



The Relationship Between Gamification User Types, Demographic Factors, and Gaming Habits

Ana Cláudia Guimarães Santos, Wilk Oliveira, Julita Vassileva, Juho Hamari & Seiji Isotani

To cite this article: Ana Cláudia Guimarães Santos, Wilk Oliveira, Julita Vassileva, Juho Hamari & Seiji Isotani (2025) The Relationship Between Gamification User Types, Demographic Factors, and Gaming Habits, International Journal of Human-Computer Interaction, 41:18, 11806-11820, DOI: [10.1080/10447318.2024.2446498](https://doi.org/10.1080/10447318.2024.2446498)

To link to this article: <https://doi.org/10.1080/10447318.2024.2446498>



© 2025 The Author(s). Published with license by Taylor & Francis Group, LLC



[View supplementary material](#)



Published online: 29 Jan 2025.



[Submit your article to this journal](#)



Article views: 1819



[View related articles](#)



[View Crossmark data](#)



Citing articles: 1 [View citing articles](#)

The Relationship Between Gamification User Types, Demographic Factors, and Gaming Habits

Ana Cláudia Guimarães Santos^a , Wilk Oliveira^a , Julita Vassileva^b , Juho Hamari^a , and Seiji Isotani^c 

^aGamification Group, Faculty of Information Technology and Communication Sciences, Tampere University, Tampere, Finland; ^bDepartment of Computer Science, University of Saskatchewan, Saskatoon, Canada; ^cHarvard Graduate School of Education, Cambridge, MA, USA

ABSTRACT

Understanding users and consequent personalization opportunities have become a major area of interest in gamification and UX research. Currently, personalization is mainly based on player typologies, which might give a partial picture of the plethora of user attributes. Addressing this challenge, in this study, we investigate the connections of the Hexad gamification user types, demographic factors, and gaming habits to understand how different user factors are related. Our results indicated significant but weak associations between user types and demographic factors and no significant association with gaming frequency-related factors. These results suggest that researchers and designers might need to consider more than the dominant factors to create personalized environments. We also provide exploratory suggestions on possible strategies to personalize gamification based on Hexad and other user factors. Our study contributes to the fields of user modeling and gamification, providing new insights into how different user characteristics are related while opening space for the conduction of new studies in the field.

KEYWORDS

Gamification; personalization; user orientations; user modeling; quantitative study

1. Introduction

For decades, video games have been a source of entertainment for various societal groups, becoming an important part of the everyday lives of millions of people (Eum et al., 2023; Koivisto & Hamari, 2019; Pessoa et al., 2024). With the advancements in technology and design, video games have evolved beyond being only a source of entertainment, also becoming a source for social engagement, education, and immersion (Gupta et al., 2021; Martinez et al., 2022; Oliveira & Hamari, 2024). One possible explanation for this is that video games can engage and have a positive impact on people's behavior (Eum et al., 2023; Högberg et al., 2019; Ndulue & Orji, 2024). To afford similar positive impacts, gamification (i.e., the design of systems, services, and activities to provide motivational benefits similar to those games usually create (Hamari, 2019; Koivisto & Hamari, 2019)) has gained popularity recently due to its potential to increase motivation and affect users' behavior (Hamari, 2019; Klock et al., 2020; Koivisto & Malik, 2021). Albeit its wide use in different fields (e.g., health (Johnson et al., 2016; Ning et al., 2022), education (Araya et al., 2019; Hallifax et al., 2020), and sustainable consumption (Guillen et al., 2021; Sun et al., 2022)), some studies have reported negative results on its use (Almeida et al., 2023; Bai et al., 2020; Koivisto & Hamari, 2019). One possible reason for these negative results is that users have different motivations and preferences over game elements and gamification designs, and

therefore, gamification outcomes vary among the users (Pessoa et al., 2024; Santos et al., 2021). Considering this, different studies started to point out that it is necessary to personalize gamified settings to create a more suitable environment for the users according to their preferences and needs (Hallifax et al., 2019; Issabek et al., 2023; Oliveira et al., 2020; Santos et al., 2021).

Overall, researchers and practitioners have created and proposed different personalization strategies based on users' characteristics (e.g., player/user typologies (Hallifax et al., 2019; Santos et al., 2021), gender (Denden et al., 2021; Issabek et al., 2023), and personality traits (Denden et al., 2021; Ferro, 2018)) to define how personalization should be designed to increase the users' motivation while using a gamified environment (Hallifax et al., 2019; Klock et al., 2020; Oliveira et al., 2023). Currently, player and user typologies are the most investigated user characteristic in the gamification field (Kirchner-Krath et al., 2024; Klock et al., 2020; Oliveira et al., 2023), and their use can influence the success of a personalization strategy (Hallifax et al., 2019). The player and user typologies (e.g., Bartle (Bartle, 1996), BrainHex (Nacke et al., 2011), and Hexad (Marczewski, 2015)) have been created to find similarities between the users, grouping them based on different aspects (e.g., behavior in games and types of motivations) (Hamari & Tuunanen, 2014; Kirchner-Krath et al., 2024; Tondello et al., 2019).

CONTACT Ana Cláudia Guimarães Santos  ana.guimaraessantos@tuni.fi  Gamification Group, Faculty of Information Technology and Communication Sciences, Tampere University, Tampere, Finland

 Supplemental data for this article can be accessed online at <https://doi.org/10.1080/10447318.2024.2446498>.

© 2025 The Author(s). Published with license by Taylor & Francis Group, LLC

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. The terms on which this article has been published allow the posting of the Accepted Manuscript in a repository by the author(s) or with their consent.

Despite the large number of studies investigating how personalization could improve gamification's results, most of them focus on understanding the relationship between the player/user type and a few users' characteristics (e.g., gender and age (Tondello et al., 2019)). At the same time, when analyzing the relationship between gaming habits and the player/user type, most studies focused only on this relationship, ignoring demographic factors (e.g., Hadi Mogavi et al., 2023). Therefore, previous literature when defining the user profile, has focused on personalization strategies based on only one or a few characteristics at the same time (Klock et al., 2020; Oliveira et al., 2023; Rodrigues et al., 2020), neglecting the fact that user profiles are shaped by multiple dimensions. This oversight limits the creation of gamified solutions capable of personalizing experiences across a broader range of factors. Considering that personalization based just on a few characteristics may only partially fit the user preferences and fail to increase their motivation (Klock et al., 2020), a further investigation of the relationship between demographic factors and gamification user orientation could lead designers and researchers to create a more effective gamification design (Klock et al., 2020).

To start to tackle this challenge, in this study, we focused on answering the following research question: "How are the user orientations from the Hexad model (i.e., Philanthropist, Achiever, Socialiser, Free Spirit, Player, and Disruptor) related to their demographic factors and gaming habits?" As specific objectives, we aimed to discover whether the association between Hexad user types and demographic variables existed, whether they were statically significant, and whether they were positive or negative. To achieve this goal, we collected data from 340 participants, where we (i) collected a set of demographic information about them (i.e., age group, gender, and educational level), (ii) collected their gaming habits (i.e., if they play and the frequency), (iii) identified their user orientations (i.e., Philanthropist, Achiever, Socialiser, Free Spirit, Player, and Disruptor), and then, (vi) analyzed the relationship between their demographic and gaming habits characteristics and their user orientations. The statistical analysis (i.e., analysis of association using Partial Least Squares Structural Equation Modeling (PLS-SEM)) showed that all the user orientations presented weak associations with the demographic aspects collected, however, no significant association with gaming habits was indicated.

These results demonstrated that even though different users' characteristics could be considered when modeling the user profile in gamified settings and consequently in defining personalization strategies, there is a necessity for different types of modeling the user profile. Moreover, the results of this study suggest that a broader set of user characteristics (e.g., race, culture, or less dominant aspects) might be necessary to effectively model user profiles in gamified settings. The results of our study can be useful for researchers and gamification designers when modeling gamified systems, suggesting possible paths to personalize gamified settings (i.e., based on the user type and their demographic factors), as well as possibilities for future studies in the field.

2. Background and related work

Even though gamification can be considered a recent field and most of the research and practical application had happened in the last fifteen years (Bai et al., 2020; Hallifax et al., 2023; Klock et al., 2020), forms of gamification were applied in the early 20th century in the Soviet Union and at the end of 20th century in the United States (Nelson, 2012). One of the most recent definitions of gamification is that gamification refers to the act of "transforming systems, services, organizations, and activities to provide similar experiences as those games usually provide" (Hamari, 2019; Huotari & Hamari, 2017; Koivisto & Hamari, 2019). Furthermore, results on gamification research have revealed several positive outcomes, for example, that students get better average performances in gamified environments when compared with those who did not use gamification (Bai et al., 2020; da Rocha Seixas et al., 2016) or that motivation can be improved and demotivation can be decreased by the use of a proper set of game elements (Hallifax et al., 2019, 2020).

Gamification has been successfully applied to increase user engagement, however, it has presented mixed user outcomes, a high context dependence, and varied among individuals (Altmeyer et al., 2021; Koivisto & Hamari, 2019; Toda et al., 2018). Recent results identified that, while gamification can foster enthusiasm and fulfill the need for recognition, it also can cause competition, anxiety, and jealousy (Bai et al., 2020; Koivisto & Hamari, 2019). Even though the buzz around gamification has produced a large number of studies, more recently researchers started to indicate the need for studies to explore the relationship between gamification and user's characteristics (Altmeyer et al., 2021; Bai et al., 2020; Klock et al., 2020), therefore, identifying that the field yet has theoretical and empirical gaps (Koivisto & Hamari, 2019).

In recent years, as a way to diminish the negative and mixed outcomes in gamification results, researchers and practitioners have worked towards the personalization of gamification. Personalization of gamification seeks to create a more suitable environment for the users by creating distinct gamified strategies to fulfill users' different characteristics and preferences (Klock et al., 2020; Pessoa et al., 2024; Tondello & Nacke, 2020). The design of these personalized gamified systems takes into account different aspects e.g., game elements (Denny et al., 2018), player/user types (Oliveira & Bittencourt, 2019), the context of the solution (Hallifax et al., 2019; Lopes et al., 2019), among other factors that can influence the experience of the user when using the system. Researchers have especially focused on the relationship between user types and game elements, whose main results demonstrated that personalization could be done using a considerable number of game elements based on the preferences of the user profile (Hallifax et al., 2023; Santos et al., 2021; Tondello et al., 2016). Moreover, prior literature has indicated that the use of a suitable set of game elements could often increase the success of a gamified setting, leading the users to higher levels of motivation while an inappropriate set of game elements could demotivate users (Hallifax et al., 2019).

