Player Types and Player Behaviors: Analyzing Correlations in an On-the-field Gamified System.

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Abstract
When the promotion of a positive behavioral change is the goal, most often persuasion techniques are used. To maximize the effectiveness of these techniques designers need to tailor the employed persuasion strategies to each individual. Many studies faced the problem of modeling players' profile by designing taxonomies. However, none of them verified if this approach works in practice. In this paper we investigate whether using a well-known player types categorization based on a questionnaire is an effective mean to represent the way players actually behave in an on-the-field gamified system.

CCS Concepts
•**Human-centered computing** $\rightarrow$ **Empirical studies in HCI;**

Author Keywords
Gamification; Player Modeling; Player Behaviors; Model Evaluation

Introduction
Building a user-centric software implies modeling the user profile and tune the system accordingly. In the literature many taxonomies that aim to identify users in games exist, so as to perform what is called player modeling [21]. The majority of those categorizations borrow ideas from psycho-

Hexad Player Types [16]:

Philanthropists are interested in helping others and in the other players' well-being.

Socialisers favor teamwork and game mechanics that allows them to interact with other players.

Free Spirits's main purpose is to explore the system and to experiment with all it has to offer.

Achievers are driven by the will of improving their knowledge, of learning new skills and of overcoming difficult challenges.

Players are motivated by extrinsic rewards and virtual goods.

Disruptors are reluctant to follow the rules and their main purpose is to test the system's boundaries.

logical theories, such as Self-Determination Theory (SDT) [16], the Five Factory Model (FFM) [19] and the Meyers-Briggs Type indicator (MBTI) [17]; while the others result in reviews of previous studies (i.e., [6]). However, a framework for profiling users in *gamified systems* lacked and this need has been addressed by Tondello et al. [20], who provided a questionnaire for the Hexad types [16]. Despite having defined and validated a survey, the downside of this approach is that it has never been tested on data from an on-the-field experimentation.

Another way of understanding how players interact with the game is to study the behaviors that they assume during the gameplay. Canossa [2], for example, suggested strategies for building meaningful models to interpret these behaviors. Other researchers investigated players' behavioral patters with a more concrete purpose, such as predicting the strategies that the players were using [10] or instructing non-playing characters from real players' actions [22]. Other applications aimed at understanding the level of enjoyment perceived by users and, hence, calculate player retention [18] and the likelihood of abandoning the game [15]. In all cases, the information extracted from each users' gameplay was extremely diverse and depending both on game and on the individual taken into account.

Behavioral analyses and player modeling help individuating the rose of possible users and can be a powerful tool in the process of dynamically adapting the game through Procedural Contend Generation (PCG) techniques, which allow to generate game content of heterogeneous nature [8]. The strength of this approach lies in the fact that through these mechanisms an highly customized game can be developed containing time and costs of production, while keeping the players entertained [3, 12], adjusting the difficulty of the levels to avoid frustration and/or boredom [5, 14] and tuning the system to players' knowledge [23, 24].

Our contribution within this work is twofold. In the first place, we suggest a set of players' abstract behaviors that can be instantiated in any gamified system. These abstract behaviors are meant to help designers to identify relevant behaviors and observe them within the game. Then, we implemented them in an actual gamified system to investigate possible correlations among those in-game behaviors and the Hexad players' types [16]. These findings are meant to have a dual purpose.
Validate the usage of players' types as a reliable mechanism to represent users preferences. In fact, having a straightforward way to profile players in real-time can be used as a powerful tool in the process of PCG algorithms to dynamically build highly customized game content to maximize the impact that the games has on every player. In this regard, the main strength of our work is that this is the fist study that conducts analysis of Hexad players' types on data gathered during a long-running open-field gamification campaign. In addition, the behavioral patterns defined in this work could assist designers in analyzing how players interact with the system so as to gain insightful information about the game and to inspire further improvements on it.

Play&Go

Play&Go is a gamified system built upon the Kazhamiakin et al. [11] framework, whose purpose is to induce a Voluntary Travel behavior Change (VTBC) [1]. The game aims at combining the municipality desires and the citizens' need with the final goal of promoting CO_2-free means of transportation and/or public transportation. This is a project ongoing from 2015 and the experimentation on the last version of the game was conducted in a six-month period (September, 2017 - March, 2018) organized in 25 weeks.

