Citizen Actuation for Smart Environments

Evaluating how humans can play a part in smart environments.

By David N. Crowley, Edward Curry, and John G. Breslin

Cisco defines the Internet of Everything (IoE) as the networked connection of people, processes, data, and things [1]. This goes beyond the concept of the Internet of Things (IoT) of connected devices alone transforming the way people live their lives. It is through this combination of people, processes, data, and things that the future of many fields in computing (such as smart cities) can be realized. Smart environments are physical worlds interwoven with sensors, actuators, displays, and computational elements, embedded seamlessly into everyday objects and connected through a continuous network [2]. A smart city/environment, by definition, needs a modern technological backbone but also relies on the natural resources of its inhabitants. The intersection of people, processes, and things is the area explored in this research. Things and people are combining to enable smart environments to become smarter, and *smarter* here is defined as optimizing/improving the environment's use of resources or the occupant's comfort. In parallel to research into the IoE, there is also a history of research into embedded systems, and this has evolved into cyber-physical systems (CPSs) and now cyber-physical social systems (CPSSs). The main difference between CPSs and IoT systems lies in the fact that IoT systems are aimed at interconnecting all the things in the physical world, while CPSs sense the physical world but are normally closed-loop systems [3].

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The interplay between an environment and its occupants plays an important role in the happiness of its occupants. This can be seen in the development of smart buildings, cities, and, more generally, smart environments. Smart environments often remove the occupant from the control loop and can lead to people feeling disengaged with their environment. For example, heating systems in smart buildings are often controlled centrally and do not allow any user input (another example of this loss of control is automated windows that open/close without any user input). This removal of the human from the loop counteracts and contradicts modern design principles such as user-centered design [4] and seems to place the building or resources as the focus of design. By combining sensors (connected things), humans through online accounts, and physical spaces (connected or unconnected things), we aim to include humans throughout the loop and enhance the smart environment. The goal of our research is to optimize smart environments by including humans in the loop, thus enabling the occupants to act as both a sensor and/or an actuator. We define these as CPSSs. In the next section, we will discuss related work in the fields of CPSs and citizen sensing.

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RELATED WORK

CPSs are physical and engineered systems with operations that are monitored, coordinated, controlled, and integrated by a computing and communication core [5] or, as Lee defines them, as an orchestration of computers and physical systems [6]. Munir et al. propose that it is necessary to raise human-in-the-loop control to a central principle in system design in CPSs [7]; this inclusion of humans inside a CPS has been called a CPSS [8] and a human-in-the-loop CPS (HiLCPS) [9]. The challenge that all these systems face is how best to incorporate human behavior as part of the system itself [7]. Crowley et al. [10] propose a CPSS that incorporates social media as the means of connecting a CPS to a building's occupants. Research such as Bull et al. examine how humans can be included in smart building/environment design and the importance of keeping users within the control loop [11]. This need for including humans in the loop is outlined in articles such as Carr, who highlights the dangers of too much automation. Carr describes this process as "human-centered automation," where systems are designed to keep engineers in the decision loop [12].

Citizen sensing describes users enabled by web connectivity to report on events in their environment through social media [13]. While citizen-sensing systems allow users to post updates and this data can be very valuable, it often does not form a complete feedback system. These systems take advantage of humans as creators or publishers but not as active agents in decision making or taking actions based on their posts. The concept of citizen actuation comes from the need to complete the loop started by a human in the loop sensing. *Citizen actuation* is formally defined as the activation of a human being as the mechanism by which a control system acts upon the environment [10], [14]. In this work, we propose a citizen actuation framework that sends a task to suitable occupants of an environment to complete. We examine one important component of the framework and outline a method for selecting users to complete a task. This component of the framework is designed to ease the burden on decision makers—by showing them the best potential-fit profiles for a task based on social media profile features. By designing a task allocation system based on profile features and not user interests, we aim to create a

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system that is portable across multiple social networks. In our experimental setup, we use Twitter as the social media platform. Twitter was selected due to its follower and following structure, as this can be informative of the Twitter user's personality traits.

We foresee use cases for citizen actuation in environments from small scale, like a neighborhood/community, or a small to middle enterprise but also to medium- and large-scale entities such as a city. We envisage citizen actuation as forming part of the design process of future smart devices and environments as a method to keep users engaged with their surroundings. Our research survey discussed in the next section gathered information regarding how people would use their own experiences and background knowledge on Twitter to pick suitable people that they would feel would complete a task.