To simplify user's complexity, different player and user typologies were developed grouping users according to their characteristics, motivations, and behavior (González-González et al., 2022; Hamari & Tuunanen, 2014; Sidekierskienė et al., 2020). These typologies, which are now the most investigated user characteristic in gamification (Hallifax et al., 2019; Rodrigues et al., 2020), started with the model proposed by Bartle (1996) with four player types. Later, Yee (2006) proposed a player motivation model, with three main components of player motivation and 10 sub-components. More recently, based on neurobiological findings, prior player typologies, patterns of play, and game emotions, Nacke et al. (2011) proposed the BrainHex Model, with seven different player types. Therefore, the game typologies were evolving over time, however, despite these typologies being created for game design, they have been largely applied in gamification (Busch et al., 2016; Volkmar et al., 2019).

Differently from the aforementioned typologies, the Gamification User Types Hexad (Marczewski, 2015) was created specifically for gamification design. This user typology was created based on the self-determination theory (SDT) (Deci & Ryan, 1985), a theory that indicates that people can be intrinsically or extrinsically motivated (Deci & Ryan, 1985). On the Hexad, the user types that are driven by intrinsic motivations are Achievers, motivated by competence; Free Spirits motivated by autonomy; Philanthropists motivated by purpose; and Socialisers motivated by relatedness, while Players, motivated by extrinsic rewards, is a type driven by extrinsic motivation. The user type Disruptor (motivated by change) is the only user type that is not derived from SDT but the observation of user behavior within online systems (Tondello et al., 2019).

The Hexad typology has been widely used in prior gamification research resulting in insights about the relationship between user types and other user characteristics. Regarding age, studies have compared different samples (Altmeyer & Lessel, 2017) or different age groups from the same sample (Mora et al., 2019; Poecze et al., 2019; Tondello et al., 2019), finding differences in the perception of game elements and user type distribution based on the age of the participants (Altmeyer & Lessel, 2017; Tondello et al., 2019). Findings about age also indicated that older users might get higher scores in the user types from intrinsic motivations (Mora et al., 2019; Tondello et al., 2019). However, studies also found results that were not statistically significant regarding the relationship between age and user types (Mora et al., 2019; Poecze et al., 2019).

Different studies have sought to establish connections between participant gender and the prevalence of user types (Alsofyani, 2023; Mora et al., 2019; Tondello et al., 2019). Nevertheless, prior research has also revealed a non-significant relationship between the Hexad user types and the gender of participants (Poecze et al., 2019). Furthermore, most of the results presented several conflicting results. For example, Şenocak et al. (2021) identified that women presented higher scores in the Disruptor sub-scale, whereas Tondello et al.

(2019) reported different results indicating that men tend to score higher in the Disruptor user type. While studies suggested a higher incidence of the Achiever user type among men (Fischer et al., 2018) or a lesser prevalence among women (Alsofyani, 2023), Mora et al. (2019) found that the Achiever user type was more commonly found among women. Considering these mixed and contradictory results, researchers and practitioners are confronted with the challenge of selecting an appropriate approach, considering the lack of consensus about how gender is related to the Hexad user type.

Although collecting gaming habits is a common strategy in gamification studies, little is known about how the user types are related to this characteristic. To older participants, games are seen as a catalyzer for social relationships, and winning the game is not as important as for the younger players (Altmeyer & Lessel, 2017). Regarding gaming-related activities, Socialisers, Players, and Disruptors might present a relationship with the frequency of reading gaming-related news (Poecze et al., 2019), and Philanthropists, Free Spirits, and Achievers with solo gaming (Poecze et al., 2019; Yildirim et al., 2021). However, other studies, e.g., Şenocak et al. (2021), indicated that multiplayer mode was preferred by Achievers, Philanthropists, Socialisers, and Players. Therefore, results regarding gaming habits and their relationship with user types are scarce and present contradictory results.

Less is known about the relationship between user types and educational levels. To the best of our knowledge, no study has analyzed the user types of people from different educational levels, and only Fischer et al. (2018) have investigated how students from different faculties affiliations were distributed over the Hexad user types. Their results indicated differences in user type distribution, where Players and Disruptors were most commonly found among students from Engineering; Philanthropists were more common among students from Mathematics/Natural Sciences and Teacher Training courses; Free Spirits were more common among students from Social Science; Socialisers were more common among students from Economics; and Achievers were more common among students from Mathematics and Natural Sciences.

In summary, prior research has demonstrated that Hexad user orientations can be related to gender, age, and gaming habits when personalizing gamification based on multiple aspects. Beyond the contradictory results, we were not able to find studies that conducted a further analysis of this relationship or analyzed several user characteristics at the same time. As far as we know, our study is the first one that analyzes the relationship between Hexad user orientations and a set of demographic information and gaming habits at the same time, thus, providing possible strategies for user modeling based on the relationship between the Hexad user types and a set of other user characteristics. In Table 1 we present a comparison between the related work and our study.

3. Study design

In this study, we analyzed the relationship between the Hexad user orientations, the demographic factors, and the gaming habits of the respondents. Therefore, we aimed to answer the following research question: “How are the user orientations from the Hexad model (i.e., Philanthropist, Achiever, Socialiser, Free Spirit, Player, and Disruptor) related to their demographic factors and gaming habits?”. As specific objectives, we aimed to discover whether the association between Hexad user types and demographic variables existed, whether they were statically significant, and whether they were positive or negative.

3.1. Materials and method

To identify the participants’ gamification user types, we used the Hexad framework (Marczewski, 2015). The Hexad scale is composed of 24 items, that are organized on a 7-point Likert scale (Likert, 1932). The respondents were asked to rate how much each of the items represented them and the items were randomly placed in the survey to avoid the identification of the items that composed the same sub-scale. We have chosen the Hexad for this study considering that this user typology was created specifically for gamification (Marczewski, 2015), it has been considered the most appropriate user typology for personalizing gamification (Hallifax et al., 2019) and has been successfully used in studies from different contexts (e.g., do Amaral Neto et al., 2023; Hallifax et al., 2020; Orji et al., 2018). Between the Hexad items, inspired in other recent studies (Hallifax et al., 2019; Oliveira et al., 2020; Ooge et al., 2020), we also inserted an “attention-check” item (i.e., “I like to be with my friends, but this question is just to evaluate your attention. Please, mark the option number 3, to let us know that you are paying attention”), to guarantee that the respondents were reading all the items while answering the survey. “Attention-check” items have as their main objective, the improvement of the quality of samples without influencing the respondents’ answers, therefore, without compromising the validity of the scale measurement (Kung et al., 2018).

3.1.1. Survey design

Initially, we designed an online survey with two different sections, the first to collect demographic information and

gaming habits, and the second to collect user orientations. In the *first section*, inspired by other recent studies in the field (Altmeyer et al., 2020; González-González et al., 2022; Hallifax et al., 2019; Krath & von Korfflesch, 2021), we collected the gender, age group, educational levels, and gaming habits and frequency of gaming. These user factors were selected for the study considering that, more than being the prevalent factors in the gamification literature, these user characteristics can be answered by any participant and are considered non-invasive questions.

In the *second section* of the survey, considering our focus on collecting data from Brazil and that most Brazilians do not have good English comprehension skills (Council, 2014), we used the Brazilian Portuguese version of the Hexad scale (Santos et al., 2022, 2023).

The study was organized in four different steps: (i) designed an online survey to identify the respondents’ user orientations (i.e., Hexad profile), demographic factors (i.e., gender, age, and educational level), and gaming habits (i.e., if play and the frequency), (ii) conducted a pilot study, (iii) applied the survey, and (iv) analyzed the data collected. Figure 1 summarizes the method.

3.1.2. Pilot study

As recommended by Connelly (2008), before the survey release we conducted a pilot study aiming to evaluate the size of the survey. To guarantee the participation of people with different demographic backgrounds (women and men, from different age groups, different educational levels, and different gaming habits), we invited ten participants through e-mail. The respondents from the pilot study also had to pass in the “attention-check” item. The feedback from the eight pilot participants was that the survey was not large. Considering this result, the survey was applied without changes.

3.2. Data gathering and participants description

After the pilot study, the survey was sent to e-mail lists and also publicized on social networks (i.e., Facebook, Twitter,

Table 1. Related works comparison.

Authors	Gender	Age	Education	Gaming Habits
Altmeyer & Lessel (2017)	No	Yes	No	Yes
Fischer et al. (2018)	Yes	No	Yes	No
Tondello et al. (2019)	Yes	Yes	No	No
Mora et al. (2019)	Yes	Yes	No	No
Poecze et al. (2019)	Yes	Yes	No	Yes
Yildirim et al. (2021)	No	No	No	Yes
Şenocak et al. (2021)	Yes	No	No	Yes
Alsofyani (2023)	Yes	No	No	No
Present study	Yes	Yes	Yes	Yes

Key: Gender: analyzed user orientations and gender; Age: analyzed user orientations and age; Education: analyzed user orientations and different educational levels; Gaming Habits: analyzed user orientations and gaming habits.

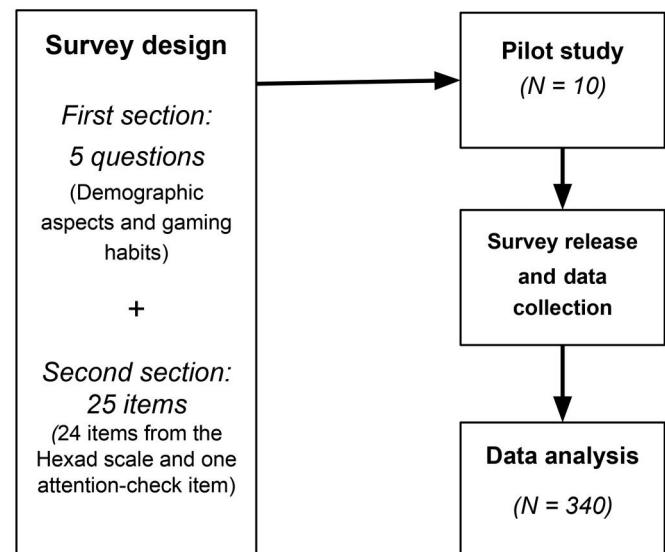


Figure 1. Method.

and Instagram), seeking the participation of academics and non-academics. A separate data collection was conducted by one of the authors, where the participants did not provide their gaming habits. The email lists were gathered from personal contacts of the authors involved in the study and from participants of previous research and conferences. The propagation through social networks was made in the researchers' accounts and on public groups/profiles about gamification, without any kind of advertising.

At the beginning of the survey, the participants were informed about the study objectives, the use of their data for scientific investigations, the contacts of the researchers, and also that they could leave the study at any moment without submitting their responses. Each respondent had to check the consent form after reading this information, indicating their agreement to participate. Participation in the study and the pilot study was voluntary (which could improve the quality of the answers (Tondello & Nacke, 2020)), thus, the participants did not receive any type of remuneration or prizes for answering the survey. We collected 375 answers, of which 340 passed in the “attention-check” item. All the demographic information about the participants can be seen in [Table 2](#).

