Improving Productivity in Citizen Science through Controlled Intervention

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ABSTRACT

The majority of volunteers participating in citizen science projects perform only a few tasks each before leaving the system. We designed an intervention strategy to reduce disengagement in 16 different citizen science projects. Targeted users who had left the system received emails that directly addressed motivational factors that affect their engagement. Results show that participants receiving the emails were significantly more likely to return to productive activity when compared to a control group.

Categories and Subject Descriptors

H.5.3 **[Group and Organization Interfaces]:** Collaborative Computing.

General Terms

Experimentation, Human Factors.

Keywords

Peer production, crowdsourcing, citizen science, intervention strategies.

1. INTRODUCTION

Volunteers have been involved in scientific research for over 100 years. More recently, technological developments have transformed the role of these non-professional scientists to active participants in large-scale endeavors, termed *citizen science*, in which volunteers collectively create or analyze data at a scale that professional researchers cannot accomplish on their own [1].

Participants in citizen science projects differ widely in contribution rates and motivation [3]. A small minority of participants are highly committed and contribute tens of thousands of tasks, also becoming involved in higher-order participation, such as forum moderation. Whilst the platform could not function without these committed, high-volume contributors, the participation patterns of users in citizen science projects exhibits a long tail distribution, and most volunteers carry out only a few tasks [4].

Prior work has showed that citizen science volunteers are driven by diverse range of motivations with varying degrees of commitment and engagement [3,4,5]. These studies were limited to analyzing isolated citizen projects, and did not attempt to implement and test intervention policies to bring back users to the system. Our work bridges this gap by moving towards a general methodology for reducing disengagement in citizen science through a controlled intervention.

Our methodology is based on the analysis of two years' worth of participation data from 16 different citizen science projects and included the following: (1) Surveys to reveal the motivations that drive users' participation in citizen science; (2) Identifying cohorts based on the survey results and the participation data; (3) Designing an intervention strategy that targets specific cohorts and is designed to increase their engagement with the system; (4) Analyzing the efficacy of this strategy over time, according to performance and persistence measures.

The study was conducted using the Zooniverse platform, the largest citizen science platform that exists today. Zooniverse includes over a million volunteers and 25 live projects spanning astrophysics, zoology, biology, medicine, climate science, and the humanities [15]. In all of these projects the volunteers identify, classify, mark, and label data, which is subsequently aggregated and analyzed in order to reach scientific conclusions. The number of active projects is steadfastly growing, from 8 live projects in the beginning of 2012, to 25 live projects in 2014, and its user base includes volunteers from varying occupations, age groups, level of education and geographical location [2].

The vast majority of participants in Zooniverse work on a few tasks and participate for just a few days before leaving the system [18]. Despite their casual participation, these users contribute a substantial fraction of the overall effort going into the projects. This is demonstrated in Figure 1, which shows the fraction of total contributions as a function of the number of contributions per user in the Galaxy Zoo project.

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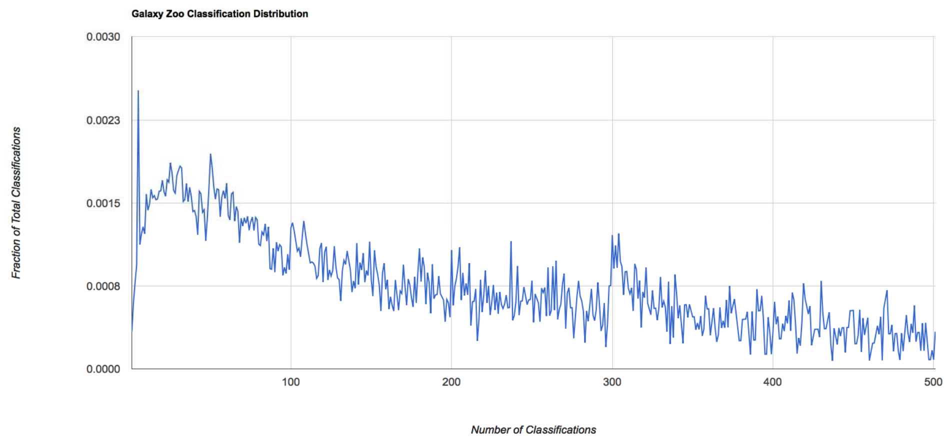

Figure 1: Fraction of total contributions (y-axis) as a function of the average number of contributions per user (x-axis) in the Galaxy Zoo project. Note the sharp spike for users with very small contribution rates on the left-hand side of the Figure.

