2015 IEEE International Symposium on Technology in Society (ISTAS) Proceedings
ISBN: 978-1-4799-8282-0

Towards a Citizen Actuation Framework for Smart Environments

David N. Crowley[1]
Creative Media & Computing
Institute of Technology, Tralee
Tralee, Ireland
Email: david.crowley@staff.ittralee.ie

John G. Breslin & Edward Curry
Insight Centre for Data Analytics[1]
Nation University of Ireland, Galway (NUIG)
Galway, Ireland

***Abstract*— Citizen Actuation is a new concept that aims to retain humans in the loop throughout a system's lifecycle. In system design, humans are (generally) just users of a system but both Citizen Sensing and Citizen Actuation rely on users being included in a Cyber Physical Social System. In this paper, we investigate employing profile features from social networks as a method for user selection. These users will then be sent small tasks to complete that might normally be undertaken by actuators. To achieve this, we conducted a survey where users evaluated profiles on a limited number of features and posts. Separately, we collected profile data from the same set of profiles and computed calculated values such as Reply Ratio to compare them with the survey findings. This study has revealed interesting insights in 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.**

Keywords—component; formatting; style; styling; insert (key words)

I. Introduction

Cisco define the Internet of Everything (IoE) as the networked connection of people, process, 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 this combination of people, process, data, and things that the future of many fields in computing (such as Smart Cities) can be realized. Here the definition of a Smart City/Environment is that a city is smart when "investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance" [2]. A Smart City by definition needs a modern technological backbone but also relies on the natural resources of its inhabitants. The intersection of people, process, and things is the area explored in this research. Things and people combining to enable smart environments to become “smarter”, and smarter here is defined as optimizing/improving the environment’s usage 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 (CPS) and now Cyber Physical Social Systems (CPSS). The main difference between CPS and IoT systems lies in the fact that IoT systems are aimed at interconnecting all the things in the physical world while CPS systems sense the physical world but are normally closed loop systems [3]. 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 are physical worlds interwoven with sensors, actuators, displays and computational elements, embedded seamlessly into everyday objects and connected through a continuous network [4]. 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). This removal of the human from the loop counteracts and contradicts modern design principles such as User-Centered Design [5], 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. These physical spaces are smart environments embedded with sensors and can be a local community area, a business premises, or to a scale of a town or city. We can describe these smart environments as CPSs. The goal of our research is to optimize smart buildings by including humans in the loop thus enabling the occupants to act as both a sensor and/or an actuator. We define these as Cyber Physical Social Systems (CPSS). In the next section, we will discuss related work in the fields of CPS and citizen sensing.

II. RELATED WORK

Cyber Physical Systems are physical and engineered systems whose operations are monitored, coordinated, controlled and integrated by a computing and communication core [6], or as Lee defines them as an orchestration of computers and physical systems. A simple CPS system is shown in Figure 1 [7].

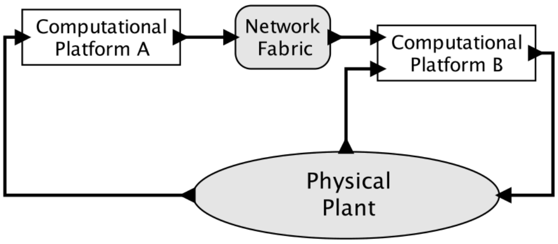

Fig. 1. Structure of a Simple Cyber-Physical System (CPS)

Munir et al propose that it is necessary to raise human-in-the-loop control to a central principle in system design in CPS [8], this inclusion of humans inside a CPS has been called Cyber-Physical Social System [9], Physical-Cyber Social Computing [10], and Human-in-the-Loop Cyber-Physical Systems (HiLCPS) [11]. The challenge which all these systems face is how best to incorporate human behavior as part of the system itself [8]. Crowley et al. [12] propose a CPSS that incorporates social media as the means of connecting a CPS to a building's occupants. Figure 2 illustrates a high-level representation of this framework. 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 [13]. 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" [14].

