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Uncovering the theoretical basis of user types: An empirical analysis and critical discussion of user typologies in research on tailored gameful design ☆

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ABSTRACT

Gamification has become one of the main areas in information systems and human–computer interaction research related to users' motivations and behaviors. Within this context, a significant research gap is the lack of understanding of how users' characteristics, especially in terms of their preferences for gameful interaction (i.e., user typologies), moderate the effects of gamification and, furthermore, how gamification could be tailored to individual needs. Despite their prominence in classifying users, current typologies and their use in research and practice have received severe criticism regarding validity and reliability, as well as the application and interpretation of their results. Therefore, it is essential to reconsider the relationships and foundations of common user typologies and establish a sound empirical basis to critically discuss their value and limits for personalized gamification. To address this research gap, this study investigated the psychometric properties of the most popular player types within tailored gamification literature (i.e., Bartle's player types, Yee's motivations to play, BrainHex, and HEXAD) through a survey study (n = 877) using their respective measurement instruments, followed by a correlation analysis to understand their empirical relations and an exploratory factor analysis to identify the underlying factors. The results confirm that user typologies, despite their different origins, show considerable overlap, some being consistent whereas others contradicted theoretically assumed relationships. Furthermore, we show that these four user typologies overall factor into five underlying and fundamental dimensions of *Socialization, Escapism, Achievement, Reward Pursuit, and Independence*, which could be considered common concepts that may essentially reflect key determinants of user motivation in gamification. Our findings imply that future research and practice in tailored gamification design should shift the focus from developing and applying ever more nuanced typologies to understanding and measuring the key underlying determinants of user motivation in gameful systems. Moreover, given the considerable interrelationships between these determinants, we also argue that researchers should favor continuous representations of users' motivations in specific situations instead of a dichotomous operationalization of user types as static manifestations of their preferences.

1. Introduction

Gamification refers to technological, economic, cultural, and sociological initiatives to make reality more game-like as a way to provide new skills, stimulate motivational benefits, and promote overall positive growth and happiness (Hamari, 2019). As an umbrella term, it encompasses playful interventions and design approaches that range

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from the integration of individual game elements in non-gaming-related contexts (Schöbel et al., 2020), e.g. a leaderboard in a fitness application, over serious games that introduce a fully-fledged fictional or virtual environment (Krath et al., 2021), to the emergent penetration and redesign of reality as a game, as in the metaverse (Hamari, 2019). Gamification has been demonstrated to influence motivation, learning, and behavior change positively (Krath et al., 2021) in diverse areas, from education to professional training, management, marketing, healthcare, and sustainability (Seaborn and Fels, 2015).

Given the paradigm shift in gamification research from investigating whether gamification works to exploring how and when it works (Nacke and Deterding, 2017), more attention has been driven to understand further how game design and the respective induced game-like experiences differ among diverse individuals (Klock et al., 2020; Schöbel et al., 2021). Tailoring gamification design to individual characteristics, needs, and motivations promises to improve intended outcomes compared to "one-size-fits-all" approaches (Klock et al., 2020), i.e., uniform designs that present the same design elements to all users. In this regard, user typologies (or player typologies) are popular approaches in tailored gamification (Rodrigues et al., 2020) since they categorize people based on their motivations (e.g., Yee's motivations to play (Yee, 2006), Hexad types (Marczewski, 2015)) or behavioral patterns (e.g., Bartle's player types (Bartle, 1996), BrainHex types (Nacke et al., 2014)).

Because of their diverse bases, user typologies have been created differently. For example, BrainHex types were derived from players' neuronal activity (Nacke et al., 2014), while Yee's motivations to play were constructed from cluster analysis of players' motivations (Yee, 2006). However, research on prevailing user typologies has already identified many overlaps and shared ideas (Hamari and Tuunanen, 2014; De Vette et al., 2015; Krath et al., 2022). As tailored gamification research and practice are rapidly adopting diverse user typologies (Rodrigues et al., 2020) according to their popularity, there is an imperative need to critically reflect on their foundations (Martin et al., 2021) to understand their benefits and limitations better (Nacke and Deterding, 2017; Oliveira et al., 2023). The need to reconsider the value of user typologies in tailored gamification becomes even more crucial given recent research observations on their inconsistency over time (Santos et al., 2021, 2023), discrepancies between self-reported preferences and actual behaviors (Krath et al., 2023b; Weber et al., 2023), and unclear effectiveness (Oliveira et al., 2023).

Consequently, in this study, we aim to contribute to future research in the tailored gamification field by reflecting on the relationships between user typologies, exploring their underlying foundations, and thereby debating their merits and limitations for personalizing gameful experiences. Therefore, we investigate the psychometric properties and relationships among the four most common user typologies in gamification research (Klock et al., 2020): Bartle's player types (Bartle, 1996), Yee's motivations to play (Yee, 2006), BrainHex types (Nacke et al., 2014), and Hexad types (Marczewski, 2015) in a large-scale quantitative study design (n = 877). Subsequently, we use exploratory factor analysis to empirically identify whether there are common underlying concepts of the typologies that appear to be essential for tailoring game-like experiences. In doing so, this work provides an empirically grounded foundation to reconsider the basis of different user typologies as a popular means for tailored gamification and to discuss their value compared to other approaches. Two research questions serve as the direction for our study to accomplish this goal:

RQ1: *Are there significant relationships between different user types within the most common user typologies?*

RQ2: *Which underlying concepts are shared between different user typologies?*

By addressing these research questions, our investigation contributes to the literature by empirically evaluating potential relationships among user types delineated in prevalent typologies, while also understanding main underlying concepts to steer future research and development in tailored gamification. In analyzing the reliability and validity of these typologies, this study emphasizes the need for a shift in gamification design away from increasingly intricate typologies. Rather, we underscore the importance of focusing on understanding and measuring the core determinants of user motivation in gameful systems. Within the same lines, instead of applying user types as static representations of user preferences, we advocate for non-dichotomous operationalizations and continuous representations of user motivations in specific contexts.

The remainder of this paper is structured as follows: Section 2 introduces tailored gamification design and describes assumptions and applications of the most commonly employed user typologies in this field. Following that, Section 3 details our research methodology, and Section 4 presents the findings. Section 5 discusses these findings and their implications for theory and practice, while Section 6 reflects on potential limitations and Section 7 provides conclusive remarks.

2. Theoretical background

2.1. Tailored gamification

Since the inception of gamification, researchers and practitioners have identified numerous factors influencing gameful experiences. On the one hand, these factors pertain to contextual elements such as environments, settings, and application domains (Koivisto and Hamari, 2019). On the other hand, scholars have explored the impact of personal attributes in shaping these experiences (De Vette et al., 2015), including demographics (Denden et al., 2021), personality traits (Jia et al., 2016; Orji et al., 2017), and goal orientations (Hakulinen and Auvinen, 2014; Auvinen et al., 2015).

In this direction, *tailored gamification* emerged as a strategy for personalization, adaptation, or recommendation that aims to align different game elements with individual and contextual needs (Klock et al., 2020). Also referred to as *adaptive gamification design*, this strategy stands as a prominent theme in the ongoing academic discourse on gamification (Schöbel et al., 2020, 2021). Different approaches to tailored gamification (e.g., manual classification, adaptation rules, recommender systems) tend to rely primarily on user modeling. Thus far, user modeling typically requires individuals to provide information about their personal characteristics and preferences, often incorporating insights from a questionnaire about game preferences and play styles (Klock et al., 2020). In this context, user typologies, representing the most prevalent approach to tailored gamification design (Klock et al., 2020; Hallifax et al., 2019b; Rodrigues et al., 2020), have received considerable scholarly attention in recent years.

2.2. User typologies

User typologies, such as Bartle's player types (Bartle, 1996) or Hexad types (Marczewski, 2015), categorize individuals based on different characteristics, motivations, needs or preferences for game design elements (Tondello et al., 2016; Nacke et al., 2014). Various studies have employed user typologies in tailored gamification in different contexts like service applications (Akasaki et al., 2016) and learning environments (Lavoué et al., 2018). However, a critical examination of previous studies indicates that the value and benefits of such user typologies ultimately remain unclear, and studies strongly advocate for understanding the suitability of user types in tailored gamification (Oliveira et al., 2023).

On the one hand, studies have demonstrated that user typologies can prove advantageous in understanding user needs, predicting user behavior, and personalizing gamification design. For instance, Lopez and Tucker (2019) observed correlations among Hexad types, individual perceptions of game elements, and user behavior in a gameful application. Previous work that has tailored gamification based on user typologies has demonstrated enhanced affective experiences and user performance in fitness (Altmeyer et al., 2021; Zhao et al., 2020), learning (Lavoué et al., 2018), and workplace (Passalacqua et al., 2021) applications.

On the other hand, an increasing number of studies also highlighted their limitations. For instance, observations by Krath et al. (2023a) and Weber et al. (2023) indicated discrepancies between certain user types' self-reported game element preferences and their actual behavior in gamified systems. Other studies found that user types exhibit high fluctuation and inconsistency over time (Santos et al., 2021, 2023). Overall, scholars have raised questions about the adequacy of modeling tailored gamification to understand users' needs based on a single dominant characteristic (Hallifax et al., 2019b).

