The Consistency of Gamification User Types: A Study on the Change of Preferences over Time

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In recent decades, several studies have suggested and validated user models (*e.g.*, Bartle, and Hexad) to represent different user profiles in games and gamified environments. However, when applying these user models in practice (*e.g.*, to personalize gamification), several studies reported contradictory outcomes. Recently, some studies outlined that one of the possible explanations for these contradictory findings is that people can present changes in their user profiles over time. In this study (N = 118), we present an analysis of the consistency of gamification user orientations after six months of the initial identification, by analyzing the association between user orientations in the first and second data collection. Overall, our results corroborate prior research demonstrating that user orientations can not be considered stable over time and also that the strongest tendency of the users might not be sufficient to determine how users change. Furthermore, we were able to identify that some user orientations can be more stable than others and model some relationships between their profiles after six months. Based on the results, we indicate a research agenda that can further the knowledge about the topic, as well as indicate a set of suggestions on how to model user profiles based on our results.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; **User studies**.

Additional Key Words and Phrases: Gamification user types, user modeling, gamification, rank-order consistency, empirical study

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1 INTRODUCTION

Over the last decades, video games have become an important source of entertainment for millions of people from different demographic backgrounds [35]. With the advancements of technology and design, video games transposed the line of entertainment, also becoming a source of immersion, education, and social interaction [24]. One reason for this is that video games can engage and positively affect people's behavior [29, 30, 35]. To create in non-game contexts similar positive experiences, gamification, *i.e.*, "the design of systems, services, and activities to provide motivation benefits as those games usually create" [28, 35], has been widely investigated and applied in the last ten years [6, 34, 35].

Although gamification has been settled as an important option to improve users' experience in Human-Computer Interaction [60], studies have also indicated mixed and even negative results in its application [6, 35, 72]. Recently, researchers started to investigate what would be the causes of these mixed and negative results in the application of gamification [6, 34, 35], indicating that one possibility could be that usually, the gamified systems are "one size fits all" (*i.e.*, designers develop the same system for all the users) [10, 63]. Since users have different preferences over game elements and gamification designs [13, 50, 67], there is a necessity for personalizing these systems according to their preferences [34]. Therefore, based on some users' characteristics (*e.g.*, user/player typology, gender, and age), researchers and practitioners have tried to model gamified systems to create experiences that would better fit the users' preferences and profiles [34].

Regarding the player and user typologies, the most researched user's characteristic in the gamification field [34, 53], some studies have indicated that the user models were dynamic [8, 12, 66, 79], *i.e.*, changes in the user orientations happen after a certain time and affect the user experience in personalized gamified systems. However, these studies were theoretical [8], only considered player typologies created for games [8, 12], or only conducted exploratory analysis about the user orientations change [66, 79]. Therefore, even though prior research has indicated that user orientations are not stable over time and consequently these changes in the user orientations implicate a necessity of dynamic modeling of gamified settings, little is known about these changes and how is possible to model user profiles based on them.

To face the challenge of better understanding how user orientations change over time, we conducted this study in two different phases measuring the consistency of gamification user orientations (*i.e.*, Achiever, Philanthropist, Socialiser, Free Spirit, Player, and Disruptor) of 118 participants after six months. The main goal was to answer the following questions: *i)* **Do gamification user orientations change after six months?**, *ii)* **What is the relationship between the gamification user orientations in the first and second data collection (after six months)?**, and *iii)* **How do the initial gamification user orientations predict the changes?** Our results indicate that *i)* some user orientations are more stable over time than others, *ii)* people who have gaming habits present slightly more stable user orientations than people who do not have gaming habits, and *iii)* that the strongest tendency of the users might not be sufficient to determine how users' orientations change over time. These results provide new insights for gamification researchers and practitioners on how to create more effective gamified systems, by indicating some patterns of associations between the user orientations and possibilities to model based on them. Moreover, the results indicate a research agenda that could be addressed in future studies.

2 BACKGROUND

In the following subsections, we present our study background (*i.e.*, user modeling in gamification and player/user typologies), as well as the main related work.

2.1 User modeling in gamification

Although being considered a recent research field, in the last years, gamification has gained popularity among practitioners and academics [35, 46, 53] due to the possibility of producing changes in people's behavior and engagement [6, 34, 35]. Gamification has been applied in a large number of contexts, however, its effects have been most investigated in education and health [34, 35]. After initial studies had indicated mixed results in its application [6, 35, 72], researchers and practitioners started modeling personalized gamified environments, *i.e.*, the personal perceptions and preferences of the users were taking into account when developing this type of system, creating a personalized environment that would be more suitable to the users' needs and preferences [2, 34].

Based on the need to personalize gamified environments, researchers started to move towards the understanding of how the game elements would affect the users' reactions and perceptions [11]. Most studies used self-reported data to investigate how this personalization could be modeled [74], considering different users' aspects such as gender [13, 50, 73], age [1, 45, 73], player or user type [26, 39, 67] or personality traits [27, 32]. Prior research also sought to understand how users were motivated in gamified systems considering different theories, for example, flow experience [18] or Self-determination Theory [19], and considering different outcomes as engagement, motivation, and sense of accomplishment [26, 52, 62, 67].

Overall, these studies considering a broad of users' aspects created different types of recommendations of how to model gamified systems, when indicated that gender differences exist when applying gamification [13], that motivation can be improved and demotivation can be decreased by the use of a proper set of game elements [26, 27], that the users' preferences over game elements or gamification designs depend on the player or user orientation of the user [50, 67], as well as that the use of gamification can foster enthusiasm [6]. Moreover, the studies of user modeling in gamification have indicated different results on its use, as well as a need for deep analysis about its effect on users [6, 34, 53].

2.2 Player and user typologies

Nowadays, the most investigated user characteristic in gamification is the player/user typologies [34, 53], being considered a major factor that could influence user motivation in personalized gamification [27]. These player or user typologies are used to "simplify" the complexity of the user [23, 69], by representing them in different user profiles in games and gamified environments. One of the first and most used player typologies, Bartle's [8] describes four-player types (*i.e.*, Killers, Achievers, Socializers, and Explorers). Even though this player typology was based on Multi-User Dungeons players (MUDs) and created for games' design, it has been largely used in the gamification field [34, 75]. Based on this player typology and on data collected from Massive Multiplayer Online Role Playing Games (MMORPGs), Yee [77] proposed a player motivation model with three main components (*i.e.*, Achievement, Social, and Immersion) and ten subcomponents (*i.e.*, advancement, mechanics, competition, socializing, relationship, teamwork, discovery, role-playing, customization, escapism) [75].

More recently, the model created by Ferro *et al.* [20], was developed based on personality traits and player types models, theoretically describing five player types (*i.e.*, Dominant, Objectivist, Humanist, Inquisitive, and Creative) [34, 73]. In the educational field, Barata *et al.* [7] proposed a player model to identify students' profiles based on their performance and gaming preferences. Their model categorizes the students into four different player types: achiever, regular, halfhearted, and underachiever [34].

Another player type model that has been largely used in gamification is the BrainHex Model [48], a player typology created based on previous player typologies, neurobiological research, patterns of play and literature on game emotions [48]. The seven-player types (*i.e.*, Seeker, Survivor, Daredevil, Mastermind, Conqueror, Achiever, and Socialiser) presented on this typology are considered an archetype that typifies a particular player experience [47]. Similar to the typology created by Bartle [8], the BrainHex typology was developed as a player typology for game design, however, it has been used in gamification [27].

To create a specific user typology for the field of gamification, Marczewski [43] developed the Gamification User Types Hexad. This typology indicates that users in gamified systems can be considered: *Philanthropists* (motivated by purpose), *Socialisers* (motivated by relatedness), *Free Spirits* (motivated by autonomy), *Achievers* (motivated by competence), *Players* (motivated by extrinsic rewards), and *Disruptors* (motivated by the triggering of change). Excepting the Disruptor user orientation, all the user orientations from Hexad were created based on the self-determination theory (SDT) [19], which indicates that people can be intrinsically motivated (when the activity supports the human psychological needs of competence, autonomy, and relatedness) or extrinsically motivated (when the reason for doing something is not an interest in the activity itself) [19, 73].

In the Hexad, although the users can present a stronger tendency towards one user orientation, they are motivated by all the other user orientations in some degree [75]. The Hexad has been largely used in the gamification field since it is considered the most appropriated user typology for personalization [27], has a scale to assess the user orientations validated in different languages [37, 42, 56, 65, 71, 73], and has been successfully used in studies from different contexts [4, 26, 57, 67].

2.3 Related work

Modeling user profiles have been indicated as an important part of the gamification design, and most of the results relied on studies that utilized player or user typologies [34]. Over the years, studies have indicated that according to the user profile, there are differences in the perception and preferences for game elements [51, 67, 75] and also that younger people might present a more heterogeneous user orientation distribution [1]. Furthermore, gaming habits might present an influence in the user orientation distribution [1, 59, 68], and also some user orientations can be most commonly found according to the faculty affiliation [21] or gender [45].

