An empirical study on factors affecting user engagement in a gamified team building environment

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Abstract

This paper presents a study on data retrieved from a gamified team building application, which promotes employees' joint sport activities. The aim of this work is to identify and evaluate behavior usage patterns, and user engagement indicators based on interaction data gained from the application and to determine key factors affecting engagement levels. In order to determine behavioral patterns, users have been tested for system use, for participation at events and competitions, and for having tendency in social interactions. The study classified three typologies of engaged users: the Achievers who are motivated by the reward of achieving long-term goals, the Socializers who enjoy interacting with others and the Conquerors who like struggling until they eventually achieve victory by defeating others. We were also able to reveal additional influencing factors beyond personal behavior patterns like the corporate culture and the importance of the 'organizers'.

Keywords: *gamification, motivational information system, user behavior patterns, network analysis*

1 Introduction

Motivation is one of the most important factors affecting human behavior and performance. Individual and group motivation levels have a great impact on all aspects of achievement. One of the key indicators to measure the level of interest is user engagement [1, 2].
The term 'user engagement' has a variety of meanings. It is considered to be a desirable human response to computer-mediated activities [3] which consists of users' activities, attitudes and goals, and it manifests itself in the form of attention, intrinsic interest, curiosity and motivation [1, 4, 5]. Several studies underline the importance of user engagement in different fields such as education [6], health-related activities [7-9] and Web applications [10]. While motivation refers to goals and values in a given area, engagement refers to behavioral displays of effort, time, and persistence in attaining desired outcomes [11, 12]. Engagement is also a critical issue in interactive mediated activities, defined as human activities supported by digital interactive technologies such as computer applications, mobile platforms, Internet, or virtual reality systems.

Yardley et al. [13] make a distinction of user engagement at the micro and macro levels. The micro level reflects the moment-to-moment interactions that occur as a user engages with features of the technology, while the macro-level engagement refers to how the user engages with the overall goal of behavioral change (e. g. towards a healthier lifestyle). The aim of our research is to propose an approach to identify users' macro-engagement and to qualify their engagement behavior from the history of users' actions collected in real time from their interactions with a gamified application, with the final goal to determine factors affecting engagement beyond personality traits. We used data gathered among the users of

Battlejungle (https://battlejungle.com/), an exercise encouragement and teambuilding application that combines three motivational design concepts [14]: gamification, quantified-self and social networking. The dataset has been provided to the authors by the service provider for research purposes. All of the user and organization related data is anonymized, and they do not store directly personal descriptive data about the users, only in aggregated form retrieved from a third-party service called *Google Analytics*. Users had to agree to the terms of use in advance in order to use the service. The service provider has ensured that their most recent privacy policy and data-handling methods meet the latest GDPR requirements.

Since users are different, a variety of classes of motivational design may have a differential fit for them. Being able to distinguish a given user's typology, motivational design could be better tailored [9, 14].

2 Related work

Over the last decades, many studies related to behavior theory and user engagement were conducted in social psychology, behavioral economics and marketing [15]. Several works focused on how to use technology to motivate healthier lifestyle [16-18]. However, some studies pointed to the limitations of the one-size-fits-all approach, especially when a change in health behavior is aimed [18].

The realization of this fact led to a growing interest in finding ways of tailoring interventions to various users. Kaptein et al. revealed that the users' personality is an important determinant of motivation [19] and Halko and Kientz showed the relationship between the users' personality and the success of different motivational strategies [20]. Approaches to measure user engagement can be divided into three main groups: self-reported engagement, cognitive engagement, and online behavior metrics. In this paper, we explore user engagement from a quantitative perspective, such as number of logins and likes per day, or time spent on using our interactive system: an application to foster joint sporting activities. We use this gamification platform as a case study for developing quantitative typologies of user engagement.

2.1 User typologies for tailored gamification

Several personality models have been published during the recent years, such as the Myers-Briggs Type Indicator (MBTI) [21], the Five Factor Model (FFM) [22], the Bartle four gamer types [23] or the BrainHex model of seven gamer types [24]. In this study we used the BrainHex model. It was originally developed specifically as a "gamer" typology. However, researchers have applied it indiscriminately in both game and gamification studies [17, 25-28]. The BrainHex model identifies the following seven types of players:

- *Achievers* are motivated by the reward of achieving long-term goals.
- *Conquerors* are challenge oriented.
- *Daredevils* are excited by taking risks.
- *Masterminds* enjoy solving puzzles, devising strategies.
- *Seekers* enjoy exploring things and discovering new situations.
- *Socializers* enjoy interacting with others.
- *Survivors* love the experience associated with frightening situations.