3.3. Data analysis

To perform the statistical analysis in our study, we used SPSS 26 software (IBM Corp, 2020) and SmartPLS software (Ringle et al., 2022). Considering that the main data analysis would be conducted using structural equation modeling, to calculate the necessary sample to detect effects, we used the technique called *a-priori* sample size calculator for the SEM (Cohen, 1988). We performed the calculations using the Online Calculator for A-priori Sample Size Calculator for Structural Equation Models proposed by Soper (Soper, 2023), which computes the sample size required for a study based on SEM, given the number of observed and latent variables in the model, the anticipated effect size, and the desired probability and statistical power levels. The calculator is based on the formulas proposed by Cohen (1988) and Westland (2010).

As we do not have previous literature with similar analyses to use as a base for defining the expected effect size, we used standard values from the literature to define the values (i.e., anticipated effect size: 0.3; desired statistical power level: 0.5; and probability level: 0.05 (Cohen, 1988; Westland, 2010)). In our study, we had six latent variables and 29 observed variables (i.e., the six latent variables were the user orientations and the 29 observed variables were the 24 items from the Hexad scale and the 5 questions from the demographic factors and gaming habits). The result indicated a minimum of 161 participants to detect an effect (considering the previous definitions), therefore, our dataset reached the minimum of participants to detect an effect and can be considered valid for the proposed study. Our complete dataset can be found in the complementary files.

4. Results

Initially, we tested the normality of the data using the Shapiro-Wilk test as recommended by Wohlin et al. (2012), finding that our data followed a non-parametric distribution. Then we measured the means and standard deviation of each Hexad sub-scale (i.e., the four items that are used to assess each user orientation). Since each sub-scale of the Hexad has four items that are rated on a 7-point Likert scale, the minimum score a sub-scale can present is 4 and the maximum is 28. The results, reported in Table 3, indicated that Philanthropists and Achievers presented the higher overall mean (i.e., are the predominant user orientations on the sample), while Disruptors presented the lower overall mean (i.e., are the least predominant user orientation on the sample). This result is similar to other recent studies (Altmeyer et al., 2020; Krath & von Korflesch, 2021; Tondello et al., 2019) that used the Hexad scale to assess the user orientations of the respondents.

Then, we measured the internal reliability of each subscale using Cronbach's α , which is widely used in social sciences to estimate scale reliability (Peterson & Kim, 2013). We found acceptable values ($\alpha \geq 0.70$) for all user orientations, except for the Disruptor, which was slightly below the acceptable. Other studies (Krath & von Korflesch, 2021; Ooge et al., 2020; Poecze et al., 2019; Tondello et al., 2019)

Table 2. Demographic information and gaming habits of the respondents.

Variable		%	Variable		%
Gender	Women	51	Age	10 to 14	0.3
	Men	48		15 to 19	9
	Other/Preferred not to answer	1		20 to 24	14
Educational Level				25 to 29	14.4
	Elementary/Middle School	2		30 to 34	17.4
	High School	9		35 to 39	12.4
	Bachelor	32		40 to 44	11.5
	Specialized Courses/MBA Courses	21		45 to 49	9.7
	M.Sc.	25		50 to 54	6.5
	PhD	11		55 to 59	3.8
Gaming Habits				Over 60	1
	Play games	67	Frequency	Every day	13
				Every week	21
				Rarely	47
				I do not know	19
	Do not play games	33			

Table 3. Descriptive and reliability analyses.

User orientation	M	SD	MD	FM	FSD	MDW	MM	MSD	MDM	α	CR	AVE
Achiever	24.0	4.75	25	23.42	5.61	25.5	24.57	3.58	25	0.879	0.914	0.728
Disruptor	14.68	5.29	15	13.9	5.46	14	15.34	4.93	16	0.673	0.775	0.471
Free Spirit	22.55	4.59	23.5	22.25	5.30	24	22.79	3.69	23	0.754	0.838	0.568
Philanthropist	24.17	4.76	26	23.88	5.46	26	24.46	3.90	25	0.885	0.920	0.743
Player	20.55	5.57	21	19.73	5.96	21	21.41	4.98	22	0.806	0.861	0.612
Socialiser	20.46	5.69	22	20.46	6.02	22	20.62	5.02	22	0.880	0.913	0.726

Key: M: Mean Scores; SD: standard deviation; MD: median; FM: Women Mean Scores; FSD: Standard deviation from women; MDW: median from women; MM: Men mean scores; MSD: standard deviation from men; MDM: median from men; α : Cronbach's; CR: Composite Reliability; AVE: Average Variance Extracted. Values in grey are $\alpha \leq 0.70$ and $AVE \leq 0.50$.

Table 4. Discriminant validity (complete bootstrapping, sample = 5000).

	Achiever	Age	Disruptor	Education	Free Spirit	Gender	If they play	Philanthropist	Player	Socialiser	Frequency
Achiever	0.853										
Age	0.070	1.000									
Disruptor	0.439	0.079	0.686								
Education	0.162	0.625	0.250	1.000							
Free Spirit	0.713	0.003	0.510	0.145	0.754						
Gender	0.116	-0.054	0.195	0.055	0.100	1.000					
If they play	0.112	-0.056	0.095	0.006	0.081	0.254	1.000				
Philanthropist	0.773	0.191	0.358	0.245	0.658	0.060	0.069	0.862			
Player	0.476	-0.123	0.358	-0.059	0.410	0.163	0.187	0.335	0.782		
Socialiser	0.547	0.182	0.258	0.138	0.465	-0.034	-0.000	0.654	0.336	0.852	
Frequency	0.085	-0.117	0.067	0.028	0.114	0.225	0.622	0.026	0.175	-0.030	1.000

Key: Words in bold are related to the user orientations, while words in italic are related to the demographic and gaming habits.

also have found $\alpha \leq 0.70$ for this user orientation. The Average Variance Extracted (AVE), which measures the amount of variance explained by a construct and must be higher than 0.5 (Fornell & Larcker, 1981), also indicated problems with the Disruptor sub-scale. Due to the tendency of Cronbach's α to underestimate reliability (Raykov, 1997), we calculated the Composite Reliability (CR), which is an option to measure reliability through structural equation modeling and is equivalent to coefficient omega (Padilla & Divers, 2016), and values between 0.7 and 0.9 can be ranged from "satisfactory to good" (Hair et al., 2019). In the CR we found acceptable values ($CR \geq 0.70$) for all user orientations, indicating the internal reliability of the data.

To ensure that the constructs measures were the expected by theory (i.e., that the intercorrelations between the variables were not too high (Kline, 2015)), we also measured the discriminant validity of our data. We found acceptable values since all the square roots of the variables' AVE were larger than the correlations that the variable had with the other variables (Fornell & Larcker, 1981), and all of the variables presented correlations between them below 0.85. The discriminant validity can be seen in Table 4.

Considering the results of the study conducted by Tondello et al. (2019) that identified a partial overlap between the user orientations, we also measured the correlation between the user orientations using Kendall's τ test. We used Kendall's τ test considering that when the data follows a non-normal distribution, the correlation coefficients need to be calculated from the ranks of the data and not from the actual values (Akoglu, 2018). Our results, which can be seen in Table 5, also indicated that the user orientations presented statistically significant correlations between them. After using the conversion table proposed by Gilpin (1993) and comparing the results with the interpretation of the strength of Pearson's correlation coefficients proposed by Dancey and

Table 5. Bivariate correlation coefficients (Kendall's τ) between the user orientations.

User orientation	Achiever	Disruptor	Free Spirit	Philanthropist	Player	Socialiser
Achiever	–					
Disruptor	0.195**	–				
Free Spirit	0.414**	0.308**	–			
Philanthropist	0.465**	0.103**	0.378**	–		
Player	0.343**	0.239**	0.312**	0.183**	–	
Socialiser	0.326**	0.081*	0.304**	0.472**	0.245**	–

Key: * $p \leq 0.05$; ** $p \leq 0.01$.

Reidy (2007), it was possible to identify that most of the correlations were moderate or weak.

Finally, inspired by other recent studies in the gamification field (Hallifax et al., 2019; 2020; Orji et al., 2018), to further answer our research question, we used Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis to measure the associations between the user orientations, demographic information, and gaming habits. The PLS-SEM is a reliable method for estimating cause-effect relationship models with latent variables (Hair et al., 2016). To model the analysis of the PLS-SEM, the six Hexad user types were modeled as latent variables, the 24 survey items from the Hexad questionnaire were modeled as observed variables, and the questions from the demographic and gaming background as observed variables. The path model that represents our conceptual model can be seen in Figure 2.

The PLS-SEM analysis also indicated significant associations between the user orientations and the demographic information. The results indicated that Disruptor ($\beta = 0.306^{***}$), Free Spirit ($\beta = 0.213^{***}$), Philanthropist ($\beta = 0.200^{***}$), and Achiever ($\beta = 0.175^{**}$) presented a significant association with educational level; Disruptor ($\beta = 0.163^{***}$) and Player ($\beta = 0.114^{**}$) presented a significant association with gender; and Socialiser presented a significant association with age ($\beta = 0.150^{**}$). In Table 6 we present the

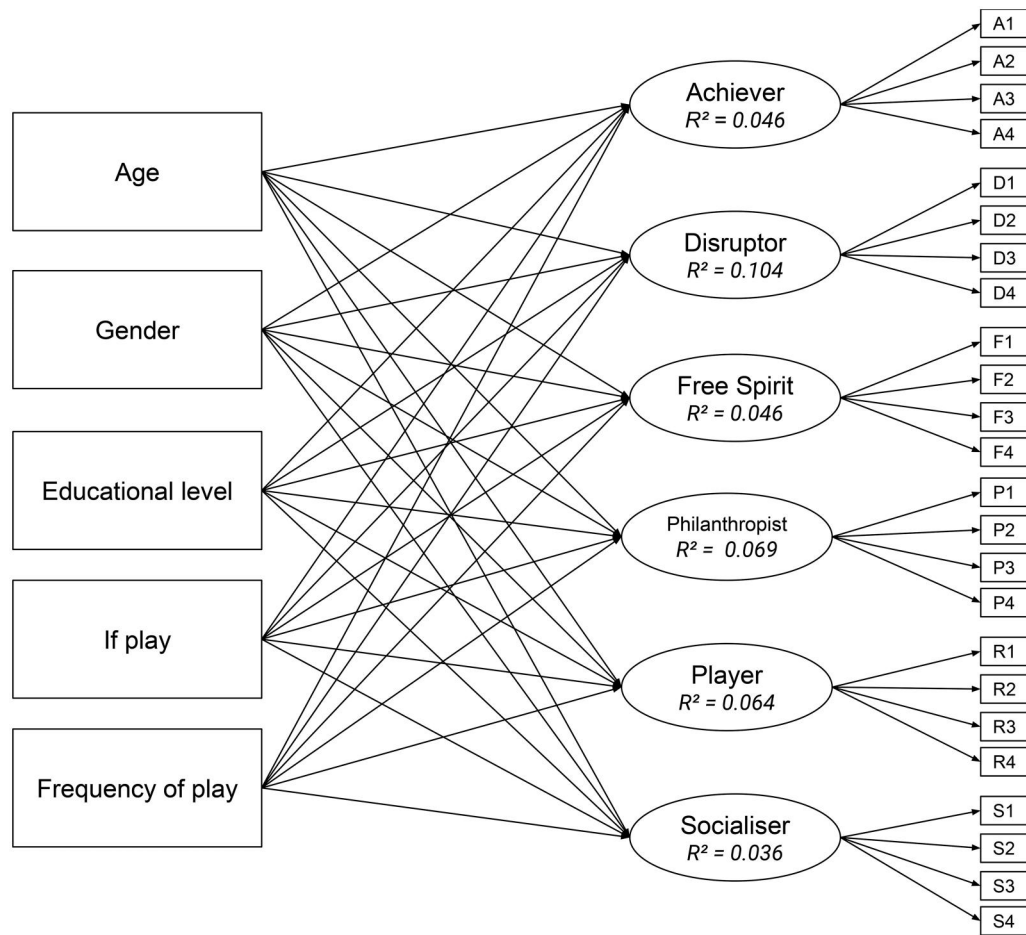


Figure 2. Model.