In summary, the studies demonstrate that the user profile is related to other different user characteristics, *e.g.*, gender, age, and gaming habits. However, this relationship could suffer influences from the stability of the user profile, affecting the gamification design [66, 79]. Despite its importance, only a few studies have sought to identify whether the player or user orientations could be considered stable over time. One of the pioneers in the definition of player typologies, Bartle [8] indicated in his study that the player types should not be considered stable. He pointed out that, even though the players could be located in one specific player type, they could change their interest freely and change to another player type over time [8]. The author also indicated that it would be possible to affect the overall player population when increasing the number of some player types and making other player types to just stop using the game, therefore, it would be possible to only have a certain type of player. However, it was also indicated that this dynamic model was imprecise, considering that it did not take into account the relationship between the players or other external factors that could influence them. Despite its importance and large use to personalize gamification, the Bartle model is often criticized since it is an informal typology [48] that was created specifically for games and should not be generalized to gamification design [75].

Using the BrainHex Model, Busch *et al.* [12] conducted two online studies to analyze the psychometric properties of the BrainHex scale. In this study, they also analyzed whether the respondents' player types were the same after six months, which results demonstrated that the player types from the BrainHex model could not be considered stable over time. To analyze the stability, the authors used only a correlation test (*i.e.* Person's) between the scores of each user type in both phases, not presenting the percentage of change, the relationship between the player types' scores or how other user characteristics could be related to the user profile changes. Moreover, despite the importance of empirically indicating that the player types would not be stable over time, similar to Bartle [8], they considered a game-based player typology, which may prevent the results to be the same in the context of gamification. Therefore, considering that they did not present further analyses about how the user profiles change over time, their study was only an exploratory study that did not indicate how to model user profiles based on the changes in the BrainHex scale.

Up to date, at the best of our knowledge, only two studies considered changes in the user orientations from the Hexad model. The first study that evaluated the stability of the Hexad model was conducted by Santos *et al.* [66], using data from 74 people and evaluating whether the Hexad user orientations would be stable after six months. Their results indicated that changes in the strongest tendency of the participants as well as their average scores in the Hexad sub-scales occurred after six months and, therefore, the user orientations from the Hexad model could not be considered stable over time. Additionally, their results indicated that users can present repeated scores in different sub-scales, that women could be more susceptible to changing their user orientations and also that change could happen in different life stages. Although these results had practical implications, the authors only conducted an exploratory analysis of the data, not presenting how the user orientations would change over time or recommendations on how to model user profiles based on the changes presented by the users.

More recently, Yildirim and Özdener [79] conducted an exploratory study with 66 participants, evaluating whether the Hexad user orientations of teacher candidates in a University in Turkey would change after 16 months. They used the data to conduct descriptive statistics and correlation analysis, finding similar results to Santos *et al.* [66], also indicating that the strongest tendency of the participants changed over time. Furthermore, their results demonstrated that the average scores of the sub-scales presented moderate similarities, with the Philanthropists sub-scale presenting the most significant change. Even though the study corroborates prior research indicating that the Hexad user orientations should not be considered stable, the authors did not conduct further analysis or tried to demonstrate how the changes occurred in the sub-scales.

Even though these studies had presented important results for the gamification field when indicating that the user profile was not stable over time, and therefore the personalization of gamified settings should be dynamic, some prior studies did not use typologies created for gamification [8, 12], did not further explored the changes the users presented [12, 66, 79], and did not indicate how to model users' profiles considering their changes. Therefore, even though these current approaches have indicated a gap in the field, they only focused on conducting exploratory analysis about whether the user orientations change without exploring how the changes occurred or which would be the relationship between the scores from different study phases. Thus, as far as we know, our study is the first study that addresses this research gap by conducting analyses on how the user orientations from the Hexad model change over time, as well as how to model user profiles based on these changes.

3 STUDY DESIGN

Our study aimed to identify how to model user profiles based on the relationship the user orientations present after six months, seeking to answer the following research questions: *i)* **"Do gamification user orientations change after six months?"**, *ii)* **"What is the relationship between the gamification user orientations in the first and second data collection (after six months)? "**, and *iii)* **"How do the initial gamification user orientations predict the changes?"**. To achieve this goal, we (1) designed a survey; (2) conducted a pilot study; (3) applied the survey in the first study's phase; (4) reapplied the survey in the second study's phase (six months after the first data collection); and (5) conducted data analyses to answer our research questions.

3.1 Materials and method

To achieve the goal of the study, we divided the study into two phases. Considering prior research [6, 54] that has indicated a lack of long-term studies in the field of gamification, and also prior research [12] that has delimited a period of six months to analyze the differences between player types, we decided to conduct the second phase of the study six months after the first phase. In both phases, we used the same survey, which consisted of 30 questions and items distributed in two different sections. The first section of the survey was employed to collect the demographic aspects (*i.e.*, gender, age group, and educational level) and an overview of the gaming habits of the respondents. To collect gender information, following other recent studies in the field [23, 37, 59], the respondents were asked to check one option between women, men, preferred not to answer, or other. Since we aimed to collect data from people with different educational backgrounds, in the question about the educational degree we presented the following options: elementary school, middle school, high school, bachelor, specialized or MBA courses, M.Sc, and Ph. D. or PostDoc. To collect the age information avoiding possible typos, we followed prior studies [59] when presenting predefined options of age groups from 15-19 years old until more than 60 years old. To provide an overview of the participants' gaming habits, the respondents were asked if they play games (we presented as options: yes or no) and the frequency (we presented as options: every day, every week, rarely, and I do not know).

In the second section of the survey, we collected the participants' user orientations, by using the Gamification User Types Hexad scale created by Tondello *et al.* [73]. Considering that we were going to focus on collecting data from one specific country (*i.e.*, Brazil) and that most Brazilians do not have good English comprehension skills [17], we used the Brazilian Portuguese version of the scale [65]. The Hexad scale consists in 24 items, where four items are used to identify each of the Hexad user orientations. The respondents had to answer each item on a 7-point Likert scale [40] and, to mitigate the possibility of identification of the items that are associated with each user orientation, the items were randomly presented in the survey. Inspired by other studies in the field [27, 55, 56] we also included an "attention-check" item in this section of the survey. This "attention-check" item (*i.e.*, "I like to be with my friends, but this question is just to evaluate your attention. Please, check option number 3.") had as main goal guarantee that the respondents were reading all the items before answering. "Attention-check" items are a good way to filter careless responses without affecting the scale validity [38].

Before the survey release, as recommended by Connelly [16], we conducted a pilot study. The main goal of this pilot study was to evaluate the survey size. Ten people were invited to answer the survey before its application and were asked to give feedback. These ten people had to pass in the "attention-check" statement, presented different demographic backgrounds (women and men, from different age groups, different educational levels, and different gaming habits), and eight of them considered the survey size as adequate. Considering the results of the pilot study, the survey was applied without modifications.

3.2 Participants and Data Analyses

To collect the data for the first research phase, the survey was released through the platform Google Forms, and the participants were invited to participate via email and social networks (Facebook, Instagram, and Twitter). The e-mail lists were from personal contacts of the authors, guaranteeing academic and non-academic participants. The propagation through social networks was made in the authors' personal accounts and not targeted at any kind of ads. These publications were made public to facilitate the propagation by others. In this phase, we collected 366 answers, of which 331 were valid according to the attention-check item. From these 331 answers, 182 respondents provided a valid e-mail authorizing the contact for other studies. Considering the study's goals and phases (*i.e.*, the participants of the first phase should provide and authorize our contact for the second phase), these 182 participants formed the sample of the first phase of the study. These 182 e-mails were from 90 people who self-reported as women (49%) and 92 people who self-reported as men (51%). Also, 71% reported that playing games was a habit. Initial analysis of the participants' user orientations has demonstrated that 56% of these 182 respondents presented only one of the six Hexad's user orientations (*i.e.*, Achiever, Philanthropist, Socialiser, Disruptor, Free Spirit, and Player) as their strongest tendency, while the other 44% presented thirteen different combinations of the six Hexad's user orientations as their strongest tendency (*e.g.*, Achiever and Philanthropist, Philanthropist and Socialiser). Therefore, in total, the participants presented nineteen different combinations of the six Hexad user orientations as their strongest tendency in the first phase of the study.

In the second phase of the study, six months after the first phase, the survey was also released through the platform Google Forms. Since we aimed to only collect answers from participants of the first research phase, in the second phase of the study the survey was sent directly to the 182 respondents that left a valid e-mail in the first phase. Were collected 87 answers, of which 74 were valid according to the "attention-check" item. In this phase, 57% of the respondents presented only one of the six Hexad user orientations (*i.e.*, Achiever, Philanthropist, Socialiser, Disruptor, Free Spirit, and Player) as their strongest tendency, while the other 43% presented fourteen different combinations of the six Hexad user orientations as their strongest tendency (*e.g.*, Achiever and Philanthropist, Philanthropist and Socialiser). Therefore, in the second research phase, twenty different combinations of the six Hexad user orientations were presented as the strongest tendency by the participants.