The BrainHex model admits that users cannot be categorized into one gamer type exclusively; we can only recognize users' primary gamer type and further types.

The benefit of identifying users by player type is that the assigned type can be used to estimate the response of players to a given action or stimulus, and to identify (within error limits depending on the environment) how to control and/or motivate them to perform a desired action.

3 Methods

We used the Battlejungle [29] social platform that gives support with organizing and encouraging (mostly) sport related events among employees within organizations. It offers competitions in a variety of sports, which can be divided into two major groups: team tournaments such as football and individual race such as running or cycling. It also supports the organization of social events such as voluntary work or blood donation. Several gamification elements help to enhance motivation and team building such as collected points, performance- and activity-based badges, leader boards, recognitions and awards. Battlejungle has a strong social dimension as it promotes sharing game events on social networks and it also promotes social interactions. Quantified-self features include activity tracking of exercise and performance indicators. Mandatory use of the service depends on the corporate culture of a particular organization. It should be noted that using the examined service with its social concepts without proper content added by the organization (e.g. launching races, organizing events, set challenges) will not make the employees more motivated or engaged.

3.1 Research model

We propose an approach of identifying engaged behaviors from the users' interactions. This study sets the following research questions:

Q1: *Can engaged behaviors be distinguished from non-engaged behaviors based on the collected data?*

Q2: *Can we identify the type of players and motivations based on the collected data?*

Q3: *What kind of factors can be identified that affect engagement beyond personality traits?*

3.2 Research

Users have been characterized by 11 use-based attributes (see Table 1) collected from the team-building application between 1 July 2016 and 31 January 2020.

Table 1. *List of use-based attributes*

Usage	period (A1)	Number of usage days (*Time period between the date of registration and the date of last login in days*)
	logins (A2)	Number of logins
Achievement	point (A3)	The collected points
	level (A4)	The reached level
	badges (A5)	Number of collected badges
Social	like (A6)	Number of positive reactions ('like') given to posts
	post (A7)	Number of written posts
	comment (A8)	Number of written comments
Activities	individual_race (A9)	Number of individual races*
	team_race (A10)	Number of team races**
	social event (A11)	Number of organized social events (e. g. voluntary work)

*a competition in which individuals participate separately (e.g. running race)
**a competition in which two teams play with each other (e.g. football)

We also used feedback answers given through service interface to map the motivations of the users and to explore trends in wellbeing. The questions can be divided into two topics:

- Motivation-related opinions (see Table 2)
- Wellbeing-related opinions (see Table 3), such as
    - changes in workplace atmosphere,
    - quality and quantity of relations between organization members,
    - frequency of doing sports.

Table 2. *Motivation-related feedback questions*

Abbreviation	Question
LB	How often do you check the main Leaderboard page (which lists all members)?
mini LB	How often do you check the mini Leaderboard box on the main dashboard (that lists only nearby players)?
Level-1	Do you like the animal theme (name and icons) of player levels and do they motivate you?
Level-2	How often do you check your and/or others' player level?
Badge	Do you like the Badges, and do they motivate you?
Point	Does the Karma[1] motivate you to participate in activities and challenges?
Profile	How often do you check others' profile page?

Please note that the contents of questions were pre-defined, and the authors could not change them during the research period. For each question, 5 answers are available (generally scale-based answers), one of which can be selected by the user. Giving the answer is always optional, and it was not possible to give self-made text-based responses. A feedback is done by answering one question, which is selected from a predetermined question bank depending on what activity has just been done by the user, what part of the system is being used and what kind of similar questions have been answered recently.

[1] Point is named Karma in the used gamified platform

Table 3. *Wellbeing-related feedback questions*

Abbreviation	Question
Atm-1	How has the atmosphere at your company changed since using Battlejungle?
Atm-2	How has the atmosphere at your company changed in the last 30 days?
Rel-1	How many new or hardly known people have you met through Battlejungle in the last 30 days?
Rel-2	Do you have better relationship with those players you have already played with?
Sport-1	Do you do more sports since using Battlejungle?
Sport-2	Has it ever occurred that you did more [sport] just to track it in Battlejungle?