PLS-SEM correlation matrix with all the associations. The coefficient of determination (R^2), which values are presented in Figure 2, measures the variance in each of the constructs and is a measure of the explanatory power of the model (Hair et al., 2019). Our results showed that the model explained 4.6% of the variance for the Achievers, 10% of the variance for the Disruptors, 4.6% of the variance for the Free Spirits, 6.9% of the variance for the Philanthropists, 6.4% of the variance for the Players, and 3.6% of the variance for the Socialisers. Thus, the R^2 values indicated a weak predictive ability of the endogenous variables.

5. Discussion

In this study, we focused on analyzing the relationship between user orientations, different demographic factors, and gaming habits. To investigate the topic, we collected 340 answers from people with different demographic backgrounds and gaming experiences.

As demonstrated on Table 3, the distribution of the user orientation scores indicated that our sample followed the distribution of other recent studies (e.g., Altmeyer et al., 2020; Manzano-León et al., 2020; Tondello et al., 2019). Moreover, in our sample the user orientations that are intrinsically motivated (i.e., Achiever, Philanthropist, Socialiser, and Free Spirit) presented a higher overall mean, which was also indicated in prior research (e.g., Fischer

et al., 2018; Manzano-León et al., 2020; Ooge et al., 2020; Tondello et al., 2019). Regarding gender, differently from prior research (e.g., Fischer et al., 2018; Tondello et al., 2019), our results indicated that men presented a higher overall mean than women in all the user orientations. The highest difference in the overall mean between the genders occurred in the Player user orientation, which corroborates prior research (e.g., Fischer et al., 2018; Mora et al., 2019; Şenocak et al., 2021; Tondello et al., 2019). A possible explanation for this difference is that men are more responsive to reward strategies (Oyibo et al., 2017), a motivational factor for the Player user orientation.

To start to answer our research question, we initially decide to analyze the correlations between the user orientations using the Kendall's τ test (see Table 5). Corroborating prior research (Krath & von Korflesch, 2021; Lopez & Tucker, 2019; Tondello et al., 2019), we found correlations between the user orientations, however, most of them were weak and few moderate. These correlations are expected considering that some user orientations' motivations are related (e.g., Philanthropists and Socialisers are motivated by interaction with others (Tondello et al., 2019)). As indicated by Tondello et al. (2019), the correlation between Achievers and Free Spirits was not predicted by the theory, however, our results corroborate theirs when reporting this correlation. Considering recent studies that have indicated that user orientations are not stable over time and also that the

Table 6. PLS-SEM associations between the user orientations and the demographic factors and gaming habits.

	β	<i>p</i> -values	CI	
			2.5%	97.5%
Age → Achiever	−0.030	0.705	−0.194	0.104
Age → Disruptor	−0.103	0.183	−0.245	0.061
Age → Free Spirit	−0.118	0.152	−0.272	0.031
Age → Philanthropist	0.070	0.327	−0.088	0.196
Age → Player	−0.099	0.162	−0.231	0.047
Age → Socialiser	0.150**	0.035	0.000	0.284
Educational level → Achiever	0.175**	0.013	0.027	0.283
Educational level → Disruptor	0.306***	0.000	0.170	0.415
Educational level → Free Spirit	0.213***	0.003	0.023	0.326
Educational level → Philanthropist	0.200***	0.002	0.071	0.314
Educational level → Player	−0.005	0.934	−0.124	0.133
Educational level → Socialiser	0.046	0.532	−0.109	0.172
Gender → Achiever	0.082	0.103	−0.021	0.175
Gender → Disruptor	0.163***	0.006	0.048	0.262
Gender → Free Spirit	0.063	0.265	−0.053	0.171
Gender → Philanthropist	0.039	0.394	−0.052	0.125
Gender → Player	0.114**	0.049	−0.021	0.207
Gender → Socialiser	−0.030	0.608	−0.145	0.083
If they play → Achiever	0.085	0.261	−0.085	0.231
If they play → Disruptor	0.066	0.335	−0.068	0.199
If they play → Free Spirit	0.013	0.872	−0.141	0.151
If they play → Philanthropist	0.081	0.258	−0.050	0.216
If they play → Player	0.110	0.140	−0.027	0.252
If they play → Socialiser	0.032	0.678	−0.107	0.194
Frequency of play → Achiever	0.005	0.943	−0.131	0.144
Frequency of play → Disruptor	−0.032	0.636	−0.148	0.111
Frequency of play → Free Spirit	0.072	0.391	−0.090	0.221
Frequency of play → Philanthropist	−0.031	0.665	−0.163	0.100
Frequency of play → Player	0.070	0.350	−0.083	0.199
Frequency of play → Socialiser	−0.026	0.736	−0.176	0.118

Key: ** $p \leq 0.05$; *** $p \leq 0.01$. The statistically significant associations are in bold.

user orientations from intrinsic motivations might change faster than the user orientations from extrinsic motivations (Santos et al., 2021, 2023; Yildirim & Özdenir, 2021), these correlations between the user orientations might present an indication of how these changes occur. Moreover, these unexpected correlations could be an indication that the Hexad scale might need improvements to better measure these user orientations.

Analyzing the associations presented in the PLS-SEM analysis, we were able to identify significant associations between the user orientations and the demographic information (i.e., gender, age, and educational level). The educational level was the demographic factor with more significant associations: Disruptor ($\beta = 0.306^{***}$), Free Spirit ($\beta = 0.213^{***}$), Philanthropist ($\beta = 0.200^{***}$), and Achiever ($\beta = 0.175^{**}$) presented a positive significant association. The majority of our sample self-reported having at least a bachelor's degree, which might indicate previous experience with learning systems. Moreover, considering that part of our data was gathered from the email lists of the authors, we believe that some of them had previous experience with gamified systems. We believe that this previous exposure to gamified systems can make people more familiar with game mechanics and therefore, present a more significant relation with their Hexad profiles. People with higher education might also have a greater experience in collaborative learning, considering that this type of learning is a common practice in universities and can help to facilitate collaboration and teamwork (León-del Barco et al.,

2018). This might resonate with users that have higher Philanthropist tendencies since this user type is motivated by helping others and contributing to their community (Santos et al., 2021; Tondello et al., 2019).

Specifically prior literature in games (Kiron & Vassileva, 2024), had indicated differences in how students engage with educational games based on their Hexad profiles. We believe that this also might occur in gamification in education. However, even though education is the most researched domain in gamification (Klock et al., 2020; Koivisto & Hamari, 2019), there is a lack of results regarding the relationship between different educational levels and Hexad user orientations. Considering that four of the six user orientations presented an association with educational level in our study, we understand that this user characteristic might represent a significant part of the definition of the user profile, and should be considered when defining user orientations in samples that are not homogeneous (i.e., with people from different educational levels).

Regarding gender and user orientations, Disruptor ($\beta = 0.163^{***}$) and Player ($\beta = 0.114^{**}$) presented a positive significant association. Also, in our study, even though women's means were lower than men's in all the user orientations, the biggest differences between the scores by gender happened in the Disruptor and Player scores. Corroborating our results, prior studies (Mora et al., 2019; Şenocak et al., 2021; Tondello et al., 2019) indicated that men might have a higher score in these two Hexad user types. Previous research (Oyibo et al., 2017) also revealed that men can be more responsive to reward strategies, which might explain the association between the Players (motivated by extrinsic rewards) and men. Therefore, considering our results and prior research, we believe that the association between Disruptors and Players with gender might be related to the origin of these user orientations.

Socialiser was the only user orientation that presented a significant association with age ($\beta = 0.150^{**}$), a result that is similar to previous research (Altmeyer & Lessel, 2017; Mora et al., 2019; Tondello et al., 2019). These prior research indicated that user orientations derived from intrinsic motivations slightly increase with age, thus, for older samples, the frequency of user orientations derived from the intrinsic motivations (e.g., Socialisers) will be higher (Altmeyer & Lessel, 2017; Mora et al., 2019; Tondello et al., 2019). Therefore, our results corroborate prior research, indicating that age is associated with Socialisers and this tendency might increase over time. Prior research in gamification has mainly focused on investigating gamification effects considering younger samples (Koivisto & Malik, 2021; White et al., 2023). However, especially after the COVID-19 pandemic, the elderly started to use more technology to connect with others, in a way to mitigate social isolation (White et al., 2023). Almost 45% of our sample self-reported being more than 35 years old and all our data collection happened during the COVID-19 pandemic. We understand that this might explain the association of Socialisers with age in our study.

Considering our research question, (i.e., “How are the user orientations from the Hexad model (i.e., Philanthropist,

Achiever, Socialiser, Free Spirit, Player, and Disruptor) related to their demographic factors and gaming habits?”), overall, our results indicate that the user orientations are related to the different demographic factors measured in the study. However, even though all the user orientations presented a significant association with some of the demographic factors collected in the survey, all of these associations were weak. Moreover, we were not able to find any significant association of Hexad user orientations with the gaming habits collected in our study. This might indicate the necessity of different types of personalization based on other aspects, such as personality traits and gender identity, or a personalization not based only on the dominant user orientation (i.e., the highest score). The use of the dominant user orientation is frequent in most of the studies about gamification (Hallifax et al., 2019; Klock et al., 2020), however, some studies have indicated that this approach might not be the best one, since people display characteristics of all the user orientations in different degrees (Tondello et al., 2019), the dominant user orientation is not sufficient to identify user preferences for game elements (Hallifax et al., 2019), and also changes over time (Santos et al., 2021, 2023; Yildirim & Özdener, 2021). Therefore, even though the user might be highly influenced by one of the user orientations, the personalization strategies should be implemented considering all the user scores.