Citizens were motivated to track their daily trips (i.e. by bus, train, bike, bike–sharing or walk), through the Viaggia Play&Go App. Tracked itineraries were checked by an automatic itinerary validation algorithm. Players received points - green leaves - for each valid trip. Points were used to calculate the weekly (and global) leader-board. Each week, physical prizes offered by sponsors were put up for grabs among the Top 50 players. To encourage players to assume sustainable mobility behaviors and to keep them engaged in the game, weekly challenges were proposed. The challenges required a personal improvement and were tailored to the player preferences and habits. To achieve that, the challenges were dynamically generated through a recommendation system [13]. The generated challenges were sorted in such a way that the chosen ones were in accord to the weekly themes, if any, but, most importantly, they had to be commensurate to the user's skills and past performances - in accord to the concept of flow [4].

Method

Play&Go has been active in the city of Trento for six months. During the whole period information regarding players' activities within the game has been stored in logs. In the final two weeks of the experiment, users were asked to fill out a survey constituted of general questions about the level of appreciation of the game and questions from the Hexad Questionnaire [20].

Among one hundred and ten citizens that answered the questionnaire, 64% of them were from Trento with the remaining equally distributed among Rovereto and other cities. More than 30% of the participants were aged between 20-35, 27% between 35-50, 27% between 50-70 and the remaining were younger than 20 years old or older than 70. In addition, participants were almost equally distributed among male (57%) and female (43%). Answers were collected on March 2018. To avoid problems due to language differences, the surveys were submitted in English or in Italian, according to the preference expressed by the users. Therefore, we assume that participants were able to understand the questions and to answer accordingly.

The game data-logs constituted another source of information. Starting from this data, we have abstracted some users' behaviors and investigated for correlations with the player types scores [16] calculated from the submitted questionnaire.

We identified the following abstract behaviors that players are likely to assume when they interact with a gamified system. Moreover, we contextualized those behaviors in the game we analyzed. In the following, we present a preliminary list of abstract behaviors that can be used by designers as guidelines to detect the elements in their gamified systems, if any, which best represent each one of them.

Easy win. Players have an *easy-win* behavior if they prefer game mechanics that allow them to gain points in an easy way.

Committed. Players have a *committed* behavior in respect to the game if they play it regularly.

Active. Players have an *active* behavior if they perform many actions in the game and, consequently, gain many points.

Competitive. Players have a *competitive* behavior if they favor game mechanics that induce competition.

Striving. Players have a *striving* behavior if they have the tendency to complete all the challenges that are proposed to them, no matter how difficult they are.

Self-improvement. Players have a *self-improvement* behavior if they tend to improve their performances in the game.

Cheating. Players have a *cheating* behavior if they try to find loopholes in the game to win it.

Purpose driven. Players have a *purpose driven* behavior if, in comparison to other actions, they prefer the ones that are more coherent with the game main purpose. This kind of behavior is especially relevant in persuasive technologies.

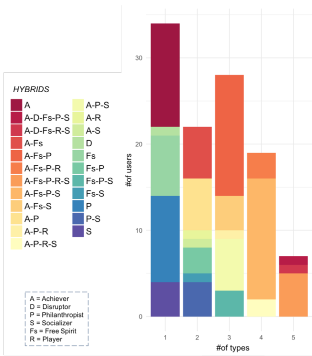

Figure 1: This image shows the distribution of types and hybrid types among the users. Where an hybrid type is defined as the combination of two or more Hexad types.

Finally, we investigated whether any correlation exists among the behaviors and their items, and the players' types. Since the scores that the users obtained in the scales were not normally distributed, the method chosen to study the correlations among the users' types and the game features is the Kendall's τ, being the best estimate for non-parametric data [9]. To unfold the meaning of the τ value, we used the Gilpin's correspondence table [7] to interpret Kendall's τ effect size according to the approximate Pearson's r equivalent, which is commonly used in these kind of tests. We, hence, considered as small effect τ = 0.20, medium effect τ = 0.34 and large effect τ = 0.50.