Participation in both phases was entirely voluntary, considering that the respondents did not receive any kind of compensation for participation. Volunteers tend to be more willing to pay attention in surveys without pressure to maximize time usage [74], which can increase the reliability of the study. In both phases, participants had to agree to participate by checking a consent term. This consent term informed the participants about the purpose of the study, the study confidentiality, that the data collected would be used in scientific research, and also the contact of the researchers and universities involved in the study. Participants also were informed about the possibility of quitting the study at any time before submitting the responses. Regarding ethical guidelines, this study has been performed in accordance with the Brazilian National Health Council resolution number 510 published on April 7th, 2016, and with the relevant guidelines and regulations set by the Universities involved.

After our data collection, another dataset was provided to us, with 53 answers from students aged between 13 and 16 years old. This data collection was conducted by a researcher who is also a teacher in a public school and was measuring the changes in the Hexad user orientations of students after six months. The teacher collected their age, Hexad user orientations, and gaming habits in two different moments, using the same scale and also including an "attention-check" statement. In accordance with the Brazilian National Health Council resolution number 510 published on April 7th, 2016, informed consent for participation was obtained from all participants and their legal guardians, and the final dataset was provided to the authors without the possibility of identification of the students. Three answers from the first phase and six answers from the second phase were removed after checking the "attention-check" item, therefore, the final dataset was formed by 44 respondents.

In the first phase of the study, 36% of the students presented Player as their strongest tendency; 34% presented Achiever as their strongest tendency; 11% presented Philanthropist as their strongest tendency; 9% presented Socialiser as their strongest tendency; 8% presented Free Spirit as their strongest tendency; and 2% presented Disruptor as their strongest tendency. In this phase, 89% of the adolescents reported that playing games was a habit. In the second phase of the collection of data from the adolescents, 28% of them presented Player as their strongest tendency, 27% presented Achiever as their strongest tendency, 18% presented Philanthropist as their strongest tendency, 13% presented Socialiser as their strongest tendency, 8% presented Free Spirit as their strongest tendency, and 5% presented Disruptor as their strongest tendency. In this phase, 82% of the adolescents reported that playing games was a habit.

Before the statistical analysis, we calculated what would be the required sample size we should have for the analysis intended. To calculate the necessary sample size of the study, we used the Online Calculator provided by Soper [70]. We indicated 6 latent variables (*i.e.*, the Hexad user orientations), 24 observed variables (*i.e.*, all the items from the Hexad scale) and considered the anticipated effect size as 0.5, the desired statistical power level as 0.8 (by convention), and probability level as 0.05 (by convention) [14, 76]. The results indicated that the minimum sample size to detect the effect in our study would be 40 participants and the minimum sample size for the model structure would be 100. Therefore, the recommended minimum sample size should be at least 100 participants.

Since both datasets were measuring the changes in the user orientations considering the same scale and collecting data in the same country (*i.e.*, the Brazilian version of the Hexad scale with the addition of an attention-check item), and also considering the same difference of time (*i.e.*, six months), we merged the datasets to conduct one unique analysis, a practice that has been considered successful in prior studies of the gamification field (*e.g.*, [36]). Most of the demographic information collected from the respondents was the same, the only information excluded before the analysis was the gender of the participants, considering that this information was not provided in the second dataset from teenage students. Table 1 presents the demographic information and gaming habits of the respondents from both datasets (first phase N = 226; second phase N =118).

Initially, using the software IBM SPSS 27 [31], we conducted a Shapiro-Wilk test to assess whether the data was following a parametric or non-parametric distribution. Then, we analyzed the *i)* descriptive statistics (mean and the standard deviation in each sub-scale), *ii)* internal reliability (using Cronbach's α), and *iii)* correlation between user orientations (using Kendall's τ). Using SmartPLS[1] software, we conducted a further analysis of the relationship between the data from both phases of the study using Partial Least Squares Path Modeling (PLS-PM), a reliable method for estimating cause-effect relationship models with latent variables [25]. Considering that Cronbach's α can be misleading due to its tendency to underestimate reliability [61], we calculated the composite reliability (CR) that is considered a good option to measure reliability since it is formulated through structural equation modeling and is equivalent to coefficient omega [58]. Finally, using Partial Least Squares Path Modeling (PLS-PM), we conducted an analysis of the association between the data collected in the first phase and the Δ values (T2-T1, *i.e.*, the differences in the average score between the phases). Our complete dataset can be found in the complementary files.

4 RESULTS

Overall, the reliability was acceptable ($\alpha \geq 0.70$, CR ≥ 0.70, AVE ≥ 0.50) for all user orientations, except for the user type Disruptor (in both phases) and Free Spirit (in the first phase). We also measured the discriminant validity finding acceptable values for most of the variables (exception

[1]https://www.smartpls.com/

Table 1. Demographic information and gaming habits of the participants from both phases

Demographic information							
		1st phase	2nd phase			1st phase	2nd phase
					13-14	19%	23%
					15-19	8%	18%
Gender*	Female	49%	55%		20-24	9%	8%
	Male	51%	45%		25-29	13%	11%
				Age	30-34	14%	8%
	Elementary/Middle/High School	27%	40%		35-39	9%	8%
	Bachelor	19%	17%		40-44	11%	12%
Education level	MBA/Specialists	20%	14%		45-49	8%	6%
	M.Sc.	24%	19%		50-54	5%	3%
	PhD/PostDoc	10%	10%		55-59	3%	3%
					Over 60	1%	1%
Gaming habits							
		1st phase	2nd phase			1st phase	2nd phase
	Play games	75%	77%	Do not play games		25%	23%
	Everyday	22%	20%				
Frequency	Every week	21%	26%				
	Rarely	41%	42%				
	I do not know	16%	12%				

Key: Gender*: considering that the database from the students did not provide gender, this information is only from the data collected by the authors (*i.e.*, first phase $N = 182$; second phase $N = 74$).

occurred between F1 and A1; F2 and A2; and D1 and D2), since the square root of the variables' AVE value was larger than the correlations the variable had with the other variables, and of the variables presented correlations between them below 0.85. The reliability results can be seen in Table 2 and the discriminant validity can be seen in Table 3.

Table 2. Reliability results

Construct	α	**RHO**	**CR**	**AVE**
Achiever1	0.816	0.988	0.857	0.603
Achiever2	0.803	0.827	0.866	0.619
Disruptor1	0.644	0.657	0.789	0.486
Disruptor2	0.613	0.619	0.775	0.464
Free Spirit1	0.577	0.641	0.703	0.394
Free Spirit2	0.725	0.729	0.826	0.545
Philanthropist1	0.840	0.846	0.893	0.678
Philanthropist2	0.842	0.868	0.892	0.674
Player1	0.766	0.790	0.848	0.582
Player2	0.812	0.820	0.876	0.639
Socialiser1	0.831	0.844	0.888	0.665
Socialiser2	0.846	0.847	0.897	0.685

Key: α: Cronbach's; RHO: Jöreskog's rho; CR: Composite Reliability; AVE: Average Variance Extracted; 1: results of the first research phase; 2: results of the second research phase; Values in grey are $\alpha \leq 0.70$, RHO ≤ 0.70, CR ≤ 0.70, AVE ≤ 0.50.

Table 3. Discriminant Validity (complete bootstrapping, sample=5000)

	A1	A2	D1	D2	F1	F2	P2	P1	R1	R2	S1
A2	0.253										
D1	0.338	0.203									
D2	0.161	0.376	0.865								
F1	0.889	0.288	0.637	0.357							
F2	0.225	0.873	0.347	0.517	0.453						
P2	0.073	0.715	0.095	0.295	0.236	0.770					
P1	0.718	0.148	0.274	0.233	0.748	0.156	0.377				
R1	0.729	0.299	0.390	0.231	0.671	0.276	0.134	0.431			
R2	0.161	0.750	0.183	0.335	0.184	0.758	0.516	0.164	0.538		
S1	0.534	0.198	0.270	0.195	0.541	0.247	0.308	0.724	0.469	0.165	
S2	0.150	0.487	0.145	0.257	0.205	0.448	0.715	0.251	0.110	0.411	0.441

Key: P1: Philanthropist first research phase; A1: Achiever first research phase; R1: Player first research phase; F1: Free Spirit first research phase; S1: Socialiser first research phase; D1: Disruptor first research phase; P2: Philanthropist second research phase; A2: Achiever second research phase; R2: Player second research phase; F2: Free Spirit second research phase; S2: Socialiser second research phase; D2: Disruptor second research phase. Values in grey (F1 and A1; F2 and A2; and D1 and D2) did not present acceptable values.