The tall spike in the left-hand side of the figure shows that the total contribution rate for users with small number of contributions forms the vast majority of volunteers. The figure also shows the long tail of decreasing contributions as the number of average contributions per user grows.

As the number of citizen science projects continues to grow, the need to be more efficient and retain volunteer engagement for longer becomes increasingly important. If volunteer disengagement (the point at which users stop participating in the system) can be delayed by just a few tasks, then overall productivity of citizen science projects could improve significantly.

We designed and administered a survey to 3,000 randomly selected users in Zooniverse who participate in a wide variety of projects. The survey identified "classification anxiety" (overestimating the effects of individual mistakes [5]), competition from other life demands and leisure activities, and boredom from specific projects as prominent causes of disengagement among volunteers. For many users the cause of classification anxiety was revealed to be a misunderstanding of the collective nature of citizen science projects, in which aggregation of data diminishes the effects of individual mistakes.

To identify target communities for the intervention we combined our analysis of the survey with findings revealed by clustering two years' worth of user participation data from 16 different projects. We focused our intervention on two cohorts who quickly left the system after an initial burst of activity. Volunteers in the first cohort spent less than a day making contributions, and those in the second spent between one and ten days as active volunteers. These cohorts are significant as they capture the vast majority of user participation in the system for all projects.

We designed interventions in the form of emails that directly addressed the causes of disengagement that were revealed in the survey and sent to each user in the two cohorts described above. We compared the effectiveness of this intervention method with a control group that included participants with similar participation patterns who did not receive any email notification.

The results showed that participants from the intervention group were significantly more likely to return to activity in their respective projects than participants from the control group, without experiencing a drop in contribution rates and activity in the system, as compared to the control group. In addition, returning participants from the intervention group resumed activity at least as fast, and remained active in the system for at least as long as returning participants from the control group.

Our work has insights for the designers of citizen science platforms in general, by 1) Providing an example of a general methodology for reducing disengagement in different citizen science projects that identifies meaningful cohorts in the population, 2) Uncovering the motivational factors that reduce participation of different groups in the system, and 3) Providing a guideline for interventions to stimulate re-engagement and bring back users to be productive contributors.

2. RELATED WORK

This paper relates to prior work on identifying participation patterns and the study of disengagement in citizen science. We relate to each of these in turn.

The majority of the labor in general peer production sites is often apportioned to 1% of users of the website [7]. Preece and Shneiderman [6] defined categories of users that are distinguished by their depth of social engagement within the community: 'readers' who lurk in the background; 'contributors' who create content and contribute to the community; 'collaborators' who work together and regularly contribute and 'leaders' who participate in the governance of the site. The ratio of contributors in citizen science projects is significantly higher than that of peer production sites, averaging at 10% [18]. Contributors in citizen science exhibit a variety of contribution styles. In particular, Eveleigh identified 'dabblers' as important classes of volunteers [5]. Dabblers exhibit a low-commitment attitude, a weak tie to projects, and an intermittent approach to participation, with occasional short bursts of activity. Nonetheless, these casual contribution styles form the majority of user contributions to Zooniverse [19] and were the focus of attention in this study.

Some studies have specifically focused on identifying disengagement in citizen science. Rotman described a 'circuit of engagement' whereby volunteers, motivated initially out of curiosity, may subsequently leave the system if they are not made to feel part of the wider scientific community [9]. Jackson et al.