Results

In the following section we illustrate the results of the analysis conducted and presented in the Methodology section. Firstly we collected the answers to the Hexad Questionnaire and calculated, for each player, the score in the 6 scales. In Figure 1 we present an overview of the number of types that characterized each user. Only 30% of the players obtained a high score in a single type, while the others presented a tie in up to 5 different types.

Then, we extracted the players' behaviors as described in Table 1, in which we show how we have instantiated the abstract behaviors within Play&Go. We associated items that are significant in Play&Go and that represent the concept expressed in the behaviors' descriptions. Interestingly, the frequency of usage item has a low variability, which could be mostly due to the fact that the considered users were the one that answered to the questionnaire and, since it was submitted at the end of the experimentation, the answers came from the most committed players. This interpretation is consistent with the values of the number of inactive weeks, since 75% of the analyzed players was inactive less than 3 weeks in the six-months period analyzed. Another insightful observation can be done on the improvements' values, calculated in terms of kilometers and trips done. These items have the highest variability, suggesting that, even though among those users the level of participation were almost homogeneous, the degree of effort put in the game were variable.

Finally, as Figure 2 depicts, we observed that the behaviors assumed by players during the gameplay show no relevant correlation with players' types.

Discussion

Well-designed games have the intrinsic property of being compelling, which is a desirable characteristic especially when dealing with persuasive technologies. In this field, it is particular important to consider the heterogeneity of users, since the final goal is so individual-dependent as the promotion of a positive behavioral change. The problem of understanding which game dynamic is best suited for each user is an open debate and a lot of models have been proposed. However, those solution are either reviews based on previous studies or, in the best case scenario, they are evaluated through self-assessment questionnaires.

Our contribution is, on the one hand, to test a well-known taxonomy in a real game scenario and, on the other hand, to put in foreground the analysis of the behaviors that users assume during the gameplay. We suggest abstract behaviors that can be instantiated both in a full-featured gamified

behaviors	Items	Min	Max	Mean	SD	RSD	1st Quartile	Median	3rd Quartile
Easy win	Recommendations	0	17	1.55	2.98	192.75	0	0	2
	Easy challenges completion rate	0	90	22.27	27.19	122.09	0	2.63	44
Committed	Daily activity	1.08	9.33	3.28	1.63	49.58	2.13	2.96	4.13
	Frequency of usage	1.74	100	60.73	27.16	44.72	42.7	64.33	83.83
	Social challenges completion rate	0	100	10	30.14	301.37	0	0	0
	Non active weeks	0	23	2.93	4.89	167.21	0	1	3.75
Active	Total green leaves	599	39983	13185.78	9949.53	75.46	4788.5	10229.5	17903
	Number of badges	5	42	19.9	7.26	36.5	14.25	19.5	24.75
	Number of trips	7	1301	319.75	305.64	95.59	74.75	200	495.25
	Number of actions	9	1316	323.77	305.44	94.34	81	205.5	500
	Challenges completion rate	0	94.12	24.78	29.97	120.96	0	1.96	52.94
Competitive	Interest in leaderboard	1	7	2.71	1.83	67.52	1	2	4
	Times in "Top Ten"	0	13	1.22	2.68	219.7	0	0	1
Striving	Challenges completion time	0	10	4.84	1.27	26.19	4.33	5	5.54
	Difficult challenges completion rate	0	96.55	26.58	32.61	122.69	0	0	54.55
Self improvement	Improvement (Walk Km)	0.04	1	0.7	0.29	41.04	0.53	0.78	0.96
	Improvement (Bus Km)	0	1	0.26	0.35	134.84	0	0.04	0.5
	Improvement (Bike Km)	0	1	0.29	0.37	130.69	0	0.04	0.56
	Improvement (Trips)	-16	4.74	0.06	1.89	3160.52	-0.29	0.02	0.57
	Improvement (Km)	-31.83	58.89	1.24	9.23	743.01	-0.61	-0.04	1.79
Purpose driven	Zero Impact Trips	0	23	2.93	4.89	167.21	0	1	3.75
Cheating	Invalid Trips Rate	0.02	0.79	0.13	0.11	86.07	0.07	0.1	0.16

Table 1: Overview of the behaviors and of the relative items.

