What Makes a Good Crowd? Rethinking the Relationship between Recruitment Strategies and Data Quality in Crowdsourcing

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ABSTRACT

Conventional wisdom dictates that the *quality of data* collected in a crowdsourcing project is positively related to how knowledgeable the contributors are. Consequently, numerous crowdsourcing projects implement crowd recruitment strategies that reflect this reasoning. In this paper, we explore the effect of crowd recruitment strategies on the quality of crowdsourced data using classification theory. As these strategies are based on knowledge, we consider how a contributor's knowledge may affect the quality of data he or she provides. We also build on previous research by considering relevant dimensions of data quality beyond accuracy and predict the effects of available recruitment strategies on these dimensions of data quality.

Keywords

Data quality, Crowdsourcing, Citizen science, Crowd recruitment

INTRODUCTION

Crowdsourcing implies "outsourcing a task to a 'crowd', rather than to a designated 'agent' (an organization, informal or formal team, or individual), such as a contractor, in the form of an open call" (Afuah & Tucci, 2012; Howe, 2006). Through crowdsourcing, information technology (IT) has been successfully used by organizations and individuals to engage large groups in many ways (Castriotta & Di Guardo, 2011; Hosseini, Phalp, Taylor, & Ali, 2014; Tarrell et al., 2013; Tripathi, Tahmasbi, Khazanchi, & Najjar, 2014). Examples include harnessing collective intelligence for decision-making and acquiring distributed or independent knowledge about a variety of interests like traffic monitoring and bird watching (Bonney et al., 2009; Buecheler, Sieg, Füchslin, & Pfeifer, 2010; Cohn, 2008; Malone, Laubacher, & Dellarocas, 2010). However, to successfully leverage the crowd for such purposes, crowdsourcers [1] of crowdsourcing projects must make a "design decision" about *who* will perform the task (Lyon & Pacuit, 2013; Malone et al., 2010). The primary decision in recruitment is whether to recruit only knowledgeable contributors or allow everyone to participate (Budescu & Chen, 2014; Lukyanenko, Parsons, & Wiersma, 2014). Understanding the consequences of these crowd recruitment options on the success of crowdsourcing projects will enable crowdsourcers to make informed staffing decisions.

The limited literature in this area has mainly assumed implicitly that expert crowds are better and therefore provide insight on strategies to ensure the knowledge of contributors (Aspinall, 2010; Budescu & Chen, 2014; Du, Hong, Wang, Wang, & Fan, 2017; Wang & Strong, 1996; Wiggins, Newman, Stevenson, & Crowston, 2011). Some have compared the quality of data provided by two groups of contributors – experts and novices – in a crowdsourcing or citizen science context; however, they have addressed only the accuracy dimension of data quality[2] (see Austen, Bindemann, Griffiths, & Roberts, 2016; Crall et al., 2011). Moreover, contributor knowledge is not binary; that is, contributors are not just either experts or non-experts, but possess knowledge at some level along a continuum (Collins & Evans, 2007). Furthermore, these crowd recruitment studies and others have indicated that expert contributors do not provide more accurate data than novices, thereby posing a challenge to the benefits of strategies that "chase after experts in the crowd" (Surowiecki, 2005 p. XIX). Increasing our understanding of the impact of knowledge-

[1] Crowdsourcer is a term used in Estellés-Arolas & González-Ladrón-De-Guevara (2012) and implies the decision makers in a crowdsourcing project who may be the sponsor or data consumers (see Parsons and Wand 2013).

[2] Data quality is measured based on its intrinsic quality (e.g., accuracy, reputation of its provider), contextual quality (e.g., completeness, timeliness or ability to provide context for the data) and its representational quality (e.g., the format and meaning of the data) (Nelson, Todd, & Wixom, 2005; Wang & Strong, 1996). Like these papers, we consider data and information to be similar and interchangeable but distinguish contributions submitted by the crowd as data and the overall data collected by the citizen science system as information. All our reference to data quality will therefore imply intrinsic data quality, contextual data quality and representational data quality.

based crowd selection strategies on the quality of crowdsourced data stands to affect the success of data crowdsourcing projects (Wang & Strong, 1996; Wiggins et al., 2011). Chiefly, we seek to understand *what is gained* and *what is lost* in terms of data quality when crowdsourcers make the choice to recruit only expert contributors, or open up their crowdsourcing projects to everyone. Our stance is that while citizen science studies may be used for surveillance or monitoring (Wiersma, 2010), novel discoveries are possible and desirable. In addition, collected data may have more uses than initially anticipated during the design of the study (Parsons & Wand, 2014).