After measuring the reliability of the data, we calculated the strongest tendency of the participants in both phases of the study, considering the highest score the participant had on the Hexad scale. To define the strongest tendency of each respondent, we calculated the score the participant had in each subscale, defining the highest score as their strongest tendency. Since each Hexad sub-scale (*i.e.*, the part of the scale that is used to define one of the user orientations) is formed by four items arranged in a 7-point Likert Scale, the minimum score a respondent can have in each Hexad sub-scale is 4 and the maximum is 28. Considering that some respondents presented a repeated score as the highest score in different sub-scales, different combinations beyond the six main Hexad user orientations were presented. Overall, twenty-eight different combinations between the Hexad scale were presented as the strongest tendency of the respondents, with some combinations appearing only in one phase of the study, which was the first indication that there was a change in the responses of the participants of the study between the phases. All the combinations can be seen in Table 4. When comparing the strongest tendency of the participants in both phases (N=118), 85 participants (72%) presented changes. Therefore, most of the participants changed their ratings over the items of the Hexad scale after six months, impacting the definition of their strongest tendency.

After calculating the strongest tendency of the participants, we calculated the average score, the standard deviation, the Δ (*i.e.*, the differences in the average score between the phases), and the bivariate correlation coefficients (Kendall's τ) for each sub-scale, which results can be seen in Table 5. Similar to prior research [5, 73, 75], in both phases of the study the participants presented the higher average score in the Philanthropist and Achiever sub-scale, while presented the lowest average score in the Disruptors sub-scale. When considering the Δ values, the biggest difference happened between Achievers (the first average score was 0.95 higher than the second) and the smallest difference happened between the Philanthropists (the first average score was 0.10 higher than the second). Disruptors and Socialisers (both -0.18) were the only user orientations that presented a higher average score in the second phase when compared with the scores from the first

Table 4. Strongest tendency of participants in both phases

User type	**1st**	**2nd**
Philanthropist	19%	20%
Achiever	17%	17%
Player	11%	8%
Free Spirit	7%	8%
Socialiser	3%	5%
Disruptor	3%	3%
Achiever/Free Spirit	1%	3%
Achiever/Free Spirit/Philanthropist	2%	3%
Achiever/Free Spirit/Philanthropist/Player	1%	-
Achiever/Free Spirit/Philanthropist/Player/Socialiser	3%	2%
Achiever/Free Spirit/Player	3%	-
Achiever/Philanthropist	14%	6%
Achiever/Philanthropist/Player/Socialiser	3%	2%
Achiever/Philanthropist/Socialiser	2%	1%
Achiever/Player	6%	4%
Achiever/Player/Socialiser	1%	1%
Achiever/Socialiser	2%	2%
Free Spirit/Philanthropist/Player/Socialiser	1%	1%
Free Spirit/Player	1%	1%
Philanthropist/Player	3%	3%
Philanthropist/Player/Socialiser	1%	-
Philanthropist/Socialiser	1%	3%
Achiever/Free Spirit/Player/Socialiser	-	1%
Free Spirit/Philanthropist/Socialiser	-	1%
Player/Socialiser	-	3%
Achiever/Disruptor/Free Spirit	-	1%
Achiever/Philanthropist/Player	-	1%
Free Spirit/Philanthropist	-	1%

Key: 1st: First research phase; 2nd: Second research phase.

phase. After the Shapiro-Wilk test result indicated that the data followed a non-normal distribution, we measured the bivariate correlation coefficients using Kendall's τ, since the data were non-parametric. Considering the conversion table proposed by Gilpin [22], the scores of Achievers, Free Spirits, and Socialisers presented a weak correlation, while the scores from Philanthropists, Disruptors, and Players presented a moderate correlation. Therefore, besides the differences in the strongest tendency presented in Table 4, the six Hexad sub-scales also presented differences in the average scores between both phases.

Considering that these initial analyses indicated that participants changed their answers in the Hexad scale between the phases of the study, we decided to conduct an exploratory analysis about how much percent of the respondents changed their strongest tendency based on their demographic characteristics. To do so, we measured the percentage of change in each group from the demographic and gaming habits collected in the second phase of the research. Based on the age of the participants, the results indicated that most of the age groups presented changes in the strongest tendency, which can indicate that changes happen during all life stages. Similar results

Table 5. Mean scores, standard deviation, and bivariate correlation coefficients (Kendall's τ)

User Orientations	Mean score	S.D.	Δ	τ
Achiever1	24.24	4.34	-0.95	0.301**
Achiever2	23.29	4.87		
Disruptor1	14.62	5.35	0.18	0.376**
Disruptor2	14.80	5.18		
Free Spirit1	22.83	3.80	-0.77	0.280**
Free Spirit2	22.06	4.65		
Philanthropist1	23.25	4.94	-0.10	0.418**
Philanthropist2	23.15	4.75		
Player1	22.10	5.16	-0.40	0.442**
Player2	21.70	45.38		
Socialiser1	20.50	5.50	0.18	0.347**
Socialiser2	20.68	5.58		

Key: τ: Kendall's tau; 1: results of the first research phase; 2: results of the second research phase; ** p<0.01; Δ: difference between the phases.

were found when considering the different educational levels presented by the participants of this study. When considering only the gaming habits, 70% of the participants that expressed that gaming was a habit changed their strongest tendency after six months against 78% of the participants that answered that they did not play games. This might indicate that people who have gaming habits could present more stable user orientations after six months. The percentage of change of each demographic group is presented in Table 6.

Table 6. Changes in the strongest tendency of the participants considering demographic and gaming habits information

		% of change			% of change
Educational Level	Elementary/Middle/High School	68%	*Age*	13-14	67%
	Bachelor	75%		15-19	71%
	MBA/Specialists	75%		20-24	80%
	M.Sc.	74%		25-29	77%
	PhD/PostDoc	75%		30-34	80%
Gaming Habits	Play games	70%		35-39	56%
	Do not play games	78%		40-44	93%
Frequency	Everyday	79%		45-49	57%
	Every week	58%		50-54	100%
	Rarely	78%		55-59	33%
	I don't Know	71%		Over 60	0%

Finally, to further calculate how well the scores of the first and second phases of the research were associated, and if it would be possible to find patterns on how to model the user orientations based on their changes in the Hexad scale, we used the Partial Least Squares Path Modeling (PLS-PM), a method of structural equation modeling that has been used in recent studies about gamification [26, 27, 57]. The PLS-PM is a reliable method for estimating cause-effect relationship models with latent variable [25] which permits the evaluation of associations between variables [26] and can produce estimates even in small samples [9]. In this analysis, we calculated the association between each of the Hexad user orientation scores from the first phase of the study with the user orientation itself and the other five Hexad user orientation scores from the second phase of the study. To do this, we considered all the scores presented by the participants, which means that all participants' tendencies scores were considered and not only the strongest tendency. This analysis has as its main objective to determine how the scores from the Hexad user orientations would vary after six months, therefore, indicating possible patterns of associations between the user orientations over time. The research model of our study is presented with the adjusted R^2 values in Figure 1 and the PLS path coefficients in Table 8.

The R^2 determines the impact of an independent variable on a dependent variable [44], defining the proportion of variance of the dependent variable explained by the independent variables [49]. Since the R^2 increases depending on the number of predictors, we calculated the adjusted R^2 which is a modified version of R^2 that adjusts the number of predictors in a regression model. The adjusted R^2 indicated that in the second phase of the study, the variance on the Achiever user type score was 9% explained by the scores from the first phase of the study; the variance on the Disruptor user type score was 29% explained by the scores from the first phase of the study; the variance on the Free Spirit user type score was 12% explained by the scores from the first phase of the study; the variance on the Philanthropist user type score was 15% explained by the scores from the first phase of the study; the variance on the Player user type score was 26% explained by the scores from the first phase of the study; and the variance on the Socialiser user type score was 18% explained by the scores from the first phase of the study.

We also measured the F^2 to find the effect size of constructs. The F^2 represents the change in R^2 when an exogenous variable is removed from the model. We found small ($F^2 \geq 0.02$) and medium ($F^2 \geq 0.15$) effect sizes for most of the user orientations, excepting Disruptor and Player sub-scales that presented large effect sizes ($F^2 \geq 0.35$) [15]. The F^2 results can be seen in Table 7.

Table 7. Effect Size (F^2)

	Achiever2	Disruptor2	Free Spirit2	Philanthropist2	Player2	Socialiser2
Achiever1	0.005	0.002	0.002	0.059	0.035	0.077
Disruptor1	0.013	**0.359**	0.008	0.002	0.000	0.002
Free Spirit1	0.046	0.004	0.074	0.029	0.004	0.002
Philanthropist1	0.054	0.016	0.028	0.070	0.065	0.010
Player1	0.027	0.005	0.004	0.008	**0.326**	0.003
Socialiser1	0.022	0.003	0.017	0.024	0.015	0.145

Key: Bold values are large effect sizes; Gray values are small effect sizes; 1: first research phase; 2: second research phase.