5.1. Discussion on possible implications to tailoring of gamification

When defining gamification strategies, researchers and designers can face several problems. Most studies in the field focused only on analyzing the users' preferences based on their user types (Klock et al., 2020; Oliveira et al., 2023), leading to a lack of indications about how to create gamification strategies considering user type and demographic factors. This lack of indications leads to modeling user profiles without considering that their profiles are formed by a plethora of attributes. Therefore, even though the study results presented weak associations between user orientations and demographic factors, indicating the necessity of further investigation of the topic, we developed initial recommendations as a foundational step, considering the lack of literature addressing certain characteristics measured in this study.

In this sense, we understand that these exploratory suggestions might help designers and researchers in the definition of gamification strategies. To create user modeling strategies based on the associations found in our results, researchers and designers may use as a strategy the combination of user orientation and educational level to personalize gamified settings for Achievers, Free Spirits, and Philanthropists; user orientation and age to personalize for Socialisers; user orientation and gender to personalize for Players; and user orientation, educational level, and gender to personalize for Disruptors. These recommendations were made considering the results from Table 6 and are summarized in Table 7.

Table 7. Preliminary suggestions to create strategies to personalize gamification.

	Educational Level	Age	Gender
Philanthropist	•	•	
Achiever	•		
Player		•	•
Free Spirit	•		
Socialiser		•	
Disruptor	•		•

Game elements are the most important part of the gamification, however, there is still confusion on their use, with researchers and designers relying on the most basic ones (i.e., Badges, Points, and Leaderboards) (Hallifax et al., 2023). Therefore, in addition to the gamification strategies, it is possible to indicate some game elements considering the factors measured in the study and the associations found. To select the game elements indicated in this section, we have refined the indications based on the game elements used with the Hexad reported by the study of Klock et al. (2020), and the Periodic Table of Gamification Elements proposed to the Hexad model (Marczewski, 2017). The Periodic Table of Gamification Elements groups 52 game elements considering the Hexad user types. We had selected these literature considering that they offer several options of game elements for the Hexad user types without considering any specific context.

When considering gender, for women with high Player tendencies, it is possible to suggest the use of Badges, Points, Prizes, Leaderboards, Virtual economy, Signposting, Feedback, and Lottery, while the suggestions for men with high Player tendencies are Points, Prizes, Feedback, and Leaderboards. For women with high Disruptor tendencies, the suggestions are the use of Signposting and Feedback, while Voting and Feedback could be used for men with high Disruptor tendencies. These suggestions of game elements considering gender and user orientations were based on the literature review conducted by Klock et al. (2020), the Periodic Table of Gamification Elements proposed to the Hexad model (Marczewski, 2017), and our results.

Considering age, fewer studies presented indications of game elements according to the age of the user. According to Klock et al. (2020), there is a scarcity of studies with suggestions of game elements for people who are less than 30 years old, and no studies with suggestions for people who are more than 30 years old were found. However, considering these prior studies, it is possible to create some suggestions for people younger than 30 years old. To personalize considering user orientation and age, for Philanthropists it is possible to use Collection and Gifting; Competition, Guilds, Social Discovery, Social Pressure, Social Networks, and Social Status can be used for Socialisers; and Badges, Lottery, Points, Prizes, and Virtual Economy for Players. Again, the following suggestions on how to personalize considering age and user orientations were based on the literature review conducted by Klock et al. (2020), the Periodic Table of Gamification Elements proposed to the Hexad model (Marczewski, 2017), and our results.

Like age, there is a scarcity of studies with suggestions of game elements considering the educational level of the users.

To create suggestions on how to personalize based on this aspect, we conducted a snowballing review in different Literature Reviews (Bai et al., 2020; Hallifax et al., 2019; Klock et al., 2020; Oliveira et al., 2023), selecting studies that indicated that the participants were from K-12 education or post-secondary education. Besides the Periodic Table of Gamification Elements proposed to the Hexad model (Marczewski, 2017) and our results, the indications here considered the study of Hallifax et al. (2020) to propose game elements for people in high school, and the studies of Tondello et al. (2016) and Bovermann and Bastiaens (2020) to create suggestions for people in post-secondary education. To make the following suggestions, we only included game elements that were indicated in the studies selected to a specific user orientation at the same time that was indicated for the same user orientation in the Periodic Table of Gamification Elements proposed to the Hexad model (Marczewski, 2017). The suggestions considering secondary education are the use of Time Pressure as a game element for Achievers, Free Spirits, and Disruptors. Considering post-secondary education, Care-Taking, Sharing Knowledge, and Purpose could be implemented for Philanthropists; Challenges Certificates, Quests, Levels/Progression, and Learning could be implemented for Achievers; Exploration, Easter Eggs, Unlockable, Customization, and Creativity Tools could be implemented for Free Spirits; and Innovation Platforms, Voting, and Development Tools could be implemented for Disruptors.

These suggestions are not intended as a definitive personalization guide, but rather, an attempt to offer an initial guide to model gamification strategies based on more than solely the user type. As highlighted in the study, the field needs to move toward representing the user profile in gamified environments as a set of user aspects to ensure a more tailored and enhanced user experience. Table 8 we summarize these exploratory suggestions.

5.2. Limitations

Overall this study has some limitations that should be considered, most of them regarding the survey used in the study. First of all, while surveys are considered useful and widely used in literature, the use of surveys has been also indicated as a limitation (Kimpfen et al., 2021; Klock et al., 2020; Rodríguez et al., 2021), since its use can lead to the collection of inaccurate data, directly influencing the study's results. Also, the survey could be considered long for some respondents, leading them to answer the survey without the necessary attention. To mitigate these limitations, we conducted a pilot study to evaluate the survey size, inserted an "attention-check" item in the second part of the survey, and only had volunteers as participants in this study.

Furthermore, also considering the way the survey was designed, we were only able to collect a small set of user characteristics, ignoring other possible variables such as the user's lifestyle, culture, and working background. This choice was made to create a shorter survey, however, has prevented us from deeply analyzing other user characteristics that can also be related to the user type. When developing the survey, similar to other studies in the field (González-González et al., 2022; Krath & von Korfflesch, 2021; Poetze et al., 2019), we used limited options of gender (i.e., man, woman, other, and preferred not to answer). The use of the term "other" can be considered offensive to people who are already marginalized in society (Spiel et al., 2019). We understand that this limitation could lead some respondents to not properly answer the survey or leave the study without submitting responses, limiting the sample size. Also by using a binary option to collect gender, the data collected prevented us from deeply analyzing more aspects of this characteristic as recommended in prior literature (Klock et al., 2020).

Regarding the data collected, our study was able to collect a limited number of responses from participants of only one country which might prevent the generalization of the results.

Table 8. Exploratory suggestions to select game elements.

	Philanthropist	Achiever	Player	Free Spirit	Socialiser	Disruptor
Women			Badges, Leaderboards, Prizes, Points, Virtual economy, Signposting, Feedback, Lottery.			Signposting, Feedback.
Men			Points, Prizes, Feedback, Leaderboards.			Voting, Feedback.
Education 1		Time pressure		Time pressure		Time pressure
Education 2	Care-Taking, Sharing Knowledge, Purpose.	Challenges, Certificates, Quests, Learning, Levels or Progression.		Exploration, Easter Eggs, Unlockable, Customization, Creativity Tools.		Innovation Platforms, Voting, Development Tools.
Age < 30	Collection, Gifting.	Badges, Lottery, Points, Prizes, Virtual Economy.			Competition, Guilds, Social Discovery, Social Pressure, Social Networks, Social Status.	

Key: Education 1 = High School; Education 2 = Post-secondary Level.

Therefore, the results here presented might not be the same considering other samples. When we consider age, we had a different number of participants in each age group, leading to age groups that were not size equivalent and this might have directly impacted the results considering age. Also, to mitigate possible typo mistakes and following prior research (Poecze et al., 2019), we presented options of age groups instead of allowing the participants to provide a specific age number. This decision made it impossible to group the participants according to their specific ages and consequently prevented us from presenting more specific and detailed considerations about the relationship between age and user orientation. Considering the game habits collected, our survey only provides an exploratory overview of the relationship between gaming habits and user orientations. This decision was taken considering that we aimed to collect data from people with no experience and/or interest in games. However, this also might prevented us from presenting more insightful results about the people who had player experiences.

Finally, using only one user typology (i.e., Hexad) also can be considered a limitation of the study. Even though the Hexad model is currently the most used typology for personalizing gamification, several studies have indicated problems with the model. Recently, the inconsistency of the user types has been indicated (Santos et al., 2021, 2023; Yildirim et al., 2021) which directly affects the personalization made based on this typology. Previous literature has indicated that one problem with the use of the Hexad model is that researchers use only the dominant type as the profile of the user (Hallifax et al., 2019; Kirchner-Krath et al., 2024; Xiao et al., 2024), when the profile is consisted of the six user types. Finally, there are studies that pointed out the several overlaps between the six user types (Santos et al., 2021; Tondello et al., 2019) and the Hexad and other models (Kirchner-Krath et al., 2024; Xiao et al., 2024). Therefore, even though Hexad is now the most used user typology, there are several limitations with the model that should be acknowledged when using this typology.

5.3. Recommendations for future studies

Gamification remains a relatively new field with several topics little explored. While our study sought to deepen the understanding of the relationship between user orientations, demographic factors, and gaming habits, its results and limitations can guide the creation of new research toward developing more specific recommendations for personalization considering the user profile as a holistic profile. Whereas we focused on collecting data from one country, recently, some studies have focused on collecting data from people of different regions (e.g., Kirchner-Krath et al., 2024). However, most studies about gamification still are conducted considering few regions (Oliveira et al., 2023). Therefore, little is known about how the user profile can differ considering the region or cultural aspects. Future studies can collect data from different countries and compare how the same user characteristics can be related to the user orientations, especially considering countries that are in the same region and that are usually not

represented in gamification research (e.g., countries from Africa and Asia). This type of study also could indicate how culture can impact the relationship between user orientations and other user's characteristics.

Our study was conducted in a context-independence process. Not having a specific context allows us to make our findings more universally applicable across various domains, offering a versatile base that can be adapted to different contexts as needed. Considering that most studies in gamification are conducted considering education and health (Klock et al., 2020), a context-independent study can help the replication of contexts that are poorly investigated. Since the effects of gamification may differ according to the field of application, future studies can focus on collecting data from people in different contexts to measure how the context affects the relationship between user orientations, demographic factors, and gaming habits.