Our analysis will be applicable to the broader sphere of crowdsourcing and other crowd-facing information systems; however, we focus on citizen science systems – "collaborations between scientists and volunteers, particularly (but not exclusively) to expand opportunities for scientific data collection and to provide access to scientific information for community members" ("Defining Citizen Science — Citizen Science Central," n.d.). Further discussions of the quality of crowdsourced data and crowd recruitment in this paper will therefore mostly align with the characteristics of citizen science crowdsourcing.

Crowd Recruitment Strategies

Crowd recruitment strategies comprise the decisions crowdsourcers make about who they will let participate in their project to increase the chance of collecting reliable and high quality data (Geiger, Seedorf, Schulze, Nickerson, & Schader, 2011). Although participation in crowdsourcing projects is voluntary, crowd recruitment strategies consist of preselection measures explicitly or implicitly implemented by crowdsourcers to choose which volunteers get to participate. The central decision is whether to recruit only knowledgeable contributors or allow everyone to participate (Budescu & Chen, 2014; Lukyanenko et al., 2014). Besides recruitment decisions, crowdsourcers make other design decisions about *the goal of the project* (for examples see Bonney et al., 2009; Cooper, Dickinson, Phillips, & Bonney, 2007; Wiggins & Crowston, 2012), *motivation to contribute (or why the crowd will participate)* (for examples see Nov, Arazy, & Anderson, 2011; Raddick et al., 2009; Rotman et al., 2012) and *how the system is designed* (Lukyanenko et al. 2014). Whereas there is ample literature that can guide management on the latter decisions, more understanding of crowd recruitment strategies and their impact on crowdsourced data in citizen science is needed. In this paper, we focus on the impact of strategies that target contributors' prior experience, training and the disparate levels of contributor knowledge (Austen et al., 2016; Crall et al., 2011). Understanding crowd recruitment strategies and their impact on crowdsourced data will not only clarify the pros and cons of recruitment decisions for data quality, but also guide crowdsourcers' other design decisions. This paper therefore continues the discussion towards providing better understanding of how the quality of crowdsourced data is affected by recruiting a crowd of knowledgeable contributors or an undefined crowd (Crall et al., 2011).

Citizen Science Data Quality

Crowdsourcers recruit crowds for their projects taking into account concerns for data quality. They may seek to implement measures to ensure data quality before, during or after data collection (Wiggins et al., 2011). For instance, to ensure data quality before data collection, crowdsourcers may train potential participants to attain a desired level of knowledge required specifically to perform the citizen science task. During data collection, participants' input may be algorithmically compared to "known states" or against an existing knowledge base for validation (Wiggins et al., 2011). After data collection, experts may subject participants' submissions to review before acceptance. A typical example is e-bird (www.ebird.org), which allows everyone to participate, but employs a team of experts to "sift through … the observations [of other contributors and] validate them (Gura, 2013). A commonality in these strategies, as evidenced in many sampled citizen science projects, is that they are undergirded by the assumption that there is "value of expertise in ensuring data quality" (Wiggins et al., 2011 p.17).

Wang & Strong (1996) defined data quality in terms whether "data … are fit for use by data consumers". They identified several data quality dimensions - attributes that represent aspects of data quality and are pertinent in establishing it. According to Nelson, Todd, & Wixom, (2005); Wang & Strong, (1996); Wixom & Todd, (2005), dimensions of data quality empirically determined to be pertinent to consumers are: (1) Accuracy – the notion that the data provided is correct and objective; (2) Completeness – the degree to which all the data and their states that may be relevant to the consumer are captured by the contributed data; (3) Context-awareness (Currency) – the degree to which data "precisely reflects the current state of the world that it represents"; (4) Format –the degree to which the data contributed is interpretable and can be understood.