In light of these considerations, it emerges essential to reconsider (a) the origins and assumptions underlying the currently popular user typologies in gamification research along with a reflection of their suitability for tailored gamification, which has been highly debated (Bateman et al., 2011; Busch et al., 2016b; Tondello et al., 2018), (b) the actual empirical interconnections between these typologies and the key underlying concepts that might be valuable to consider in tailored gamification (Krath et al., 2022), as studies have indeed emphasized the significance of these typologies, and (c) the implications of both shared characteristics and distinctive differences for their merits and limitations in tailored gamification design (Oliveira et al., 2023).

2.3. Common user typologies in tailored gamification

As the most prominent user typologies in gamification research (Klock et al., 2020), this study focuses and, hereby, explains the origins and assumptions of Bartle's player types (Bartle, 1996), Yee's motivations to play (Yee, 2006), BrainHex types (Nacke et al., 2014), and Hexad types (Marczewski, 2015). In addition, we present the current scientific debate on their applicability for tailored gamification design.

2.3.1. Bartle's typology

Bartle's typology (Bartle, 1996) is among the earliest classifications for video game player types (Dixon, 2011). By examining the fundamental motivations that drive players in Multi-User Dungeon (MUD) games, Bartle conducted a qualitative analysis of bulletin board posts that inquired about players' motivations in MUDs, leading to the identification of two primary dimensions for categorizing players: (1) action vs. interaction; and (2) player orientation vs. world orientation. Through the interrelationship between these two dimensions, Bartle (1996) identified four distinct player types, each characterized by unique motivations and behaviors within MUDs: those who prefer to *act* in the *world* to reach higher levels (i.e., **Achievers**); those who prefer to *interact* with the *world* to learn all the tricks and locations available in the game (i.e., **Explorers**); those who prefer to *act* and impose themselves on other *players* (i.e., **Killers**); and those who prefer to chat and *interact* with fellow *players* (i.e., **Socializers**). Although these types are quite distinct, they are not mutually exclusive, and the player can be a predominant type, a combination of some types, or even all types. Bartle's player types can be assessed with a questionnaire, such as the 12-item player type scale by Kocadere and Çağlar (2018).

Despite being regularly employed in gamification research, this typology has faced criticism over time. This critique includes its limited applicability, as it was rooted in players' motivations within a very specific setting (MUDs), restricting its generalizability to gamification in a broader sense (Bateman et al., 2011). Furthermore, the absence of empirical validation poses a significant concern, raising questions about its utility for scientific purposes (Bateman et al., 2011; Busch et al., 2016b).

2.3.2. Yee's typology

Building upon Bartle's typology and qualitative research, Yee (2006) investigated players' motivations to play Massively-Multiplayer Online Role-Playing Games ("MMORPGs"). Yee created a list of 40 items to assess what makes people engage in these games and what keeps them playing, later sharing it among 3000 MMORPG players via online surveys. Based on a two-phase clustering approach to these responses, Yee identified ten motivations, which were grouped into three main components. Motivations related to **Achievement** were *Advancement*, *Mechanics*, and *Competition*. **Social** motivations included *Socializing*, *Relationship* and *Teamwork*. Lastly, motivations related to **Immersion** consisted of *Discovery*, *Role-Playing*, *Customization*, and *Escapism*. A questionnaire to assess a score in each of the three main components has been provided (Yee et al., 2012).

Although these findings are very relevant to understanding player motivation, Yee's motivations to play are very domain-specific (i.e., they were derived based on MMORPG players), similar to Bartle's typology. This limitation has been acknowledged by Yee et al. (2012) themselves. Thus, the generalizability of the proposed three-factor model and these motivations for gamification is potentially limited.

2.3.3. BrainHex typology

The BrainHex typology (Nacke et al., 2014) derives from demographic game design studies and neurobiological research. This typology relates players' motivation to the neurobiological reactions of the human body, describing seven different user types: **Achievers** are motivated by overcoming challenges, attaining goals, and the satisfaction of completing collections; **Conquerors** are motivated by defeating impossibly difficult foes, struggling until they achieve victory, and defeating other players; **Daredevils** are motivated by the thrill of the chase, the excitement of risk-taking, and playing on the edge; **Masterminds** are motivated by the strategic planning, puzzle-solving, and making optimal choices; **Seekers** are motivated by interest, curiosity on game worlds, and moments of wonder; **Socializers** are motivated by social interactions, engaging with other players, offering assistance, and socializing in virtual realms; and **Survivors** are motivated by frightening in-game situations and the intensity of the associated experience.

Despite over 50,000 people completing the BrainHex survey (Nacke et al., 2014) and self-selecting their types based on descriptive texts, this typology faces challenges similar to those of other typologies. For instance, Busch et al. (2016b) found that only two types, Socializer and Achiever, could be reliably differentiated through confirmatory factor analysis, and issues related to test-retest reliability emerged over time. Additionally, when attempting to employ BrainHex types as predictors of the game experience with appropriate game mechanics, Busch et al. (2016a) discovered no significant relationships. Furthermore, Tondello et al. (2018) re-evaluated the 50,000+ BrainHex survey responses via exploratory factor analysis, discerning only three stable factors instead of the original seven proposed. These findings cast doubt on the seven-factor structure advocated by BrainHex, impairing its scientific validity.

2.3.4. Hexad typology

The Hexad typology (Marczewski, 2015) was developed to assess and investigate user preferences within gamified systems (Orji et al., 2018; Tondello et al., 2016). It finds its basis in self-determination theory (Ryan and Deci, 2000), drives theory (Pink, 2011) and practical gamification design expertise (Tondello et al., 2016). This typology establishes six user types, each varying in their emphasis on autonomy, relatedness, competence, and extrinsic motivation (as introduced in self-determination theory), and their orientation towards purpose (derived from the four drives theory) (Marczewski, 2015). In detail, the Hexad types are **Achievers**, whose core driving force arises from overcoming obstacles and mastering challenging tasks; **Disruptors**, who are driven by the satisfaction of pushing the boundaries of systems and the desire to effect (positive or negative) change; **Free Spirits**, whose

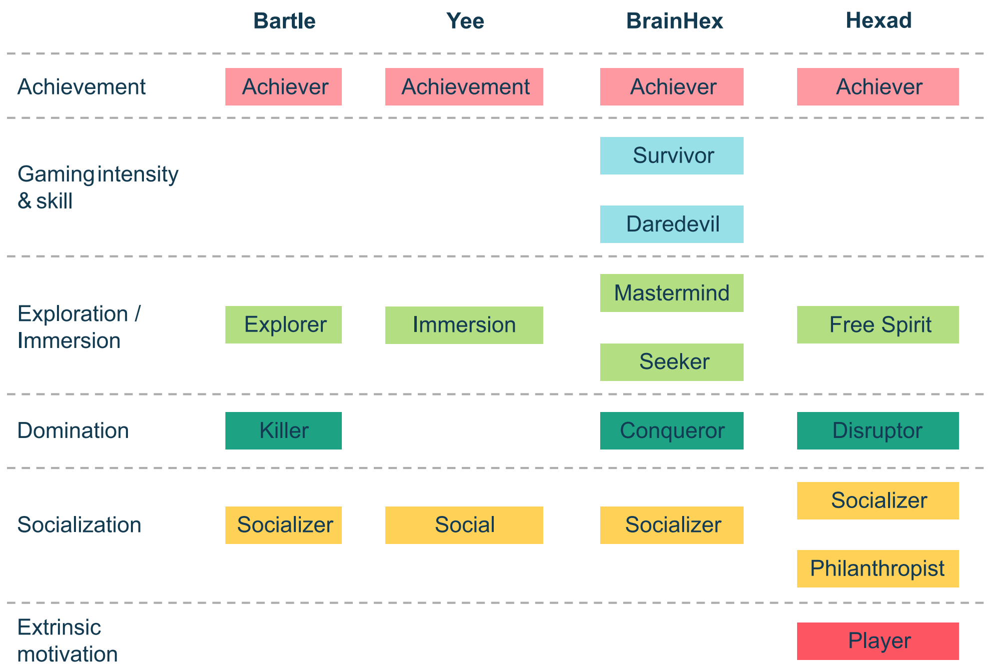


Fig. 1. Theoretically assumed relationships and shared concepts between common user typologies based on Hamari and Tuunanen (2014), Nacke et al. (2014), De Vette et al. (2015) and Krath et al. (2022).

motivation derives from autonomy, thriving when they can act without external constraints and valuing their independence and freedom to make choices; **Philanthropists**, who are driven by a sense of purpose, especially appreciating social interactions, taking on responsibilities, and actively sharing knowledge with their peers; **Players**, who are primarily striving to achieve extrinsic rewards, making these rewards a central focus of their engagement; and **Socializers**, who prioritize interactions with others as their primary motivation, with a significant emphasis on nurturing connections and relationships (Marczewski, 2015).

