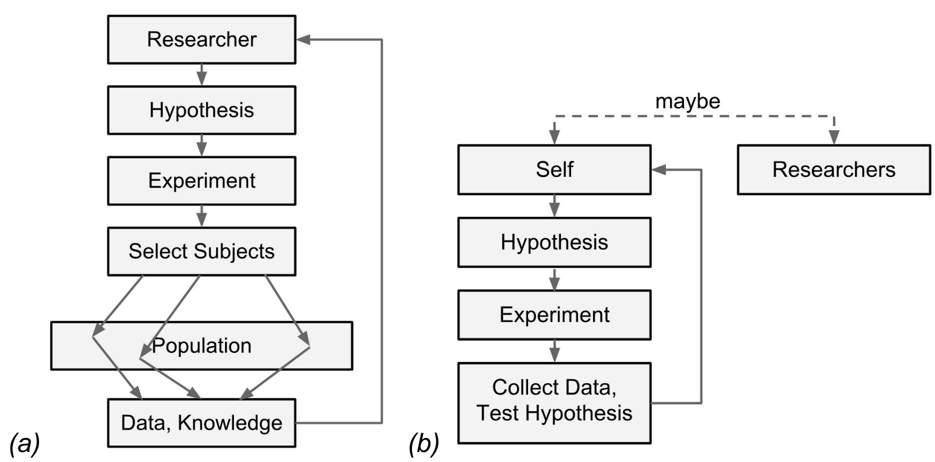

Figure 1: Standard research (a) starts with a researcher’s hypothesis, which uses the subjects from the population to acquire knowledge. Self-science (b) starts at an individual with a hypothesis willing to experiment to learn about themselves; they may optionally share the experimental setup and data with researchers.

II. Enabling Technologies

IoT devices and smartphones allow much of the self-science procedure in Figure 1(a) to be automated, as they can provide 1) automated actuation and measurement; 2) randomization of the condition; and 3) statistical analyses. In sum, these components can ease the work of conducting a randomized controlled trial (RCT).

A. Automated actuation and measurement

IoT devices are fundamentally sensors or actuators or both. For example, our Utah-modified Dylos sensor has an airborne particulate matter (PM) sensor, a temperature sensor, and a humidity sensor [4]. A smart thermostat typically can sense temperature and what state the A/C or heater is, and can control the HVAC system. As another example, the Phillips Hue light can report if a light is powered on or off (a sensor) and can turn the light on or off and set its color (actuator).

We should also remember that people are sensors and actuators as well, and we can use a smartphone or smart speaker (e.g., Google Home) to interact with them. The system can have a smartphone automatically push survey questions to a person, for example, asking in the morning how rested they feel, or how much they are feeling a particular symptom being monitored. The system can ask people to do certain things as well, for example by sending them a text message to ask them to open or close a window, or remind them to take a medication.

B. Randomization of the condition

For an individual, a RCT does not need to generalize to the population as a whole, it simply needs to hold for them. The RCT should be to repeatedly run trials on the single individual themself. This is called a *repeated measures* trial, a category which includes the crossover trial and the randomized repeated measures trial. In the latter, the independent variable is randomly selected for each measurement period. A smart device can randomly select the condition at each measurement period; or it can select the condition according to a prearranged schedule for a crossover trial. When the user is not otherwise aware of the condition, then the RCT is also a “blind” trial to the subject and experimenter (who are the same person). For example, if the condition is altering environmental conditions while the person is sleeping, then the user would not normally be aware of the random condition on any typical night.

C. Statistical Analysis

We envision that a smartphone app or web interface could help the user through the experimental design, and then based on that design, select the appropriate statistical test for the hypotheses. At the conclusion of the trial (or when there is sufficient evidence, in case of a Wald sequential test design) the software would provide the data to the user and its conclusion about whether the null hypothesis is accepted or rejected, and the *p*-value.

It will be critical to develop tutorial material for users which explains how the data is being processed, what the statistics mean, and the philosophy of the methods. Work towards providing this educational material will be part of the goal of expanding the understanding of scientific methods and terminology to a broader segment of the public. By explaining methods and jargon as applied to a user's particular experiment, we hope to make them more critical and thus better consumers of scientific news in the public press.

III. Initial Work

Two of our recent studies indicate the capability and motivation of the proposed ideas. In the first work, we developed a prototype software architecture we call *thing-enabled self-science* (TESS) [4]. TESS provides software for the three elements described at the start of Section II, and is programmed in Python. Parameters such as the measurement period and list of conditions can be provided to TESS via text files. TESS is built upon Home Assistant, an open-source home automation system that has "components" to connect to most IoT devices and to read and control them [6]. We ran TESS on a Raspberry Pi, a low-cost small Linux computer, attached to the user's WiFi router, and used two UMDS air quality sensors and an Ecobee smart thermostat in the user's home.

We used TESS to test the ability of a system that would improve indoor air quality by turning on the HVAC fan whenever the airborne PM was high. The system was proposed by a student who tested it on his own home (with University of Utah IRB approval). By turning the fan on when the air was its worst, the air is pulled through the furnace filter thus cleaning the air. However, by leaving the fan off when the PM was low, the system saves energy compared to leaving the fan on all of the time. For people with asthma, air pollution can be a trigger. Some families with asthma are told to turn the fan on all of the time, but this can cost hundreds of dollars per year in additional electric energy consumption. The goal of the proposed system would be to improve their air as well as if the fan were on all of the time, but with less energy use. We had the system randomly, each night at midnight, randomly select one of five conditions:

- *Normal*: The HVAC system operated as normal without a PM sensor, and the fan is turned on only when the system is active heating or cooling the home.
- *Always On*: The HVAC system used the fan 24 hours per day.
- *SmartAir*: The fan is used as Normal but is also on whenever the air quality is poor (with PM sensor value above a threshold).
- *Runtime X*: The furnace fan is run as normal without the PM sensor, but the fan is additionally turned on to make sure it is on at least X minutes every hour, where 5 < X < 55 minutes.