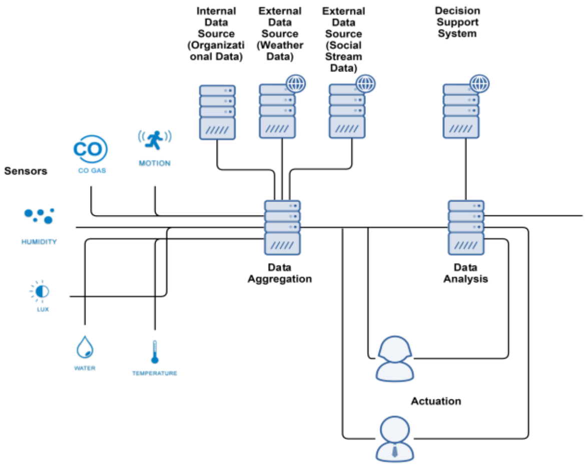

Fig. 2. Proposed CPSS Framework

Citizen sensing describes users enabled by web connectivity to report on events in their environment through social media [15], [16]. Written as social media posts, these reports are user observations on an event. Citizen Actuation is a concept that tries to enable "citizens" of a given environment to affect it. While citizen sensing systems allow users to make posts and this data can be very valuable it often does not form a complete feedback system. The 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 human in the loop sensing. Citizen Actuation formally defined is the activation of a human being as the mechanism by which a control system acts upon the environment [12], [17]. In this work, we propose a Citizen Actuation framework that sends a task to suitable occupants of an environment to complete. We also 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 system that is portable across multiple social networks. We envisage small and larger systems that will or should encourage human engagement (and human aided decision-making) and investigate methods of selecting people based on their social media profiles. In our experimental setup, we use Twitter as the social media platform. Twitter was selected due to its follower and following structure. This can be informative of the Twitter user's personality traits. In related work, Quercia et al. [18] examined the big five personality traits (Openness, conscientiousness, extraversion, agreeableness, and neuroticism) on Twitter. The authors use these traits and features from a Twitter's profile to place users into personality trait types. They relate conscientiousness as being very high in influential people but as discussed later in our Section 4, influence can be seen as being tied into social structure while the networks we examine are often based around social objects or location. By selecting and showing a small set of profiles, we allow the decision maker to have the final decision (using their experience and knowledge) instead of having to find suitable candidates themselves.

We foresee use cases for Citizen Actuation in environments from small scale, like a neighbourhood/community or a small to middle enterprise but also to medium and large-scale entities such as a city. As a result having the ability to find a set of suitable candidates from a small to large population will ease the mental load on the people tasked with sending requests. 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. In a Smart City example, the government official might have a large number of the public to assign a small task to, but our system would narrow down the choices to the people that would be more likely to complete the task. One goal of our research in designing systems is to include humans in the loop but also allowing a person to make the final decision to choose the right person or to complete the assigned task (shown as Decision Support System in Figure 2).

III. SURVEY

Our survey ran from 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% were 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. [18] we define these respondents as active users. Figure 3 displays the age distribution of survey respondents. 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 (time wise) 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.

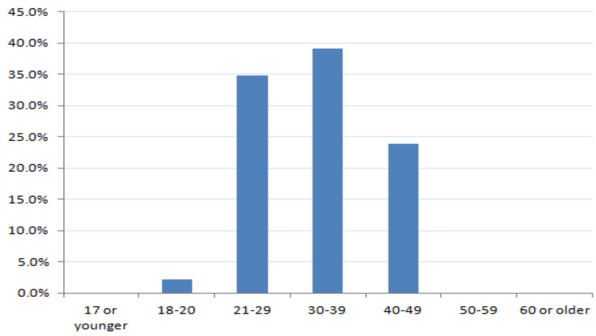

Fig. 3. Survey Age Distribution

For this study, we decided to pick users based on geographic location, thus trying to ensure that the respondents to our survey would not have any social connection to the profiles and would not be connected to the user profiles through Twitter. Geographic proximity heightens the likelihood of connections on Twitter for general users as shown by [19], [20]. Due to the research team's location in Europe, the decision was made to select a town/city in a location geographically remote from Europe. Fairbanks, Alaska was chosen as a remote location and for its size to allow availability of Twitter users. Twitter's API allows 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 [22]. Followerwonk was chosen as it allowed sorting of profiles by all the desired features used in the survey. Twenty profiles were originally selected at random using selection criteria such as accounts with the most followers, the most following, tweet counts, and accounts that were in the middle of some or all of these. Removal of three accounts was necessary due to suspicions of them being spam accounts. Three more accounts had to be removed owing to adult/inappropriate content on their profile.