The original questionnaire to identify people's Hexad user types was created by Tondello et al. (2016) and has been validated empirically multiple times (Tondello et al., 2019; Ooge et al., 2020), while a shorter version was also created more recently by Krath et al. (2023a). While this typology can explain preferences for game elements across various domains (Tondello et al., 2016), studies have also identified difficulties in the psychometric properties of certain types (e.g., Free Spirits, Ooge et al. (2020) and Tondello et al. (2019)) and pointed to difficulties in its application to predicting actual behavior (Weber et al., 2023; Krath et al., 2023b).

2.4. Relationships between common user typologies

Several relationships and shared concepts can be observed based on how the different typologies characterize their user types. These observations were analyzed and discussed as part of existing research. For instance, Hamari and Tuunanen (2014) conducted a literature review on user typologies in games research and suggested synthesizing them into seven key dimensions: Skill, Achievement, Exploration, Sociability, Killer, Immersion and In-game demographics. However, it must be considered that BrainHex and Hexad were not yet available during their review. Thus, their findings rely on Yee's motivations, Bartle's player types and other rather context-specific typologies or extensions of Bartle's or Yee's models (e.g., Zackariasson et al. (2010) and Tseng (2011)). Also, the key dimensions were derived based on analyzing and grouping specific ideas that recurred across papers, i.e., without empirical evidence for these key dimensions. Similarly, when introducing the BrainHex typology and explaining the different archetypes, Nacke et al. (2014) discussed relationships between them and existing typologies, such as Yee's and Bartle's typologies. Likewise, De Vette et al. (2015) provide an overview of existing typologies (Hexad, Bartle's player types, Yee's motivations) to conceptualize gamification approaches that specifically target older adults. Lastly, Krath et al. (2022) contribute valuable insight into potential relationships between user typologies by analyzing users' behavioral data in a gamified fitness application to identify clusters. Based on the seven clusters they identified, the paper discusses potential relationships between these behavioral clusters and existing user typologies but also draws conclusions about how existing typologies (Hexad, BrainHex, Yee's motivations, and Bartle's player types) interrelate.

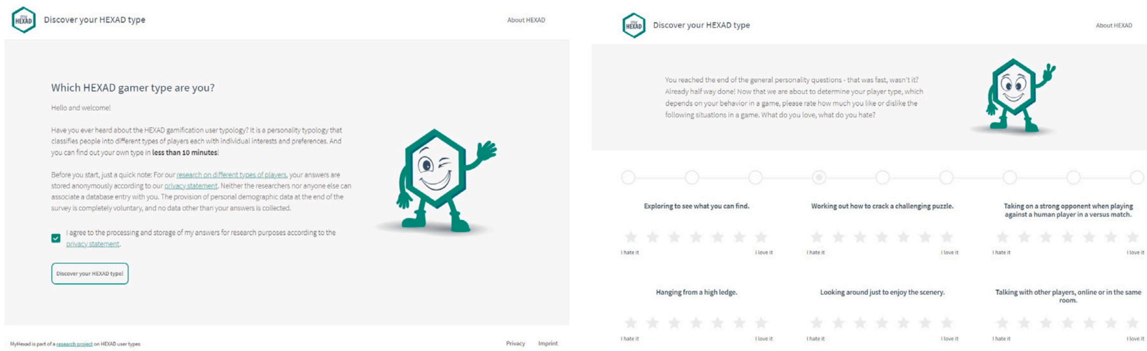
Based on these theoretical assumptions, we derive a conceptual model of the underlying dimensions shared across the four different typologies that we focus on in this paper. An overview of this conceptual model can be found in Fig. 1. In contrast to previous research efforts, our study focuses on contributing an empirical investigation of this conceptual model and investigating whether the hypothesized relationships between the different typologies can be empirically supported.

3. Method

To empirically investigate significant relationships between user types (RQ1) and shared underlying concepts of common user typologies (RQ2), we performed a quantitative survey design with the four most popular user types in gamification research (Klock et al., 2020), as previously introduced: Bartle's player types (Bartle, 1996), Yee's motivations to play (Yee, 2006), BrainHex types (Nacke et al., 2014), and Hexad types (Marczewski, 2015). Specifically, we collected the results of the subscales of the different user typologies from $n = 877$ participants from all over the world and first analyzed the psychometric properties of the scales, then their correlations and, finally, through an exploratory factor analysis, the common factors underlying the scales.

3.1. Data collection

We set up an online survey with 57 items from validated questionnaires that capture the user types of each of the aforementioned typologies, as shown in Tables 5 to 8 in Appendix. Specifically, we



(a) Title page. (b) Exemplary page of the survey.

Fig. 2. Title page and an exemplary page of the survey.

opted for short versions of the user type scales whenever possible to shorten the overall survey length and, consequently, lower the chances of dropouts and random answering (Herzog and Bachman, 1981; Bansak et al., 2018). Therefore, we used the 12-item Bartle's player type scale (Kocadere and Çağlar, 2018), the 12-item online gaming motivations scale (Yee et al., 2012), the 21-item BrainHex questionnaire (Busch et al. (2016b), referring to Nacke et al. (2014)), and the 12-item short version of the Hexad scale (Krath et al., 2023a). Furthermore, since the questionnaires used different scaling (e.g., BrainHex items are measured on a 7-point Likert scale from "I love it" to "I hate it" and refer to situations in a game, while Hexad items are measured on a 7-point Likert scale from "totally disagree" to "totally agree" and describe more general statements about oneself as a player), we decided against random ordering.

To avoid the question order bias (Perreault, 1976) imposed by this decision and keep attention and interest throughout the survey, we kept the items grouped regarding their focus (i.e., general questions about one's preferences of Bartle's player types and Hexad, specific in-game motivations of Yee and specific behaviors of BrainHex) and divided the survey into multiple pages with distinct sections labeled for easier cognitive processing (Müller et al., 2014). Accordingly, we framed the survey as a single "player type personality test" that entailed different questions about oneself (i.e., Hexad and Bartle typologies), one's behavior while playing (i.e., BrainHex typology), and one's motivations to play a game (i.e., Yee typology), which was later calculated solely based on Hexad typology. The survey began with the questions about oneself, with the Hexad questions displayed first, followed by Bartle's player type scale, after which the behavior-related questions (i.e., BrainHex) were displayed, and concluded with Yee's motivations to play to progress from more general to more specific questions. Whereas the survey always followed this specific order, the survey pages would still randomize the questions within each measurement tool to avoid order effects bias. We decided to display only the Hexad results, as the Hexad typology calculation was already implemented in the survey system, and we believed that displaying multiple user types from different typologies could lead to cognitive overload for participants. Fig. 2(a) shows the title page of the survey, Fig. 2(b) illustrates a page of the survey with a section explanation on top, and Fig. 3 shows the results page of the survey with the personal player type profile calculated based on the answers to Hexad items.

At the end of the user typologies questions, we also asked participants to optionally provide information on their age, gender, and country of origin. We kept those questions voluntary to avoid dropouts based on this personal information.

We advertised the survey as a player type personality test on Facebook, targeting adult users (age 18–60) as user typologies have been shown not to be universally applicable to adolescents or children (Ooge et al., 2020), originating from five continents (Europe, America, Africa, Asia, and Australia) and speaking English (to avoid any bias caused by language barriers and misunderstanding). In addition, we focused our advertising on users interested in gaming and gaming-related terms, e.g., e-sports, video games, Steam, or MMORPGs. The reason why we decided to use targeted advertising as opposed to recruiting on common crowdsourcing sites (e.g., Amazon MTurk, Prolific) where participants are compensated for survey completion is that such sites have been criticized for low answer quality due to inattention from crowd workers and missing representativeness of the general population (Harms and DeSimone, 2015; Hauser et al., 2019). With our approach based on curiosity rather than compensation, users decided freely to take part in the survey, and it is more likely that they answered the survey honestly and attentively to get a true player type at the end.

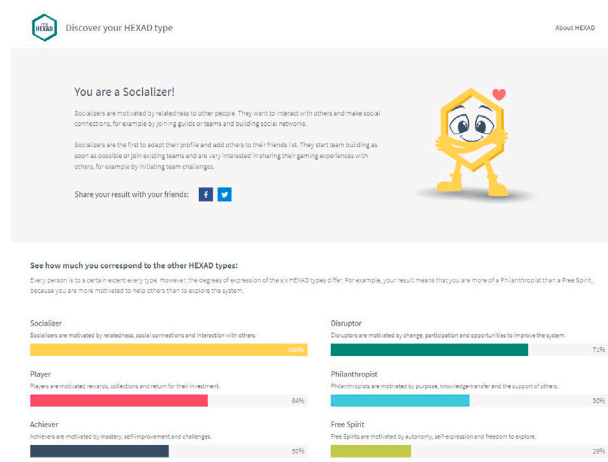


Fig. 3. Results page of the survey with the personal player type calculated based on the answers to the Hexad items.

3.2. Participants

From 1026 participants who completed the online survey, we decided to exclude 74 participants whose participation lasted less than two minutes or more than 15 min, potentially indicating inattention. For the remaining 952 participants, the mean duration was 326 s (5:26 min), with a median of 292 s (4:52 min).