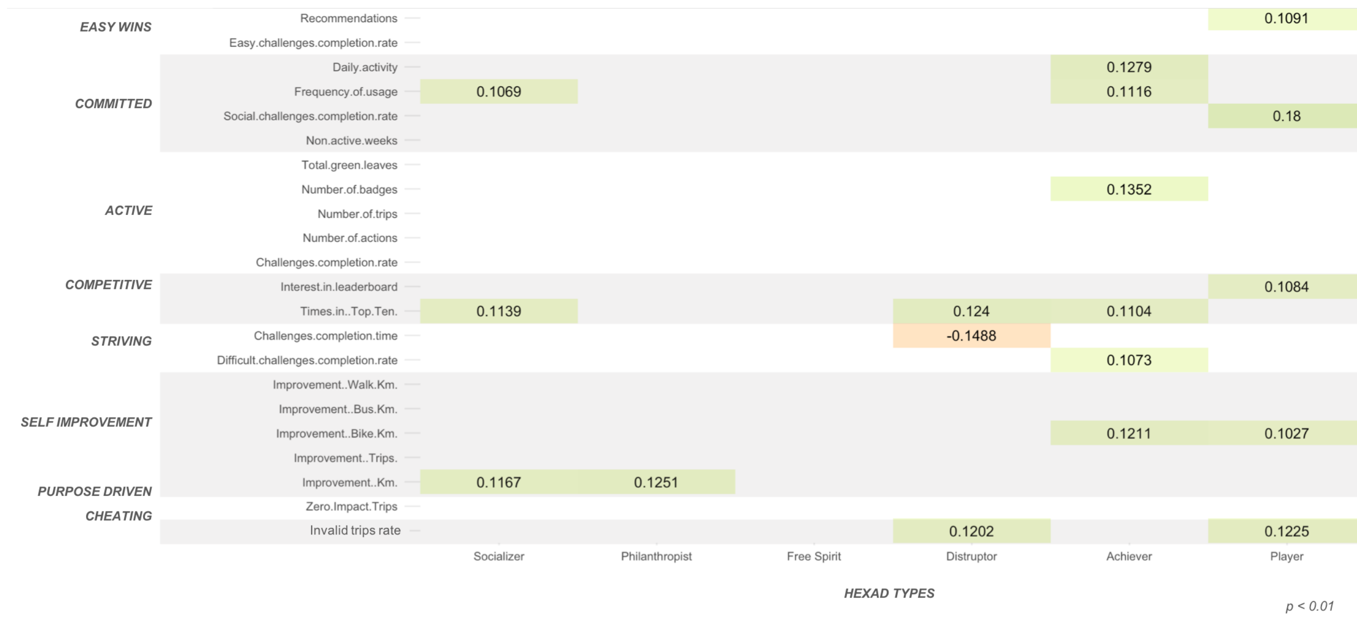

Figure 2: Correlations among players' behaviors and players' types. The blank spaces indicate a non-statistically significant relation, while the colored cells represent the entity of the relation: whether it is positive or negative (the intensity representing its strength)

system and in a simpler point-based system. Such behaviors function as an instrument which works both off-line, for game evaluation, and on-line, for dynamically generating game content tailored to each user. Unlike what we expected, our study's outcomes show that the behaviors extracted manifest very little correlation with the Hexad types. Considering that we observed some medium and strong correlations among the different scales, already detected by Tondello et. al [20], our hypothesis is that this taxonomy is not suited for our game. In fact, an elevated percentage of users were represented by several types (presenting tie scores in the scale), which hindered the process of identifying meaningful profiles. At the same time, most of the values collected for each behavior showed a significant variability (SD column in Table 1), suggesting that the users indeed behaved heterogeneously.

This paper presents a preliminary work, whose obtained insights will guide the design of future extensions of Play&Go game mechanisms to cover the kind of users' overlooked. We aim at observing the behaviors on-line to concurrently adapt the game and to extend and further validate our list of abstract behaviors. At the same time, we will correct the currents flaws so as to improve ours findings' validity and offer other designers a framework to support the designing process and the improvement of their gamified systems.

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