After the exclusions fourteen accounts remained, and after examining these accounts the ten best representative accounts were chosen (accounts that were very similar feature wise were removed). Ten profiles had been the original goal of the selection process to allow the survey to be of a reasonable length to encourage completions. Test surveys were completed with up to fifteen profiles but participants commented that they felt the survey was overly long. Screen shots of the profiles were taken and edited to show the desired content. The usage of screen shots allowed each participant to view the profile in the same state and with the same tweets and features. The participants only saw the same 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 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) No. of tweets
b) No. of followers
c) No of people following
d) Description text
e) Other

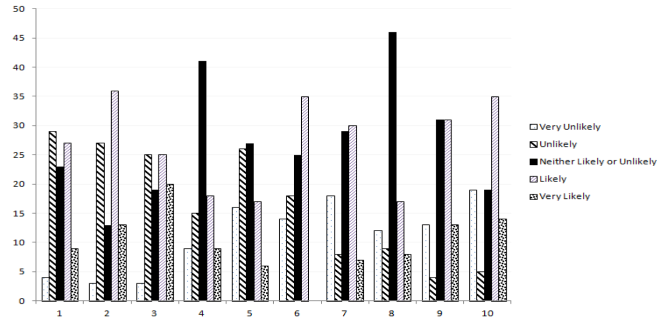

Fig. 4. Question 1 Results

Figure 3 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 was there 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 Section 4. As mentioned earlier, 59.4% of our respondents stated that they posted to Twitter at least once or twice a week as 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

TABLE I. PROFILE 1-10 QUESTION 1 RESULTS AND COMPUTED VALUES (TPT = TIME PER TWEET)

Profile	Question 1	Followers (A)	Following (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	11.665	3358	85.059	Y	0.315	0.08
10	4.16	2974	1505	1.976	29231	204.238	Y	0.045	0.61

responses overall. This could be attributed to the survey design and questions that highlighted to participants where all the major features of a profile were.

IV. Computed Results

In parallel with our survey, Twitter's API was used to collect information from the 10 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 (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. This data indicates that people were making decision 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-centred 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 have a mode of 4. While the average can be a misleading data point for Likert scale data [22], 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:

"Once again the text of the tweets - this user is engaging with other and not just posting links"

and

"is a real user, engages with people, uses account for engagement with people & organisations"

These answers illustrate how participants found the engagement with other users as 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 above 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-centred. These observations might be related in the high tweet count of the account (25,522) and the Time Per Tweet (TPT) which is the lowest of any of the accounts at 61.881 minutes 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.

V. Conclusion

In this paper, we have 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 our data, this egotism could be signified by having a high Retweet Ratio, a high Reply Ratio, and a low TPT. This conjecture would need further experimentation as our profile sample is too small as it only contains one profile with these features. We see this paper as the first building block of a larger study that would include measures from both our survey and computed values to select people to complete tasks and to measure the success rates of this proposed method.

This paper builds on the previous work of Crowley et al. [12], [17] by expanding on Citizen Actuation and examining one component of the Citizen Actuation framework, task assignment to specific user profiles and selecting the best possible fit. In future work, we aim to expand on this by creating an environment to test this automatic profile selection by letting the system assign tasks. In future studies, the temporal analysis of people's tweeting habits will need to be accounted for, as one way to measure success could be how long it took a specific user to complete a task. We are conscious that this type of analysis could be flawed as users might only use social media outside of work or mainly at certain times but analysis of their posts could aid in creating better measures of success. We note that Michelson et al. [23]) have examined modelling of Twitter posting behaviour temporally and this could be an approach used. In our computed values, we have not examined the possibility of using the time taken to reply as another input into our profile selection as this could also be seen as a useful measure of user engagement. The timing of sending the task could also be examined as research has shown the optimum time for sending social media updates to achieve maximum click-through rates and reads [24]. 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/organisational use to encourage users to engage and stay engaged [25]. Studies like Quercia et al. [26] make use of external services such as Klout [27] that measure a user's influence within a network. We chose not to use a service like that in this current work due to our networks not necessarily being connected socially but through social objects.