Furthermore, 847 of these 952 participants provided information on their age. Since we focused on adults, we excluded an additional 75 participants who indicated to be 17 years old or younger and may either have been forwarded the survey by others or got the advertisement by accident, resulting in a final sample of 877 participants.

Table 1
Distribution of countries of origin from the participants.

Country	No.	%
Europe	**430**	**56.7%**
France	75	9.9%
Italy	65	8.6%
Portugal	53	7.0%
Spain	41	5.4%
Czechia	32	4.2%
Germany	18	2.4%
Belgium	16	2.1%
Poland	16	2.1%
Hungary	15	2.0%
Other (Netherlands, Finland, Sweden, United Kingdom, Austria, Norway, Denmark, Cyprus, Armenia, Latvia, Ireland, Slovakia, Ukraine, Romania, Croatia, Serbia, Bosnia and Herzegovina, Estonia, Bulgaria, North Macedonia, Albania, Greece, Andorra, Turkey)	99	13%
America	**296**	**39%**
Canada	158	20.8%
United States of America	120	15.8%
Brazil	8	1.1%
Venezuela	3	0.4%
Other (Chile, Argentina, Cuba, Peru, Ecuador)	7	0.9%
Asia	**25**	**3.3%**
Philippines	6	0.8%
India	4	0.5%
Pakistan	4	0.5%
Indonesia	3	0.4%
Other (Sri Lanka, Nepal, Myanmar, Bangladesh, Republic of Korea, Kazakhstan)	8	1.1%
Africa	**4**	**0.5%**
South Africa	3	0.4%
Cabo Verde	1	0.1%
Australia	**4**	**0.5%**

Of these 877 participants (out of which 772 provided age information), the mean age was 27.6 years old ($MD = 26.0, SD = 7.46$), with a minimum of 18 and a maximum of 50 years old.

Moreover, 763 of the 877 participants provided information on their gender. Out of them, 248 identified as women (32.5%), 453 identified as men (59.4%) and 62 identified as other than women or men (8.1%). In addition, 759 of the 877 participants provided information on their country. As Table 1 shows, the majority of participants were from Europe, followed by America. Only a minority stemmed from Asia, Africa and Australia.

3.3. Data analysis

We performed our data analysis to address our research questions in three steps using the open-source statistics software Jamovi.

First, we considered the psychometric properties of the user typologies' subscales as a basis to reflect on their suitability for tailored gamification design and decide whether the user typologies can be confidently considered in the subsequent analyses of empirical relationships (RQ1) and underlying concepts (RQ2) (Fabrigar et al., 1999). Therefore, we assessed convergent validity by analyzing composite reliability (CR) (with a cutoff of >.70, Zaiţ and Bertea (2011)) and average variance extracted (AVE) (with a cutoff of >.50, Fornell and Larcker (1981)). In addition, we considered the model fit of the different typologies through confirmatory factor analysis and analyzed the χ^2 test (with $\frac{\chi^2}{df} < 3$ indicating a good fit, Schermelleh-Engel et al. (2003)) and the root mean square error of approximation (RMSEA) (with RMSEA <.06 indicating a good fit, Fabrigar et al. (1999)).

Second, we performed a correlation analysis of the subscales to investigate the empirical relationships between user typologies (RQ1). In order to decide whether to opt for Pearson's correlation coefficient or Kendall's τ_b, we checked whether the subscales were normally distributed through the Shapiro–Wilk test.

Table 2
Model fit values of the four user typologies.

	Bartle	Yee	BrainHex	Hexad
$\frac{\chi^2}{df}$	7.083	8.235	4.214	2.513
RMSEA	0.083	0.091	0.061	0.042

Third, we performed an exploratory factor analysis of the subscales to explore the underlying factors shared by the different user typologies (RQ2). The exploratory factor analysis is particularly suitable to uncover the number and nature of common factors needed to account for the pattern of correlations (Fabrigar et al., 1999). We explicitly used exploratory factor analysis based on the common factor model, as opposed to principal component analysis, because our main goal was to identify latent constructs rather than reduce data (Fabrigar et al., 1999). As preconditions, we checked the Kaiser–Meyer–Olkin criterion as a measure of sample size adequacy and Bartlett's Test of Sphericity to test if data exhibited enough relationships for detecting factors (Shrestha, 2021). Afterward, we performed parallel analysis to determine the number of factors to extract, which has been stated to be more accurate than the Kaiser-Criterion (which tends to over-factoring) and the Scree Plot analysis (which is mostly subjective) (Fabrigar et al., 1999). After that, we decided to use the principal axis (PA) method because research has shown that it works better than the maximum likelihood method under most circumstances (De Winter and Dodou, 2012). Lastly, we chose an oblique Promax rotation for factor extraction, as previous research had found correlations between user types within the typologies (Tondello et al., 2019; Krath et al., 2023a). We also assumed there would be correlations between the underlying factors, suggesting an oblique rotation (Fabrigar et al., 1999).

4. Results

4.1. Psychometric properties of the user typologies

The analysis of AVE and CR of the subscales as measures of convergent validity showed that all Hexad types and Yee's Social and Immersion dimensions have acceptable convergent validity (CR >.70, Zaiţ and Bertea (2011), AVE >.50, Fornell and Larcker (1981)). Moreover, Bartle's Killer, Socializer and Explorer showed acceptable convergent validity, as well as BrainHex's Seeker, Survivor, Socializer and Achiever.

Regarding model fit (Table 2), only the Hexad typology had an acceptable model fit ($\frac{\chi^2}{df} < 3$, Schermelleh-Engel et al. (2003) and RMSEA < .06, Fabrigar et al. (1999)), with BrainHex at least on the edge of the RMSEA criterion. Overall, except for Hexad, all typologies show room for improvement in model fit.

Investigating potentially problematic items, we excluded AY4 from the Achievement subscale of Yee's motivations, which led to an acceptable convergent validity (AVE = 0.60, CR = 0.82). In addition, we excluded COBH2 from the Conqueror subscale of BrainHex, which increased AVE and CR to acceptable values. No single problematic item could be identified for the other scales that still showed severe issues in terms of convergent validity (Bartle's Achiever, BrainHex's Daredevil, and BrainHex's Mastermind). Thus, we excluded those types from further analysis due to the risk of commonalities (Fabrigar et al., 1999).

4.2. Empirical relationships between user typologies

The Shapiro–Wilk test, which is the most powerful statistical test for normal distribution (Razali et al., 2011), indicated a violation of the assumption of normality for all user typologies subscales. Consequently, we used Kendall's τ_b to examine the relationship between user types of the different typologies. To facilitate understanding, we only illustrated

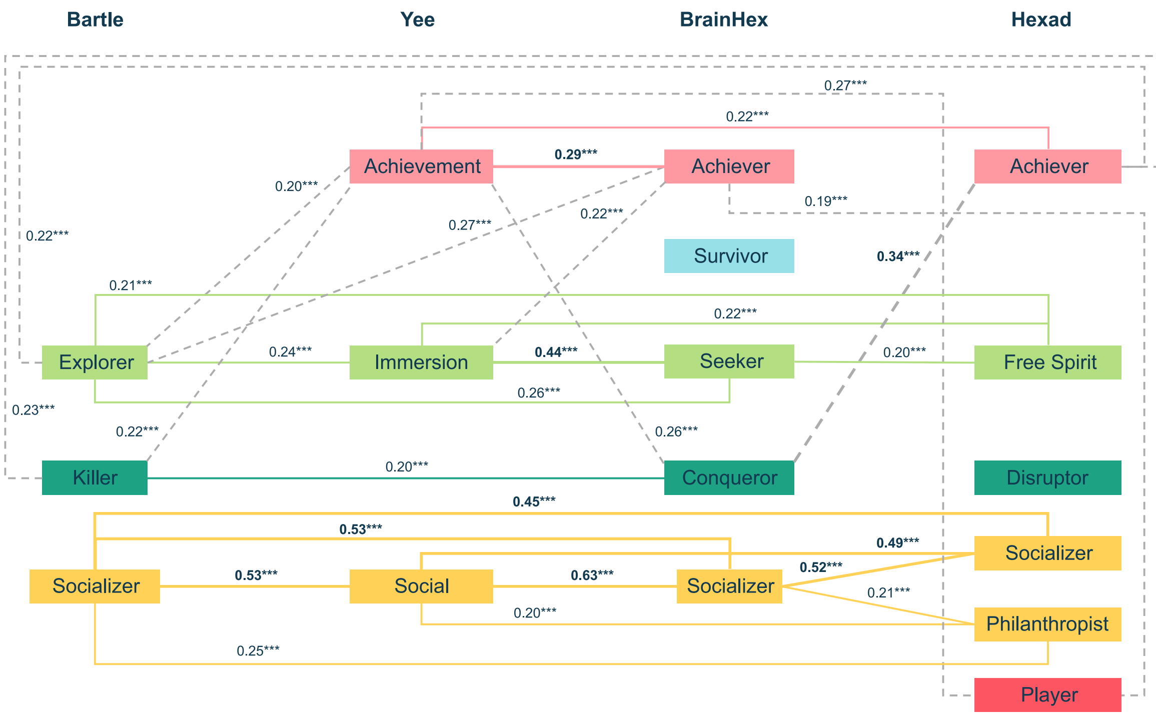


Fig. 4. Correlations between the user types of different user typologies. Straight lines indicate relationships in accordance with theoretical assumptions (Hamari and Tuunanen, 2014; De Vette et al., 2015; Nacke et al., 2014; Krath et al., 2022), dotted lines illustrate unexpected relationships (*** = $p \leq .001$).

at least moderate ($\tau_b \geq 0.19$, Botsch (2011)) relationships between the user types of different user typologies in Fig. 4, with interrelationships within the typologies not displayed to enhance the overview of relations between the typologies. The totality of the results can be found in the Appendix (Tables 9 and 10).