3.3 Participants in our study

Participants (N = 6076) ranged in age from 18 to 64. 49.7% were 25–34 years old, the second largest group were between the ages of 35 and 44 (26.5%), slightly more than a tenth (12.2%) of our participants were between the ages of 18 and 24, 8.6% were 45-54 years old and the rest (2.9%) were in the age group of 55-64. There were more males (60.4%) than females (39.4%). In terms of country-by-country classification, Hungary ranks first (34.5%), followed by users from USA (28.1%), and the third largest group is from the UK (13.3%). Looking into the industry segment of participants' company we found that consultancy (26%) and software development (21%) corporations are almost equally represented. In addition, organizations that are active in the field of financial (13%) and travel services (9%) are also heavily involved. Due to the anonymity and the limitations of the data provider service (Google Analytics), only descriptive statistics could be derived from the data that describes the users as a whole population.

4 Result and Discussions

Our first question was whether users can be distinguished as engaged and non-engaged users on a behavioral basis. Users were divided into the following three groups:

1. **new users**: they registered less than 100 days ago.
2. **engaged users**: they registered at least 100 days ago, they used the service at least 60 days (*A1>=60*) and they returned at least five times (*A2>4*) to the application.
3. **non-engaged users**: they registered at least 100 days ago, but they did not use the service for at least 60 days (*A1<60*) or they did not return more than four times to the application after the registration (*A2<=4*).

As a result of grouping, 4.8% of the users (N=290) were categorized as '*new user*', 19.4% (N= 1178) as '*engaged user*' and 75.8% (N=4608) as '*non-engaged user*'.
We need to mention that no chiseled definitions of new users, engaged users, non-engaged users based on usage can be found in the literature. Designating 100 days as the limit that separates new and non-new users is a bit contingent. Therefore, we examined how changing the 100-day limit to 80, 90, 110, 120 days, affects the number of new users. The results obtained are summarized in Table 4.

Table 4. *Number of new users over usage days*

Days	Number of new users	Change in number of new users
0-70	73	-169
0-80	180	-110
0-90	242	-48
0-100	290	0
0-110	302	12
0-120	322	32

The data show that setting different limits does not dramatically affect the number of new users.

We also examined the definition of engaged users. Other settings than 60-day usage and at least five-time returns were considered. We set the usage from 70 up to 120 days and returns from 5 to 7 times to separate the engaged and non-engaged users. Our findings can be seen in Table 5.

Table 5. *Number of new non-engaged users*

At least 5 logins

Days	Number of new non-engaged users
0-60	-
0-70	8
0-80	15
0-90	21
0-100	25
0-110	33
0-120	37

At least 6 logins

Days	Number of new non-engaged users
0-60	77
0-70	141
0-80	237
0-90	276
0-100	316
0-110	363
0-120	424

At least 7 logins

Days	Number of new non-engaged users
0-60	139
0-70	198
0-80	292
0-90	327
0-100	363
0-110	405
0-120	462

Please note that increasing the usage from 60 to 120 days, there will be only 37 new non-engaged users adding to 4608. Even if we increase the usage from 60 to 120 and the returns from 5 to 7 then we have only 462 new non-engaged users. We also examined the compound of engaged users under different settings. We found that AHC defined 4 different clusters in each case (data not shown). Adding together, the different settings does not significantly affect the main message of the manuscript.

Looking at the data, it is striking that the attributes describing **new users**' average daily service usage (e.g. number of logins) and social activities (e.g. likes) are significantly higher than those of the other two groups. If we look at average daily service usage, we find that it drops by half in the first three months. (data not shown). A possible explanation for these could be the feeling of novelty and curiosity towards the service. This increased user behavior of the first period is supported by the findings of other studies [30-32].

The group of non-engaged users is very large, so we looked at it a little more closely. Examining the data, we found that more than half of the non-engaged users (54%) did not log in after registration. From the text analysis of the comments, we found that these users were mostly corporate subscriptions, i.e. they cannot be considered as 'real' registered users. If we subtract from our data users who have never logged in (2495), the percentage of non-engagement drops from 74.8% (N= 4608) to 59.0% (N=2113) immediately. Figure 1 shows how the dropout rate varies for non-engaged users comparing to their usage time.