Our results indicated that the lowest and non-significant associations happened between the Achiever1 - Achiever2 (β = 0.087) and the Free Spirit1 - Free Spirit2 (β = 0.310). The other user orientations presented higher and significant associations (Philanthropist1 - Philanthropist2 (β = 0.327*), Player1 - Player2 (β = 0.583***), Socialiser1 - Socialiser2 (β = 0.433***), and Disruptor1 - Disruptor2 (β = 0.545***)) however, all the associations were under 0.7. When considering the significant associations between the user orientations, Philanthropist2 was negatively associated with Achiever1 (β = -0.296*); Socialiser2 was negatively associated with Achiever1 (-0.336*); Achiever2 was negatively associated with Philanthropist1 (-0.299*); and Player2 was negatively associated with Philanthropist1 (-0.295*). Therefore, all the significant associations between one user orientation and the others were negative.

To answer the third research question of the study (*i.e.*, how does the initial gamification user orientations predict the changes?), we conducted a new PLS analysis considering the associations

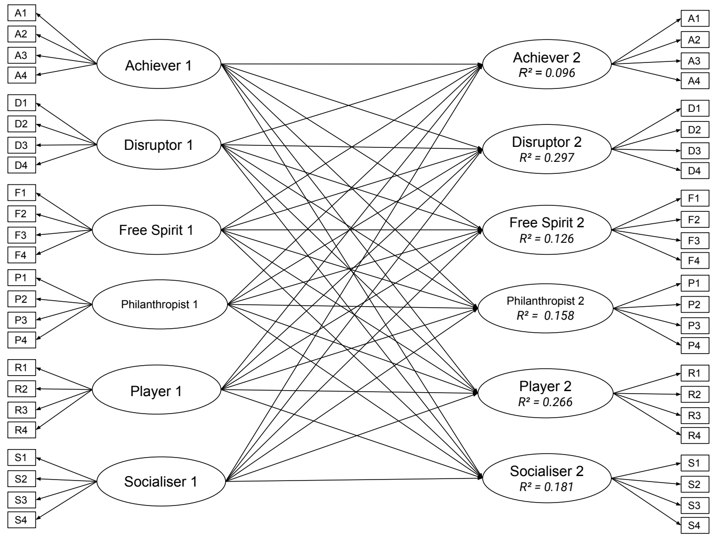

Fig. 1. Research model

between the score of the first phase and the Δ values (*i.e.*, the differences in the average score between the phases). The research model of this analysis can be seen in Figure 2 and PLS path coefficients are presented in Table 9.

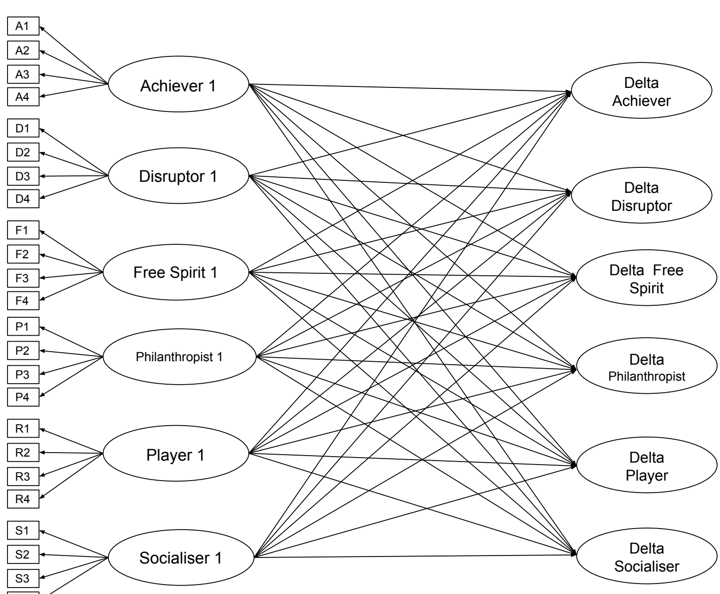

Fig. 2. Second research model

In this analysis, all the associations were under 0.6 and most of them were non-significant. Besides the associations between all the user orientations and their DELTA (*i.e.*, Achiever1 with ΔAchiever

Table 8. PLS-PM path coefficients

			CI	
	β	*p*-value	2.5%	97.5%
Achiever1 → Achiever2	0.087	0.696	-0.331	0.508
Achiever1 → Disruptor2	-0.049	0.706	-0.348	0.169
Achiever1 → Free Spirit2	0.051	0.787	-0.287	0.453
Achiever1 → Philanthropist2	**-0.296***	0.050	-0.593	-0.002
Achiever1 → Player2	-0.215	0.128	-0.478	0.093
Achiever1 → Socialiser2	**-0.336***	0.035	-0.639	-0.002
Disruptor1 → Achiever2	-0.117	0.379	-0.363	0.144
Disruptor1 → Disruptor2	**0.545*****	0.000	0.322	0.692
Disruptor1 → Free Spirit2	0.090	0.426	-0.151	0.297
Disruptor1 → Philanthropist2	-0.040	0.709	-0.242	0.177
Disruptor1 → Player2	0.015	0.864	-0.159	0.191
Disruptor1 → Socialiser2	0.041	0.682	-0.152	0.241
Free Spirit1 → Achiever2	0.248	0.184	-0.153	0.555
Free Spirit1 → Disruptor2	0.062	0.615	-0.189	0.290
Free Spirit1 → Free Spirit2	0.310	0.057	-0.106	0.555
Free Spirit1 → Philanthropist2	0.192	0.148	-0.108	0.405
Free Spirit1 → Player2	0.064	0.582	-0.200	0.265
Free Spirit1 → Socialiser2	0.051	0.721	-0.228	0.320
Philanthropist1 → Achiever2	**-0.299***	0.034	-0.598	-0.060
Philanthropist1 → Disruptor2	-0.142	0.303	-0.415	0.125
Philanthropist1 → Free Spirit2	-0.212	0.099	-0.473	0.016
Philanthropist1 → Philanthropist2	**0.327***	0.010	0.008	0.527
Philanthropist1 → Player2	**-0.295***	0.012	-0.554	-0.088
Philanthropist1 → Socialiser2	0.119	0.285	-0.083	0.346
Player1 → Achiever2	0.186	0.310	-0.251	0.464
Player1 → Disruptor2	0.073	0.484	-0.107	0.302
Player1 → Free Spirit2	0.070	0.617	-0.192	0.349
Player1 → Philanthropist2	-0.095	0.461	-0.350	0.145
Player1 → Player2	**0.583*****	0.000	0.365	0.770
Player1 → Socialiser2	-0.055	0.571	-0.231	0.151
Socialiser1 → Achiever2	0.176	0.197	-0.118	0.407
Socialiser1 → Disruptor2	-0.061	0.557	-0.245	0.179
Socialiser1 → Free Spirit2	0.154	0.189	-0.080	0.385
Socialiser1 → Philanthropist2	0.178	0.111	-0.045	0.395
Socialiser1 → Player2	0.130	0.166	-0.052	0.315
Socialiser1 → Socialiser2	**0.433*****	0.000	0.195	0.610

Key: Bold values are significant associations; * p<0.05, *** p<0.01; β: Regression Coefficient; CI: Confidence Interval; 1: first research phase; 2: second research phase.

(β = -0.597***), Free Spirit1 with ΔFree Spirit (β = -0.597***), Philanthropist1 with ΔPhilanthropist (β = -0.514***), Player1 with ΔPlayer (β = -0.374***), Socialiser1 with ΔSocialiser (β = -0.505***), and Disruptor1 with ΔDisruptor (β = -0.506***)), we only found significant associations between

Table 9. PLS-PM path coefficients - second analysis

			CI	
	β	*p*-value	2.5%	97.5%
Achiever1 → ΔAchiever	**-0.597*****	0.000	-0.826	-0.361
Achiever1 → ΔDisruptor	-0.031	0.813	-0.277	0.244
Achiever1 → ΔFree Spirit	0.018	0.883	-0.198	0.292
Achiever1 → ΔPhilanthropist	**-0.250***	0.017	-0.459	-0.050
Achiever1 → ΔPlayer	**-0.234***	0.034	-0.456	-0.014
Achiever1 → ΔSocialiser	-0.244	0.084	-0.530	0.018
Disruptor1 → ΔAchiever	-0.022	0.808	-0.208	0.158
Disruptor1 →ΔDisruptor	**-0.506*****	0.000	-0.655	-0.326
Disruptor1 → ΔFree Spirit	0.095	0.346	-0.116	0.277
Disruptor1 →ΔPhilanthropist	-0.000	0.996	-0.161	0.177
Disruptor1 →ΔPlayer	0.054	0.488	-0.112	0.198
Disruptor1 → ΔSocialiser	0.027	0.765	-0.151	0.204
Free Spirit1 →ΔAchiever	-0.007	0.956	-0.268	0.188
Free Spirit1 →ΔDisruptor	0.057	0.633	-0.184	0.284
Free Spirit1 →ΔFree Spirit	**-0.597*****	0.000	-0.801	-0.401
Free Spirit1 →ΔPhilanthropist	0.017	0.866	-0.200	0.183
Free Spirit1 → ΔPlayer	0.002	0.987	-0.192	0.189
Free Spirit1 →ΔSocialiser	0.058	0.615	-0.164	0.287
Philanthropist1 →ΔAchiever	-0.143	0.106	-0.311	0.037
Philanthropist1 →ΔDisruptor	-0.141	0.309	-0.425	0.113
Philanthropist1 →ΔFree Spirit	-0.153	0.087	-0.337	0.011
Philanthropist1 → ΔPhilanthropist	**-0.514*****	0.000	-0.702	-0.299
Philanthropist1 →ΔPlayer	**-0.207***	0.047	-0.417	-0.002
Philanthropist1 →ΔSocialiser	0.109	0.278	-0.089	0.309
Player1 → ΔAchiever	0.097	0.396	-0.117	0.331
Player1 → ΔDisruptor	0.077	0.481	-0.140	0.285
Player1 → ΔFree Spirit	0.069	0.540	-0.145	0.287
Player1 →ΔPhilanthropist	- 0.086	0.388	-0.265	0.122
Player1 →ΔPlayer	**-0.374*****	0.000	-0.560	-0.149
Player1 → ΔSocialiser	-0.086	0.332	-0.239	0.103
Socialiser1 → Δ Achiever	0.112	0.288	-0.093	0.321
Socialiser1 →ΔDisruptor	-0.072	0.487	-0.266	0.150
Socialiser1 →ΔFree Spirit	0.154	0.132	-0.039	0.359
Socialiser1 →ΔPhilanthropist	0.133	0.195	-0.068	0.332
Socialiser1 → ΔPlayer	0.123	0.187	-0.055	0.314
Socialiser1 → ΔSocialiser	**-0.505*****	0.000	-0.665	-0.329