In accordance with the theoretical assumptions of previous work on user typologies (Hamari and Tuunanen, 2014; De Vette et al., 2015; Nacke et al., 2014; Krath et al., 2022), we find strong ($\tau_b \geq 0.29$, Botsch (2011)) relationships between all socially-oriented types of the four typologies and moderate relationships between Yee's Social motivation and Bartle's and BrainHex's Socializer with Hexad's Philanthropist.

Similarly, we find empirical evidence for theoretically assumed relationships among exploration-oriented types (i.e., BrainHex's Seeker, Yee's Immersion motivation, Bartle's Explorer, and Hexad's Free Spirit), with strong ($\tau_b = .44$) relationships between the Seeker and the Immersion motivation and moderate relationships between the other exploration-oriented types.

Moreover, we find evidence for relationships between the achievement-oriented types of the BrainHex, Yee and Hexad typologies (as Bartle's Achiever was excluded based on its low reliability and convergent validity), even though only some are directly related. Specifically, BrainHex's Achiever is strongly associated with Yee's Achievement motivation but not with Hexad's Achiever. However, Hexad's Achiever is also moderately related to Yee's Achievement motivation.

Looking into the types that are theoretically assumed to reflect the concept of dominance (Hamari and Tuunanen, 2014; De Vette et al., 2015; Krath et al., 2022) (i.e., BrainHex's Conqueror, Bartle's Killer and Hexad's Disruptor), empirical relations were less clear. While a moderate relationship between the Conqueror and the Killer appeared, they were both related to Hexad's Achiever rather than Disruptor, and they also show moderate relationships with Yee's Achievement motivation. Meanwhile, Hexad's Disruptor does not seem to be associated with any other user type apart from a moderate interrelationship with Hexad's Free Spirit.

BrainHex's Survivor, which is particularly characterized by seeking thrill and excitement while playing (Nacke et al., 2014), seems to indeed represent a unique user type among the typologies, as it was not related to any other user type, except for a moderate interrelationship with BrainHex' Conqueror (see Table 9).

Finally, regarding Hexad's Player as the sole extrinsically motivated type of the four typologies (Marczewski, 2015), the analysis shows moderate relations to other user types, particularly Yee's Achievement motivation and BrainHex's Achiever, in contrast to theoretical suggestions.

4.3. Underlying factors shared by different user typologies

The Kaiser–Meyer–Olkin test (KMO > 0.6 for all subscales) and Bartlett's test for sphericity ($\chi 2 = 4799$, df = 136, p < .001) demonstrate the suitability of the data for factor analysis (Shrestha, 2021). The parallel analysis suggests the extraction of five factors, with the resulting rotated factor matrix based on the PA extraction indicating largely strong factor loadings (>0.6, Beavers et al. (2013)) with two cross-loadings. Table 3 shows the factor loadings, with all loadings >0.3 as at least moderate loadings represented (Tavakol and Wetzel, 2020).

In line with the observations from the correlation analysis, the first factor appears to unite all the socially related types of the four typologies. In addition, Hexad's Philanthropist also appears to load mainly on the first factor, although the loading is comparatively low at 0.32.

The second factor seems to reflect the concept of immersion or exploration. BrainHex's Seeker and Yee's Immersion dimension show strong loadings on this factor, and Bartle's Explorer shows at least a moderate loading. Unexpectedly, Hexad's Free Spirit, with a comparatively low loading of 0.32, does not load particularly well on this factor, having a higher loading on Factor 5.

Factor 3 and Factor 4 seem surprising in light of previous theoretical assumptions that distinguish user types based on achievement orientation, domination orientation and extrinsic motivation (Hamari and Tuunanen, 2014; De Vette et al., 2015; Nacke et al., 2014; Krath et al., 2022). On the one hand, Factor 3 combines the domination-oriented types (BrainHex's Conqueror and Bartle's Killer, even if the

Table 3
Results of the exploratory factor analysis. Extraction method: Principal axis. Rotation: Promax.

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
Social (Yee)	0.94					0.21
Socializer (BrainHex)	0.90					0.23
Socializer (Bartle)	0.86					0.32
Socializer (Hexad)	0.74					0.38
Philanthropist (Hexad)	0.32					0.71
Seeker (BrainHex)		0.74				0.41
Immersion (Yee)		0.69				0.50
Explorer (Bartle)		0.44				0.66
Conqueror (BrainHex)			0.72			0.51
Achiever (Hexad)			0.64			0.59
Survivor (BrainHex)			0.39			0.81
Killer (Bartle)			0.31			0.55
Achievement (Yee)				0.67		0.46
Achiever (BrainHex)		0.41		0.57		0.54
Player (Hexad)				0.50		0.74
Disruptor (Hexad)					0.64	0.66
Free Spirit (Hexad)		0.32			0.35	0.72

Table 4
Inter-factor correlations of the five factors identified in the exploratory factor analysis.

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1	–	0.028	0.316	−0.016	−0.263
Factor 2		–	0.183	0.151	0.024
Factor 3			–	0.489	0.305
Factor 4				–	0.359

Killer's loading is comparatively low) with Hexad's Achiever and BrainHex's Survivor. On the other hand, Factor 4 is represented by Yee's Achievement motivation, BrainHex's Achiever and Hexad's Player. Although this result is consistent with the results of the correlation analysis, which showed strong to moderate relationships between the Conqueror and Killer and Hexad's Achiever and moderate relationships between Hexad's Player and Yee's Achievement as well as BrainHex's Achiever, it does not correspond to the theoretical assumptions of previous studies.

Finally, the Disruptor from Hexad and the Free Spirit from Hexad load the most on the fifth factor. Again, although the result of the correlation analysis suggests that the Disruptor is unrelated to any of the other types, it is surprising that the Free Spirit appears more closely related to the Disruptor than the other exploration-oriented types.

An analysis of the inter-factor correlations reveals that they do not appear independent. Instead, they show considerable intercorrelations (Table 4). Factor 1 and Factor 3, in particular, are closely related, and Factor 3 is likewise linked to Factor 4 and Factor 5. Finally, Factor 4 and Factor 5 also show a remarkable correlation. It is also interesting to note that Factor 1 and Factor 5 have a remarkable negative relationship.

5. Discussion and implications

5.1. Key findings

Since there is an increasing focus on user typologies in tailored gamification, researchers and designers are reflecting on the merits and limitations emerging from this personalization. In line with this, the presented work empirically investigated the relationships (RQ1) and shared underlying factors (RQ2) of common user typologies in gamification research to support tailored gamification. Our analysis has led to three key findings that entail important implications for theory and practice:

(1) We found that **most common user typologies have room for improvement in terms of reliability and validity**. By analyzing the psychometric properties of the four examined user typologies, we see that all but the Hexad typology present issues in the convergent validity of the measurement instrument concerning the factors in at least some sub-scales and the overall model fit. Although user typologies take a variety of approaches to differentiating players (e.g., Hexad and Bartle concentrate on general self-report questions, Yee on motivations to play, and BrainHex on in-game behaviors), this initial finding suggests that not all of the dimensions of user needs or behaviors assumed by the typologies may be based in empirical data and accurately captured by the measurement instruments, which supports concerns of their validity (Bateman et al., 2011; Busch et al., 2016a; Tondello et al., 2018). Given that several studies have found considerable overlap between different user types (Krath et al., 2023a; Tondello et al., 2019), we can assume that not all proposed types within a user typology are justified and, even that some of these types may be measuring nuances of a similar underlying concept, as shown in Table 9.

