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Profiles of engagement in online communities of citizen science participation

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ABSTRACT

Citizen participation in online communities of scientific investigations has recently become more popular. Enhancing the engagement of citizens within these communities is a focus of attention for researchers and practitioners who want to amplify the impact on learning, science and society. This study investigates the relationship between engagement factors and behaviour patterns in an online community that requires high levels of citizen participation. While other studies explore engagement in communities where citizens contribute data, the current research investigates a community to support citizens in facilitating their own scientific investigations. Data were collected from log files and questionnaires, and multiple measures of engagement were examined: engagement metrics, roles, motivation, attitude, satisfaction and belonging to the community. The results allowed comparison of the engagement levels among different types of citizen participation communities and categorised members in engagement profiles, according to their behaviour patterns. Findings indicate a need for differing design approaches based on the type of citizen participation community and individual engagement profiles.

1. Introduction

There is increasing interest in involving the public in shared scientific activities and science understanding. In particular, citizen science projects engage volunteers to participate in science research and collaborate with scientists to answer real-world questions.

Stebbins (1982) names this participation in after-work activities *serious leisure*, where volunteers, hobbyists or amateurs are fascinated by activities that provide them with a sense of being part of a shared social world, or offer a challenging routine to those who are not in full-time employment. Furthermore, serious leisure provides lifestyles and identities to people that can be viewed as behavioural expressions of their central life interests. From a different lens, citizen participation in social activities has been examined as a link to citizen power (Arnstein, 1969). The integration of the public in political and economic related activities has been assessed to be the strategy by which they can contribute to social reforming, and share in the benefits of a more prosperous society. In the same way, the involvement of citizens in authentic scientific inquiry activities requires them to adopt a sense of shared responsibility for issues regarding their communities and become active during the change process, contributing to the well-being of the community and hence their personal lives.

Similarly to Arnstein's ladder of participation which refers to eight rungs of citizen participation, ranging from *non-participation* to *tokenism* and to *citizen power* (Arnstein, 1969), the public participation in scientific research projects has also been categorised in several typologies. Some typologies categorise the projects, according to the level of collaboration between scientists and citizens, into *contributory, collaborative* and *co-created* projects (Bonney et al., 2009), while some others focus on the level of participation and engagement, and cluster projects as *crowdsourcing, distributed intelligence, participatory science* and *extreme citizen science* (Haklay, 2013). Therefore, the inquiry activities that citizens are involved in may range from contributing data (contributory or crowdsourcing) to participating in the entire process and taking part in publications (co-created or extreme citizen science). Results from a review of different types of citizen participation projects demonstrate that the more that individuals are involved with all the aspects of the scientific process, the more likely they will increase science learning outcomes (Bonney et al.,

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2009). To this end, *citizen inquiry* projects have emerged as a way to open up the scientific process to distributed communities of citizens to create and facilitate their own projects, and report inquiry-led results (Aristeidou, Scanlon, & Sharples, 2013; Sharples et al., 2013).

Despite extensive research into the scientific outcomes of citizen participation communities, little research has been yet undertaken around participants' engagement and community sustainability. Due to the high attrition rate that has been noted in these communities (Nov, Arazy, and Anderson, 2011b, 2011a;; Ponciano & Brasileiro, 2015) and the dabbling behaviour (Eveleigh, Jennett, Blandford, Brohan, & Cox, 2014) more work needs to be carried out in relation to the factors that draw and sustain participants. Current studies recognise user engagement as a necessary ingredient for the success of virtual environments (Verhagen, Swen, Feldberg, & Merikivi, 2015) and emphasize the behaviour of volunteers who invest personal resources such as cognitive power, physical energy and time, in order to provide assistance to others (Lehmann, Lalmas, Yom-Tov, & Dupret, 2012; O'Brien & Toms, 2008).

Human Computer Interaction research can empower citizen participation and considerably increase success in what and how it is done, enhancing learning and amplifying the impact on society, globally and locally (Preece, 2016). Research into the principles of Human Computer Interaction emphasises the importance of the design elements for attracting and engaging users in citizen participation projects (Eveleigh et al., 2014; Kim, Robson, Zimmerman, Pierce, & Haber, 2011; Wald, Longo, & Dobell, 2015) and other online communities (Burke, Marlow, & Lento, 2009; Ren & Kraut, 2013). An in-depth study by Ren and Kraut (2013) on managing online conversations proposes that communities are often less successful than they could be as many design decisions are driven by intuition and trial and error instead of being based on the systematic understanding of users' motivation and contribution. For instance, results of their research regarding motivation suggest that personalised moderation increases members' commitment and contribution, as users can view different messages matched to their personal interests. Therefore, exploring engagement factors facilitates in taking design decisions about the community, as one size does not fit all.

Studies on motivation for participating in citizen science projects focus on the psychological factors of users and explore motivation for joining and staying in the project. This is done through survey data, interviews and forum posts (Aristeidou, Scanlon, & Sharples, 2015b; Curtis, 2015; Raddick et al., 2010, 2013; Reed et al., 2013; Rotman et al., 2012). Findings identify personally-focused reasons (e.g. Aristeidou et al., 2015b; Rotman et al., 2012) or altruistic factors (e.g. Curtis, 2015; Raddick et al., 2013) as main motivations for joining the projects. Some other studies go a step further and assess the influence of motivational orientation on contribution and participation (Borst, 2010; Nov, Arazy, & Anderson, 2011a; Eveleigh et al., 2014). Results suggest that members with intrinsic motives have novel contributions (Borst, 2010), enhanced participation frequency (Nov et al., 2011a), increased (Borst, 2010; Eveleigh et al., 2014) and longer participation (Eveleigh et al., 2014). However, these studies focus on the influence of motivation on participation, without taking into account other engagement factors, such as attitude, satisfaction and belonging to the community.

Another way of investigating user engagement in citizen participation communities is by tracing behaviour patterns. Tracing behaviours and determining user engagement enables project and platform moderators to make decisions, perform actions to avoid dropouts, improve the technologies and adapt the structures or content to users (Cruz-Benito, Therón, García-Peñalvo, & Pizarro Lucas, 2015). Ponciano and Brasileiro (2015) focus on the behaviours of people engaging with contributory citizen participation projects, clustering users based on log data of the activity, daily devoted time, relative activity duration, and variation in periodicity ratios. The resulting engagement profiles are ‘hardworking’, ‘spasmodic’, ‘persistent’, ‘lasting’ and ‘moderate’.