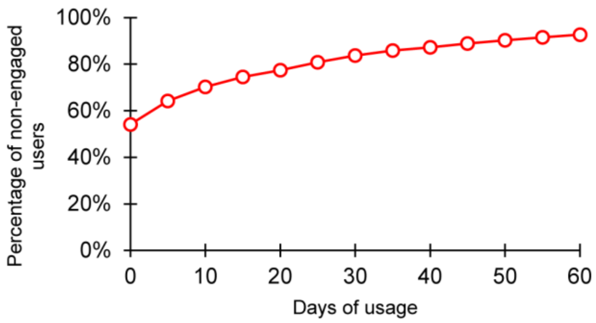

Figure 1. *Growth of dropout rate of non-engaged users over time*

We statistically tested our three groups, and the distributions of the aforementioned populations – according to the attributes described in Table 1 – were compared with the Kolmogorov-Smirnov test. Based on the results, there were significant distribution differences in cases of the eleven attributes. As for answering **Q1**, the separation rules that have been applied seem to be properly set as there is a significant difference between the general activities of the three populations.

4.1 Identifying behavior types

Agglomerative Hierarchical Clustering (AHC) was done by using Pearson Correlation Coefficient to identify the behavior types within engaged users using the eleven collected attributes (see Table 6).

Table 6. *Summary statistics of the use-based attributes for engaged user*

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11
Min.	61	5	0	1	0	0	0	0	0	0	0
Max.	1181	1141	16106	15	52	137	29	106	45	6	46
Mean	256.6	32.6	1006.5	3.9	3.1	1.4	0.4	1.1	2.8	0.5	3.3
Std. dev.	218.1	65.1	1305.6	2.0	4.7	6.7	1.7	5.2	4.1	0.9	4.2

One advantage of AHC algorithm is that no preselection of the final cluster number is required as the AHC method works from the dissimilarities between the objects to be grouped together. A type of dissimilarity can be suited to the subject studied and the nature of the data. Thus, this algorithm can be applied successfully to both regularly and irregularly shaped clusters. One of the results is the dendrogram which shows the progressive grouping of the data. The dendrogram divided these users into four major clusters (see Figure 2).

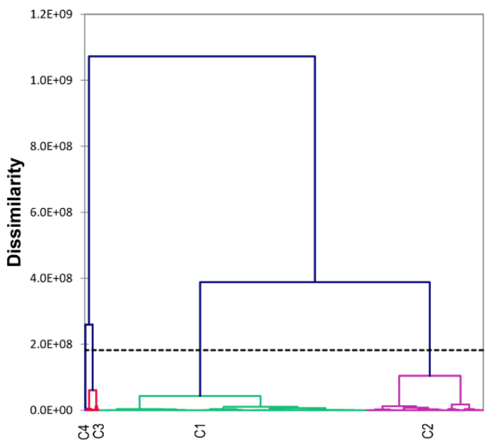

Figure 2. *Dendrogram of the Agglomerative Hierarchical Clustering (AHC) analysis with Euclidean distance and Ward agglomeration resulting in four clusters.*

The first cluster (***class-1***) encompasses 790 individuals, the second cluster (***class-2***) has 344 and the third cluster (***class-3***) has 40 and the fourth cluster (***class-4***) has 4 individuals. The variance decomposition for the optimal classification values are 16.8% for within class variation while 83.2% for the between-class differences and the cophenetic correlation is 0.76.

First the ***class-4*** group was examined. Only 0.3% of engaged users belong to this group, but the mean of their points is more than double the mean of the points of members of all other groups and similarly outperforms the other groups' daily login and average daily like numbers. Text mining of the comments made by the members of ***class-4*** shows that they also act as organizers within the company. They organized competitions and inspired others. A possible explanation can be that they work in the HR department of the organization and they are dedicated to improving the well-being through this gamified platform. The behavior of this group members is greatly influenced by factors other than personality traits thus ***class-4*** was excluded from the analysis of behavior types. The influence of the corporate culture on engagement will be explored in more detail in the next section.