Key: Bold values are significant associations; * p<0.05, *** p<0.01; β: Regression Coefficient; CI: Confidence Interval; 1: first research phase; Δ: the difference in the average score between the phases (T2-T1).

Achiever1 and ΔPhilanthropist (β = -0.250*), Achiever1 and ΔPlayer (β = -0.234*), and between Philanthropist1 and ΔPlayer (β = -0.207*). All significant associations were negative. Therefore, our results indicated that higher Achiever scores are associated with lower Philanthropist and Player scores after six months, while higher Philanthropist scores are associated with lower Player scores after six months.

5 DISCUSSION

In this study, we focused on conducting further analysis on how people can change their answers in the Hexad user orientations scale over time and therefore affect which is considered their Hexad user profiles (*i.e.*, Achiever, Disruptor, Free Spirit, Philanthropist, Player, and Socialiser). We focused on this analysis to discover whether it would be possible to find patterns in these changes and therefore on how to model user orientations based on them. By conducting different statistical analyses, we analyzed how the answers to the Hexad scale of 118 participants changed after six months, and which main results indicated that most of the participants presented changes in their strongest tendency over time. Furthermore, the scores in the six Hexad user orientations were different after six months and analysis of associations between the phases' scores indicated that the lowest association between the phases was presented in the Achiever user orientation sub-scale.

5.1 Distribution and correlations between the user orientations

The distribution of the Hexad user orientations scores (presented in Table 5) indicated that our sample distribution followed other recent studies that used the Hexad model [5, 42, 71, 73, 80] when indicating that respondents present high scores in the Achiever and Philanthropist sub-scales and lower scores in the Disruptor sub-scale. Therefore, our results corroborate prior research indicating that Achievers and Philanthropists are the most common strongest tendency of users and Disruptors the least common. Overall, the Hexad user orientations that are intrinsically motivated presented a higher score in our results, which was also similarly found in prior research [21, 42, 56, 73]. When comparing the Δ values from both phases of the study (see Table 5), there was a little difference in the scores, which was a first indication of changes in the answers of the scale. Even though the differences in the scores can be considered small, we understand that when the scores of all Hexad's items are considered and compared, the participants' changes may produce an offsetting change in the scores. As a result, some participants may have increased a certain item while others dropped it, resulting in an offsetting change in the final user orientation score.

The analysis considering only the strongest tendency (*i.e.*, the highest scores of the participants) indicated that 72% of the participants showed a change in their strongest tendency between the phases. Therefore, after six months 72% of the participants changed their answers in the Hexad scale, decreasing their score in items they had a high score in the first phase, and increasing in items that had a lower score before. As presented in Table 4, some of the user orientations combinations have presented significant changes between the phases of the study (*e.g.*, the combination of Achiever/Philanthropist dropping of 14% to 6% in the second phase). It is also notable that in both study phases, some combinations of user orientations have completely changed (*e.g.*, Player/Socialiser did not appear in the first phase of the study while 3% of the sample presented this combination as their strongest tendency in the second phase of the study). However, even when we consider the changes in the user orientations of the participants, Philanthropists and Achievers were the most common strongest tendency users presented. This might indicate that even though the user changes the answers in the scale and consequently change the user profiles over time, the majority will still keep scoring higher in the Philanthropist and Achievers sub-scales. This result is in accordance with prior research [1, 73] that has indicated that over time people would present a tendency to score higher in user orientations that are derived from intrinsic motivation.

When analyzing the correlations presented between both phases using Kendall's τ test (see Table 5), even though all of them were significant, they were weak and moderate correlations. The highest correlation was presented between the scores from the Players sub-scale ($\tau = 0.442^{**}$), a result that is similar to prior research about the stability of the Hexad user orientations[79]. These results might be an indication that some user orientations are more stable over time than others, findings that are consistent with prior research [12, 79], however, the scores from some sub-scales still present moderate similarities over time [79]. Therefore, our results indicate that users present changes in their strongest tendency over time and consequently their user orientations from the Hexad model can not be considered stable.

5.2 Exploratory findings about the changes based on the demographic characteristics

Based on the initial indications of changes participants presented in their highest scores of Hexad user orientations, we conducted an exploratory analysis of how much percent the highest scores of the participants changed considering their demographic data and gaming habits. While prior research has focused on analyzing the changes based on gender [79], we analyzed how much percent of the users have changed based on their age groups, educational levels, and gaming habits. However, the results of changing considering these demographic aspects demonstrated that it can be difficult to find patterns of change when considering these characteristics. While 67% of the youngest part of the sample (13-14 years old) presented changes after six months in their strongest tendency, half of the age groups measured in this study presented a change of more than 70%. Only participants from one age group (50 to 54 years old) presented 100% of change in their strongest tendency, while none of the participants from the oldest group (older than 60 years old) presented changes. Therefore, it was not possible to identify patterns of chance (*e.g.*, patterns of change decreasing sequentially with the oldest sample), which might be an indication that changes can happen during all life stages. Considering the age and the Hexad user orientations, prior research has indicated that there is a tendency for user orientations derived from intrinsic motivations (*i.e.*, Achiever, Philanthropist, Free Spirit, and Socialiser) to increase with age [1, 73]. Aligned with our results, this might indicate that, differently from personality traits, gamification user orientations might not reach a stability level after some age.

When we consider the educational level of the participants, people that self-reported being or having finished Elementary/Middle/High School changed less (68%) than others. Overall, the percentage of changes was very similar, especially considering the groups that self-reported to have a Bachelor, MBA, M.Sc., or Ph.D. degree. Even though education is currently the most researched context in gamification [6, 34], prior research has majority focused on one educational level instead of analyzing different groups in the same study. Regarding findings relating the Hexad user orientations with education, prior research [21] has indicated that some user orientations from the Hexad model are more frequently found when considering the faculties affiliations of the students. Therefore, even though our results indicate that the educational level of the respondents might not influence the changes in their user orientations, prior research has indicated that the distribution of Hexad user orientations might have a relationship with this user aspect.

Regarding gaming habits, people who self-reported not playing games changed more their strongest tendency than people who self-reported playing games as a habit. Prior studies [59, 68] indicated that some user orientations from Hexad could present different gaming preferences from others, as for example Philanthropists, Free Spirits, and Achievers might have an association with solo gaming [59]. When we consider the frequency of playing, our results indicate no pattern of change, which can be related to the fact that prior research has indicated that the Hexad user orientations might not be associated with the amount of time that users spend playing daily [78]. Therefore, even though the relationship between user orientations and gaming habits might explain why people who have gaming as a habit have more stable scores over time, the frequency of playing might not be sufficient to be used as the only aspect to model the user orientation changes.

5.3 Is the strongest tendency enough to determine the changes?

Prior research [27] has indicated that only considering the strongest tendency from the Hexad model would not be sufficient to differentiate users' preferences over game elements in gamified systems. However, this still is the main way researchers and designers define the user profile of users when considering the Hexad model. When we analyze the results from the differences in the scores from both phases of the study (see Table 5), it was not possible to find $\Delta > 1$. Therefore, any of the user orientations presented a change that had surpassed 1 point in the score between the phases even though all the scores from the first phase were under the maximum the scale can be (*i.e.*, 28). The exploratory results of how much the strongest tendency of each demographic group collected in this study changed after six months, also did not indicate patterns of change. In both cases, we understand that even though an offsetting change in the scores might happen, our results go towards the same conclusion of prior research [27], by indicating that only the strongest tendency might not be sufficient to differentiate users' changes in their profile over time.