Nevertheless, research stresses the importance of capturing both behavioural and psychological aspects of engagement. Calder and Malthouse (2015) differentiate actual behaviour from engagement, which is the motivational force to make something happen. Therefore, there is need to explore the actual behaviour as the consequence of the motivational force and not in isolation. Ponciano and Brasileiro's study (2015) provides insight into measuring the level of engagement with the project tasks, but it has not yet captured the psychological factors lying behind those engagement profiles.

Thus far, there has been little research around the motivational force behind the engagement profiles. Most studies either investigate the motivations or the contribution, without further exploring the relationship between them, or taking into account the importance of capturing different facets of psychological engagement (Appleton, Christenson, Kim, & Reschly, 2006; Boyle, Connolly, & Hainey, 2011). Moreover, we are not aware of any previous empirical research studies of behaviour or engagement in participation projects where citizens facilitate their own investigations (e.g. citizen inquiry). A comparison between communities of various levels of citizen participation may indicate differences in the level and type of engagement. To this end, the current research aims to investigate the relationship between engagement factors and the behaviour patterns in citizen inquiry by capturing multiple measures, and relate the observations to results from contributory projects and to possible future design actions and decisions.

We compare the level and type of a citizen inquiry community (Weather-it) to two other citizen science projects (Milky Way project and Galaxy Zoo), finding that the level of activity for Weather-it members was lower than Milky Way Project and similar to Galaxy Zoo, but with longer participation. We employed cluster analysis to derive five types of member profile, according to the type and level of members' activity, and psychological engagement factors. Our analysis has found that two engagement profiles detected in Milky Way project and Galaxy Zoo were also present in Weather-it (hardworking and persistent), and three new engagement profiles emerged to better describe the behaviour of Weather-it members (loyal, lurking and visitors). Surveying the psychological engagement factors behind each profile provided us with answers to why members have a variety of behaviours. Lack of time, website usability, fear, and quality of contributions, as well as reasons for joining, and feelings of belonging to the community are some of the reported factors that determine members' participation behaviour. Design that takes into account these factors may provide a more personalised moderation according to the community behaviour and contribute to scaling up and sustaining the community.

In this study we put forward the following contributions: (a) we extend the framework for assessing engagement profiles proposed by Ponciano and Brasileiro (2015) by adding ‘lurking ratio’ to the metrics and capturing different facets of psychological engagement (roles, motivation, attitude, satisfaction and belonging) for each profile; (b) we provide a first study that measures engagement of members in a community that requires high levels of citizen participation, and a comparison to communities with other types of citizen participation; and (c) our findings and recommendations may inform design guidelines for recruitment and sustainability of citizen participation communities.

2. Material and methods

2.1. Participants and procedure

The current study was conducted on nQuire-it (www.nquire-it.org), a platform that originates from the idea of having citizens act as scientists by allowing them to initiate, manage, share and complete crowdsourcing projects of their own interest (Herodotou, Villasclaras-Fernandez, & Sharples, 2014). At the time of the data collection, Weather-it, a citizen inquiry community around weather investigations was hosted on the platform. In Weather-it, the participants, of all levels of meteorology expertise, could create or join weather investigations and also invite their social network to join. The investigations could be weather questions they have in their everyday life (e.g. identify clouds), phenomena they want to investigate further (e.g. extreme weather), or something related to climate (e.g. climate change). Creating an investigation through the inquiry-led platform required setting questions and inquiry steps (e.g. data collection methods) for other people to join and contribute to answering them. In this way, citizens created their own personally meaningful inquiries, in collaboration with scientists, while participating in all the inquiry phases, instead of just contributing with their data (Aristeidou, Scanlon, & Sharples, 2015a). Joining an investigation allowed them to add posts and ideas related to the topic, and like or comment on other posts. Additionally, the members could use the forum to discuss their questions and ideas. The detailed actions that occurred within nQuire-it were recorded and stored in log files that could be analysed as part of the evaluation process. In total, there were 1560 data items: 422 contributions (images, sensor recordings and text responses), 441 comments, 485 likes, 188 forum posts and 24 mission and forum thread creations. For this study, data from 14 weeks (23/11/2014–1/3/2015) were exported from the nQuire-it database and we had access to data from 77 users. A 6-item questionnaire was sent to all 77 users and received a 70% response.

2.2. Methods

A systematic review of methods for researching engagement in online communities by Malinen (2015) shows that behavioural patterns and user type identification have been analysed through activity logs; satisfaction, motivations, values, needs and user roles through qualitative techniques; and change in user behaviour over time through observation and field research. A previous study of nQuire-it user engagement has shown, through social network graphs, how the community behaviour has changed over time (Aristeidou et al., 2015b). The various evolution stages have been enriched with survey data that provided engagement and disengagement reasons that caused the particular evolution. While that study offered insight into the big picture of the community, the study reported here aimed to investigate the behaviour of particular groups of users within the community. To this end, activity logs and metrics were used to draw user engagement profiles and then each engagement profile was described utilising data around user roles, motivation, attitude, experience and belonging to the community.

2.2.1. Engagement metrics

The log data helped in calculating metrics indicating the engagement/disengagement level of the participants. Metrics used for measuring engagement have been developed by Ponciano and Brasileiro (2015), who applied them in measuring engagement in two contributory citizen participation projects. Similarly to the work by Ponciano and Brasileiro (2015), only Weather-it members that had at least two days of activity are included in these metrics.

Fig. 1 shows an example of the timeline of a member during participation in Weather-it. The member had active days in the project (black boxes) and during these days contributed with data, comments, likes, forum posts and mission/forum creation. During a lurking day (white boxes), the member just visited the community without getting involved in any activity, other than browsing. Finally, the dotted boxes represent the days of the project that the member did not visit the community. The number of days between the first and last active/lurking visiting day, show the total days the member was linked to the project.

From these data, based on the measures from Ponciano and Brasileiro (2015), the engagement metrics for each Weather-it member are calculated as follows:

Activity ratio: It is the ratio of days on which the member was active and executed at least one task in relation to the total days they remained linked to the project. The closer to 1 the more active a volunteer is during the days they are linked to the project.