[20] identified ways in which the technical features of the projects may serve as motivational factors leading participants towards sustained participation. Eveleigh [5] cited competition with other life activities, anxiety over making mistakes and boredom as main reasons driving disengagement. Kittur added low work quality and inappropriate task assignment as major reasons for early disengagement [10]. Mao et al. [8] used machine learning to predict disengagement in the Galaxy Zoo project, focusing on disengagement after 5 minutes and 30 minutes sessions, respectively.

There is no prior work on alleviating disengagement in citizen science through controlled intervention studies. Wiggins and Crowston [19] emphasized the importance of fitting the project environment to its specific goals and characteristics in order to enhance participation. Some projects, like foldit [16, 21], are framed in the context of a game in order to enhance user engagement. A few citizen science projects exhibit badges and leader boards functionalities, although there is evidence that competitive game elements may be counterproductive and work to de-motivate casual contributors and reduce the quality of the work [11, 12, 13].

In the following sections we describe a four stage multidisciplinary process consisting of: (1) Surveying volunteer populations to understand reasons for participation and disengagement; (2) Profiling volunteer populations to reveal distinct cohorts that may be targeted by interventions; (3) Intervention design to target the cohorts and address the motivational factors uncovered in the survey; (4) Evaluation and follow-up to determine effectiveness of intervention strategy.

3. UNDERSTANDING PARTICIPATION AND DISENGAGEMENT (STAGE 1)

To guide our intervention approach we implemented a questionnaire to uncover reasons for patterns of engagement and disengagement within Zooniverse. Our survey included 25 questions and was sent on July 7th 2014 to 3,000 participants randomly selected out of those who had logged in to the system at least once in the previous 3 months. The purpose for this timespan was to target citizen scientists who had disengaged but had contributed sufficiently recently to still be inclined to respond to the survey. The survey took approximately ten minutes to complete by participants, and there was no monetary (or other) reward offered. The survey was composed as follows: Initial questions (Q1 to Q9) focused on demographics, including age, education level, employment status, occupation, and country of residence to ascertain how our sample compares to the general population. Q10 to Q13 were included to gain insight into how participation in citizen science fits into participants' lives particularly in relation to daily routines, and where contributions are made. Q14 to Q17 asked about participants' experience of forums and chat, their motivations and what might encourage greater participation. Q18 probed if anxiety around the accuracy of contributions was common experience, and if so, how participants dealt with their anxiety. Q19 ascertained if this anxiety leads to disengagement. Q20 to Q22 focused on trying to understand what makes projects engaging, whereas Q23 and Q24 elicited what makes some projects less engaging and probed reasons for disengagement. Finally, Q25 prompted respondents for additional comments on their participation and for suggestions of improvements that might increase engagement. In this paper we report mainly on responses to questions about anxiety and disengagement.

We based our analysis on 257 completed responses to the survey that were obtained over the course of a month (July-August 2014); an 8.6% response rate. Out of the submitted responses, 35% of users reported to be living in the US, and 30% in the UK. The remainder of the responses came from 31 different countries spanning Europe, Asia, Africa, North America, and Australia. 59% of the responses were from males while 39% were from females, with 2% preferring not to answer. The mean age of participants was 44, with a flat distribution of ages ranging from 18 to 79. The open-ended questions were analyzed using thematic analysis [22].

Our findings are consistent with the study by Eveleigh et al. [12] for the 'Old Weather' project regarding classification anxiety. However, we extended this study in revealing the causes and effects of this anxiety on users' participation. We focus on this topic first as it illustrates the collective nature of participation in citizen science platforms, a topic we address in detail in our discussion. A significant majority - 82% of respondents - indicated that they had experienced classification anxiety during their participation. Around 25% of anxious participants report disengaging from projects or the site as a whole. In free text responses statements like "*Rather than accidentally marking everything wrong, I chose to stop instead*" were common.