Moreover, when we consider previous studies about the psychometric properties of the Hexad scale [56, 65, 73], the factor loadings (*i.e.*, the correlation between an item and the specific factor this item measures) present some overlaps, which suggests that some items of the Hexad scale would probably fit better in another sub-scale [73]. If for example, a user presents the highest score in one item that would better fit in another user type, we could not guarantee that the strongest tendency of this user is being measured properly. Therefore, some items from the Hexad scale might not properly evaluate the user orientations, limiting the identification of the user profile. In addition, there are several studies that indicated different levels of correlation between the Hexad user orientations (*e.g.*, [37, 41, 65, 73]). Thus, when we use the Hexad model to assess the user profile in gamified systems, we might be not measuring what would be the real behavior of the user in a gamified system, or only measuring partially. Researchers and designers ignore these results when developing personalization strategies that only use the strongest tendency of the user to personalize gamification. As a consequence, this choice can lead to a design that only partially fits the user's preferences. Therefore, when designing a gamified solution, we understand that designers and researchers should consider the user profile as the combination of all the Hexad user orientations scores, sequentially going to the strongest tendency until the less dominant ones, instead of only defining personalized game elements to the highest tendency of the user.

5.4 Associations between the user orientations' scores after six months

To conduct a deeper analysis, considering that the users are motivated by all the Hexad tendencies [3, 73], and the strongest tendency might not be sufficient to differentiate users' preferences [27], we conducted a statistical analysis between the scores of each sub-scale in both research phases using PLS-PM. The lower association was presented between the scores of the Achievers ($\beta = 0.087$), thus we can conclude that the scores of the Achiever sub-scale were the ones that presented more differences when comparing both phases of the study. Since this user orientation is considered one of the prevalent [5, 73, 75], (*i.e.*, people usually present a high average score in its sub-scale), this result might indicate why static personalization could present mixed or negative results over time, and highlight the necessity of constant analysis of the users' profiles.

Excepting the Free Spirit user orientation ($\beta = 0.310$), all the other user types presented significant associations between the scores of both phases. Philanthropists ($\beta = 0.327^{*}$) and Socialisers ($\beta = 0.433^{***}$) presented associations bellow 0.5 while Players ($\beta = 0.583^{***}$) and Disruptors ($\beta = 0.545^{***}$) presented associations higher than 0.5. Therefore, even though there were changes in the scores of the Hexad user orientations over time, four of the six user orientations presented significant associations between the scores of the study's phases. Moreover, these results indicated that scores from user orientations derived from extrinsic motivations (*i.e.*, Player and Disruptor) present a stronger association after six months than the scores from user orientations derived from intrinsic motivations (*i.e.*, Achiever, Philanthropist, Free Spirit and Socialiser). Therefore, our results indicate that people who have high scores in the user orientations with extrinsic motivation might present more stable user orientations over time.

Considering all the associations, our results indicate that Philanthropists in the first phase of the research presented a significant negative association with the Player (β = -0.295*) and Achiever (β = -0.299*) user orientations' second scores. Philanthropists presented negative associations with four of the five other user orientations' scores in the second phase and also presented the second highest correlation between phases considering Kendall's τ test (0.418*). Besides being the strongest tendency with the highest percentage in our sample in the first and second phase of the study, Philanthropist was present in other 13 combinations of strongest tendencies (*i.e.*, they were the highest score of the participants however, the participants had the same score repeated in other user orientations) in the first phase and second phase of the study. Besides corroborating prior research that has indicated them as a prevalent user orientation overall [21, 42], the association results from PLS analyses might indicate that Philanthropists are the most stable user orientation when considering only the user orientations derived from intrinsic motivation.

The Achiever user orientation in the first phase of the research presented negative and significant associations with the scores from Philanthropist (β = -0.296*) and Socialiser (β = -0.336*) in the second phase of the research. They also presented a negative association with Disruptor (β =-0.049) and Player (β =-0.215) scores from the second phase. Overall, this user orientation presented the highest changes in the scores' means between the phases (Δ = 0.95) and the second lowest correlation between phases considering Kendall's τ test (0.301*). Thus, even though being considered one of the prevalent user orientations in the Hexad Model [5, 73, 75], we understand that this user orientation can be considered less stable over time. Considering the association between Achievers' first score and Free Spirits' second score (β = 0.051) and Free Spirits' first score and Achievers' second score (β = 0.248), we believe that people who score higher in the Achiever sub-scale, over time tend to decrease their score in this sub-scale and increase in the Free Spirit items.

Based on prior research [3, 5] that has indicated the prediction of the user orientations could be a possibility, we included one more analysis where we tried to predict how initially reported user orientations would predict the changes. All the user orientations presented significant negative associations with their own Δ, which is an indication that users will change their scores over time, by scoring lower on their own orientations. When considering the user orientations and the other Δ values, our results indicated a significant negative association between Achiever1 and ΔPhilanthropist (β = -0.250*), Achiever1 and ΔPlayer (β = -0.234*), and between Philanthropist1 and ΔPlayer (β = -0.207*). These results indicate that when higher the score users present in the Achiever sub-scale, more chances of these users presenting a lower score in the Philanthropist and Player orientations over time. In the same way, Philanthropists seem to score lower on the Player orientation over time.

When we consider the non-significant associations, Achiever1 presented an association with ΔFree Spirits (β = 0.018), which corroborates the results presented in Table 8. Therefore, there is an indication that users with a higher score in the Achiever orientation will score higher in the Free Spirit orientation after six months. Philanthropist1 presented an association with ΔSocialiser (β = 0.109) at the same time that Socialiser1 presented an association with ΔPhilanthropist (β = 0.133). Considering the origin of these two user orientations, users that present a high tendency towards one of them might freely change their tendencies between them. This might occur depending on the context, the task, or even the gamification design. Considering that prior research [73] has indicated a correlation between these two user orientations, this result also might be an indication that these user types are more related than predicted by theory. Overall, all the non-significant positive associations were lower than 0.2, results that indicate that the prediction of the changes in user orientations might be a challenge in the future.

5.5 Suggestions on how to model user orientations

As outlined, after six months most people present a different user orientation from previous evaluations. Since the use of the Hexad scale to evaluate the user profile is currently the most common way researchers and designers define user profiles [3, 34], the user orientations from the Hexad model can not be considered stable. In our study, the majority of the participants presented different strongest tendencies after six months and the average scores of the user orientations also differed in both phases, indicating that people probably continue to score higher in some items, and therefore, some user orientations might present more stable scores than others. Our findings demonstrated that when modeling user profiles based on Hexad user orientations, it is critical to evaluate the user orientations after a certain period of time to track how the users change their preferences over time. In this way, the personalization of gamified environments adapts to the user's changing, ensuring that the personalization continues to support the user preferences.

In our study, we found a small difference in the mean scores from the user orientations when comparing both phases, as well as weak/moderate correlations, and only a few associations between the scores from the user orientations. Therefore, our results indicate that it might be difficult to find patterns of change and as a consequence, define a proper guideline on how to model user profiles when considering the changes people can present over time. However, our results indicate some insights about the changes. When considering user orientations and age, our results indicate that changes might happen during all life stages. As prior research has indicated that people might have the tendency to increase their scores in user orientations derived from intrinsic motivations while getting older [1, 73], researchers and designers that implement gamified solutions considering these aspects, should reevaluate the user orientations scores of the users before completing six months of the first evaluation. When considering our results and prior research that has shown that gaming habits might have a relationship with some user profiles [59, 68], it would be important to assess with frequency the user orientations' scores from people that do not have gaming habits. Our results indicated that only considering the educational level of the users might not be the best strategy to create personalized gamified environments, since the educational level of the respondents seems to not indicate patterns of change in their user orientations' scores after six months.

Considering the results of the associations of the scores from the Hexad user orientations, we can also suggest some possibilities to develop or adapt gamified environments. Considering people that have presented a high score in the Socialiser user orientation in the first evaluation, researchers and designers should consider initially implementing game elements that are considered most suitable for this user orientation and over time also starting to implement game elements that are suitable for Achievers, Philanthropists, and Free Spirits. For people that have presented a high score in the Free Spirit user orientation, researchers and designers should consider initially implementing game elements that are considered most suitable for this user orientation and over time start to implement game elements that are also indicated for Achievers. Moreover, our results demonstrated that people with a high score in user orientations that are derived from intrinsic motivation (*i.e.* Achiever, Socialiser, Free Spirit, and Philanthropist) might be less stable over. Therefore, designers and researchers should measure the user orientations of people who present high scores in the Socialiser, Achiever, Philanthropist, and Free Spirit sub-scales before completing six months of the first evaluation. In Table 10 we summarize these suggestions of how to model user orientations considering the results found in this study.