Relative activity duration: It is the ratio of days during which a member is linked to the project to the total number of days from their joining to the end of the research project. The closer to 1, the longer a volunteer remains linked (persistent) to the project, from their joining to the end of the project.

Variation in periodicity: It is the standard deviation of the multiset of number of days elapsed between each pair of sequential active days (Fig. 1). The closer to 0 the steadier the rate by which a volunteer returns to the project. For instance, if a member visited the community on 1, 2, 15, 20, 22 and 28 of December then the multiset that standard deviation would be applied to is {1, 13, 5, 2, 6}.

In addition, we propose the following metric for measuring lurking (non-active contribution), based on research by Preece, Nonnecke, and Andrews (2004) on the extent of lurking in online communities:

Lurking ratio: It is the proportion of days on which the volunteer was lurking in relation to the total days they visited the project. The closer to 1 means the more a volunteer lurks (i.e. logs into the platform and browses content but does not contribute) during the days they are online.

Another metric used by Ponciano and Brasileiro is the 'daily devoted time' which shows the averaged hours a volunteer remains doing tasks on each active day. However, this metric has not been used in this study, as no reliable information on the login duration could be extracted from the nQuire-it log files.

An example of data in calculating metrics can be found in Table 1. The names members used on the platform were changed to ones inspired by cloud and wind types. The members in the table below represent different engagement clusters. Those listed have the smallest distance, in comparison to other cluster members, from the cluster centre. For instance, Stratus was active 17 out of the 37 days that he was linked to the project (activity ratio = 0.459) and Cirrocumulus was lurking one out of the four days he visited the

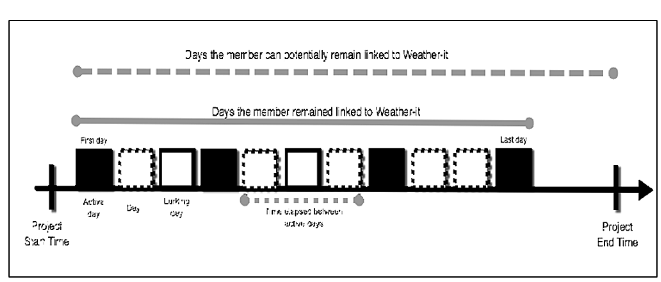

Fig. 1. Timeline-example of a Weather-it member, with the days they visited (lurking, active) and did not visit the community.

Table 1
Example of data - calculating metrics.

Member	Active days	Lurking days	Total days linked to project	Days until project finishes	SD periodicity	Activity ratio	Relative Activity duration	Lurking ratio	SD periodicity
Stratus (loyal)	17	2	37	39	1.256	0.459	0.949	0.105	0.087
Mistral (hardworking)	7	0	11	97	0.471	0.636	0.113	0.000	0.033
Cirrocumulus (lurker)	3	1	15	21	5.437	0.200	0.714	0.250	0.354
Typhoon (persistent)	14	3	86	90	6.811	0.163	0.956	0.176	0.699
Abroholos (observing visitor)	1	0	1	87	N/A	1.000	0.011	0.000	N/A
Chinoo (active visitor)	2	1	37	92	N/A	0.054	0.402	0.333	N/A
Maestro (hesitant visitor)	0	1	4	90	N/A	0.000	0.044	1.000	N/A

platform (lurking ratio = 0.25).

2.2.2. Clustering

Clustering methods were used to produce engagement profiles. The engagement profiles characterise the level of engagement of members that belong to the specific profile. Cluster analysis was performed with SPSS.

For the identification of the engagement profiles, the metrics' results were used and a clustering method similar to the one used by Ponciano and Brasileiro (2015) was adopted. Prior to the clustering the values of the engagement metrics were normalized in the interval [0,1]. Then, members were separated into two groups; active members (those who were active more than two days) and visitors (those with two or fewer active days). Active members were clustered based on the four metrics whereas visitors were placed in a different category in advance, and were clustered with 'Variation in periodicity' metric excluded, as it was not possible to calculate it with only two active days. The clustering outcomes were visualised through comparative bar charts that represented the engagement metrics of each profile.

A hierarchical agglomerative clustering algorithm was used and two dendrograms were plotted, for active members and for visitors, to provide suitable intervals to test the number of clusters for each category. The position of each member was plotted in Euclidean space, based on the engagement metrics from Section 2.2.1. The Euclidean distances between members were calculated to evaluate the proximity of members (Jain, Murty, & Flynn, 1999). A hierarchical clustering technique was then used to group together those separated by the shortest distances. The dendrograms graphically display the distances at which members and clusters are joined, on a scale of 0–25. The potential numbers of clusters were formed by drawing vertical lines at the dendrograms and counting the number of lines that they intersect.

The clustering quality was evaluated by Davies-Bouldin index (Davies & Bouldin, 1979) and Average Silhouette (Rousseeuw, 1987). Davies-Bouldin Index evaluates intra-cluster similarity and inter-cluster dissimilarities. The best clustering scheme has to minimise the Davies-Bouldin index (no cluster to be similar to another). Thus, the number of clusters for which the value is the lowest, is a good guide on how many clusters exist in the data. Average silhouette shows how cohesive the clusters are, with values close to −1 indicating poor clustering and close to 1 excellent clustering. A strong structure is found when values are between 0.71 and 1 while a reasonable range is between 0.51 and 0.70 and a weak below 0.51 (Struyf, Hubert, & Rousseeuw, 1996).

K-means was then utilised to classify the data through the number of clusters found through the Average Silhouette and Davies-Bouldin index. The *a priori* fixed clusters reduce the iteration time (Lu, Tang, Tang, & Yang, 2008). K-means was preferred over a two-step method as the data did not include categorical variables with three or more levels (Norusis, 2007). The resulting engagement profiles were validated and described in combination with qualitative data of the participants that belong to each profile.

2.2.3. Survey

The focus of the questionnaire was to gather information about the motivations for participating, user roles in the community according to their level of weather expertise, belonging, attitude and satisfaction. This information was used to further describe the specific engagement profile linked to each survey respondent's behaviour. Motivations, user roles, current activity status, belonging to the community and attitudes were translated into percentages, while open-ended responses regarding satisfaction were thematically analysed, following inductive coding and theme development (Braun & Clarke, 2008). The questionnaire was completed by 54 out of 77 clustered members.