Table 1: Citizen Science projects used in study

Project	Project Description	Total Users
MWP	Find and draw circles on infrared image data from the Spitzer Space Telescope	14556
Notes from Nature	Digitize the world biological collections one record at a time	5821
Galaxy Zoo	Classify galaxies according to their shapes	82620
Planet Hunters	Look for planet around other stars	172364
Planet Four	Help explore the surface of Mars	43335
Snapshot Serengeti	Classify different animals caught in millions of camera trap images in Serengeti National Park	31000
Condor Watch	Track the location and social behavior of condors	3038
Radio Galaxy Zoo	Help astronomers discover super massive black holes	5338
Disk Detective	Discover the birthplace of planets in never-before seen data	5137
Sunspotter	Organize sunspot images in order of complexity	2530
Cyclone Center	Help scientists analyze over 30 years of tropical cyclone satellite imagery	7351
OWD	Open up the information that is currently locked away in First World War diaries by data tagging	9403
Seafloor Explorer	Identify species and ground cover in images of the seafloor	21273
Bat Detective	Classify bat calls to track their behavior and population	2637
Plankton Portal	Understand where and when plankton occur at different depths in the ocean	5882
Worm Watch Lab	Help scientists discover how genes affect behaviour in nematode worms	7002

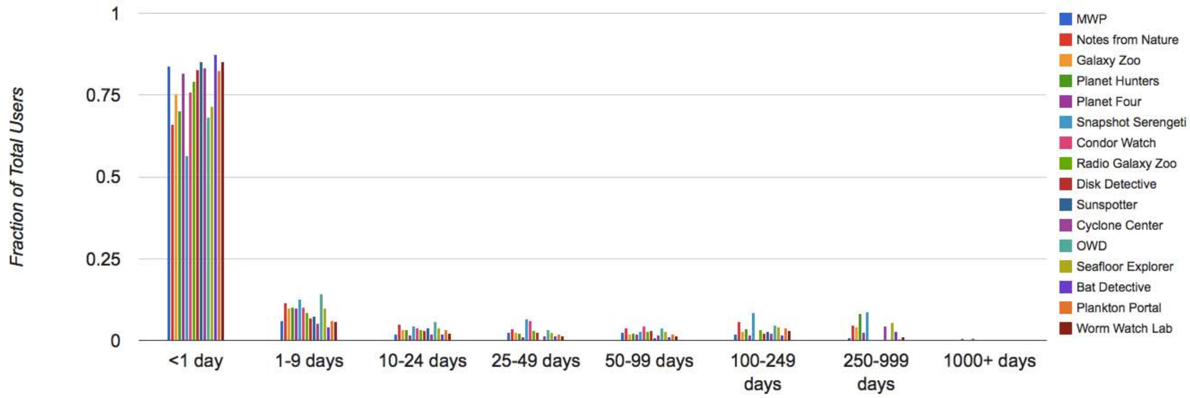

Figure 2: Activity Patterns in 16 Citizen Science Projects

We argue this classification anxiety is rooted in a misunderstanding of the collective nature of citizen science. In scientific data analysis that is carried out by paid professionals, accuracy is crucial for valid results; scientists undergo years of training to become expert at gathering and analyzing data. Citizen Science is a place where these principles of conventional scientific practice are almost entirely inverted. Volunteers are invited to classify objects almost immediate they land on a project homepage, typically after only the briefest of tutorials. But in contrast to conventional scientific practice, in citizen science, mistakes typically do not destroy the validity of the results. Due to the collective nature of citizen science many participants complete each task, and techniques such as majority voting and statistical aggregation serve to alleviate the effects of individual mistakes on the analysis. In fact, 'mistakes' often give scientists important information, for example, telling them that an object is ambiguous or otherwise hard to interpret. It seems that volunteers fail to perceive that they are actually contributing as part of a collective but instead retain a conventional model of scientific practice with the attendant anxiety about individual mistakes which may lead them towards disengaging from the platform.