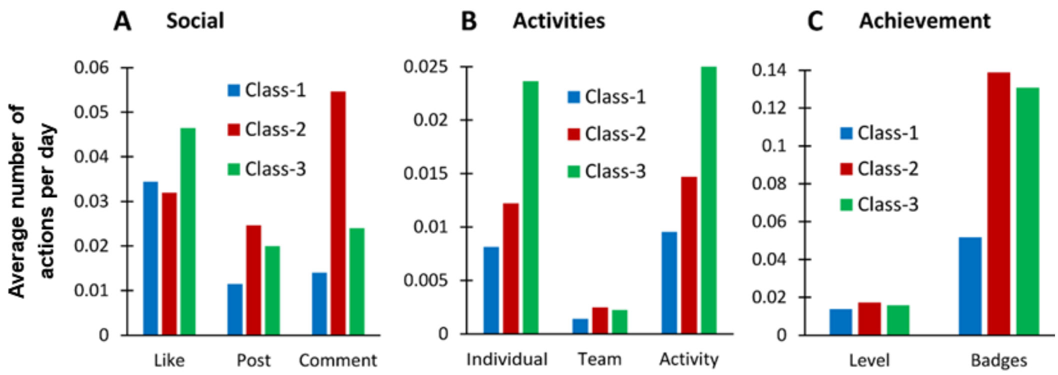

Figure 3. *Average number of a particular type of actions of engaged users in the different classes*

The characterization of the ***class-1*** user group is somewhat challenging, as they are moderately active socially (see in Figure 3), they give likes, but not posts or comments. They took part in the least number of competitions. If we depict engaged users by class (see Figure 4 Panel B), we can immediately notice that ***class-1*** users are most interested in leaderboard, levels, others' profile based on their responses to feedback questions. Overall, they are the 'Conquerors' in BrainHex model who "*like defeating impossibly difficult foes, struggling until they eventually achieve victory*" [24].

We can immediately notice that ***class-2*** users logged in and took part in group competitions the most, reached the highest level and collected the most badges in a given time period. Also, they are socially very active, they write a large number of posts and comments. If we consider their responses to feedback questions (see in Figure 4), it appears that those in this group are reported to meet the most hardly known or new people and have better atmosphere at their company. Thus, these users like to interact with each other, collaborate in carrying out their tasks, or compare themselves with others. So, taken together these users are stimulated by interaction with others, that is, they are the 'Socializer' type based on the BrainHex model. It is worth noting that 30% of engaged users are in this cluster.

In Figure 3 we see that the ***class-3*** members have participated in most tournaments, have collected almost the highest number of the badges. If we look at Figure 4, which reveals users' motivation, we can see that users from ***class-3*** are very motivated by points, but they are less interested in others' performance. Furthermore, members of class-3 reported in their feedback responses that they are doing more sports since the application was in use. In the BrainHex list we could identify them as 'Achievers' who are motivated by the reward of achieving long-term goals. They are the smallest cluster of engaged users

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(3% of all engaged users). It is worth noting that users of ***class-3*** t are the ones who use the application for the longest time on average (data not shown).

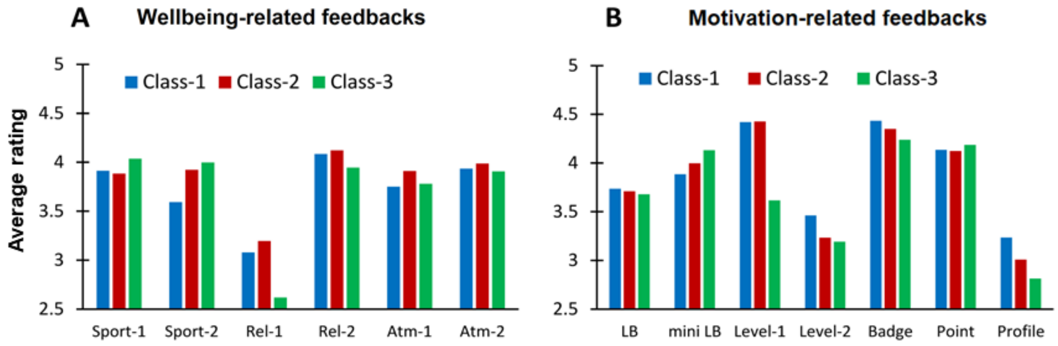

Figure 4. *Average value of ratings for feedback questions given by engaged users.*

Proportion of respondents from engaged users: Sport-1 19.86%, Sport-2 20.46%, Rel-1 7.30%, Rel-2 6.37%, Atm-1 16.13%, Atm-2 15.62%, LB 6.28%, mini LB 5.94%, Level-1 6.37%, Level-2 6.03%, Badge 5.86%, Point 6.45%, Profile 11.88%.
(The questions associated with the abbreviations can be seen in Table 3 (Panel A) and Table 2 (Panel B).)