3. Results

3.1. Metrics

Table 2 shows the descriptive statistics of engagement metrics of members in Weather-it dataset in comparison to those of 'Milky Way' and 'Galaxy Zoo' projects, produced by Ponciano and Brasileiro (2015). The metrics used for this analysis are described in the Methods Section. For the calculation of the engagement metrics, several data for each user were collected, such as the number of active days, the number of lurking days, the total days a user remained linked to the project and the number of days between joining and end of the project.

The results show that Weather-it members were less active during the days they were linked to the project in relation to those

Table 2
Comparison of average engagement metrics in three projects.

	Weather-it	Milky Way	Galaxy Zoo
Activity ratio	mean = 0.32, sd = 0.35	mean = 0.40, sd = 0.40	mean = 0.33, sd = 0.38
Daily devoted time	no data	mean = 0.44, sd = 0.54	mean = 0.32, sd = 0.40
Relative activity duration	mean = 0.43, sd = 0.44	mean = 0.20, sd = 0.30	mean = 0.23, sd = 0.29
Variation in periodicity	mean = 5.11, sd = 5.36	mean = 18.27, sd = 43.31	mean = 25.23, sd = 49.16
Lurking ratio	mean = 0.35, sd = 0.39	no data	no data

of Milky Way but almost as active as the volunteers in Galaxy Zoo (activity ratio). The daily duration users spent in the community was not calculated as there was no reliable information in the log data (daily devoted time). In Weather-it, members seem to be more persistent and linked to the project for longer than those of the other two projects, but with larger standard deviation (relative activity duration). Furthermore, Weather-it members were more constant with their visit frequency (variation in periodicity). Finally, there is no data for comparing the lurking ratio, though research showed that a small number of volunteers do a disproportionate amount of the work whilst others prefer to be observers (Curtis, 2015). The lurking ratio in Weather-it indicates that members were lurking in approximately one out of three visits.

3.2. Profiles

The engagement profiles of Weather-it members were created based on the clustering described in Section 2.2.2. First, the members with two or fewer active days composed a separate engagement profile named ‘visitors’. Then the rest of the members were clustered to engagement profiles according to the individual results of the lurking ratio and the metrics proposed by Ponciano and Brasileiro (2015), with daily devoted time excluded.

The dendrogram report (see Fig. 2) displays active members at the left side of the plot. Rows that are joined close together the branching diagram show members with small dissimilarities (e.g. Austru and Tramontana), while rows that link up higher in the diagram indicate greater differences between members. The hierarchical clustering algorithm indicated between 2 and 6 clusters as the interval to be tested. The potential number of clusters were formed at four cluster cut-off testing values by drawing vertical lines at the scale values ‘20’, ‘15’, ‘13’, ‘11’ and counting the number of lines that the vertical line intersects. Fig. 3 presents the results from the clusters' cohesion (Average Silhouette width) for each potential number of clusters, and Fig. 4 demonstrates the similarities between clusters (Davies-Bouldin index). The cross validation between the two methods for determining the optimal number of clusters show that 4 is the best option. This number of groups returns an Average Silhouette statistic of 0.68 (reasonable to strong structure) (Struyf et al., 1996) and Davies-Bouldin index of 0.74 (minimum inter-cluster similarities) (Davies & Bouldin, 1979).

K-means, as described in the Methods Section, was then used for the classification of the data with K = 4 and the centroids that were produced by the hierarchical clustering algorithm; the four generated categories represent member engagement profiles. A name for each profile (Loyal, Hardworking, Persistent, Lurker, Visitor) was chosen, or borrowed from Ponciano and Brasileiro (2015), so that it characterises the main behaviour of a specific group of members within the Weather-it community. Fig. 5 shows a comparative chart with the metrics average for each engagement category, with each bar representing one engagement metric, the horizontal axis the engagement categories and the vertical axis the scores for each

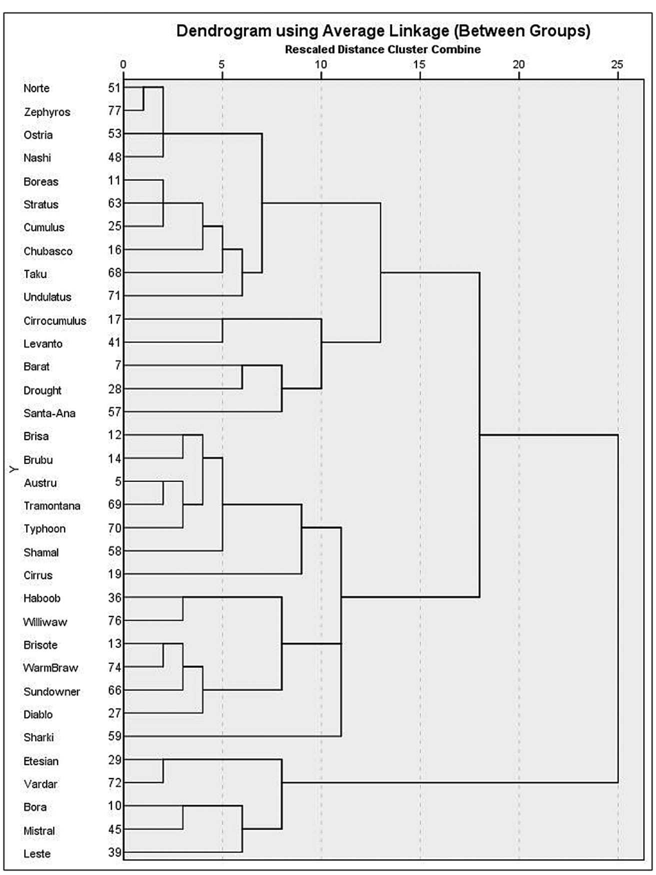

Fig. 2. Dendrogram of active members, arising from the hierarchical clustering algorithm, with Euclidean distance.