Contributed data is accurate when it is factually correct with respect to the entity it represents. However, when data incorrectly identifies one entity as another, the eventual dataset is not only inaccurate but also incomplete. In the same vein, contextual data about the current state of entities under study can provide significant insights (sometimes unanticipated) to consumers about the phenomenon.

Consistent with previous studies, we contend that, for data to be of sufficient quality to meet anticipated and unanticipated uses, all these dimensions must be considered. We will therefore consider high quality data as giving contextual information where available, representing more completely the available instances of phenomena, being accurate, and being easy for the consumer to understand. In this study, we will define low quality crowdsourced data as data collected through crowdsourcing however constrained so that it does not fulfill all the necessary dimensions of data quality explicated herein. On the other hand, we will consider a crowdsourced data to be of high quality if it covers all the relevant dimensions of data quality. Accordingly, recruitment strategies that lead to the collection of the a low quality dataset is considered less desirable while those that avail the crowdsourcer the opportunity to collect data that meets all quality dimensions addressed herein will be considered ideal.

Contributor Knowledge in Citizen Science

Contributors to citizen science projects may have different levels of measurable knowledge about a phenomenon under study (Collins & Evans 2007). Therefore, we propose that participants in citizen science projects may contribute data based on one or more of these types of knowledge.

Domain Knowledge (DK): we refer to prior domain knowledge as the knowledge participants have about the phenomenon under study. This knowledge may have been acquired through some training and is usually broad, covering more than just the phenomena being studied in a citizen science project.

Task Knowledge (TK): some citizen science projects train potential participants on the task to be performed in the project and assess their knowledge based on the training. We refer to this type of training as task training. In this case, participants do not necessarily have prior knowledge of the domain of study.

No Knowledge (NK): It is also possible for potential participants to have no knowledge of a domain of scientific inquiry. Such a participant would be referred to as a novice.

Domain and Task Knowledge (DKTK): Although it is difficult to claim absolute ignorance (Kloos & Sloutsky, 2008), it is plausible to have a mixture of some level of domain or task knowledge. In this case, different combinations of task and domain knowledge are possible; for example, a contributor may be highly knowledgeable about insects (high DK), but not have the knowhow to perform a citizen science task of classifying bees (low TK). Conversely, they may have low DK and high TK and many other possible variations of both knowledge types.

The different crowd recruitment strategies employed in citizen science emphasize one or more of these types of knowledge. In the next section, we explore theoretical perspectives on the likely consequences of these types of knowledge and, concomitantly, recruitment strategies, on the quality of crowdsourced data collected in citizen science projects.

THEORETICAL FOUNDATION

Since recruitment decisions are centered on the relevance of contributor knowledge to achieving high quality crowdsourced data, we must understand how knowledge affects data quality. Furthermore, the eventual quality of information collected in a citizen science project is determined by the quality of data contributed by the individual crowd members. We therefore take a microscopic view of data quality and its dimensions and how an individual contributor's knowledge determines the quality of data he or she contributes. Humans identify or classify by matching attributes of newly observed entities to known attributes of similar entities. In a microscopic view of data quality, the dimensions of quality become more granular: accuracy is viewed as the correct identification of the attributes of instances. Completeness is the capacity of contributors to consider all relevant attributes of a phenomenon that may be useful in classifying it and not just the diagnostic ones. Context-awareness refers to the capacity of contributors to identify attributes external to the entity under study, but in interaction with it. Format will imply their capacity to report the entity either using its attributes or the determined class of the entity based on those attributes.

Classification theory provides a useful foundation for understanding and exploring the interaction between knowledge and data quality. Classification (or categorization) is a fundamental human capability. We classify to make efficient use of our cognitive resources by organizing our existing knowledge about phenomena mainly through their similarities, allowing us in turn to make predictions about new instances and events (Best, Yim, & Sloutsky, 2013; Parsons & Wand, 2008, 2013). Classes are therefore useful abstractions of the similarities of the classified phenomena. Classification theory and its relevance to information system (IS) analysis and design have been extensively discussed (see Parsons, 1996; Wand, Monarchi, Parsons, & Woo, 1995).