While using data from surveys and questionnaires is still a common practice, a recent concern raised in the gamification field is how similar is the user orientation when comparing data collected and their behavior in a real gamified environment. Considering recent studies (Altmeyer et al., 2019; 2020; Kimpen et al., 2021) that have worked on the prediction of the Hexad user orientations, future studies can focus on making comparisons between the self-reported user orientations and the predicted user orientation on how both approaches to assess the user orientations can influence the relationship with the other user characteristics.

Education is the most researched context in gamification, and our results indicated that most user orientations presented a significant association with educational level. However, there is a lack of studies that analyzed how different educational levels are related with the user orientations from the Hexad. We understand that future studies can focus on further investigations about how different educational levels or educational areas might impact the user orientation, improving the personalization of educational gamified settings. Moreover, considering the lack of studies about gaming habits and user types and the limitations of our study, future studies can focus on how gaming habits or gaming experience influence user orientations from extrinsic motivations and further our results by analyzing the relationship between the user orientations and a more diverse set of gaming habits. This would be helpful for researchers and industry in the development of gamified systems for people who have player experiences.

Prior literature has widely investigated how gamification can benefit users' health, however, there is a lack of studies considering gamification and older samples. Considering the propagation of the use of technologies, especially during the COVID-19 pandemic, we believe adults and the elderly are now more confident in using gamified technologies. Moreover, we believe that this might be highly useful to monitor health issues and to increase their socialization. Therefore, future studies can focus on investigating how gamification can be applied considering older samples. We understand that gameful interventions will highly benefit this population.

6. Concluding remarks

In this study, we focused on understanding the potential associations between user orientations from the Hexad model, demographic, and gaming aspects. Answering our specific objectives, we found that all the user orientations presented at least one significant association with the demographic factors measured in the study, however, all these associations were weak. Our results highlight the necessity of a further investigation into how to personalize gamified settings based on other aspects than the dominant user orientations and demographic characteristics. We also analyzed the distribution of the Hexad user types from the sample, where corroborating prior studies, our analysis indicated that Achievers and Philanthropists are the most common user orientations and Disruptors the least common. While our findings contribute to advancing the gamification literature, they also open space for the conduction of new studies. In future studies, we intend to replicate the analyses with a broader sample including new demographic information (e.g., work field and marital status), the personality traits of the respondents, and preferences for game elements in the survey. We also will focus on collecting answers from younger (≤ 20) and older (≥ 50) respondents, aiming to understand more the role that age might have in user orientations.

Ethical statements

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. Informed consent was obtained from all participants and their legal representatives.

Author contributions

ACGS and WO were involved in the conceptualization of the study, wrote the main manuscript text, and were responsible for the data collection, analysis, and interpretation. JV was responsible for the writing review of the manuscript. WO, JV, and JH were responsible for the supervision. SI and JH were involved in the conceptualization of the study. All authors approved this current version.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001. We acknowledge the financial support provided by the Emerging Leaders in the Americas Program (ELAP). This work has been supported by the Academy of Finland Flagship Programme [Grant No. 337653 – Forest-Human-Machine Interplay (UNITE)].

ORCID

Ana Cláudia Guimarães Santos  <http://orcid.org/0000-0002-3498-0049>

Wilk Oliveira  <http://orcid.org/0000-0003-3928-6520>

Julita Vassileva  <http://orcid.org/0000-0001-5050-3106>

Juho Hamari  <http://orcid.org/0000-0002-6573-588X>

Seiji Isotani  <http://orcid.org/0000-0003-1574-0784>

Data availability statement

The authors confirm that the data supporting the findings of this study is available in its supplementary materials.

References

- Akoglu, H. (2018). User's guide to correlation coefficients. *Turkish Journal of Emergency Medicine*, 18(3), 91–93. <https://doi.org/10.1016/j.tjem.2018.08.001>
- Almeida, C., Kalinowski, M., Uchôa, A., & Feijó, B. (2023). Negative effects of gamification in education software: Systematic mapping and practitioner perceptions. *Information and Software Technology*, 156(C), 107142. <https://doi.org/10.1016/j.infsof.2022.107142>
- Alsofyani, M. M. (2023). Eleven game elements for female nonadaptive gamification courses. *Heliyon*, 9(1), e12699. <https://doi.org/10.1016/j.heliyon.2022.e12699>
- Altmeyer, M., & Lessel, P. (2017). The Importance of Social Relations for Well-Being Change in Old Age-Do Game Preferences Change As Well? *Proceedings of the positive gaming: Workshop on gamification and games for wellbeing* (Vol. 2055, pp. 1–5).
- Altmeyer, M., Lessel, P., Jantwal, S., Muller, L., Daiber, F., & Krüger, A. (2021). Potential and effects of personalizing gameful fitness applications using behavior change intentions and hexad user types. *User Modeling and User-Adapted Interaction*, 31(4), 675–712. <https://doi.org/10.1007/s11257-021-09288-6>
- Altmeyer, M., Lessel, P., Schubhan, M., & Krüger, A. (2019). Towards predicting Hexad user types from smartphone data [Paper presentation]. Extended Abstracts of the Annual Symposium on Computer-Human Interaction in Play Companion Extended Abstracts, New York, NY, USA. Association for Computing Machinery, CHI PLAY '19 Extended Abstracts, p. 315–322. <https://doi.org/10.1145/3341215.3356266>
- Altmeyer, M., Schubhan, M., Lessel, P., Muller, L., & Krüger, A. (2020). Using Hexad user types to select suitable gamification elements to encourage healthy eating [Paper presentation]. Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems, New York, NY, USA. Association for Computing Machinery, CHI EA '20, p. 1–8. <https://doi.org/10.1145/3334480.3383011>
- Altmeyer, M., Tondello, G. F., Krüger, A., & Nacke, L. E. (2020). HexArcade: Predicting Hexad user types by using gameful applications [Paper presentation]. Proceedings of the Annual Symposium on Computer-Human Interaction in Play, in, New York, NY, USA. Association for Computing Machinery, CHI PLAY '20, p. 219–230. <https://doi.org/10.1145/3410404.3414232>
- Araya, R., Arias Ortiz, E., Bottan, N. L., & Cristia, J. (2019). *Does gamification in education work? experimental evidence from Chile*. Tech. Rep., IDB Working Paper Series.
- Bai, S., Hew, K. F., & Huang, B. (2020). Does gamification improve student learning outcome? evidence from a meta-analysis and synthesis of qualitative data in educational contexts. *Educational Research Review*, 30, 100322. <https://doi.org/10.1016/j.edurev.2020.100322>
- Bartle, R. (1996). Hearts, clubs, diamonds, spades: Players who suit muds. Retrieved June 1, 2021, from <https://mud.co.uk/richard/hcds.htm>
- Böckle, M., Novak, J., & Bick, M. (2017). Towards adaptive gamification: A synthesis of current developments. in *Proceedings of the 25th European Conference on Information Systems (ECIS)*. pp. 158–174.
- Bovermann, K., & Bastiaens, T. J. (2020). Towards a motivational design? connecting gamification user types and online learning activities. *Research and Practice in Technology Enhanced Learning*, 15(1), 18. [pphttps://doi.org/10.1186/s41039-019-0121-4](https://doi.org/10.1186/s41039-019-0121-4)
- Busch, M., Mattheiss, E., Orji, R., Fröhlich, P., Lankes, M., & Tscheligi, M. (2016). Player type models: Towards empirical validation [Paper presentation]. Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems, New York,