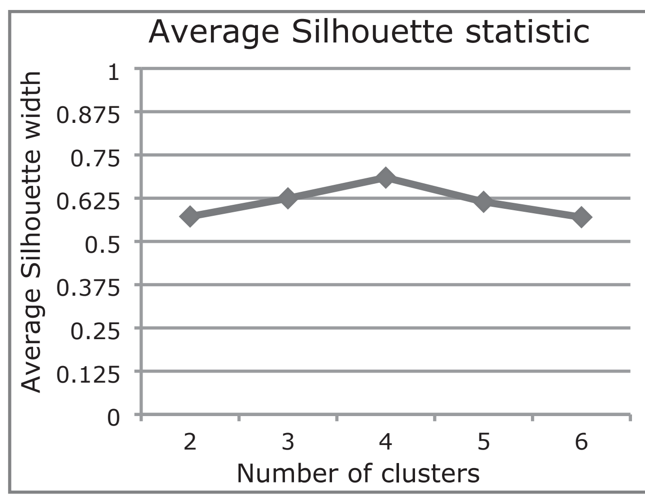

Fig. 3. Average Silhouette statistic for potential number of clusters.

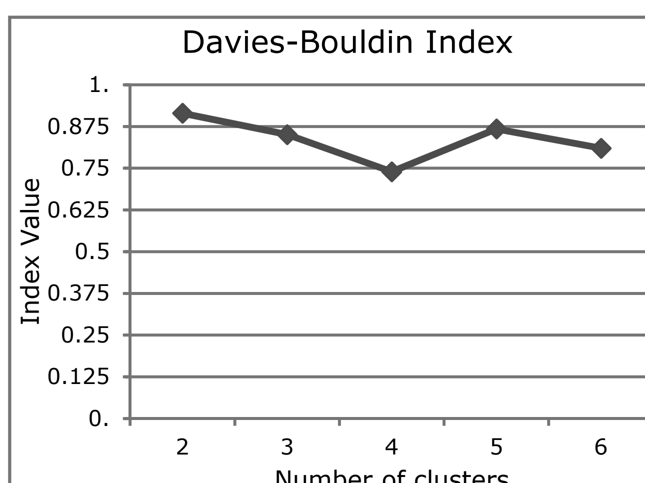

Fig. 4. Davies-Bouldin index for potential number of clusters.

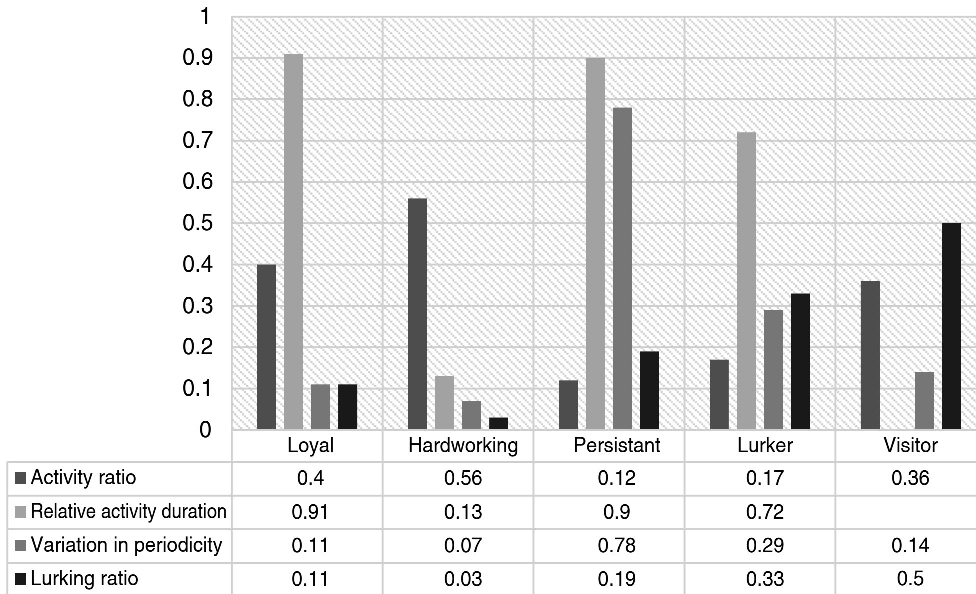

Fig. 5. Weather-it engagement profiles.

Table 3
Engagement profiles — summary of main features.

Engagement profile	Loyal (10)	Hardworking (5)	Persistent (14)	Lurker (5)	Visitor		
					Active (12)	Hesitant (17)	Observing (14)
Surveyed	9	4	14	4	6	12	4
Beginners	4	4	8	3	3	8	2
Intermediate	4	0	5	1	2	1	0
Experts	1	0	1	0	1	3	2
Motivations (descending order)	weather community software friends science	weather/ software/ friends	friends community weather software inquiry curiosity	weather/ community/ friends	weather software/ community/ science	weather/friends software community interest	weather friends
Attitudes (descending order)	enthusiastic/ interested/active excited inspired not bored guilty	interested active proud enthusiastic	interested active enthusiastic	interested inspired proud determined	attentive/excited curious enthusiastic inspired alert guilty active	interested enthusiastic active distressed/afraid/ashamed/ scared/confused	interested inspired/guilty ashamed/determined/afraid/ enthusiastic/active

metric. Table 3 (at the end of the description of engagement profiles) summarises the main features of each profile.

3.2.1. *Loyal engagement*

Members of the loyal engagement profile demonstrate the largest relative activity duration, combined with moderate activity ratio and low variation in periodicity. This means that members of this category remain linked to the project the longest with steady visiting rates, and they are active nearly half of the days they are linked to it. In addition to that, the low lurking ratio indicates the small number of days that they visit Weather-it without being active. Nine out of ten members in this category were surveyed with eight of them still being active on the data of survey; the ninth one had left the project as the mission they joined for had finished. Respondents consisted of four beginners, four intermediate and one expert. According to the survey, the main reasons that attracted initial participation in the project are 'weather' (47%) and 'community' (20%), followed by 'software', 'friends', and 'science'. Respondents joined missions of all types, from one to eight, and contributed their data. All of them felt part of the community and eight out of nine would like to remain members. Their attitudes towards the project are mainly 'enthusiastic' (25%), 'interested' (25%) and 'active' (25%), followed by 'excited', 'inspired' and 'not bored'. Moreover, one member chose 'guilty' adding *"when I do it during work time"*. Overall, loyal members are satisfied with the project as experts *"are willing to help"* and *"explain things in a better way"*, and there is *"variety of members and topics"* and *"plethora of topics to discuss"*. Learning was also a reason for feeling satisfied, with comments: *"insight into some topics"* and *"new information"*. In relation to the community there were comments such as *"sharing is fun"*, *"the members are friendly"*. Finally, the expert in this category *"likes explaining phenomena to non-experts"*.