The most common reason given for intermittent contributions was due to distracting life events. In response to the question "When do you participate in Zooniverse?", thirty eight percent of respondents agreed with the statement: "Sometimes I don't contribute for a while, but then I pick it up again", corresponding to the category of 'dabblers' described by Eveleigh [5]. For the follow-up question: "What made you stop", of those who responded the vast majority (66%) cited distraction, time pressure, work, family obligations and competing leisure interests as reasons for disengagement. Some respondents express their experience of disengagement as akin to 'forgetting' ("I just get other things to do and forget about it"). They also describe how re-engagement is associated with remembering or being reminded, ("When I have a lull and I remember, I have a look at the Zooniverse."; "I need to be nudged"). Some of these respondents also report that they become bored or find a project less appealing than they initially thought ("I get a little bored, and forget about it."), sometimes, because of the way that the Zooniverse site is structured, not realizing there are other projects they might find more appealing ("I've been participating at GalaxyZoo for a few weeks and it is only now in this survey I realize all the other projects that I can join.").

Taken together, these responses suggest there is a significant 're-engagement potential' for participants who disengage, which might be activated by a suitable reminder. Such a reminder might usefully provide reassurance about classification accuracy, as well as directing 'bored' participants towards other projects they could try. We describe our intervention strategy in greater detail in section 5.

4. PROFILING VOLUNTEER POPULATIONS (STAGE 2)

To understand which citizen science sub-population we might usefully target with an intervention (i.e. which may be prone to distraction, anxiety or boredom) we analyzed the engagement patterns of volunteers in 16 different projects. This sample is representative of the gamut of different topics in Zooniverse (e.g., biology, nature, astronomy) and popularity with volunteers, as measured by the number of registered users as of July 2014.

Table 1 provides a general description of these projects. Data was collected beginning September 2012 for all projects, with the exception of the Planet Hunters project, for which data was already available from December 2010.

We measured users' activity in the system by the number of days elapsed since their first and last seen login. Let t_k be the current timestamp. Let t_i be the timestamp of the user's first login to the system. Let t_j be the timestamp representing the user's most recent login to the system. We measured a user's activity as the difference between t_j and t_i. Figure 2 describes users' activity in the system for all of the supplied projects. The X-axis shows range groups of participation time spans, and the Y-axis shows the ratio of users that fall into each group.

The figure clearly identifies two distinct groups that make up the vast majority of activity in the system. The largest cohort of users consists of those who spent less than a day as active users, which we will denote the "1-day" cohort. This cohort included 56 to 87 percent of volunteers. Another large cohort consists of volunteers who spend between one to nine days as active users in the system, which we will denote the "10-day" cohort. This cohort included 4 to 14 percent of volunteers. Together these cohorts make up at least 60% of the user population in Zooniverse. We thus decided to focus our intervention strategy on these two cohorts. Even a small increase in the contributions of these populations can lead to significant benefits to the total contributions of the projects.

5. INTERVENTION DESIGN (STAGE 3)

The goal of the intervention was to bring back the disengaged 1-day and 10-day cohorts to being productive users in the system. We randomly assigned the users in the 1-day and 10-day cohort to a control and an intervention (test) group. The intervention group received a reminder email that was designed to encourage them to return to the their respective projects and to make contributions. We evaluated this approach by measuring whether (and how quickly) these users return to being active users following the intervention, and the difference in contribution rates (i.e., persistence) after returning to the system.

The email directly addressed the motivational issues that were uncovered in our survey, emphasizing the collective nature of the projects, the tolerance to individual mistakes by volunteers, and the availability of other projects on the system. The control group received no such email. The email sent out to the intervention group was sent a week after the user's last login to the system. The mail for the 1-day cohort was as follows:

"*Thanks for trying PROJECTNAME, we appreciate your clicks! You're not alone on PROJECTNAME - thousands of people take part every month. You can discuss the images you see on PROJECTNAME with the community, and the project's research team, by visiting Talk at PROJECTTALKURL. Get involved again at PROJECTURL.*
We know that some people worry that they aren't very good at PROJECTNAME - but this isn't the case. We can use all volunteers' clicks to learn about the data, and multiple people will see each image. We use statistical techniques to get the most from everyone's answers, and the occasional error does not affect the results.
If PROJECTNAME didn't suit you, then check out all of the other Zooniverse citizen science projects at www.zooniverse.org, or if you would rather not receive these emails you can unsubscribe at www.zooniverse.org/account/newsletters. You can see your contributions to all Zooniverse projects by visiting http://zooniverse.org/me. We look forward to seeing you again, Rob and the Zooniverse Team."