Future research areas could also provide scope for including work done on semantically describing crowdsourcing tasks such as SLUA (Semantic Linking of Users with Actions) [28] to allow description of different task types and also to allow the tasks to be sent to users on different social platforms. Hasan et al. created the SLUA ontology that aims to model users and tasks in crowdsourcing systems in terms of the relevant actions, capabilities, and rewards and could be used to model our tasks, users, and gamification system (rewards). Related research such as Bozzon et al.[29] and ul Hassan et al. [30] could be examined to find users that are more suited to certain tasks (through interests or post content). This was not included in this study as one of the goals of our system was to create the ability to find suitable users that had their privacy setting on Twitter set to protected this setting only allows designated users to read the account's posts. We could further examine user profiling techniques such as those found in Orlandi et al. [31] for discovering user interests on the Social Web. While this work's main contribution is to recommend new entities of interest of the user, we believe it could be used to find user interests and allocate tasks based on the user's interest in the task or related tasks. In future research, we will implement the insights from this work including important features such as Followers, Reply Ratio, Retweet Ratio, and Time per Tweet to send tasks to selected profiles. We will also create short lists of suitable profiles to reroute tasks to if the task is not completed in a set period. We envisage collecting user profiles that match different criteria from this research and further examining the links between user profile features, calculated features, and the user's propensity to complete tasks. We see this work fitting into Smart City design to include citizens in the decision making process and to aid in the overload of information available to city officials.

REFERENCES

[1] "Connections Counter: The Internet of Everything in Motion - The Network: Cisco's Technology News Site." [Online]. Available: http://newsroom.cisco.com/feature-content?type=webcontent&articleId=1208342. [Accessed: 12-May-2014].

[2] A. Caragliu, C. Del Bo, and P. Nijkamp, "Smart Cities in Europe," J. Urban Technol., vol. 18, no. 2, pp. 65–82, 2011.

[3] H. D. Ma, "Internet of things: Objectives and scientific challenges," J. Comput. Sci. Technol., vol. 26, no. 6, pp. 919–924, 2011.

[4] M. Weiser, "The computer for the 21st century," Sci. Am., vol. 265, no. 3, pp. 94–104, 1991.

[5] C. Abras, D. Maloney-Krichmar, and J. Preece, "User-centered design," Bainbridge, W. Encycl. Human-Computer Interact. Thousand Oaks Sage Publ., vol. 37, no. 4, pp. 445–456, 2004.

[6] R. Rajkumar, I. L. I. Lee, L. S. L. Sha, and J. Stankovic, "Cyber-physical systems: The next computing revolution," in Design Automation Conference (DAC), 2010 47th ACM/IEEE, 2010, pp. 731–736.

[7] E. A. Lee, "The Past, Present and Future of Cyber-Physical Systems: A Focus on Models," Sensors, vol. 15, no. 3, pp. 4837–4869, 2015.

[8] S. Munir, J. A. Stankovic, C. M. Liang, and S. Lin, "Cyber Physical System Challenges for Human-in-the-Loop Control," in The 8th International Workshop on Feedback Control (Feedback Computing '13), 2013.

[9] Z. Liu, D. S. Yang, D. Wen, W. M. Zhang, and W. Mao, "Cyber-physical-social systems for command and control," IEEE Intell. Syst., vol. 26, no. 4, pp. 92–96, 2011.

[10] A. Sheth and P. Anantharam, "Physical cyber social computing for human experience," Proc. 3rd Int. Conf. Web Intell. Min. Semant. - WIMS '13, p. 1, 2013.

[11] G. Schirner, D. Erdogmus, K. Chowdhury, and T. Padir, "The Future of Human-in-the-Loop Cyber-Physical Systems," Computer (Long. Beach. Calif)., vol. 46, no. 1, pp. 36–45, 2013.

[12] D. N. Crowley, E. Curry, and J. G. Breslin, "Closing the Loop-From Citizen Sensing to Citizen Actuation," in 7th IEEE International on Digital Ecosystems and Technologies, 2013.