(2) We found **significant empirical relationships between user types of different typologies**, and we identified **five underlying factors** that seem to unite certain types of different typologies. The underlying dimensions (Table 3) are consistent with the relationships found in the correlation analysis, which are illustrated in Fig. 4. Also, similar to various user types within different typologies (Krath et al., 2023a; Tondello et al., 2019), the factors show remarkable intercorrelations (i.e., *they do not seem to be independent of each other*). In critical consideration of the item level, they appear to reflect five concepts:

- *Socialization:* The first factor combines all user types of the four typologies that relate to the concept of socialization, be it characterized by their social motivations to play (e.g., keeping in touch with friends and teaming up with other players), their behaviors (e.g., cooperating with strangers), or general statements about themselves (e.g., liking to be part of a team). In addition to Bartle's, BrainHex's and Hexad's Socializer and Yee's Social dimension, this first underlying factor also includes Hexad's Philanthropist, whose altruistic tendency (e.g., liking to help others) was distinguished to reflect their sense of purpose (Marczewski, 2015). Given their substantial relationships with the socially oriented types of the other typologies, their underlying drive may still be primarily social in nature.
- *Escapism:* The second factor combines Bartle's Explorer, Yee's Immersion dimension and BrainHex's Seeker. Hexad's Free Spirit also loads lightly on this factor but loads heavier on another factor with Hexad's Disruptor. Given the theoretical assumptions that classify all four types as exploration-oriented (De Vette et al., 2015; Hamari and Tuunanen, 2014; Krath et al., 2022), this factor initially seems surprising. However, when looking at the items that measure these types, it becomes clear that the first three types relate to concepts such as curiosity and discovery (Explorer, Immersion, Seeker) as well as immersion and enjoyment of the story (Immersion, Seeker), while the Free Spirit items tend to

reflect the concept of independence (Krath et al., 2023a). Considering that this factor, therefore, primarily represents discovery and immersion in a fictional game environment or story *distinct* from the real world, the moderate cross-loading of BrainHex's Achiever could also be explained since it reflects their desire to complete everything (i.e., including the story) in a game.

- *Achievement:* The third factor challenges the distinction between achievement and dominance made in theoretical discussions of the relationships among user typologies (De Vette et al., 2015; Hamari and Tuunanen, 2014). It combines Bartle's Killer, BrainHex's Conqueror and Survivor, and Hexad's Achiever. Again, a critical look at the item level reveals an underlying factor related to the concept of overcoming a challenge, either for oneself (Conqueror, Survivor, Achiever) or against others (Killer). While the Conqueror and Survivor were differentiated based on their preferred in-game behaviors (i.e., enjoying challenging scenarios or frightening situations, respectively Nacke et al. (2014)), both seem to relate to the general concept of achievement.
- *Reward Pursuit:* The fourth factor, in combination with the third factor, questions the theoretical assumption that all achievement-named user types reflect the same concept (Hamari and Tuunanen, 2014; De Vette et al., 2015; Krath et al., 2022). It combines BrainHex's Achiever, Yee's Achievement motivation, and Hexad's Player, which is surprising as the latest was conceptualized as an extrinsically motivated user type (Marczewski, 2015). However, examining the items, it becomes clear that BrainHex's Achiever does indeed refer to in-game behavior to obtain and collect in-game items, which could be experienced as a form of extrinsic reward, similar to collecting badges (Schürmann and Quaiser-Pohl, 2022; Shields and Chugh, 2017). Similarly, Yee's Achievement motivation refers to acquiring rare items and optimizing the character, possibly by obtaining valuable in-game items and augments. In this regard, it is easily perceived that these user types share a general focus on rewards and obtaining returns for their efforts.
- *Independence:* The fifth factor unites only two types from the Hexad typology, namely the Disruptor and the Free Spirit. Despite theoretical assumptions about connections between Bartle's Killer, BrainHex's Conqueror and Hexad's Disruptor (De Vette et al., 2015; Krath et al., 2022), we did not find any empirical relationships in the correlation analysis. Looking at the item level, we can see that the Free Spirit, as already explained, is concerned with independence. This core drive also appears to be expressed in the Disruptor, albeit in a more anti-authoritarian form (they consider themselves rebels and do not like to follow rules). We can, therefore, assume that both the Free Spirit and the Disruptor value, in different nuances, an underlying concept of independence.

(3) While the underlying factors seem to be fairly clear, we can also see that several types tend to show low and sometimes inconsistent loadings on the factors, which is particularly reflected in the two cross-loadings. While Yee's motivations and BrainHex's types often load comparatively strongly on the factors, Bartle's and Hexad's types load rather moderately on the factors and exhibit greater uniqueness, i.e., they contribute less to the variance of the factor model (Schreiber, 2021). In this regard, when looking at the items, it becomes apparent that the specific in-game motivations (Yee) and behaviors (BrainHex) seem to influence the factor structure more than general questions about one's own preferences (Bartle, Hexad). This underscores the suggestion that user types as a means of personalization work best for specific motivations and preferences in a particular setting (Santos et al., 2021, 2023).

5.2. Explanation and interpretation of the key findings

Our results show that, despite the different origins of the user typologies in our study, all user types seem to converge on a common theoretical basis, i.e., the five underlying concepts of Socialization, Escapism, Achievement, Reward Pursuit, and Independence. The closer the original typology is to this factor structure (e.g., distinct Hexad types are prevalent in four out of five factors, whereas Bartle's player types are reflected in only three of these factors), the better the model fit of the original typologies. At the same time, some highly nuanced types, such as the Mastermind and Daredevil of the BrainHex typology, which refer to very specific in-game behaviors that may not occur in every gameful system, do not show acceptable convergent validity. To interpret and discuss *why* we find that the typologies converge on these five underlying factors, which appear to be fairly clear despite some inconsistent loadings of individual types, we want to return to the origins of the typologies in an attempt to understand the reason certain typologies have a better or worse model fit and what these five concepts could actually reflect or summarize.

Reviewing the origins and developments of the typologies, it becomes apparent that Bartle (1996), Yee (2006), and Nacke et al. (2014) used *inductive* approaches to create their user categorizations. In this regard, Bartle (1996) adopted a qualitative approach to distinguish users based on their preferred actions and interactions with the world and other players in MUD games, while Yee (2006) opted for a quantitative clustering approach to identify game motivations in the context of MMORPGs. Nacke et al. (2014) did not focus on a specific game genre, but approached the distinction of different user types based on the neurobiological reactions of diverse players to different situations in games. In contrast, Marczewski (2015) *deductively* developed the Hexad model by building on self-determination theory (Ryan and Deci, 2017) and drive theory (Pink, 2011) to derive six user types that diverge in their emphasis on the basic psychological needs of autonomy, relatedness and competence, extrinsic rewards, and purpose.

Considering the model fit of the typologies, we observe that Hexad's deductive approach, guided by motivation theory, performs best in distinguishing different user types in gameful systems. In comparison, the inductive approaches show poorer model fit, which could be due to either their measurement approach or their domain specificity, as also echoed in several previous works (Bateman et al., 2011; Busch et al., 2016a,b; Tondello et al., 2018). Revisiting the main factors underlying the typologies we have identified from this theoretical perspective, we see that several types of different typologies might converge on common factors in conjunction with the three basic psychological needs that promote intrinsic motivation and varying regulations of extrinsic motivation of self-determination theory (Ryan and Deci, 2017), which guided the development of the Hexad. In particular, **Socialization** seems to coincide with the satisfaction of the need for *relatedness* (Ryan and Deci, 2017), as all user types in this concept emphasize social motivations to play and social behaviors (Xi and Hamari, 2019). The user types united in the concept of **Achievement** refer to the expectations of individual development and mastery of skills through overcoming challenges within a gameful environment. Thus, it could be related to the satisfaction of the need for *competence* in self-determination theory (Ryan and Deci, 2017; Xi and Hamari, 2019). **Independence** might connect to the satisfaction of the need for *autonomy*, i.e., a sense of freedom of choice and the absence of external coercion and pressure (Ryan and Deci, 2017; Sailer et al., 2017). Both the Disruptor and Free Spirit types from the Hexad model, which converge on this factor, express a desire for freedom of choice, either in an anti-authoritarian form or as a core drive (Marczewski, 2015). Finally, the **Reward Pursuit** factor converges user types with a shared focus on rewards, such as collecting in-game items, badges, or character optimization, all of which could foster *more or less autonomous forms of extrinsic motivation* (as opposed to intrinsic motivation, which is elicited by satisfying basic psychological needs through the mere action itself) (Richter et al., 2015; Ryan and Deci, 2017; Shields and Chugh, 2017). Therefore, we interpret that key determinants of intrinsic and extrinsic motivation as described in self-determination theory can explain a large part of the factor structure we found, i.e., we hypothesize that multiple types of the different typologies converge because they measure the same underlying configuration of the basic psychological needs and/or their satisfaction.

However, none of the Hexad types clearly converge on **Escapism**, apart from a cross-loading of the Free Spirit. Accordingly, it is not distinctively mirrored in self-determination theory but rather conflates the user types of all three inductively created typologies, which are characterized by specific in-game motivations and behaviors of curiosity and discovery as well as immersion in the story (Bartle, 1996; Yee, 2006; Nacke et al., 2014). To a certain extent, these concepts could be linked to the basic need for autonomy, as autonomy can be satisfied not only through freedom and independence but also through the experience of task meaningfulness (Sailer et al., 2017), which could explain the cross-loading of Hexad's Free Spirit. However, as the factor clearly distinguishes from **Independence**, interest theory (Hidi and Renninger, 2006; Harackiewicz and Knogler, 2017) could provide an additional insightful perspective to explain the convergence of these types. Interest theory declares curiosity as an important component in the development of *interest* (Hidi and Renninger, 2006) in certain content or activities, which in turn strengthens intrinsic motivation (Silvia, 2018). Therefore, Escapism could potentially unite the different types because they reflect intrinsic motivation through interest as an additional, fourth intrinsic motivational determinant beyond the three basic psychological needs of self-determination theory, which seems to be of utmost importance for certain users in gameful environments.