The email to the 10-day cohort varied slightly in addressing the volunteers as regular contributors rather than newcomers and providing users with a link to a service which tracks their contributions to Zooniverse. It was sent two weeks after the user's last login to the system.

The intervention was conducted between the dates of August 15th, 2014 and September 24th, 2014. On each day, we sent out the relevant email to the volunteers in the intervention groups. In total, the intervention group consisted of 306 randomly selected volunteers from the 1-day cohort and 541 volunteers randomly selected from the 10-day cohort. The control group consisted of 292 randomly selected volunteers from the 1-day cohort and 540 volunteers from the 10-day cohort. Note that volunteers that were assigned to both cohorts and received both mails were removed from the analysis. To measure the interventions impact, Zooniverse supplied us contribution data for the two groups for the aforementioned dates, including user ID, task ID and timestamp of task contribution.

We wished to examine the following hypotheses:

1. Sending emails to the intervention group will have a significant and positive effect on the return of volunteers to activity as compared to the control group.
2. Returning volunteers from the intervention group will resume activity at least as fast as returning volunteers from the control group.
3. Returning volunteers from the intervention group will be at least as persistent (remain active in the system) as returning volunteers from the control group.
4. Returning volunteers from the intervention group will provide at least as many contributions as returning volunteers from the control group.

6. ASSESSMENT OF EFFECTIVENESS OF INTERVENTION (STAGE 4)

We first compared the number of volunteers from the intervention and control groups that returned to activity in the system. Figure 3 shows the ratio of returning volunteers from both groups. As can be seen, the ratio of volunteers who returned to the system following the intervention was significantly higher for the intervention group than for the control group (Chi square $p<0.03$). The bars in the figure represent 95% confidence intervals. There was no significant difference in the returning ratio results of subjects between the 1-day and 10-days cohorts.

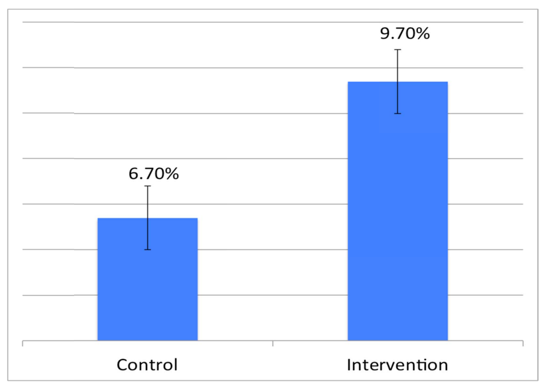

Figure 3: Return ratio for intervention and control groups

Table 2: Persistence for intervention and control groups

Group	Contributions Before (num. of tasks)	Contributions After (num. of tasks)	Days active After
Intervention	20	18	1.5
Control	21	23.5	1.2

We next compared the speed in which volunteers returned to the system in both groups as measured by the number of days from sending out the email to their first login back to the system. We found that the average return time for volunteers in the intervention group (4.1 days) was less than that of the control group (5.7 days), although this result was not statistically significant (one-tailed non-paired t-test, $p=0.052$).

One may suspect that although email interventions are able to bring back more volunteers, their activity in the system is lower than that of volunteers in the control group, who return to the system on their own accord. To check this, we looked at the median number of classifications before and after the reminder for both groups, as shown in the Table 2. The results show that there was no statistically significant difference between the two groups in the number of classifications before and after the intervention. We chose to present the median rather than the average contribution rate to offset the effect of "outlier" volunteers whose contribution rates are exceptionally high. When looking at average contribution rates, we see a decrease for both groups in the number of classifications before and after the intervention (not shown in the table). However, this decrease was significantly more pronounced for the control group than for the intervention group (non-paired t-test, $p<0.03$).