To classify instances of phenomena, humans learn to manage limited cognitive resources by paying selective attention to only relevant features that aid in identifying instances of the class, while irrelevant features (those not useful for predicting class membership) can be safely ignored. Although selective attention leads to efficient learning, especially when making connections between instances with very sparse similarities and dense dissimilarities, it has costs. The primary cost of selective attention is a learned inattention to features that are not "diagnostic" in the present context (Colner & Rehder, 2009; Hoffman & Rehder, 2010). If these features, however, become diagnostic in another context, then the ability to make predictions and transfer knowledge is lost.

We consider two perspectives on selective attention in literature.

First, the tendency for selective attention and classification occurs naturally in humans as we acquire knowledge about entities in our world. Nonetheless, the absence of this tendency is "a developmental default" (Gelman, 1988; Gelman & Coley, 1990; Gelman & Markman, 1986; Kloos & Sloutsky, 2008). It forms with development to aid classification as a mechanism for coping with the deluge of information around us. For this reason, the capacity to classify is a distinguishing factor between adults and infants. For example, experiments conducted by Best et al. (2013), comparing the ability of infants and adults to selectively attend to attributes of instances based on prior or current knowledge, show that infants do not have the capacity for selective attention. Infants reason about classes by observing all the features of individual instances (Gelman & Markman, 1986). We contend they are naturally comparable to novices in the domain of a distributed knowledge crowdsourcing project. Like infants, novices also lack prior knowledge. Infants can, therefore, help us understand how novices and less knowledgeable contributors – people with incomplete knowledge – perceive instances (Keil, 1989; Kloos & Sloutsky, 2008).

Conversely, the tendency of adults to selectively attend to attributes of phenomenon about which they have knowledge can help us understand knowledgeable contributors in crowdsourcing projects. Knowledge of the domain or subject of research of a citizen science project will help contributors identify instances observed (Harnad, 2005). We predict that this knowledge will lead experts to focus on relevant features; thus, we expect them to be less likely to attend to non-diagnostic attributes than novices. We therefore make the following proposition:

Proposition 1: *Crowdsourced Data collected through recruitment strategies that emphasize high contributor domain knowledge will contain less contextual properties, will be less complete and less accurate (lower quality data) than those that do not impose a domain knowledge requirement.*

In other words, we predict that any recruitment strategy that restricts participation in a citizen science project based on domain knowledge, risks collecting lower quality data than one that does not, as participants' domain knowledge increases their tendency to ignore attributes that may otherwise have resulted in higher quality data. We make this argument considering the role a contributor's knowledge plays in his or her ability to consider observable attributes, and not just diagnostic ones, and consequently provide accurate classification (that will eventually lead to a more complete dataset for the citizen science project).

Second, Hoffman and Rehder (2010) showed the need to differentiate supervised classification – engendered by some form of explicit training (e.g., by a teacher) with sufficient feedback to improve the classifier's skill – from unsupervised classification – classification formed without explicit training (self-taught). They argued that the latter "may involve less rule-based processing" and consequently, more attentiveness to attributes. They emphasized the tendency for supervised learning (i.e. training with feedback to ensure that the person learns) to lead to formation of rules if they were not already explicitly taught, and selective attention to diagnostic attributes. They explained that "expert classification involves the same sort of attention optimization that characterizes supervised classification learning" (p. 336), which is due to extensive training and the type of task. We therefore contend that contributors trained in the citizen science task to be performed will show more selective attention than those who have not been trained. That is, if contributors are trained to perform a specific citizen science task, their tendency to selectively attend to only attributes that fit their training and ignore changes to other aspects of the phenomenon under study increases when compared to those who have not been trained.

Proposition 2: *Crowdsourced Data collected through recruitment strategies that emphasize training will show a higher level of incompleteness, lack of context and inaccuracy than those that do not.*

In other words, we predict that strategies that include training of participants also increases their tendency to prioritize some dimensions of data quality over others and, in some instances, ignore attributes of entities that are not considered in the training received. This will lead to lower quality data. In addition, we also predict that the effect of training on contributors will be similar regardless of the level of domain knowledge they possess before the training. Nonetheless, we expect that, even though domain knowledge can itself be polarizing as expressed in Proposition 1, it will mitigate the effect of task knowledge. This implies that the higher the level of domain knowledge a contributor has, the lower their tendency to fixate on only attributes that are congruent with their training.