Table 10. Suggestions on how to model user orientations

User aspect	Study's result	Suggestion
Age	% of change (see Table 6)	Changes in the user orientation might happen during all life stages, therefore, the user orientation should be assessed before completing six months of the first evaluation and then being measured with regularity.
Gaming Habits	% of change (see Table 6)	People who do not have gaming habits seem to present less stable user orientations over time. Their user orientation should be assessed before completing six months of the first measurement.
Philanthropist	Associations (see Table 8)	People seem to present higher scores in the Philanthropist user orientation after six months, however, they can also increase a little their Socialiser tendencies over time.
Achiever	Associations (see Table 8)	People who present a higher score on this user orientation, seem to increase their score in the Free Spirit sub-scale after six months.
Player	Associations (see Table 8)	People seem to maintain a high score in the Player user orientation but can also increase a little in the Achiever tendencies. People who present a high score on this user orientation are probably the ones who present the most stable scores over time.
Free Spirit	Associations (see Table 8)	People tend to maintain a high score in the Free Spirit user orientation but also can increase in the Achiever tendencies over time.
Socialiser	Associations (see Table 8)	People tend to maintain a high score in the Socialiser user orientation however, can increase the Philanthropist, Achiever, and Free Spirit tendencies over time.
Disruptor	Associations (see Table 8)	People tend to maintain a high score in the Disruptor user orientation. People who present a high score on this user type will probably present more stable scores over time.

5.6 Limitations

During its conduction, this study has presented some limitations concerning different aspects. Our study was able to collect a limited number of responses from participants of only one country (*i.e.,* Brazil), which might prevent the generalization of the results. Therefore, the results here presented might not be the same considering other samples. Regarding the user profile, we used the Gamification Hexad user type to define the profile of the respondents and included exploratory analyses about the changes based on some other user aspects (*i.e.*, gender, age, educational level, and gaming habits). This definition of user profile and aspects that could influence the changes might be considered not enough to define user profiles, since prior research [34] has indicated that personalized gamification should analyze the users from beyond the view of strongest tendency or the binary biological sex. Also regarding the survey, differently from other studies [59, 68], we have decided to collect only basic information about the gaming habits of the respondents. Considering this, the information about gaming habits collected in the study might not be enough to characterize this user characteristic, which prevented us to provide more solid recommendations about how gaming habits can influence user profile changes.

Overall, the use of surveys to collect responses has been indicated as a research limitation in the field [33, 34, 64]. The use of surveys (or questionnaires), can lead to the collection of inaccurate data, directly influencing the study's results. Therefore, the use of surveys might not be the most suitable option to assess the respondents' user orientations. Regarding the data collected, when considering the age reported by the participants, the groups in our sample did not have the same size, *e.g.*, 12% of the participants were placed in the 40-44 years old group while only 1% of the participants were older than 60 years. This might have directly impacted the results by age, which indicated no patterns of change. This result might not remain the same when using homogeneous samples.

We also have sought to mitigate some of the foreseeable limitations of the study. Considering the aforementioned problems surveys can implicate in research, we used a validated scale to assess the user orientation of the participants and applied different statistical reliability tests to mitigate problems with the data. To improve the quality of the answers, all the respondents were volunteers and we used an "attention-check" item, eliminating the responses that did not pass this validation before the data analysis. Also, since a survey with 30 questions/items could be considered long by the respondents, we conducted a pilot study to evaluate whether the survey size could be considered adequate before its application.

6 AGENDA FOR FUTURE STUDIES

Based on the results and limitations of this study, it is possible to suggest a series of new studies that could further the understanding of user profiles in gamified environments. Although recent studies [3, 5, 33] demonstrated that the prediction of the user orientations might be a possibility, the user orientation is still mostly accessed through surveys and questionnaires [34]. However, the use of questionnaires has been indicated as a limitation of the field [33, 34, 64], considering that when answering a questionnaire, the respondent can deliberately give inaccurate information [34] or random responses [33, 64]. Our study results imply the necessity of constant analysis of the users' orientations, which would make the process of modeling user orientations more expansive and also could provide not reliable user orientations results. Considering our results and the problems with the use of questionnaires and surveys indicated in prior research, we understand that a good possibility would be the automation of the assessment of the user orientations. The community should move towards the automation of this process, focusing on predicting people's user orientations based on interaction data or based on prior user profile assessments.

The impacts of gamification can vary depending on the context [27], and considering that there are only a few studies available whose results indicated changes in the player/user orientations [8, 12, 66, 79], we have chosen to conduct this study investigating the changes without considering a specific domain. Literature reviews [34, 35] have previously emphasized the need for more research in the gamification field to better understand the impact that context has in gamified environments. Also, the study about user orientation stability conducted by Yildirim and Özdener [79] has found that in the educational domain, the user profiles are not stable over time. Based on this, future studies should replicate this study considering different contexts, to further the state of the art on how the context influences user orientation changes.

Prior research [1, 73] have indicated that age could directly affect the chances of a person having an intrinsically motivated user orientation (*i.e.*, Achiever, Philanthropist, Socialiser, and Free Spirit).

However, these studies did not make comparisons of the same group over time, instead, they compared the age of the participants [73] or different samples [1]. Our results demonstrated that it can be difficult to find patterns of change when considering age as the main user characteristic. At the same time, one limitation of our study is that the age groups were not equivalent (*i.e.*, some age groups had more participants than others). To better analyze how well age influences user orientation over time, as well as, to better create recommendations on how to model user orientations based on age, we suggest the conduction of studies where the number of participants in each age group is the same, therefore, increasing the possibility of finding patterns on how age influences the user orientations changes.

Similar to Busch *et al.* [12], we waited six months before analyzing if there were changes in the user orientations of the respondents, while Yildirim and Özdener [79] have waited for 16 months before measuring the changes in the user orientations. An important advancement in this orientation of research would be measuring whether users can show changes in their user profile sooner (*e.g.*, after two or three months), as well as if they can revert to the first user orientation after a longer length of time (*e.g.*, after two years). We propose that future research should incorporate more phases when replicating this study (*e.g.*, two months, a year, two years), with the stability of the user orientations being evaluated over a shorter and longer period of time. We understand that studies with more phases could improve the chances of determining how user orientations change over time, as well as provide a larger sample size and consequently, a higher power of generalization of the results.

When defining the user profile, we used the Gamification Hexad user type as the main user aspect that should be considered as their profile and only included age, educational level, and gaming habits as other factors that could impact the changes. This decision was made considering that these users' characteristics are currently the most researched users' aspects of gamification. However, besides the influence contexts or tasks can present when defining user profiles, prior research [34] has indicated a need for gamification research of a broader sample of user characteristics that goes beyond the strongest tendency or the binary biological sex. We suggest that future studies about the stability of user orientation consider the user profile as a group of different user aspects, rather than using only the strongest tendencies, analyzing how other less dominant tendencies can influence the user profile changes.

Gamification is a recent field and consequently, some research topics in the area are still little explored. Considering this, in this paper we focused on analyzing the changes in the user orientations based on the associations between the scores from different data collection, and on creating suggestions on how to model user orientations to support user changes over time. Therefore, while prior research [66, 79] has focused on *whether* the user orientation change, we focused on *how* these changes happen. Future studies should move towards this orientation of knowledge by focusing on *why* the user orientations change. This would benefit researchers and practitioners by indicating possible reasons and ways to avoid or delay the changes.

In Table 11 we summarize the research agenda.

7 CONCLUSION

In this study, divided into two different phases, we conducted a comparison of how 118 people presented changes in their Hexad user orientations' scores, and consequently on their user orientations, after six months. The goal of this comparison was to identify how the user orientations from the Gamification User Types Hexad (Achiever, Philanthropist, Socialiser, Free Spirit, Player, and Disruptor) present changes over time, as well as whether it could be possible to model user profiles based on these changes. Our initial results showed that the strongest tendency of most of the participants presented changes after six months, and furthermore, the average scores of the

Table 11. Research agenda summary

Recommendation	Motivation
Automation of the user orientations assessment	Facilitate the user profile assessments and increase the reliability of the results
Replication of the study considering different contexts	Analyze how contexts affect the stability of the user orientation
Further analysis of the impact of age	Determination of patterns of change based on age
Conduction of longitudinal studies	Evaluation of how the stability of the user orientations can be over a shorter and longer period of time
Further analysis of less dominant user aspects	Determination of the influence from other user aspects can have on user profile changes
Analysis of why the user orientations change	Indication of possible factors that influence the changes and ways to avoid or delay them.

user orientations in both phases were also different, indicating that neither the strongest tendency nor less strong tendencies can be considered stable. Moreover, our results indicate that, when defining the user profile, only the dominant characteristic might not be sufficient to guarantee a proper gamification design. By using a set of different statistical analyses, our results indicated that the Achiever might be the less stable user orientation score and Player the most stable user orientation score from the Hexad model. Based on our results, we indicate suggestions on how to model user orientations based on their changes. Moreover, our results indicated insights into how user orientations change based on their educational level, age group, and gaming habits. Our results implicate that when designing a gamified environment based on the Hexad user orientation, it is important to develop a design that can support the user orientation changes after a certain period of time. As future studies, we aim to focus on measuring how user orientations can present changes considering different periods of time (*i.e.*, a year), contexts, and demographic backgrounds (*i.e.*, people from more than one country).

NOTES

This article is an extension of the paper of Santos *et al.* [66].

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