- NY, USA. Association for Computing Machinery, CHI EA '16, p. 1835–1841. <https://doi.org/10.1145/2851581.2892399>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd Ed.). Lawrence Erlbaum Associates.
- Connelly, L. M. (2008). Pilot studies. *Medsurg Nursing*, 17(6), 411–412. <https://link.gale.com/apps/doc/A192589717/AONE?u=anon~34442940&sid=googleScholar&xid=90ec7dcc>
- Council, B. (2014). *Learning English in Brazil: Understanding the aims and expectations of the Brazilian emerging middle classes*. British Council.
- da Rocha Seixas, L., Gomes, A. S., & de Melo Filho, I. J. (2016). Effectiveness of gamification in the engagement of students. *Computers in Human Behavior*, 58, 48–63. <https://doi.org/10.1016/j.chb.2015.11.021>
- Dancey, C. P., & Reidy, J. (2007). *Statistics without maths for psychology*. Pearson education.
- Deci, E. L., & Ryan, R. M. (1985). Conceptualizations of intrinsic motivation and self-determination, in *Intrinsic motivation and self-determination in human behaviour* (pp. 11–40). Springer.
- Denden, M., Tlili, A., Essalmi, F., Jemni, M., Chen, N. S., & Burgos, D. (2021). Effects of gender and personality differences on students' perception of game design elements in educational gamification. *International Journal of Human-Computer Studies*, 154(3), 102674. <https://doi.org/10.1016/j.ijhcs.2021.102674>
- Denny, P., McDonald, F., Empson, R., Kelly, P., & Petersen, A. (2018). Empirical support for a causal relationship between gamification and learning outcomes [Paper presentation]. Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. Association for Computing Machinery, New York, NY, USA p. 1–13. <https://doi.org/10.1145/3173574.3173885>
- do Amaral Neto, J. R., Oliveira, W., Hamari, J., Dantas, P., & do Nascimento, I. M. (2023). Exploring the use of social gamification during and after emergency remote teaching caused by Covid-19 [Paper presentation]. 2023 IEEE International Conference on Advanced Learning Technologies (ICALT). IEEE, pp. 97–99. <https://doi.org/10.1109/ICALT58122.2023.00034>
- Eum, K., Lee, S., Jo, M., & Doh, Y. Y. (2023). Growing up with cerebral palsy (CP) and games: Case study on the accessible gameplay experiences of the young players with CP and their families through the lens of developmental task perspective. *Proceedings of the ACM on Human-Computer Interaction*, 7(CHI PLAY), 484–502. <https://doi.org/10.1145/3611038>
- Ferro, L. S. (2018). An analysis of players' personality type and preferences for game elements and mechanics. *Entertainment Computing*, 27(1), 73–81. <https://doi.org/10.1016/j.entcom.2018.03.003>
- Fischer, H., Heinz, M., & Breitenstein, M. (2018). Gamification of learning management systems and user types in higher education. *ECGBL 2018 12th European Conference on Game-Based Learning. Academic Conferences and Publishing Limited*, p. 91.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.2307/3151312>
- Gilpin, A. R. (1993). Table for conversion of kendall's tau to spearman's rho within the context of measures of magnitude of effect for meta-analysis. *Educational and Psychological Measurement*, 53(1), 87–92. <https://doi.org/10.1177/0013164493053001007>
- González-González, C. S., Toledo-Delgado, P. A., Muñoz-Cruz, V., & Arnedo-Moreno, J. (2022). Gender and age differences in preferences on game elements and platforms. *Sensors*, 22(9), 3567. <https://doi.org/10.3390/s22093567>
- Guillen, G., Hamari, M. J., & Quist, J. (2021). Gamification of sustainable consumption: A systematic literature review [Paper presentation]. Proceedings of the 54th Hawaii International Conference on System Sciences. pp. 1345–1354. <https://doi.org/10.24251/HICSS.2021.163>
- Gupta, A., Lawendy, B., Goldenberg, M. G., Grober, E., Lee, J. Y., & Perlis, N. (2021). Can video games enhance surgical skills acquisition for medical students? A systematic review. *Surgery*, 169(4), 821–829. <https://doi.org/10.1016/j.surg.2020.11.034>
- Hadi Mogavi, R., Deng, C., Hoffman, J., Haq, E. U., Gujar, S., Bucchiarone, A., & Hui, P. (2023). Your favorite gameplay speaks volumes about you: Predicting user behavior and hexad type. *International Conference on Human-Computer Interaction* (pp. 210–228). Springer.
- Hair, J. F., Jr, Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of pls-sem. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hallifax, S., Altmeyer, M., Kölln, K., Rauschenberger, M., & Nacke, L. E. (2023). From points to progression: A scoping review of game elements in gamification research with a content analysis of 280 research papers. *Proceedings of the ACM on Human-Computer Interaction*, 7(CHI PLAY), 748–768. <https://doi.org/10.1145/3611048>
- Hallifax, S., Lavoué, E., & Serna, A. (2020). To Tailor or not to tailor gamification? An analysis of the impact of tailored game elements on learners' behaviours and motivation. In I. I. Bittencourt, M. Cukurova, K. Muldner, R. Luckin, & E. Millán (Eds.), *Artificial intelligence in education* (pp. 216–227). Springer International Publishing.
- Hallifax, S., Serna, A., Marty, J. C., & Lavoué, É. (2019). Adaptive gamification in education: A literature review of current trends and developments. In M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Ioannou, & J. Schneider (Eds.), *Transforming learning with meaningful technologies* (pp. 294–307). Springer International Publishing.
- Hallifax, S., Serna, A., Marty, J. C., Lavoué, G., & Lavoué, E. (2019). Factors to consider for tailored gamification [Paper presentation]. Proceedings of the Annual Symposium on Computer-Human Interaction in Play, New York, NY, USA. Association for Computing Machinery, CHI PLAY '19, p. 559–572. <https://doi.org/10.1145/3311350.3347167>
- Hamari, J. (2019). Gamification. In *The Blackwell Encyclopedia of Sociology* (pp. 1–3). John Wiley & Sons, Ltd. <https://onlinelibrary.wiley.com/doi/abs/10.1002/9781405165518.wbeos1321>
- Hamari, J., & Tuunainen, J. (2014). Player types: A meta-synthesis. *Transactions of the Digital Games Research Association*, 1(2), 29–53. <https://doi.org/10.26503/todigra.v1i2.13>
- Högberg, J., Hamari, J., & Wästlund, E. (2019). Gameful experience questionnaire (gamefulquest): An instrument for measuring the perceived gamefulness of system use. *User Modeling and User-Adapted Interaction*, 29(3), 619–660. <https://doi.org/10.1007/s11257-019-09223-w>
- Huotari, K., & Hamari, J. (2017). A definition for gamification: Anchoring gamification in the service marketing literature. *Electronic Markets*, 27(1), 21–31. <https://doi.org/10.1007/s12525-015-0212-z>
- IBM Corp. (2020). IBM SPSS Statistics for Windows (Version 27.0) [Computer software]. Retrieved from <https://www.ibm.com/br-pt/analytics/spss-statistics-software/>
- Issabek, A., Oliveira, W., Hamari, J., & Bogdanchikov, A. (2023). Understanding the effects of gender, age, and cultural orientation on users' flow experience during the use of a gameful educational system [Paper presentation]. 2023 IEEE International Conference on Advanced Learning Technologies (ICALT). IEEE, pp. 124–126. <https://doi.org/10.1109/ICALT58122.2023.00042>
- Johnson, D., Deterding, S., Kuhn, K. A., Staneva, A., Stoyanov, S., & Hides, L. (2016). Gamification for health and wellbeing: A systematic review of the literature. *Internet Interventions*, 6, 89–106. <https://doi.org/10.1016/j.invent.2016.10.002>
- Kimpen, R., De Croon, R., Vanden Abeele, V., & Verbert, K. (2021). Towards predicting hexad user types from mobile banking data: An expert consensus study (pp. 30–36). In *Extended Abstracts of the 2021 Annual Symposium on Computer-Human Interaction in Play*.
- Kirchner-Krath, J., Altmeyer, M., Schürmann, L., Kordyaka, B., Morschheuser, B., Klock, A. C. T., Nacke, L., Hamari, J., & von Korflesch, H. F. (2024). Uncovering the theoretical basis of user types: An empirical analysis and critical discussion of user typologies in research on tailored gameful design. *International Journal of Human-Computer Studies*, 190, 103314. <https://doi.org/10.1016/j.ijhcs.2024.103314>
- Kiron, N., & Vassileva, J. (2024). How Hexad Player Types Affect Student Behaviour in Three Versions of a Peer-Quizzing Game. In

- International Conference on Human-Computer Interaction*. Springer, pp. 57–68.
- Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.
- Klock, A. C. T., Gasparini, I., Pimenta, M. S., & Hamari, J. (2020). Tailored gamification: A review of literature. *International Journal of Human-Computer Studies*, 144, 102495. <https://doi.org/10.1016/j.ijhcs.2020.102495>
- Koivisto, J., & Hamari, J. (2019). The rise of motivational information systems: A review of gamification research. *International Journal of Information Management*, 45, 191–210. <https://doi.org/10.1016/j.ijin-fomgt.2018.10.013>
- Koivisto, J., & Malik, A. (2021). Gamification for older adults: A systematic literature review. *The Gerontologist*, 61(7), e360–e372. <https://doi.org/10.1093/geront/gnaa047>
- Krath, J., & von Korflesch, H. F. O. (2021). Player types and game element preferences: Investigating the relationship with the gamification user types HEXAD scale. In X. Fang (Ed.), *HCI in Games: Experience design and game mechanics* (pp. 219–238). Springer International Publishing.
- Kung, F. Y., Kwok, N., & Brown, D. J. (2018). Are attention check questions a threat to scale validity? *Applied Psychology*, 67(2), 264–283. <https://doi.org/10.1111/apps.12108>
- León-del Barco, B., Mendo-Lázaro, S., Felipe-Castaño, E., Fajardo-Bullón, F., & Iglesias-Gallego, D. (2018). Measuring responsibility and cooperation in learning teams in the university setting: Validation of a questionnaire. *Frontiers in Psychology*, 9, 326. <https://doi.org/10.3389/fpsyg.2018.00326>
- Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology*, 22(140), 55.
- Lopes, V., Reinheimer, W., Medina, R., Bernardi, G., & Nunes, F. B. (2019). Adaptive gamification strategies for education: A systematic literature review. *Brazilian Symposium on Computers in Education*, Vol. 30, p. 1032.
- Lopez, C. E., & Tucker, C. S. (2019). The effects of player type on performance: A gamification case study. *Computers in Human Behavior*, 91, 333–345. <https://doi.org/10.1016/j.chb.2018.10.005>
- Manzano-León, A., Camacho-Lazarraga, P., Guerrero-Puerta, M. A., Guerrero-Puerta, L., Alias, A., Trigueros, R., & Aguilar-Parra, J. M. (2020). Adaptation and validation of the scale of types of users in gamification with the spanish adolescent population. *International Journal of Environmental Research and Public Health*, 17(11), 4157. <https://doi.org/10.3390/ijerph17114157>
- Marczewski, A. (2015). *Even ninja monkeys like to play*. CreateSpace Indep. Publish Platform, Charleston, Chapter User Types. pp. 69–84.
- Marczewski, A. (2017). The periodic table of gamification elements. Retrieved November 11, 2022, from <https://www.gamified.uk/2017/04/03/periodic-table-gamification-elements/>
- Martinez, L., Gimenes, M., & Lambert, E. (2022). Entertainment video games for academic learning: A systematic review. *Journal of Educational Computing Research*, 60(5), 1083–1109. <https://doi.org/10.1177/07356331211053848>
- Mora, A., Tondello, G. F., Calvet, L., González, C., Arnedo-Moreno, J., & Nacke, L. E. (2019). The Quest for a Better Tailoring of Gameful design: An analysis of player type preferences [Paper presentation]. Proceedings of the XX International Conference on Human Computer Interaction, New York, NY, USA. Association for Computing Machinery, Interacción '19. <https://doi.org/10.1145/3335595.3335625>
- Nacke, L. E., Bateman, C., & Mandryk, R. L. (2011). BrainHex: Preliminary results from a neurobiological gamer typology survey. In J. C. Anacleto, S. Fels, N. Graham, B. Kapralos, M. Saif El-Nasr, & K. Stanley (Eds.), *Entertainment Computing – ICEC 2011* (pp. 288–293). Springer Berlin Heidelberg.
- Ndulue, C., & Orji, R. (2024). The impact of persuasive framing on the perceived effectiveness of a game for behaviour change. *International Journal of Human-Computer Interaction*, 1–15. <https://doi.org/10.1080/10447318.2024.2355390>
- Nelson, M. J. (2012). Soviet and American precursors to the gamification of work [Paper Presentation]. Proceeding of the 16th International Academic MindTrek Conference, pp. 23–26. <https://doi.org/10.1145/2393132.2393138>
- Ning, Y., Jia, Z., Zhu, R., Ding, Y., Wang, Q., & Han, S. (2022). Effect and feasibility of gamification interventions for improving physical activity and health-related outcomes in cancer survivors: An early systematic review and meta-analysis. *Supportive Care in Cancer*, 31(1), 92. <https://doi.org/10.1007/s00520-022-07550-0>
- Oliveira, W., & Bittencourt, I. I. (2019). Selecting the most suitable gamification elements for each situation. In *Tailored gamification to educational technologies* (pp. 55–69). Springer.
- Oliveira, W., & Hamari, J. (2024). Global trends in flow theory research within gameful environments: A scoping review, bibliometric analysis and agenda for future studies [Paper presentation]. Proceedings of the 57th Hawaii International Conference on System Sciences, pp. 1318–1327. <https://doi.org/10.24251/HICSS.2023.163>
- Oliveira, W., Hamari, J., Shi, L., Toda, A. M., Rodrigues, L., Palomino, P. T., & Isotani, S. (2023). Tailored gamification in education: A literature review and future agenda. *Education and Information Technologies*, 28(1), 373–406. <https://doi.org/10.1007/s10639-022-11122-4>
- Oliveira, W., Toda, A., Palomino, P., Shi, L., Isotani, S., Bittencourt, I. I., & Vassileva, J. (2020). Does tailoring gamified educational systems matter? The impact on students' flow experience [Paper presentation]. Hawaii International Conference on System Sciences, Vol. 20. <https://doi.org/10.24251/HICSS.2020.152>
- Ooge, J., De Croon, R., Verbert, K., & Vanden Abeele, V. (2020). Tailoring gamification for adolescents: A validation study of Big Five and Hexad in Dutch [Paper presentation]. Proceedings of the Annual Symposium on Computer-Human Interaction in Play, New York, NY, USA. Association for Computing Machinery, CHI PLAY '20', p. 206–218. <https://doi.org/10.1145/3410404.3414267>
- Orji, R., Tondello, G. F., & Nacke, L. E. (2018). Personalizing persuasive strategies in gameful systems to gamification user types [Paper presentation]. Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, pp. 1–14. <https://doi.org/10.1145/3173574.3174009>
- Oyibo, K., Orji, R., & Vassileva, J. (2017). Investigation of the persuasiveness of social influence in persuasive technology and the effect of age and gender. In *Ppt@ persuasive* (pp. 32–44).
- Padilla, M. A., & Divers, J. (2016). A comparison of composite reliability estimators: Coefficient omega confidence intervals in the current literature. *Educational and Psychological Measurement*, 76(3), 436–453. <https://doi.org/10.1177/0013164415593776>
- Pessoa, M., Lima, M., Pires, F., Haydar, G., Melo, R., Rodrigues, L., Oliveira, D., Oliveira, E., Galvão, L., Gadelha, B., Isotani, S., Gasparini, I., & Conte, T. (2024). A journey to identify users' classification strategies to customize game-based and gamified learning environments. *IEEE Transactions on Learning Technologies*, 17, 527–541. <https://doi.org/10.1109/TLT.2023.3317396>
- Peterson, R. A., & Kim, Y. (2013). On the relationship between coefficient alpha and composite reliability. *The Journal of Applied Psychology*, 98(1), 194–198. <https://doi.org/10.1037/a0030767>
- Poecze, F., Roncevic, A., & Zlatic, S. (2019). Further differentiating factors of gamers' hexad player types. *Economic and Social Development: Book of Proceedings*, 98–108.
- Raykov, T. (1997). Estimation of composite reliability for congeneric measures. *Applied Psychological Measurement*, 21(2), 173–184. <https://doi.org/10.1177/01466216970212006>
- Ringle, C. M., Wende, S., Becker, J.-M. (2022). SmartPLS 4 [Computer software]. Retrieved October from <https://www.smartpls.com>.
- Rodrigues, L., Toda, A. M., Palomino, P. T., Oliveira, W., & Isotani, S. (2020). Personalized gamification: A literature review of outcomes, experiments, and approaches [Paper presentation]. Eighth International Conference on Technological Ecosystems for Enhancing Multiculturality, New York, NY, USA. Association for Computing Machinery, TEEM'20, p. 699–706. <https://doi.org/10.1145/3434780.3436665>
- Rodrigues, L., Toda, A. M., Palomino, P. T., Oliveira, W., & Isotani, S. (2020). Personalized gamification: A literature review of outcomes, experiments, and approaches [Paper presentation]. Eighth international conference on technological ecosystems for enhancing