The preceding discourse, which attempted to explain the different model fit as well as the divergences and convergences of the user typologies on the underlying factors based on their origins and the perspective of motivational theory, suggests that the five underlying concepts might manifest themselves as *shared essential motivational dimensions inherent to all user typologies*. These dimensions hold distinct significance for diverse users as they interact within a gameful environment. Specifically, different user motivations to engage with gameful systems could arise from a combination of situational factors such as the satisfaction of basic psychological needs (Ryan and Deci, 2017), extrinsic rewards offered (Ryan and Deci, 2017) and interest aroused (Harackiewicz and Knogler, 2017; Hidi and Renninger, 2006). The key observation that all of the 20 diverse types of the four typologies, despite their different origins, converge on only five underlying concepts that could be interpreted as motivational dimensions has important implications for future research and practice in the field of tailored gamification design.

5.3. Implications for research and practice

Our findings and their discussion provide an informed foundation for both future research in the tailored gamification field and practical efforts to better adapt gameful design to the needs and preferences of individual users. In this section, we outline the main implications of our findings that shed light on the role of user typologies for tailored gamification design in the future, resulting in critical reflection on the use cases in which they can be helpful and those in which we need to reconsider how we use and operationalize them.

Rather than developing more detailed and nuanced user typologies, we should shift our focus to understanding and measuring underlying determinants of motivation.

While the earliest user typologies included in our analysis (Bartle's player types and Yee's motivations to play) consisted of four and three factors, respectively, the BrainHex typology proclaims seven user types. The Hexad user types, representing the most recent typology in our analysis, initially suggested six factors (Marczewski, 2015). However, Marczewski later added more user types to their model, so that a new version assumes that twelve user types exist.[1] Similarly, Bartle (1996) attempted to identify further types within their player types, which resulted in a three-dimensional, eight-player type model (Ferro et al., 2013). Recent meta-studies on user typologies in gamification show that the development of new and more differentiated user typologies has increased considerably over the last decade (Martin et al., 2021; Carneiro et al., 2022).

In contrast to these developments, our results show that all 20 user types of the four most popular user typologies can be attributed to five underlying key factors. Thus, we extend previous research that has discussed relationships between different user typologies (Hamari and Tuunanen, 2014; De Vette et al., 2015; Krath et al., 2022) and point out the value of discovering the main underlying foundations (Martin et al., 2021) from a theoretical perspective with empirical evidence for these five underlying key dimensions. This result suggests that increasing the dimensionality of user typologies beyond these five factors may not contribute much explanatory power. The trend towards identifying new user typologies consisting of more and more factors might not be most advantageous. Although such developments may be useful in practice, i.e., when such typologies are used as a framework for designing gameful experiences, there seems to be no additional benefit when they are used for empirical studies. Consequently, taking a step back to ask what the user typologies actually represent and what the corresponding instruments really measure is necessary.

Through our analysis, we have obtained answers to these questions. As discussed in the previous section, we can see that the underlying factors are strongly related to motivation theory in the sense that all the user typologies we examined could essentially measure motivation. However, user typologies are usually interpreted as static manifestations of personal preferences (i.e., as different classes) (Oliveira et al., 2023). Considering that an individual's current motivation is not a purely stable concept, it may be misleading to refer to different sources of motivation as "user types" or "player types". Therefore, we argue for a reconsideration of how we use user typologies and whether we should continue to refer to them as *types*. For example, conceptualizing them as *determinants* of motivation might be less misleading. In this regard, similar to observations made by Fritz and Stöckl (2023) in the context of video player typologies, there is great merit in shifting the focus of tailored gamification research to understanding the essential motivational determinants underlying user typologies rather than developing more nuanced types and exploring whether adaptive design based on these motivational determinants can overcome both the psychometric limitations of user typologies (Bateman et al., 2011; Busch et al., 2016b; Tondello et al., 2018), as well as the gaps between assumed user type preferences and actual behavior reported in previous work (Krath et al., 2023a; Weber et al., 2023).

We should refrain from a dichotomous operationalization of user types in empirical studies.

Apart from reconsidering our understanding of user typologies, the finding that they appear to measure underlying determinants of motivation also bears implications for their operationalization. We discussed that some user typologies, such as the Hexad (Marczewski, 2015), already build on motivation theory (specifically self-determination theory, Ryan and Deci (2017)), which measures motivation *continuously* (e.g., a user's need for competence is satisfied to a certain degree) and not dichotomously (e.g., a user's need for competence is either satisfied or not, or, in the present context, a user is either an Achiever or not). However, if we look at how previous research has employed user typologies, we find that many have treated them as distinct archetypes, with users or players having a dominant manifestation of these types (Challco et al., 2014; Lavoué et al., 2018; Ferro et al., 2013; Hallifax et al., 2019b; Oliveira et al., 2023).

[1] The Dodecad of User Types: https://www.gamified.uk/user-types/, last accessed June 14, 2024.

This level of abstraction makes it tempting to use them for personalization purposes. Once a user type is known, game elements in a gamified system can be adapted to the respective primary user type. In this way, especially practical endeavors to personalize gamification can be simplified, where a rapid classification and abstraction of a large user base are essential to prioritizing features in user experience design (Krath et al., 2023b; Rammstedt and John, 2007). This approach has been valuable in providing a practical way of personalizing gamified systems, as shown, e.g., by Altmeyer et al. (2022). The study demonstrated that a personalization approach relying on the highest Hexad user type score increased enjoyment, positively-valenced affective experiences and participants' absorption in the current task.

However, for research purposes, we question the conceptualization as different archetypes, as we find different (inter)relationships between user types within and between different typologies and can show that all these different typologies can be traced back to a common theoretical basis. Apparently, the theoretical basis reflects different motivations for using a system, which are not independent of each other. Thus, we should critically reflect on how we operationalize user types. In our view, they should be seen as a way to measure what motivates users in the specific context in which they are applied, not as categorical manifestations of user archetypes. This dynamic nature is not a drawback of user types per se; it is rather an inherent feature of their underlying theoretical foundation in motivation. Since positively affecting motivation is a core element of gameful design (Koivisto and Hamari, 2019), user typologies represent an important approach to tailoring such systems. Yet, they must be applied in an appropriate manner. A more holistic understanding of the individually relevant combination of motivational characteristics could be helpful to do so. In summary, supporting suggestions from previous studies that have pointed in this direction (Hallifax et al., 2019a,b), this means that the typologies should not be considered as categorical types but rather as continuous representations of a user's current motivations, which can potentially change in different contexts and situations.

6. Limitations

Our study has several limitations arising from the choice of typologies, data collection process, sample, and analysis process.

First, we would like to emphasize that we focused on examining the relationships and underlying foundations of the four most common user typologies in gamification research (Klock et al., 2020); however, there are a variety of other user typologies (Carneiro et al., 2022) that we did not consider. Consequently, the five factors we identified as essential motivational determinants represent a hypothesis based on the four models we examined that deserves further exploration regarding their parallels with other user typologies applied in tailored gamification.

Second, while we tried as much as possible to avoid question order bias due to the different scaling of the typologies by grouping the questions according to their focus and guiding participants from more general questions to more specific questions formulated as single player type personality test, we still needed to maintain a specific order of the four scales in order to uphold a coherent narrative in the section labels that should facilitate cognitive processing. Therefore, we cannot completely preclude the possibility that the order of the questionnaires may have caused a bias in participants' responses towards greater inattention to the BrainHex and Yee questions at the end of the survey. In this regard, confirming our results with a randomized order of the questionnaires would be valuable.

Third, although we aimed for a diverse sample of English-speaking participants, we must acknowledge limitations in our sample composition that may restrict our findings' universal applicability. On the one hand, due to the high representation of European and American descent, we must consider that our sample is likely to represent White people from Western cultures in terms of ethnicity and culture. In contrast, other ethnicities and cultures may be underrepresented. Because culture inherently shapes how people perceive and behave in gamified systems (Toda et al., 2022), we call for future research to investigate whether the factors we identified can be confirmed in more diverse samples.

Finally, we decided to exclude one user type from Bartle's typology (Achiever) and two user types from the BrainHex typology (Daredevil and Mastermind) because they showed insufficient convergent validity, which could pose a risk for commonalities in our main analysis (Fabrigar et al., 1999). However, this decision limited our ability to examine whether these types also fit into the five-factor model of common underlying concepts we identified. In this context, we also acknowledge that we have not yet confirmed the scientific validity of our five factors through our exploratory approach, and we cannot conclude whether these five factors are indeed forming a coherent new model of motivations. Further research is warranted to explore how best to measure

Table 5
Items to capture the Hexad types, measured on a 7-point Likert scale from "totally disagree" to "totally agree" (Krath et al., 2023a).