Pearson's correlation coefficient was used to explore the strength of relationship between the collected attributes (see in Figure 5). We found an unexpectedly large strength of association (0.9) between the number of participations in individual races and the number of participations in different social events. A possible explanation might be that users of the ***class-1*** group, who prefers individual competitions, may be attracted by the extra points for participating in community events. High positive correlation can be seen between acquired points and the reached level (0.8) and points and badges (0.6). Medium strength of association can be seen between number of posts and comments (0.5).

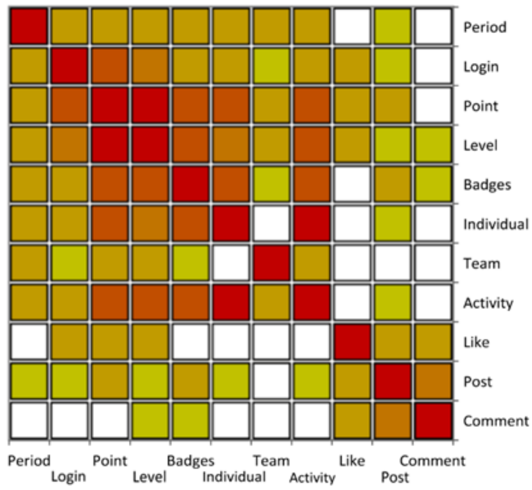

Figure 5. *Heat map of Pearson's correlation matrix*

We have also generated a word cloud from all comments of engaged users (see Figure 6). Three words in the cloud caught our eye in particular: "challenge", "play" and "run". This would appear to demonstrate that the gamified service is linked in some way to add value in wellbeing. More detailed examination reveals that the terms "lunch", "morning" and "today" are frequently used. This implies that engagement level can be increased by being allowed to play tournaments during working hours.
Other interesting words to emerge from the word cloud are "team" and "group", reflecting the importance of social gathering. As colleagues known each other on a personal level it encourages collaboration. Further factors affecting engagement are revealed in the next section.

Figure 6. *Word cloud of comments of engaged users*

Adding together, question **Q2** could be answered as we could identify different motivations based on the data collected.

4.2 Corporate culture

To answer the third research question (**Q3**), we investigated the proportion of committed participants depending on the number of participants in the organization (see Figure 7). Based on the data, it can be said that the number of registered users within the organization varies within a relatively large range (1-385) and higher levels of engagement can be observed in the case of intermediate (65-120 registered users) organization 'size'. Text-mining of users' comments revealed that the rate of engagement is influenced by an 'organizer' or 'personal' factor, i.e. one or two people within the organization act as organizers. This corresponds to the "Social proof theory" [33] and implies that individuals are more likely to engage in behaviors which they perceive others are also engaged in.

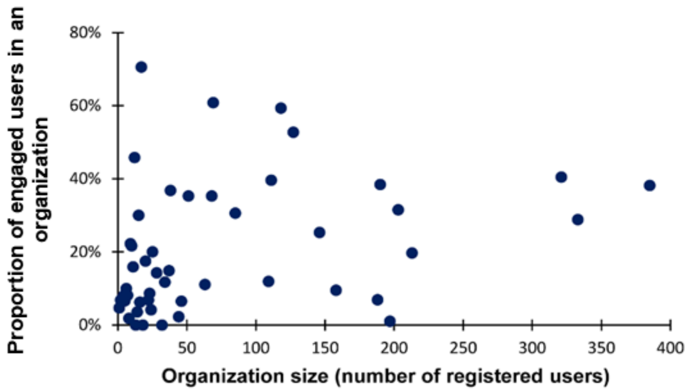

Figure 7. *Proportion of engaged users within organizations depending on the size of the organization*

It is worth noting that these organizers post and comment a great deal and the cluster analysis has created a separate group for them as we described in the previous section.
In order to explore the evolution in the quantity and quality of connection network within a corporation, we selected a single company to examine the network of relationships that occur when users participate at company organized events. The company used in the current

study has 118 registered users with no new users, i.e. no one is registered in the last 100 days. 48 out of 118 users are categorized as non-engaged and 70 are engaged ones, meaning that the engagement rate is 59% for this company.