3.2.2. *Hardworking engagement*

Members of this category exhibit low variation in periodicity and lurking ratio. This means that they visit the platform at regular time intervals and they are nearly always active during their visits. However, this category has the largest activity ratio and the shortest relative activity duration compared to other profiles, which shows that although they are considerably active during the days they are linked to the project, they do not remain linked to it for a long time. Survey findings from four out of five hardworking members, all beginners, reveal that they joined the community at its launch and their motives for initiating participation include ‘weather’ (33.3%), ‘software’ (33.3%) and ‘friends’ (33.3%). In contrast to the loyal members, ‘community’ is not in their motives, and only half of them feel members of the community and would remain linked to it. None of the hardworking members remained linked to the project to the end. Their attitude towards the project community are mainly positive with ‘interested’ (25%) being first, followed by ‘active’ (17%), ‘proud’ (17%), and ‘enthusiastic’ (17%). Finally, a negative response was ‘nervous’ but the member added *“nervous if I identified a subject correctly but it's part of the excitement”*. Overall, hardworking members are satisfied with Weather-it as it is *“open and helpful to beginners”* and *“the community was discussing the missions and not just submitting data”*.

3.2.3. Persistent engagement

This category consists of 14 members and is characterised by the largest variation in periodicity and the relative activity duration which is almost as high as in loyal members. Thus, persistent members remain linked to the project the longest but they do not visit Weather-it at a steady rate. At the same time, activity ratio is quite low indicating the small number of active days they have during the period they are linked to the project. However, lurking ratio is also low, suggesting they are active during their visiting days. All but one members of this category were active until the end of Weather-it and 14 responded to the survey. Eight of them were beginners, five were intermediates and there was also one expert. ‘Friends’ (37%) is the most frequently motive for initiating participation, followed by ‘community’ (26%) and ‘weather’ (16%). Other responses include ‘software’, ‘inquiry’, and ‘curiosity’. All but three would remain members of the community. The most common attitude for participating in Weather-it is ‘interested’ (28%) followed by ‘active’ (23%) and ‘enthusiastic’ (20%). The ‘active’ response however is in contrast to the activity ratio result, which may suggest their satisfaction with the number of active days during their visits. Persistent members seem to be satisfied with *“diversity in topics and people”* and *“learning about things”*, and characterised the members as *“friendly”* and the community *“scientific but friendly and funny”* and *“certainly not boring”*. However, there was some criticism in relation to the investigation and participation aspects such as *“I would like the missions to be more informed”* and *“more participation needed”*. Moreover, the expert of this category did not understand in which way experts can be useful.

3.2.4. Lurking engagement

Members have comparatively high relative activity duration and low variation in periodicity, and thus they remain linked to the project for a long time and visit it at a good rate. However, the low activity ratio combined with the comparatively high lurking ratio, indicate that they are active for only a few days during their stay in the project and exhibit lurking behaviour during the one third of their visiting days. Four out of the five lurkers responded to the survey, three beginners and one intermediate. ‘Weather’, ‘community’ and ‘friends’ are equally important motives for initiating participation, followed by ‘contribution’. Only two members were active until the end of the project. The two lurkers who dropped out, did not feel as a part of the community because *“some of the members seemed to be fairly young and I am not”* and *“because I felt not like a forum. It was a little bit impersonal, no participation in the extent I wanted”*. However, three of them would like to remain members in the community and the fourth one said that they *“did not understand the point of the community”*. The lurkers' attitudes towards the project are solely positive with most important being ‘interested’ (50%), followed by ‘inspired’ (25%), ‘proud’ and ‘determined’, with the obvious absence of ‘active’ which appears in the other categories. Members are mainly satisfied with the project as it is *“well-organised”*, and *“software bugs are fixed”*, however somebody added that it should have been “more collaborative” whilst another expected *“an automatic system able to process uploaded photo and then to detect the weather”* instead of a community.

3.2.5. Visitors

Members of this profile only contributed to the project on one or two days, or even never, and thus their variation in periodicity cannot be compared. Their second main characteristic is the short relative activity which is similar to that exhibited by hardworking members who do not stay for a long time in the project. Moreover, the activity ratio is similar to the loyal members' one and the lurking ratio higher than the lurkers. This category embraces the majority of the members (43) and as it includes many new members and diversity in results further analysis was carried out.

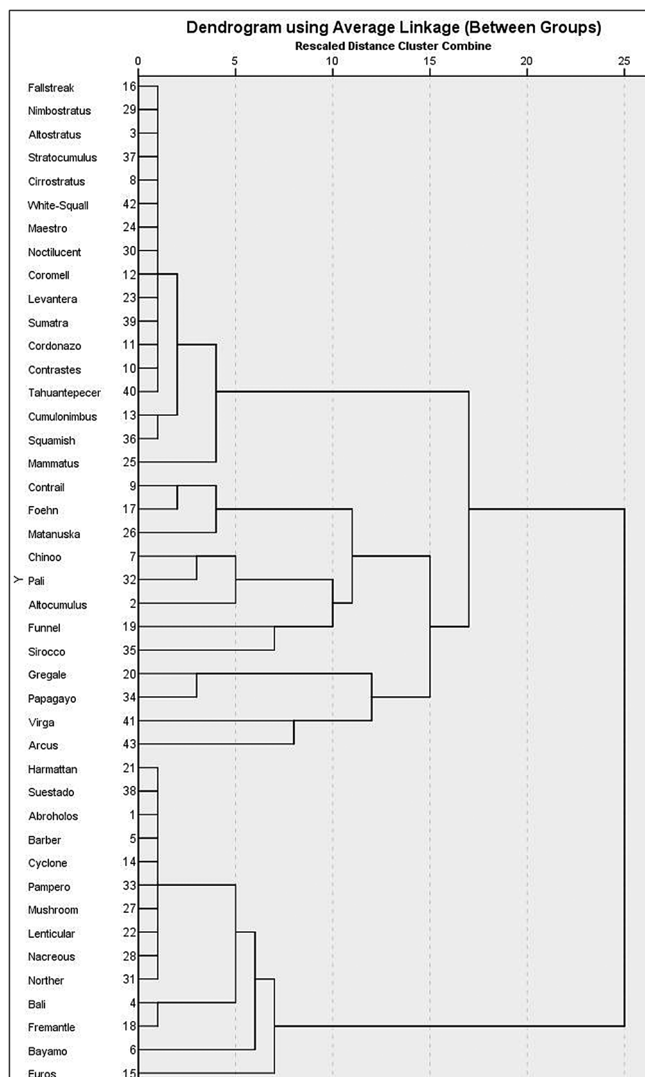

Fig. 6. Dendrogram of visitors, arising from the hierarchical clustering algorithm, with Euclidean distance.