No.	Item	AVE	CR
Philanthropist		0.73	0.84
P1	It makes me happy if I am able to help others.		
P4	The well-being of others is important to me.		
Socializer		0.73	0.84
S2	I like being part of a team.		
S4	I enjoy group activities.		
Free Spirit		0.63	0.77
F1	It is important to me to follow my own path.		
F3	Being independent is important to me.		
Achiever		0.73	0.84
A2	I like mastering difficult tasks.		
A4	I enjoy emerging victorious out of difficult circumstances.		
Player		0.69	0.81
R2	Rewards are a great way to motivate me.		
R4	If the reward is sufficient, I will put in the effort.		
Disruptor		0.70	0.82
D3	I see myself as a rebel.		
D4	I dislike following rules.		

Table 6
Items to capture Bartle's player types, measured on a 7-point Likert scale from "strongly disagree" to "strongly agree" (Kocadere and Çağlar, 2018).

No.	Item	AVE	CR
Killer		0.54	0.78
KB1	The only important thing to me in the game is to defeat others.		
KB2	I make moves to have other players defeated.		
KB3	I do everything needed in order to win the game.		
Socializer		0.60	0.81
SB1	I share the things I discovered about the game with my friends in the game.		
SB2	The important thing to me in the game is to socialize.		
SB3	I like to communicate with other players in the game.		
Achiever		X	X
AB1	Accomplishing tasks with success is more important to me than beating others.		
AB2	I focus on the challenge I need to do rather than other players' situations.		
AB3	I compete with myself rather than competing with other players.		
Explorer		0.54	0.78
EB1	It is important for me to discover secret features of the game.		
EB2	I try to find out details that no one else in the game knows about.		
EB3	I am curious about new things I will see as the game progresses.		

Table 7
Items to capture the BrainHex types, measured on a 7-point Likert scale from "I love it" to "I hate it" (Busch et al., 2016b).

No.	Item	AVE	CR
Seeker		0.55	0.79
SEBH1	Exploring to see what you can find.		
SEBH2	Looking around just to enjoy the scenery.		
SEBH3	Wondering what's behind a locked door.		
Survivor		0.52	0.76
SUBH1	Frantically escaping from a terrifying foe.		
SUBH2	Feeling relief when you escape to a safe area.		
SUBH3	Feeling scared, terrified or disturbed.		
Mastermind		X	X
MABH1	Working out how to crack a challenging puzzle.		
MABH2	Devising a promising strategy when deciding what to try next.		
MABH3	Working out what to do on your own.		
Conqueror		0.40, 0.60 after COBH2 excl.	0.62, 0.76 after COBH2 excl.
COBH1	The struggle to fight a difficult boss.		
COBH2 (excl.)	Taking on a strong opponent when playing against a human player in a versus match.		
COBH3	Completing a punishing challenge after failing many times.		
Socializer		0.69	0.87
SOBH1	Playing in a group, online or in the same room.		
SOBH2	Talking with other players, online or in the same room.		
SOBH3	Co-operating with strangers.		
Daredevil		X	X
DABH1	Responding quickly to an exciting situation.		
DABH2	Being in control at high speed.		
DABH3	Hanging from a high ledge.		
Achiever		0.67	0.86
ABH1	Picking up every single collectible in an area.		
ABH2	Finding what you need to complete a collection.		
ABH3	Getting 100% (completing everything in a game).		

these five underlying determinants of motivation that we hypothesize and to investigate their validity through confirmatory analyses.

7. Conclusion

Given the increasing research activity based on user typologies as a means for tailored gamification, coupled with recent studies that have criticized their applicability and effectiveness, this study aimed to reconsider the foundations of common user typologies (specifically Bartle's player types, Yee's motivations to play, BrainHex types, and Hexad types) by empirically examining their relationships and underlying common concepts. Using a quantitative survey approach, we found that most existing user typologies exhibit problems regarding their psychometric properties but share considerable relationships and that the diverse user types suggested in the different typologies can be boiled down to five underlying factors.

These five factors show parallels to the basic psychological needs, extrinsic motivation, and interest and appear to measure key motivational determinants crucial for user preferences and behavior in gamified systems. Based on these findings, we hypothesize that user types conceptualized as distinct archetypes may be helpful for the adaptation of systems in practice. However, research efforts should shift to focusing on understanding and operationalizing user types as continuous – rather than dichotomous – motivational determinants that can potentially change in different contexts and situations.

CRediT authorship contribution statement

Jeanine Kirchner-Krath: Writing – original draft, Visualization, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Maximilian Altmeyer:** Writing – review & editing, Writing – original draft, Conceptualization. **Linda Schürmann:** Writing – review & editing, Writing – original draft, Conceptualization. **Bastian Kordyaka:** Validation, Methodology, Formal analysis, Conceptualization. **Benedikt Morschheuser:** Writing – review & editing, Conceptualization. **Ana Carolina Tomé Klock:** Writing – review & editing, Conceptualization. **Lennart Nacke:** Supervision, Conceptualization. **Juho Hamari:** Supervision, Conceptualization. **Harald F.O. von Korflesch:** Resources, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Benedikt Morschheuser reports financial support was provided by Federal Ministry of Education and Research Bonn Office. Ana Carolina Tome Klock reports financial support was provided by European Union. Juho Hamari reports financial support was provided by Academy of Finland. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used DeepL and Grammarly to check the spelling, grammar, and wording of the text. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

Appendix. List of questionnaire items used in the survey

See Tables 5–10.

Table 8
Items to capture Yee's motivations, measured on a 7-point Likert scale from "not important at all" to "extremely important" (Yee et al., 2012).

No.	Item	AVE	CR
Social		0.67	0.89
SY1	Chatting with other players.		
SY2	Being part of a guild.		
SY3	Grouping with other players.		
SY4	Keeping in touch with your friends.		
Immersion		0.51	0.80
IY1	Learning about stories and lore of the world.		
IY2	Feeling immersed in the world.		
IY3	Exploring the world just for the sake of exploring it.		
IY4	Creating a background story and history for your character.		
Achievement		0.41, 0.60 after AY4 excl.	0.68, 0.82 after AY 4 excl.
AY1	Becoming powerful.		
AY2	Acquiring rare items.		
AY3	Optimizing your character as much as possible.		
AY4 (excl.)	Competing with other players.		

Table 9
τ_b correlations between different user types of the four typologies. Grey cells mark moderate relationships; bold numbers illustrate strong relationships.

		Bartle			BrainHex				
		Explorer	Killer	Socializer	Achiever	Conqueror	Seeker	Socializer	Survivor
Bartle	Explorer	–							
	Killer	0.06**	–						
	Socializer	0.06*	0.03	–					
BrainHex	Achiever	0.27***	−0.01	−0.04	–				
	Conqueror	0.12***	0.20***	0.07**	0.11**	–			
	Seeker	0.26***	−0.09***	0.05*	0.26***	0.16***	–		
	Socializer	0.01	0.11***	**0.53*****	0.00	0.17***	0.05*	–	
	Survivor	0.08**	0.12***	0.07**	0.11***	0.24***	0.17***	0.12***	–
Yee	Achievement	0.20***	0.22***	−0.03	**0.29*****	0.26***	0.16***	0.06**	0.12***
	Immersion	0.24***	−0.09***	0.01	0.22***	0.09***	**0.44*****	−0.00	0.15***
	Social	0.03	0.14***	**0.53*****	−0.01	0.15***	0.03	**0.63*****	0.11***
Hexad	Philanthropist	0.10**	−0.11***	0.25***	0.08**	0.04	0.14***	0.21***	0.08**
	Socializer	−0.02	0.11***	**0.45*****	−0.05	0.09***	−0.02	**0.52*****	0.08***
	Free Spirit	0.21***	−0.01	−0.11***	0.11***	0.07**	0.20***	−0.15***	0.04
	Achiever	0.22***	0.23***	0.07**	0.12***	**0.34*****	0.11***	0.09***	0.16***
	Player	0.13***	0.17***	0.00	0.19***	0.10***	0.14***	0.04	0.14***
	Disruptor	0.15***	0.11***	0.00	0.01	0.07**	0.10***	−0.02	0.06**

* $p \leq .05$.
** $p \leq .01$.
*** $p \leq .001$.

Table 10
τ_b correlations between different user types of the four typologies. Grey cells mark moderate relationships; bold numbers illustrate strong relationships (continued).

		Yee			Hexad					
		Achievement	Immersion	Social	Philanthropist	Socializer	Free Spirit	Achiever	Player	Disruptor
Yee	Achievement	–								
	Immersion	0.15***	–							
	Social	0.13***	0.02	–						
Hexad	Philanthropist	0.00	0.12***	0.20***	–					
	Socializer	0.02	−0.03	**0.49*****	0.27***	–				
	Free Spirit	0.13***	0.22***	−0.12***	0.02	−0.17***	–			
	Achiever	0.22***	0.08**	0.10***	0.11***	0.11***	0.15***	–		
	Player	0.27***	0.07**	0.04	0.06*	0.04	0.08**	0.22***	–	
	Disruptor	0.09***	0.08**	0.01	−0.10***	−0.06*	0.19***	0.06*	0.01	–

* $p \leq .05$.
** $p \leq .01$.
*** $p \leq .001$.

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