DISCUSSION AND CONCLUSION

The quality of information gathered through citizen science is pertinent to stakeholders. In addition, there is value in ensuring high quality data, ranging from reliability for decision-making and predictions to capacity for multiple uses and perhaps even unanticipated uses. The literature suggests that *the level of knowledge of the crowd* we recruit correlates with the quality of data we get. However, from the theoretical perspectives explicated here, the correlation may not necessarily be positive for all dimensions of data quality. In fact, classification theory suggests that a contributor's high level of knowledge may be detrimental to their ability to provide quality data along some dimensions. We posit that restrictive recruiting strategies lead to crowds that minimize the contextual characteristics and differences in the non-diagnostic attributes of entities when these differences exist, focusing instead on commonalities in diagnostic attributes. On the other hand, ideal recruitment strategies will lead to a good crowd - one that is sensitive to similarities as well as differences between instances of phenomena, considering all their attributes.

For this reason, crowd recruitment strategies may support or deter novel discoveries and usefulness of data. Even strategies than include using experts to filter collected data may be sub-optimal for data quality especially because there is a tendency for people to only permit data they consider congruent to their existing knowledge, a phenomenon termed "cognitive disfluency" (Owen, Halberstadt, Carr, & Winkielman, 2016). Therefore, as recruitment strategy may inform the design of citizen science systems, it may correspondingly determine the system's ability to acquire and access accurate, complete, and context aware data, especially unanticipated or atypical ones (Lukyanenko et al., 2014; Parsons & Wand, 2014). Additionally, research objectives may not be fully formed at the time of project's commissioning (Lukyanenko et al., 2016; Newman et al., 2012). Therefore, recruitment choices that affect the data collected will also affect the capacity of the project to support changes in its goals, limiting its ability to accommodate and engender novel discoveries.

We are currently designing experiments to test the propositions developed in this paper.

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REFERENCES

1. Afuah, A., & Tucci, C. L. (2012). Crowdsourcing as a solution to distant search. *Academy of Management Review*, *37*(3), 355–375.
2. Aspinall, W. (2010). A route to more tractable expert advice. *Nature*, *463*(7279), 294–295.
3. Austen, G. E., Bindemann, M., Griffiths, R. A., & Roberts, D. L. (2016). Species identification by experts and non-experts: comparing images from field guides. *Scientific Reports*, *6*. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5028888/
4. Best, C. A., Yim, H., & Sloutsky, V. M. (2013). The cost of selective attention in category learning: Developmental differences between adults and infants. *Journal of Experimental Child Psychology*, *116*(2), 105–119.
5. Bonney, R., Cooper, C. B., Dickinson, J., Kelling, S., Phillips, T., Rosenberg, K. V., & Shirk, J. (2009). Citizen science: a developing tool for expanding science knowledge and scientific literacy. *BioScience*, *59*(11), 977–984.
6. Budescu, D. V., & Chen, E. (2014). Identifying expertise to extract the wisdom of crowds. *Management Science*, *61*(2), 267–280.
7. Buecheler, T., Sieg, J. H., Füchslin, R. M., & Pfeifer, R. (2010). Crowdsourcing, Open Innovation and Collective Intelligence in the Scientific Method-A Research Agenda and Operational Framework. In *ALIFE* (pp. 679–686).
8. Castriotta, M., & Di Guardo, M. C. (2011). Open Innovation and Crowdsourcing: The Case of Mulino Bianco. In *Information Technology and Innovation Trends in Organizations* (pp. 407–414). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-3-7908-2632-6_46
9. Cohn, J. P. (2008). Citizen science: Can volunteers do real research? *BioScience*, *58*(3), 192–197.
10. Collins, H., & Evans, R. (2007). Rethinking expertise University of Chicago Press. *Chicago IL*.
11. Colner, B., & Rehder, B. (2009). A new theory of classification and feature inference learning: An exemplar fragment model. In *Proceedings of the 31st Annual Conference of the Cognitive Science Society* (pp. 371–376). Retrieved from http://csjarchive.cogsci.rpi.edu/proceedings/2009/papers/68/paper68.pdf
12. Cooper, C., Dickinson, J., Phillips, T., & Bonney, R. (2007). Citizen science as a tool for conservation in residential ecosystems. *Ecology and Society*, *12*(2). Retrieved from http://www.ecologyandsociety.org/vol12/iss2/art11/main.html
13. Crall, A. W., Newman, G. J., Stohlgren, T. J., Holfelder, K. A., Graham, J., & Waller, D. M. (2011). Assessing citizen science data quality: an invasive species case study. *Conservation Letters*, *4*(6), 433–442. https://doi.org/10.1111/j.1755-263X.2011.00196.x
14. Defining Citizen Science — Citizen Science Central. (n.d.). Retrieved March 7, 2017, from http://www.birds.cornell.edu/citscitoolkit/about/definition
15. Du, Q., Hong, H., Wang, G. A., Wang, P., & Fan, W. (2017). CrowdIQ: A New Opinion Aggregation Model. In *Proceedings of the 50th Hawaii International Conference on System Sciences*. Retrieved from http://scholarspace.manoa.hawaii.edu/handle/10125/41365