This investigation also refines one of users' feedbacks related to wellbeing (Rel-1, see Table 3 for the question), which wanted to explore how many new or hardly known colleagues were being met through the corporate organized events. Engaged users claimed, irrespective of the different groups, that they met 6-9 new employees within the last month on average. However, looking at the time difference in responses, the number of new colleagues met decreases.

Thus, we examined the answer to the question whether within a company users always play with the same group (that is, the established social networks are not connected) or the participants change and a connected network can be seen.

According to the collected data, 35 events were organized, of which 24 were organized by the same user, 7 were organized by another one and the remaining four events were organized by four different users. The events organized by a given organizer are marked with the same marker and the number of participants as a function of time can be seen in Figure 8.

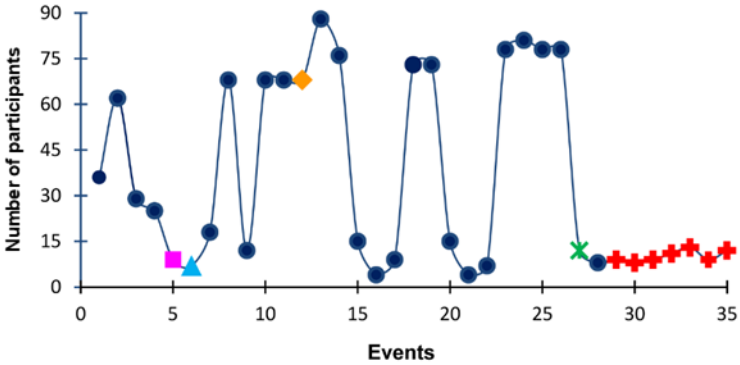

Figure 8. *Number of participants in events over time*
Note that different markers refer to different organizer of the event

As 13 events were attended by more than 50 people and there was only a total of 118 registered users, multiple users must have attended more than one event. However, an interesting question is, to what extent users stick to a particular organizer and how well an individual organizer can create a challenge to users.

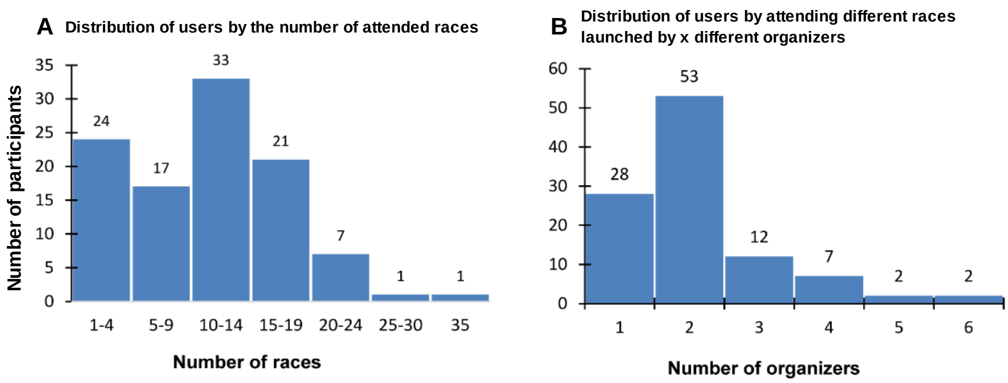

Figure 9. *Distribution of the number of participants within one organization*

The distribution of participants showed (see Figure 9 Panel A) that most of the 118 users participated in more than 10 out of 35 organized events. Panel B shows the distribution of users based on attending different events organized by only 1, 2 etc. organizers. Nearly a quarter of the players preferred only events organized by 1 particular organizer, while 51% of users typically attended events organized by 2 different organizers. In addition, several users participated in events organized by all of the organizers.

To explore the social network structure and registered users' behavior within the company, a network analysis was performed, and a network map was generated (see Figure 10). The set of the points (actors) is the set of registered users of the company; a line connects two users if they participated in the same event at least once.