The dendrogram in Fig. 6 displays visitors at the left side of the plot. The arrangement of the branching tells us that the bottom one, which is distinctively separate from the others, forms a group. A closer look at the metric results suggested that the two large clusters at the right of the diagram form two further groups, with the upper one standing out due to a lurking ratio that equals 1 for all group members. For example, member Coromell has one lurking day on the platform, whilst Pali has one active and one lurking. Survey responses enriched the description of each group. Briefly, twelve visitors exhibited more active behaviour, twelve exhibited hesitant behaviour, and 17 lurking behaviour. Responses to the survey came from 23 members, 14 beginners, three intermediate and six experts.

Active visitors joined Weather-it because they are interested in 'weather' (57%), 'software' (14%), 'community' (14%) and 'science' (14%) and during their short stay made contributions within the project. Six out of twelve members completed the survey; the respondents consist of three beginners, two intermediates and one expert. Four out of six were not active at the end of the project as they *"participate in other citizen science projects"*, "*lack of time"* and *"joined late and did not get around to participating in any of the projects";* the remaining two are new members. Three reported feeling like members of the community due to the "updates" or because although they are new members they *"could see themselves as active members of the community"* and four would remain in the project. 'Attentive' (20%) and 'excited' (20%) are the main attitudes towards the project with 'curious', 'enthusiastic', 'inspired', 'alert', 'guilty', and 'active' following. Furthermore, a respondent adds *"I'm excited to see other people interested in the topic but guilty for not getting involved".* This is the only category that 'interested' is not in the listed attitudes. Active visitors are mainly satisfied with the project, some *"desire to spend more time"* and some others wonder what it was like for the people who joined at the beginning of the project *"I liked what I saw, I am not sure for the people who joined at the beginning and there were no missions".* Yet, an intermediate member found the *"level of discussion lower than expected".*

Hesitant Visitors group consists of 17 members, of which twelve responded to the questionnaire; eight beginners, one intermediate and three experts. A main thing that differentiates this group from all the other categories is that only four out of twelve members joined because of the topic and hence it was mentioned four times (33.3%). A motive of equal importance to the topic was 'friends' followed by 'software', 'community' and 'interest'. Four out of twelve left the project because they had "no time" or they found the software "complicated"; three members feel like members of the community. The main attitude of hesitant visitors towards the project was 'interested' (38%) followed by 'enthusiastic' and 'active'. However, for first time in this group there is a variety of negative attitudes such as 'distressed', 'afraid', 'ashamed', 'scared' and in addition *"confused with the website, yet I was interested in the topic".* Overall when asked whether they are satisfied there were no negative comments as they found the project *"useful to read other people's interpretations"* with satisfactory *"range and quality of responses and contribution".* Finally, ten out of twelve hesitant visitors would like to stay linked to the project.

Observing Visitors had more lurking days than active days during their short stay. This group consists of 14 members of which four responded to the survey. The motives for the two beginners and two experts for initiating participation in the community were 'weather' (68%) and 'friends' (32%) and thus there was no interest in the community and the software. Two out of four are new members and these were active until the end of the project and three out of four feel like a part of the community because of the *"excellent project communication"* and *"due to the updates in the inbox".* Moreover, a new member adds *"I could feel like a member if I had joined earlier but I think you can easily become one as the environment is friendly".* The attitude towards the project was 64% positive and 36% negative with 'interested' (27%) being the most important, followed by equally mentioned 'inspired' (18%) and 'guilty' (18%) and then 'ashamed', 'determined', 'afraid', 'enthusiastic' and 'active'. A comment by a member is *"I'm feeling ashamed and guilty for not doing anything due to the lack of time".* Overall, the fact that three out of four would like to stay in the project in combination with their comments indicate their satisfaction with the project: *"I was expecting a discussion forum so it is much better", "I love the interactive approach to learning. It's great that people can contribute to science using technology in a fun and interactive manner".*

4. Discussion

The main objective of this study was to investigate citizen behaviour in citizen inquiry communities, where members can start and facilitate their own investigations, and to explore the links between engagement factors and behaviour patterns, by using multiple measures.

4.1. Level of engagement in citizen inquiry

Weather-it was a citizen inquiry community and thus targeted to involving members more in facilitating their investigations, through an inquiry-led platform, by comparison to contributory citizen science projects. When it comes to the level of engagement with the investigations, the results of the current study show that Weather-it members' relative activity duration (mean = 0.43) was higher than for Milky Way (mean = 0.20) and Galaxy Zoo (mean = 0.23) and thus, Weather-it members remain in the community for a longer time. It has also become clear that Weather-it members were visiting the community more periodically, with variation in periodicity (mean = 5.11) to be much lower than the one of the contributory projects.

4.2. Engagement factors and behaviour patterns

The key objective of mapping the behaviour of the community members is to detect the desirable and non-desirable community behaviours and how these were prompted. In addition, it is important to understand how the causes of those behaviours can be enhanced or eliminated.

Ponciano and Brasileiro (2015) found five engagement profiles within their data of Milky Way and Galaxy Zoo projects: 'hardworking', 'spasmodic', 'persistent', 'lasting' and 'moderate'. These categories were identified after clustering engagement metrics that placed emphasis on the degree and duration of engagement. In Weather-it, the daily devoted time has not been included and a lurking metric was added. As the results of this study showed, 'hardworking' (7%) and 'persistent' (19%) engagement profiles have been found, but the other profiles were not spotted within the Weather-it dataset. For instance, unlike in Ponciano and Brasileiro's study, all the profiles had distinguishable engagement metrics and thus, a 'moderate' category has not been created. Instead, new engagement profiles emerged to describe the participation main behaviour of members in Weather-it; 'loyal' (13%), 'lurking' (7%) and 'visitors' (55%).