16. Estellés-Arolas, E., & González-Ladrón-De-Guevara, F. (2012). Towards an integrated crowdsourcing definition. *Journal of Information Science*, *38*(2), 189–200.
17. Geiger, D., Seedorf, S., Schulze, T., Nickerson, R. C., & Schader, M. (2011). Managing the Crowd: Towards a Taxonomy of Crowdsourcing Processes. In *AMCIS*. Retrieved from http://aisel.aisnet.org/cgi/viewcontent.cgi?article=1396&context=amcis2011_submissions
18. Gelman, S. A. (1988). The development of induction within natural kind and artifact categories. *Cognitive Psychology*, *20*(1), 65–95.
19. Gelman, S. A., & Coley, J. D. (1990). The importance of knowing a dodo is a bird: Categories and inferences in 2-year-old children. *Developmental Psychology*, *26*(5), 796.
20. Gelman, S. A., & Markman, E. M. (1986). Categories and induction in young children. *Cognition*, *23*(3), 183–209.
21. Gura, T. (2013). Citizen science: Amateur experts. *Nature*, *496*(7444), 259–261. https://doi.org/10.1038/nj7444-259a
22. Harnad, S. (2005). To cognize is to categorize: Cognition is categorization. *Handbook of Categorization in Cognitive Science*, 20–45.
23. Hoffman, A. B., & Rehder, B. (2010). The costs of supervised classification: The effect of learning task on conceptual flexibility. *Journal of Experimental Psychology: General*, *139*(2), 319.
24. Hosseini, M., Phalp, K., Taylor, J., & Ali, R. (2014). The four pillars of crowdsourcing: A reference model. In *Research Challenges in Information Science (RCIS), 2014 IEEE Eighth International Conference on* (pp. 1–12). IEEE. Retrieved from http://ieeexplore.ieee.org/abstract/document/6861072/
25. Howe, J. (2006). The rise of crowdsourcing. *Wired Magazine*, *14*(6), 1–4.
26. Keil, F. C. (1989). *Concepts, kinds, and conceptual development*. Cambridge, MA: MIT Press.
27. Kloos, H., & Sloutsky, V. M. (2008). What's behind different kinds of kinds: Effects of statistical density on learning and representation of categories. *Journal of Experimental Psychology: General*, *137*(1), 52.
28. Lukyanenko, R., Parsons, J., & Wiersma, Y. F. (2014). The IQ of the crowd: understanding and improving information quality in structured user-generated content. *Information Systems Research*, *25*(4), 669–689.
29. Lukyanenko, R., Parsons, J., Wiersma, Y., Sieber, R., & Maddah, M. (2016). Participatory Design for User-generated Content: Understanding the challenges and moving forward. *Scandinavian Journal of Information Systems*, *28*(1), 37–70.
30. Lyon, A., & Pacuit, E. (2013). The Wisdom of crowds: methods of human judgement aggregation. In *Handbook of Human Computation* (pp. 599–614). Springer.
31. Malone, T. W., Laubacher, R., & Dellarocas, C. (2010). The collective intelligence genome. *MIT Sloan Management Review*, *51*(3), 21.
32. Nelson, R. R., Todd, P. A., & Wixom, B. H. (2005). Antecedents of information and system quality: an empirical examination within the context of data warehousing. *Journal of Management Information Systems*, *21*(4), 199–235.
33. Newman, G., Wiggins, A., Crall, A., Graham, E., Newman, S., & Crowston, K. (2012). The future of citizen science: emerging technologies and shifting paradigms. *Frontiers in Ecology and the Environment*, *10*(6), 298–304.
34. Nov, O., Arazy, O., & Anderson, D. (2011). Dusting for science: motivation and participation of digital citizen science volunteers. In *Proceedings of the 2011 iConference* (pp. 68–74). ACM. Retrieved from http://dl.acm.org/citation.cfm?id=1940771
35. Owen, H. E., Halberstadt, J., Carr, E. W., & Winkielman, P. (2016). Johnny Depp, Reconsidered: How Category-Relative Processing Fluency Determines the Appeal of Gender Ambiguity. *PLOS ONE*, *11*(2), e0146328. https://doi.org/10.1371/journal.pone.0146328
36. Parsons, J. (1996). An information model based on classification theory. *Management Science*, *42*(10), 1437–1453.
37. Parsons, J., & Wand, Y. (2008). Using cognitive principles to guide classification in information systems modeling. *Mis Quarterly*, 839–868.
38. Parsons, J., & Wand, Y. (2013). Extending classification principles from information modeling to other disciplines. *Journal of the Association for Information Systems*, *14*(5), 245.
39. Parsons, J., & Wand, Y. (2014). A foundation for open information environments. Retrieved from http://aisel.aisnet.org/ecis2014/proceedings/track17/7/
40. Raddick, M. J., Bracey, G., Gay, P. L., Lintott, C. J., Murray, P., Schawinski, K., … Vandenberg, J. (2009). Galaxy zoo: Exploring the motivations of citizen science volunteers. *arXiv Preprint arXiv:0909.2925*. Retrieved from https://arxiv.org/abs/0909.2925
41. Rotman, D., Preece, J., Hammock, J., Procita, K., Hansen, D., Parr, C., … Jacobs, D. (2012). Dynamic changes in motivation in collaborative citizen-science projects. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work* (pp. 217–226). ACM.