The simplest measure of network structure with which network connectivity can be assessed is network density. Density is the actual number of ties divided by the possible number of ties [34]. A weakly connected undirected graph was obtained with graph density of 0.04. While density is a frequently used measure of overall connectivity, it is possible to have a densely connected network that is fragmented into two or more subgroups. As a check on fragmentation we also calculated geodesic distance measures for our network. Geodesic distance is the average number of links between one person and every other person in the network [34]. The average degree of points is 4, the average geodesic distance is 2.25 and no structural holes can be detected. Looking into the graph we can see that most connections are dense and local, but a few long bridge connections between far-flung influence users also exist. This is very similar to the "small world" structure where small groups of tightly bound actors are connected with each other through a few ties which bridge the gaps between them. According to studies [35, 36] the more a network exhibits characteristics of a "small world" network, the more connected actors are to each other and connected by persons who know each other well through past collaborations. This network structure can explain the high engagement rate.

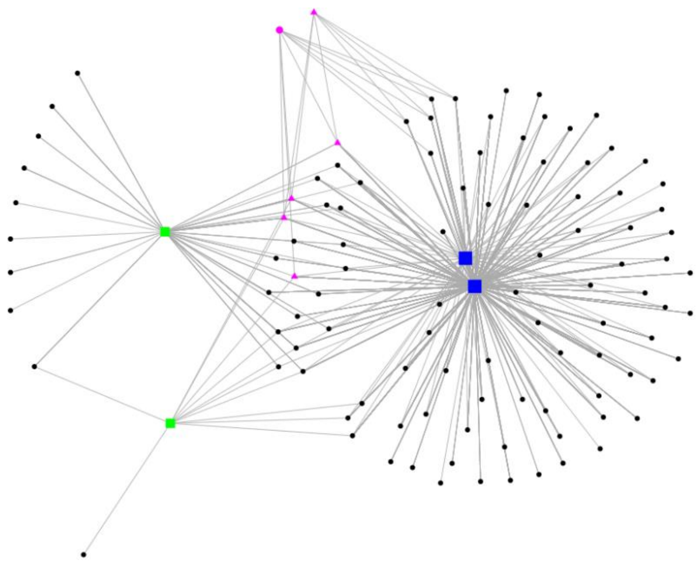

Figure 10. *Network analysis interrelating participants of events*

These results confirm the assumption of aforementioned statement that the general willingness of using the service on a regular basis can be enhanced by having a few users with the role of organizer who can manage the events and can create social type contents for their company in the service. Smaller groups can form within a company who tend to attend on events mostly only if other members from the same group attend too. Therefore, it should be considered for the companies and for the service provider to place more effort on persuading opinion leader people, so they can influence others to participate more. However, this concept needs additional investigation. Further research is needed to examine the effect of organizers at smaller and larger companies.

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4.3 Limitations and future research directions

The key limitation of this study is the use of data from only one gamified application. We could not compare our findings with data from other applications. Additionally, we obtained only the user log-data of Battlejungle and we did not have the opportunity to generate a more detailed picture of the effect of gamification by testing a control user group who participated in the same sport and community programs but did not use a gamified application.

Our study is limited also by the fact that the feedback responses gathered by the Battlejungle application are self-reported. Use of self-reported data is likely to affect the results as the users responding are most probably actively engaged with the service, and eager to participate in activities related to it. The fact that use of the examined service is generally not mandatory within companies makes the examination of non-engaged users challenging.

Moreover, the formulation of the feedback questions and the wording of the possible answers do not always comply with the principles of impartiality and non-influence. Unfortunately, it was not possible to modify or reformulate them.

In this study, we focused on engaged users, trying to identify and characterize them in as much detail as possible. We did not examine the reasons why non-engaged users decided to quit the application. The significant dropout rate highlights the need for further research on this topic.

5 Conclusion

In conclusion, it has been found that behavior patterns among users (who use the gamified service) can be distinguished significantly by their usage time. After separation, we could identify different behavioral patterns for engaged and non-engaged users. Users who are already engaged can be well distinguished by their behavioral traits, and these clusters can help to identify the Socializers, Achievers and Conquerors. The study was also able to reveal additional influencing factors beyond personal behavioral patterns like corporate culture and the importance of the ‘organizers’.

It should be noted that specifically this kind of gamified service (exercise encouraging and teambuilding fostering service for companies) has a major dependence on the corporate culture and on the capability of users with organizer role to provide content continuously. The gamification principle can multiply the effect on motivation and engagement but cannot create them if there cannot be find them at least in a minimum level.

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