SURVEY

Our survey ran July–October 2014 and was shared through online social networks. In total, 136 people entered the survey, and 92 people completed the survey. Only fully completed responses were taken into consideration for analysis. The respondents were 69.6% male, and 30.4% female. 82.6% of the respondents replied that they had a Twitter account, and 59.4% of these stated that they posted to Twitter at least once or twice a week; similarly to Java et al. [15], we define these respondents as "active users." Our survey aims to measure the participant's opinion on whether the owner of a user profile would complete a small task. We defined small task as being a short (timewise) action taken to effect or report on the person's environment (for example, opening or closing a window, turning off electrical appliances, or taking a picture on their smartphone and posting it to Twitter). In particular, the questions looked at requests (to complete tasks) sent to users through a microblogging platform and their likelihood to complete these tasks based on profiles and their features.

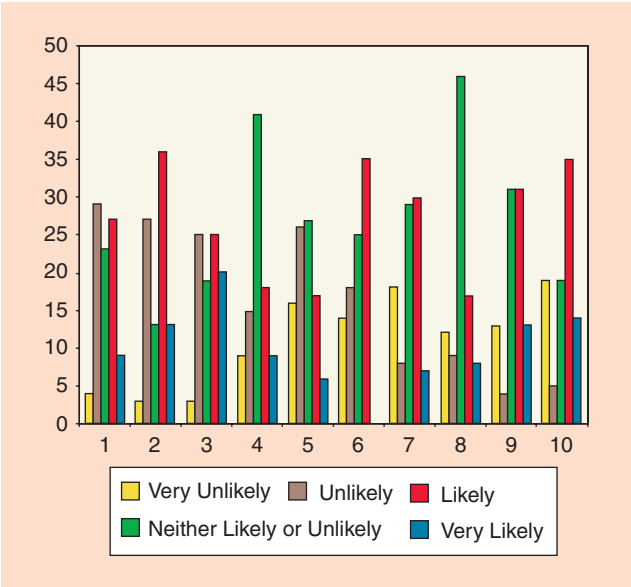

FIGURE 1. Question 1 results.

Twitter's API allows for the programmatic exploration of user profiles and users' posts. After initial experimentation with Twitter's API, it was discovered that we could not rely on just using Twitter's API to get users, as users were required that varied in a wide range of activity levels, and this method would generally return users that are more active. Followerwonk, a Twitter analytics tool, was used to select users from the chosen location, as this allows selecting/sorting Twitter users through multiple measures. Screenshots were taken of the chosen profiles and then edited to show the desired content. The use of screen shots allowed each participant to view the profile in the same state, with the same tweets and features. The participants only saw the eight tweets from each user profile. The main questions asked in relation to the chosen profiles in the survey are shown below. The users viewed the profiles shown in a random order to minimize question order bias.

- Q1 In your opinion how likely, would this Twitter account holder be to complete a task?
- Q2 Rate the importance of different features of the profile in helping you form that opinion of the profile:
  a) number of tweets
  b) number of followers
  c) number of people following
  d) description text
  e) other.

Figure 1 shows the survey results from Question 1, which relate to the participants' opinions on how likely each profile is to complete a task. Question 2e was an open question asking whether there were any other elements of the profile that influenced the participants' answers to Question 1. These answers mainly related to tweet content and opinions people formed around the tweet content and will be discussed further in the "Computed Results" section. As mentioned previously, 59.4% of our respondents stated that they posted to Twitter at least once or twice a week, and we defined these as active users. In our analysis of our survey data, we also compared our active user data separately to all our data and to our less active users and found no significant difference in their responses overall. This could be attributed to the survey design and questions that highlighted for participants where all the major features of a profile were.

COMPUTED RESULTS

In parallel with our survey, Twitter's API was used to collect information from the ten profiles to examine any links between the survey results and profile features. The main features extracted were the number of followers, the number of people the profile follows (following count), a calculated

ratio between these two values, status count, time per tweet (TPT) (calculated over the last 200 tweets), profile description, retweet ratio, and reply ratio. The calculated values for each profile can be seen in Table 1. Table 1 highlights the differences between the profiles, which can be seen from features such as number of followers that varies from 2 to 29,995 or following that has a low of 1 to a high of 2,568 and in the ratio of followers to following, which ranges from 0.7 to 153.5. These data indicate that people were making decisions based on tweet content. For example, Profile 3 seems to have similar characteristics to other accounts but scores comparatively low in Question 1. In answering Question 2e, participants noted the profile engaged with other users but in a possibly egotistical or self-centered manner.

We can see from examining the profile data in Table 1 that profiles 2, 6, 7, and 10 all have a high mean (over 3.5) and a mode of 4. While the average can be a misleading data point for Likert scale data [16], it is used in our analysis with mode, median, and the underlying data to get a clearer picture of the survey results. Participants in the survey all chose Question 2a and 2d to be important in their decision for all four profiles with the highest mean. The survey results for Profile 2 show that Question 2a, b, c, and d all have a mode of 4. Profiles 2, 6, 7, and 10 also have the highest reply ratio out of the ten profiles (apart from Profile 3), and in answering Question 2e, participants often describe these accounts with phrases like "this user is engaging with others and not just posting links" or "is a real user, engages with people, uses account for engagement with people and organizations."