Retrieved from http://dl.acm.org/citation.cfm?id=2145238

42. Surowiecki, J. (2005). *The wisdom of crowds*. Anchor.
43. Tarrell, A., Tahmasbi, N., Kocsis, D., Tripathi, A., Pedersen, J., Xiong, J., … de Vreede, G.-J. (2013). Crowdsourcing: A snapshot of published research. Retrieved from http://aisel.aisnet.org/amcis2013/EndUserIS/GeneralPresentations/2/
44. Tripathi, A., Tahmasbi, N., Khazanchi, D., & Najjar, L. (2014). Crowdsourcing typology: a review of is research and organizations. *Proceedings of the Midwest Association for Information Systems (MWAIS)*. Retrieved from http://aisel.aisnet.org/cgi/viewcontent.cgi?article=1018&context=mwais2014
45. Wand, Y., Monarchi, D. E., Parsons, J., & Woo, C. C. (1995). Theoretical foundations for conceptual modelling in information systems development. *Decision Support Systems*, *15*(4), 285–304.
46. Wang, R. Y., & Strong, D. M. (1996). Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems*, *12*(4), 5–33.
47. Wiersma, Y. (2010). Birding 2.0: citizen science and effective monitoring in the Web 2.0 world. *Avian Conservation and Ecology*, *5*(2).
48. Wiggins, A., & Crowston, K. (2012). Goals and tasks: Two typologies of citizen science projects. In *System Science (HICSS), 2012 45th Hawaii International Conference on* (pp. 3426–3435). IEEE.
49. Wiggins, A., Newman, G., Stevenson, R. D., & Crowston, K. (2011). Mechanisms for Data Quality and Validation in Citizen Science. In *2011 IEEE Seventh International Conference on e-Science Workshops* (pp. 14–19). https://doi.org/10.1109/eScienceW.2011.27
50. Wixom, B. H., & Todd, P. A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, *16*(1), 85–102.