Lastly, there was no statistically significant difference between the number of days active in the system after the intervention between the intervention group (1.5 days) and the control groups (1.2 days, one-tailed non-paired t-test, $p=0.32$). Thus, we conclude that our reminder intervention ensures persistence, which does not fall from the persistence of those returning without a reminder.

7. DISCUSSION AND CONCLUSIONS

In this paper we presented a general methodology for reducing disengagement in citizen science that is based on the analysis of two years of participation data in 16 citizen science projects. This methodology included: (1) Surveys to reveal the motivations that drive users' participation in the different projects; (2) Identifying cohorts based on the survey results and the participation data; (3) Designing an intervention strategy that targets specific cohorts and addresses the motivational issues revealed in the survey; (4) Analyzing the efficacy of this strategy over time, according to performance and persistence measures.

Applying the methodology revealed that disengagement is triggered by life distractions, classification anxiety, and boredom. We identified target communities for the intervention that capture the vast majority of user participation in the system for all projects. We designed interventions in the form of emails that directly addressed underlying issues uncovered by the survey. The methodology was shown to successfully promote re-engagement of users across 16 different citizen science projects. Returning participants from the intervention group resumed activity at least as fast, and remained active in the system for at least as long as returning participants from the control group. Our methodology is an example of the new engineering approach combining social and computational elements [14,15] and the work by Burke et al. [17] suggesting to target intervention to specific users to increase their social contribution.

We now mention three issues with our approach and explain how each corresponds to a type of trade-off inherent when designing interventions for "non-uniform" populations in which volunteers vary widely in the extent of contribution.

First, we identified two cohorts, those who disengage after a day, and those who remain in the system for up to 10 days before disengaging. But as far as our intervention is concerned, we treat these as a single population. On the one hand this is sensible because combined they represent the larger population of contributors who rapidly disengage (corresponding to Eveleigh et als' 'drop-outs' [5]). On the other hand, better tailored interventions may be more effective for each cohort as presumably those disengaging after a day have a different shared experience to those disengaging after a few days. Moreover, it may be possible to disaggregate these populations even further based on finer differentiations of engagement patterns and underlying motivational issues, enabling increasingly more focused and efficient interventions. That said, we have been successful with a relatively simple (yet crude) instrument, and ever more refined approaches would incur correspondingly greater overheads in terms of cost and complexity.

A second issue relates to the presumption that our survey findings map onto the experience of those 1-day and 10-day cohorts identified in the participation profile. We are assuming that distracting life-events, anxiety and boredom count as significant reasons for disengagement within these cohorts, without being able to precisely identify what the actual reasons are for any individual who disengages, nor denying that there may well be a mix of other reasons that we have yet to encounter. This imprecision is related to methodological limits of qualitative research, particularly surveys, where generalizations need to be made in order to map from the survey sample to the overall population. Again, there is a trade-off here, since greater precision attracts overheads – not least ultimately the risk of annoying or alienating volunteers.

Finally, the e-mail intervention works much less like a hunting spear and much more like a net in the way that it ensnares several (presumed) sub-populations simultaneously (those who have been distracted from their project, are anxious or who are bored). These messages may also act in concert on those occasions where both reassurance and a reminder are needed, but they may also miss the mark where disengagement occurs for some other reason. On the plus side, the e-mail message has a degree of generality, it can speak to multiple audiences simultaneously, but this increases the challenges of assessing its effectiveness.

While the work described here has produced a significant improvement in productivity from a specific intervention, we believe further cyclic iterations of the 4-step methodology will uncover additional insights into the motivations of other citizen science projects. Future work will target interventions to users during their online interaction with the system using machine learning models and consider other intervention channels such as task recommendations and modal messages as well as other reward schemes.

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