These answers illustrate how participants found the engagement with other users a very important aspect of their opinion-forming process. This engagement mentioned by survey participants correlates with the profiles' reply ratio of 0.59, 0.3, 0.225, and 0.61. As mentioned previously, Profile 3 has a relatively high reply ratio of 0.275, but the participants in their responses to Question 2e stated that this profile seemed self-centered. These observations might be related to the high tweet count of the account (25,522) and the TPT, which is the lowest of any of the accounts at 61.881 min per tweet. Profile 3 also has the highest retweet ratio of 0.445, which points to the fact that almost half the profile's posts are retweets, so this might lessen the participants' belief that this profile would complete a task.

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CONCLUSION

In this work, we proposed a method of selecting users to complete tasks based on features of their social media account (in this instance, Twitter). We conducted a survey to examine how people would judge user profiles and the user's likelihood of undertaking a task. In parallel with this, we calculated related scores from data available from Twitter's API. This study has uncovered interesting insights in relation to what the survey participants find important in relation to social media profiles and completing tasks. These include insights such as how they view the number of tweets, the profile description text, and how a user interacts with other users as being important when forming an opinion on a profile. Furthermore, while the participants indicated the profile's posts as an important part of their opinion-forming process, it would be very difficult currently for a machine to differentiate between an engaged user and an egotistical user as described by the survey participants. From

Table 1. Profile 1–10 question 1 results and computed values.

Profile	Question 1	Followers (A)	Followers (B)	A/B	Status Count	TPT (mins)	Profile Description	Retweet Ratio	Reply Ratio
1	3.00	19618	1563	12.552	1000	571.842	N	0.005	0.06
2	3.65	117	82	1.427	4099	8876.058	Y	0.04	0.59
3	2.76	764	605	1.263	25522	61.881	Y	0.445	0.275
4	3.32	2928	1172	2.498	2282	539.103	Y	0.08	0.04
5	2.79	2	1	2.000	147	12133.924	N	0	0
6	3.56	196	144	1.361	312	9284.767	Y	0.045	0.3
7	3.88	1114	1591	0.700	916	3664.471	Y	0.19	0.225
8	3.06	13511	88	153.534	2610	1090.481	Y	0.77	0.105
9	2.86	29955	2568	11.655	3358	85.059	Y	0.315	0.08
10	4.16	2974	1505	1.976	29231	204.238	Y	0.045	0.61

A related approach called *soft actuation* has also emerged in this area and could be used in conjunction with citizen actuation.

our data, this egotism could be signified by having a high retweet ratio, a high reply ratio, and a low TPT.

In related work, Crowley et al. proposed gamification as a method of engaging, rewarding, and maintaining user interest in a similar system for citizen sensing (or social reporting), but this could also be suitable for community/organizational use to encourage users to engage and stay engaged [17]. A related approach called *soft actuation* [18] has also emerged in this area and could be used in conjunction with citizen actuation as the approaches have similarities (a request or hint can be ignored), but soft actuation relies on visual hints while citizen actuation relies on prompts through social media. Citizen actuation can be seen as a means to negate the need for retrofitting existing buildings with actuators, but it is a principle that could be used in the design of buildings, devices, and environments. This is where ethical concerns could be examined, such as using open social media accounts as the source of finding people in an environment, especially in work situations where users would be examined based on their personal accounts. Additionally, with building smart devices and smart infrastructures, citizen actuation should be proposed as a method of actuation that allows users more control over their environment. In future research, we will implement the insights from this work, including important features such as followers, reply ratio, retweet ratio, and TPT, to send tasks to selected profiles.

ABOUT THE AUTHORS

David Crowley (david.crowley@staff.ittralee.ie) is a researcher at the Insight Centre for Data Analytics, National University of Ireland, Galway. He is currently a lecturer at the Institute of Technology, Tralee's Computing, Creative Media, and IT Department. His research interests include smart environments, human in the loop sensing/actuation, mobile sensing, and human centered design.

Edward Curry (edward.curry@insight-centre.org) earned his Ph.D. degree in computer science from the National University of Ireland (NUI), Galway. He is a research leader and lecturer at the Insight Centre for Data Analytics at the NUI, Galway. His research interests include the Internet of Things, event-based systems, enterprise-linked data, energy informatics, semantic information management, and crowdsourcing.

John Breslin (breslin@ieee.org) is a senior lecturer in electronic engineering at the National University of Ireland, Galway. He is also a coprincipal investigator at the Insight Centre for Data Analytics. He cocreated the semantically interlinked online communities framework, implemented in hundreds of applications on over 25,000 websites. He is cofounder of boards.ie (Ireland's largest social media website), adverts.ie (classified ads website), and StreamGlider (real-time streaming newsreader app). He is cofounder of Startup Galway and the Galway City Innovation District/PorterShed.

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