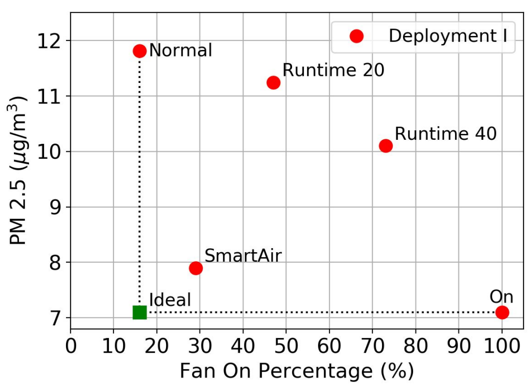

Figure: SmartAir achieves a significantly lower airborne particulate matter less than 2.5 μm in diameter (PM2.5) than Normal HVAC system operation in this home. While SmartAir uses the fan more than Normal, it uses it significantly less vs. when the fan is always On.

The PM sensor reads the fan on percentage (which determines the electrical energy usage of the HVAC fan) and the average daily PM level in the home. These two are the dependent variables. The hypotheses tested are whether or not SmartAir significantly changes the daily PM level compared to either Normal or Always On.

TESS ran the experiment for more than 100 days. As shown in Figure 2, TESS found that on average, in this home, SmartAir significantly reduced the PM level compared to Normal; but SmartAir and Always On were not significantly different in PM level. SmartAir increased the energy consumption compared to Normal, but it was considerably less than Always On.

In the second study, our team deployed UMDS particulate matter (PM) sensors, and provided residents with the tools to visualize the PM levels over time and to annotate the data with the activity that may have caused changes in the levels. A tablet-based monitor showed a plot of PM levels. Whenever the PM level spiked, residents were either sent a text message through their phone or an audio message through their Google Home asking them “We see that the pollution level spiked, any idea what caused it?”. Their reply annotated the event, and all annotations were also displayed on the monitor [5]. Unprompted, some found ways to experiment with their activities to improve their air quality. One person realized they could improve the air for an asthmatic child visitor by vacuuming the day before, rather than just before the child’s visit, as they saw that the air pollution is worse for several hours after the act of vacuuming. Another person started experimenting, systematically stir-frying the same food in different oils, to determine which one produced the least air pollution [5].

IV. Discussion

Several avenues of investigation are recommended in this area of development:

- *Ethical research*: People designing and conducting research on themselves will open new questions about ethical research. Can software help people identify potential risks to themselves and others who may interact with them? How can self-science experiment software be shared between people in a way that minimizes the chance for coercion and maximizes the privacy of personal information?
- *Broadening research*: How do we ensure that a diverse segment of the population is served by these new tools and devices? If the pool of people who use self-science are also heavily concentrated among those with class, race, and gender privilege, we will not be serving social justice via these tools. We suggest that systems be available to be borrowed, for example from public libraries and schools. The borrow model is particularly appropriate because, if an experiment shows that a “smart system” doesn’t help the user, they wouldn’t want to keep it for themselves, and another potential user could try it.

- *Reducing Barriers*: This proposal requires the development of new technologies to reduce the barriers-to-entry to research, and to make the deployment and maintenance of secure and reliable networking and data storage and analysis easy for non-technical users. The easier it is to set up experiments, the more broad segment of users will be empowered to conduct them.

V. Conclusion

We present here a discussion of the ability of people to conduct investigations into questions about their own lives. Self-science follows trends in personalized medicine, n-of-1 trials, and the quantified self movement. We anticipate that enabling such research could increase the diversity of people asking research questions, and of the types of questions being asked. IoT devices, particularly over time as they reduce in cost, will help to enable self-science. We provide two examples of our work in air quality sensing and systems that show how people can find ways of reducing their exposure to indoor air pollution through formal and informal experimentation. We point to particular research questions that may become more important as such systems expand their reach.

References

[1] "Beddit", Beddit Sleep Monitor, Online: https://www.beddit.com/.

[2] Quantified Self, Self knowledge through numbers, Online: http://quantifiedself.com/about/.

[3] Gabler, Nicole B., Naihua Duan, Sunita Vohra, and Richard L. Kravitz. "N-of-1 trials in the medical literature: a systematic review." *Medical Care* (2011): 761-768.

[4] Min, Kyeong T., Philip Lundrigan, Neal Patwari, Katherine Sward, and Scott C. Collingwood, "Smart home air filtering system: A randomized controlled trial for performance evaluation", *IEEE/ACM Conf. on Connected Health: Applications, Systems, & Engineering (CHASE 2018)*, 26 Sept. 2018, Online: http://span.ece.utah.edu/pub/CHASE_2018_Min_final.pdf

[5] Moore, Jimmy, Pascal Goffin, Miriah Meyer, Philip Lundrigan, Neal Patwari, Katherine Sward, and Jason Wiese, "Managing in-home environments through sensing, annotating, and visualizing air quality data", *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT)(Ubicomp '18)*, 2(3): doi:10.1145/3264938, Sept. 2018.

[6] Home Assistant, Open source home automation software, Online: https://www.home-assistant.io/.