The 'loyal' category captures the long stay of some members in the project, as does the 'persistent' one, but also combines higher levels of activity, as in the 'hardworking' one. Hence, 'loyal' exhibits a desired engagement profile in which volunteers remain both linked in and active in the project. The 'lurking' category may also be related to the 'persistent' but it is distinguished due to the relatively high lurking levels. Therefore, members of this engagement profile remain linked to the project but they are mainly observers. The last category, ‘visitors’, was created in order to gain some insight into the profiles of people who had two or fewer active days in the project, and draw some conclusions in relation to the attrition rates within the project. The findings around visitors suggest a variety of behaviours, as some are hesitant visitors with the prospect of moving on eventually to another category, and some others are more active or lurking visitors. The main reason for not visiting the community was ‘lack of time’ and ‘new member’ while ‘website usability’ has also been mentioned as a reason for having a negative attitude towards the community. Moreover, feelings of fear were detected only in visitors' engagement profile. Explanations about this negative attitude may be linked to the software use or the quality of contributions. Nevertheless, the majority of survey respondents (77%) would like to stay linked to Weather-it, which shows a potential for moving to other engagement profile categories.

Survey results have also enriched the engagement profiles providing information about the motivations for initiating participation in the project. Understanding those motivations is important for sustaining participation (Romeo & Blaser, 2011; Wiggins & Crowston, 2010; Nov et al., 2011a,b). ‘Weather’ is the first motive in all the categories apart from ‘persistent’ in which members have more social motives to participate, such as ‘friends’ and ‘community’, placing ‘weather’ third. This result goes against the finding by Nov et al. (2011a,b) that associates intrinsic motivation with enhanced participation frequency. Moreover, ‘hardworking’ was the only category mentioning ‘software’ as many times as ‘weather’. From these findings there is a suggestion that interest in the software may bring in more active volunteers, but for a short period, whilst motivation by friends within the community may cause longer stay in the community. The latter may have happened because of existing ties, people who are already friends with the volunteers, who have joined the project enhancing the bond-based commitment to the project (Ren & Kraut, 2012).

On the other hand, loyal volunteers, who were both active and linked for a long time to the project, did not choose ‘friends’ to such a great extent as the other categories. It seems that the volunteers of this category are attached to the project and its purpose, enhancing their identity-based commitment and as a result they are more stable in the face of membership turnover (Abrams, Ando, & Hinkle, 1998). This finding is in line with theory (Haythornthwaite, 2009) and research (Eveleigh et al., 2014) that associate intrinsic motives with a greater number of contributions, but it also suggests that intrinsic motives, such as interest in the topic, is linked to longer stay in the community.

An overall comparison between the categories shows ‘persistent’ members to be the least satisfied with the missions and the participation, and this may explain their low activity level in combination with their long stay. In contrast, ‘loyal’ members demonstrate high levels of satisfaction in relation to the community, the members, the missions, and finally the learning experience combined with experts' presence.

5. Conclusions

At the core of this study is the engagement and behaviour of members participating in citizen science communities. The paper compares general levels of engagement from two previous studies, for the Milky Way and Galaxy Zoo projects, with engagement for Weather-it, a citizen inquiry project where participants formed and facilitated their own investigations supported by researchers and experts. The engagement metrics combined with findings from a participant survey have produced useful evidence about the overall engagement and the individual engagement profiles.

As the findings of this study showed, not all of the engagement profiles found in Ponciano and Brasileiro (2015) were identified within Weather-it. Instead, some new engagement profiles have emerged from the data analysis to describe the behaviour of citizen inquiry participants. This variation highlights the importance of different design approaches based not only on the engagement profiles but also on the type of citizen participation community. For example, in citizen inquiry communities, the ‘loyal’ category represents a desirable combination of long and active participation, so the software platform might be enhanced to recognise such people and support them in facilitating investigations and mentoring newcomers.

A limitation encountered while replicating the method developed by Ponciano and Brasileiro (2015) was the absence of data for calculating daily devoted time. Instead, the current study calculated the lurking ratio, as lurking is considered to be a puzzle in online communities where citizens voluntarily participate and contribute (Curtis, 2015; Eveleigh et al., 2014). In response to lurking, commitment to the community has been identified as key leverage for sustaining a community (Bateman, Gray, & Butler, 2010). Similarly, previous research has shown that having a sense of belonging to the community is associated with remaining in the community (Aristeidou et al., 2015b). To this end, this research considers the sense of belonging as an important engagement factor that affects members' behaviour and therefore, design should focus towards committing members to one another and to the community.

Studies that investigate citizen participation communities through user behaviour (e.g., Eveleigh et al., 2014) propose a number of design considerations based on the behaviour of the entire population. The significant difference from the behaviour patterns identified in this study is that one size does not fit all, and similar to research on online communities (Ren & Kraut, 2013) this suggests a more personalised moderation according to the behaviour. For instance, the sceptical behaviour by hesitant visitors has to be examined further to form the basis of enhancing the supporting mechanism within the community, so that ‘fear’ will not exist anymore in their attitude list. Also, the design should be aiming at improving software usability by engaging usability experts or by maintaining ongoing feedback, as lack of it forms one of the reasons for visitors not to return to the community.

An overall conclusion drawn from the engagement profiles of this study is that extrinsic engagement factors, such as software and community aspects, attract and activate members; and intrinsic factors, such as interest in the topic, are the main reasons that sustain members in the community for longer periods. A design example that takes into account the balance between extrinsic and intrinsic factors, is the development of a recruitment strategy by which entertaining software and community life will be promoted in places where people may be interested in the topic.

The findings and recommendations of this research contribute to general design considerations and practices, and facilitate both recruitment and sustainability of citizen participation communities, where personalisation is difficult due to large numbers of members and limitation in resources. Future research exploring engagement and behaviour in communities of different levels of citizen participation could improve theory and practice, help generalise the results of this study or facilitate the development of an engagement evaluation framework. Finally, while surveys provide sufficient information on the psychological factors, clearly, more experimentation needs to be done concerning specific design aspects that engage and disengage members from citizen participation communities.

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