[13] [R. Bull, P. Fleming, K. N. Irvine, and M. Rieser, "Are people the problem or the solution ? A critical look at the rise of the smart / intelligent building and the role of ICT enabled engagement," pp. 1135–1145.

[14] N. Carr, "Automation Makes Us Dumb," Wall Street Journal, 2014. [Online]. Available: http://online.wsj.com/articles/automation-makes-us-dumb-1416589342.

[15] A. Sheth, "Citizen sensing, social signals, and enriching human experience," Internet Comput. IEEE, vol. 13, no. 4, pp. 87–92, Jul. 2009.

[16] M. F. Goodchild, "Citizens as sensors: the world of volunteered geography," GeoJournal, vol. 69, no. 4, pp. 211–221, Nov. 2007.

[17] D. N. Crowley, E. Curry, and J. G. Breslin, "Leveraging Social Media and IOT to Bootstrap Smart Environments," in Big Data and Internet of Things: A Roadmap for Smart Environments, N. Bessis and C. Dobre, Eds. Springer, 2014, p. To appear.

[18] A. Java, X. Song, T. Finin, and B. Tseng, "Why We Twitter : Understanding Microblogging," in Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 workshop on Web mining and social network analysis, 2007.

[19] C. A. Davis, G. L. Pappa, D. R. R. de Oliveira, and F. De, "Inferring the location of twitter messages based on user relationships," Trans. GIS, vol. 15, no. 6, pp. 735–751, 2011.

[20] J. Kulshrestha, F. Kooti, A. Nikravesh, and K. Gummadi, "Geographic Dissection of the Twitter Network," Sixth Int. AAAI Conf. Weblogs Soc. Media, pp. 202–209, 2012.

[21] "Followerwonk." [Online]. Available: https://followerwonk.com/. [Accessed: 08-Jun-2015].

[22] I. E. Allen and C. A. Seaman, "Likert scales and data analyses," Qual. Prog., vol. 40, no. 7, pp. 64–65, 2007.

[23] M. Michelson, E. Segundo, and J. Bumgarner, "Temporal Modeling of Twitter Posting Behavior : An Empirical Study," in International Conference on Artificial Intelligence ICAI'14, 2014, pp. 26–30.

[24] D. Agarwal, B.-C. Chen, and P. Elango, "Spatio-temporal models for estimating click-through rate," Proc. 18th Int. Conf. World wide web WWW 09, vol. 6, no. 1, p. 21, 2009.

[25] D. N. Crowley, J. G. Breslin, P. Corcoran, and K. Young, "Gamification of Citizen Sensing through Mobile Social Reporting," in 2012 IEEE International Games Innovation Conference, 2012, pp. 1–5.

[26] D. Quercia, M. Kosinski, D. Stillwell, and J. Crowcroft, "Our Twitter Profiles, Our Selves: Predicting Personality with Twitter," in 2011 IEEE Third Int'l Conference on Privacy, Security, Risk and Trust and 2011 IEEE Third Int'l Conference on Social Computing, 2011, pp. 180–185.

[27] "The Klout Score," Klout. [Online]. Available: https://klout.com/corp/score.

[28] U. ul Hassan, S. O'Riain, and E. Curry, "Slua: Towards semantic linking of users with actions in crowdsourcing," Crowdsourcing, the, Semant. Web, 2013.

[29] U. ul Hassan and E. Curry, "A Capability Requirements Approach for Predicting Worker Performance in Crowdsourcing," Proc. 9th IEEE Int. Conf. Collab. Comput. Networking, Appl. Work., 2013.

[30] A. Bozzon, M. Brambilla, S. Ceri, M. Silvestri, G. Vesci, and P. Milano, "Choosing the Right Crowd : Expert Finding in Social Networks Categories and Subject Descriptors."

[31] F. Orlandi, P. Kapanipathi, A. Sheth, and A. Passant, "Characterising concepts of interest leveraging Linked Data and the Social Web," in Proceedings - 2013 IEEE/WIC/ACM International Conference on Web Intelligence, WI 2013, 2013, vol. 1, no. i, pp. 519–526.