- multiculturalism, New York, NY, USA. Association for Computing Machinery, TEEM'20, in, p. 699–706, Available at <https://doi.org/10.1145/3434780.3436665>
- Rodríguez, I., Puig, A., & Rodríguez, A. (2021). We are not the same either playing: A proposal for adaptive gamification. *Artificial Intelligence Research and Development*, 339, 185–194. <https://doi.org/10.3233/FAIA210133>
- Santos, A. C. G., Muramatsu, P. K., Oliveira, W., Joaquim, S., Hamari, J., & Isotani, S. (2023). Psychometric investigation of the gamification hexad user types scale with Brazilian Portuguese adolescents speakers. *Scientific Reports*, 13(1), 18645. <https://doi.org/10.1038/s41598-023-45544-y>
- Santos, A. C. G., Oliveira, W., Altmeyer, M., Hamari, J., & Isotani, S. (2022). Psychometric investigation of the gamification hexad user types scale in Brazilian Portuguese. *Scientific Reports*, 12(1), 4920. pp <https://doi.org/10.1038/s41598-022-08820-x>
- Santos, A. C. G., Oliveira, W., Hamari, J., & Isotani, S. (2021). Do people's user types change over time? An exploratory study. In *Proceedings of the 5th International GamiFIN Conference, GamiFIN 2021* (pp. 1–10). CEUR-WS.
- Santos, A. C. G., Oliveira, W., Hamari, J., Joaquim, S., & Isotani, S. (2023). The consistency of gamification user types: A study on the change of preferences over time. *Proceedings of the ACM on Human-Computer Interaction*, 7(CHI PLAY), 1253–1281. <https://doi.org/10.1145/3611068>
- Santos, A. C. G., Oliveira, W., Hamari, J., Rodrigues, L., Toda, A. M., Palomino, P. T., & Isotani, S. (2021). The relationship between user types and gamification designs. *User Modeling and User-Adapted Interaction*, 31(5), 907–940. <https://doi.org/10.1007/s11257-021-09300-z>
- Şenocak, D., Büyüç, K., & Bozkurt, A. (2021). Examination of the hexad user types and their relationships with gender, game mode, and gamification experience in the context of open and distance learning. *Online Learning*, 25(4), 250–266. <https://doi.org/10.24059/olj.v25i4.2276>
- Sidekierskienė, T., Damaševičius, R., & Maskeliūnas, R. (2020). Validation of student psychological player types for game-based learning in university math lectures. In *International Conference on Information and Communication Technology and Applications* (pp. 245–258). Springer.
- Soper, D. (2023). A-priori sample size calculator for structural equation models [software]. Retrieved April 5, 2023, from <https://www.daniel-soper.com/statcalc>
- Spiel, K., Haimson, O. L., & Lottridge, D. (2019). How to do better with gender on surveys: A guide for HCI researchers. *Interactions*, 26(4), 62–65. <https://doi.org/10.1145/3338283>
- Sun, S., Wang, Z., Wu, Q., & Wang, W. (2022). Research on incentive mechanism and evaluation of gamification application for sustainable consumption in the context of China. *Frontiers in Sustainability*, 3, 846774. <https://doi.org/10.3389/frsus.2022.846774>
- Toda, A. M., Valle, P. H. D., & Isotani, S. (2018). The Dark Side of gamification: An overview of negative effects of gamification in education. In A. I. Cristea, I. I. Bittencourt, & F. Lima (Eds.), *Higher education for all. From challenges to novel technology-enhanced solutions* (pp. 143–156). Springer International Publishing.
- Tondello, G. F., & Nacke, L. E. (2020). Validation of user preferences and effects of personalized gamification on task performance. *Frontiers in Computer Science*, 2, 29. <https://doi.org/10.3389/fcomp.2020.00029>
- Tondello, G. F., Mora, A., Marczewski, A., & Nacke, L. E. (2019). Empirical validation of the gamification user types Hexad scale in English and Spanish. *International Journal of Human-Computer Studies*, 127, 95–111. <https://doi.org/10.1016/j.ijhcs.2018.10.002>
- Tondello, G. F., Wehbe, R. R., Diamond, L., Busch, M., Marczewski, A., & Nacke, L. E. (2016). The gamification user types Hexad Scale [Paper presentation]. Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play, New York, NY, USA. Association for Computing Machinery, CHI PLAY '16, p. 229–243. <https://doi.org/10.1145/2967934.2968082>
- Volkmar, G., Pfau, J., Teise, R., & Malaka, R. (2019). Player types and achievements – Using Adaptive game design to foster intrinsic motivation [Paper presentation]. Extended abstracts of the annual symposium on computer-human interaction in play companion extended abstracts, New York, NY, USA. Association for Computing Machinery, CHI PLAY '19 Extended Abstracts, p. 747–754. <https://doi.org/10.1145/3341215.3356278>
- Westland, J. C. (2010). Lower bounds on sample size in structural equation modeling. *Electronic Commerce Research and Applications*, 9(6), 476–487. <https://doi.org/10.1016/j.elerap.2010.07.003>
- White, B. K., Martin, A., & White, J. (2023). Gamification and older adults: Opportunities for gamification to support health promotion initiatives for older adults in the context of Covid-19. *The Lancet Regional Health-Western Pacific*, 35, 1–7. <https://doi.org/10.1016/j.lanwpc.2022.100528>
- Wohlin, C., Runeson, P., Höst, M., Ohlsson, M. C., Regnell, B., & Wesslén, A. (2012). *Experimentation in software engineering*. Springer Science & Business Media.
- Xiao, Y., Chen, X., Jin, Y., & Hew, K. F. (2024). Player types in gamified learning: Conceptualization, validation, and profiling. *International Journal of Human-Computer Interaction*, 1–19. <https://doi.org/10.1080/10447318.2024.2338664>
- Yee, N. (2006). Motivations for play in online games. *Cyberpsychology & Behavior: The Impact of the Internet, Multimedia and Virtual Reality on Behavior and Society*, 9(6), 772–775. <https://doi.org/10.1089/cpb.2006.9.772>
- Yildirim, O. G., & Özdener, N. (2021). An exploratory study on the change of students' gamification user types over time. In *8th Instructional Technologies and Teacher Education Symposium*. pp. 356–364.
- Yildirim, O. G., Ozdener, N., & Geris, A. (2021). Gamification user types and game playing preferences of university students. *Global Journal of Information Technology: Emerging Technologies*, 11(2), 55–67. <https://doi.org/10.18844/gjit.v11i2.5287>

About the authors

Ana Cláudia Guimarães Santos is a Doctoral Researcher at Gamification Group, Faculty of Information Technology and Communications, Tampere University, Finland. Her main teaching/research focuses are Gamification, Human-Computer Interaction, User Experience, and Computing Applied to Education.

Wilk Oliveira is a researcher at the Gamification Group, Faculty of Information Technology and Communications, Tampere University, Finland. His main areas of activity are Educational Technologies, Gamification, Game-Based Learning, User Experience, and Computing Education.

Julita Vassileva is a professor at the University of Saskatchewan. Her research is in human-centered computing: user modeling, personalization and social computing, recommender systems, intelligent tutoring systems, incentive, trust and reputation mechanisms, persuasive technology, and behavior change.

Juho Hamari is a Professor at the Faculty of Information Technology and Communications, Tampere University. He leads the Gamification Group and the Research Centre of Gameful Realities. His group focus on multidisciplinary and multi-methodological gamification research and extended realities situated in domains striving for ecological, economical, and social sustainability.

Seiji Isotani is a Professor at the University of São Paulo, a Visiting Scholar at the Harvard Graduate School of Education, and the President-Elect of the International Society for AI in Education. He has made groundbreaking contributions to the fields of AI in Education, Gamified Learning, and Educational Technologies.