

A Systematic Mapping on Player's Profiles: Motivations, Behavior, and Personality Characteristics

Nayana Carneiro  [Universidade Federal do Ceará | nayanatcl@alu.ufc.br]

David Miranda  [Universidade Federal do Ceará | dmottamiranda@gmail.com]

Geórgia Pereira  [Universidade Federal do Ceará | georgia@virtual.ufc.br]

Glaudiney Mendonça  [Universidade Federal do Ceará | glaudiney@virtual.ufc.br]

Ticianne Darin  [Universidade Federal do Ceará | ticianne@virtual.ufc.br]

Abstract

Digital games have become part of the daily life of a large part of the world population, reaching audiences of different ages, genders, and cultures. Games are also becoming an increasingly explored research topic in Human-Computer Interaction (HCI), and several studies have sought to deepen the knowledge about players, identifying individual differences. Although the literature is rich in works that typify and classify players, the lack of objective comparisons can make it difficult to adopt such types to support game design or future research. Thus, this research investigates players' taxonomies and typologies regarding their motivations, behavior, and personality characteristics, analyzing how they explore these traits. We conducted a systematic mapping of the literature and analyzed 19 studies that propose or update players' types, observing how they explore the above mentioned traits. The main contribution of this paper is to offer an overview of the identified taxonomies and typologies, comparing them and mapping their attributes and applications. Such knowledge is a tool for designing games and gamified systems and can support game designers to promote engagement and motivation in complementary ways in their games. It also allows researchers and practitioners to compose a multidimensional view of the different players' types.

Keywords: *player types, player profiles, typology, taxonomy, engagement, player motivations, player behavior, personality characteristics, digital games, gamified systems*

1 Introduction

In recent years, digital games have become part of the routine of a large part of the world's population, reaching audiences of different ages, genders, and cultures (Rozen, 2020). Consequently, games have become an increasingly explored research topic in academia, both globally and nationally. In Human-Computer Interaction (HCI) and related disciplines, such as Games User Research (GUR), for example, several studies investigate various issues related to games and their potential for the most diverse applications, which go beyond the single focus on entertainment.

Examples of this are studies that deal with the use of games in health (Orji et al., 2017) (for example, for rehabilitation (Adisusilo et al., 2020; Alankus et al., 2010)), in tourism (Shen et al., 2020) and in education (Mendoza and Baranauskas, 2019; Miranda et al., 2019), with special emphasis on edutainment (Aksakal, 2015; Wang and Nunes, 2020) and game-based learning (Bahrini et al., 2020), in addition to the growing adoption of gamification, which applies game elements in different types of applications and contexts (Bitrián et al., 2021; Toda et al., 2020).

Much of the success of purpose-built games like the ones mentioned above depends on player engagement (Hookham and Nesbitt, 2019; Orhan Göksün and Gürsoy, 2019; Adisusilo et al., 2020). Engagement is a quality of user experience characterized by the depth of an actor's investment when interacting with a digital system (O'Brien and Cairns, 2016), which is more than being satisfied with such a system (Cairns, 2016). Affective engagement – which includes a sense of pleasure, immersion, and spontaneous flow – is fundamental for players to follow the gameplay complexity so that fun

and high-level engagement correlate to the gaming experience itself (Gee, 2005; Voulgari and Komis, 2010).

No wonder this construct has aroused increasing interest in the HCI community, and many studies have explored its nature and definitions and ways to increase and measure it, inside and outside the gaming context (O'Brien et al., 2018; Wiebe et al., 2014; Martins et al., 2020; de Souza Filho et al., 2019; Vasconcelos et al., 2018). Studies investigating more general issues surrounding games are common, such as their effects, strategies, and evaluation methods, and which elements make up a successful game – for example, (Santos et al., 2015; Evelin et al., 2016; Silva et al., 2020; Carneiro et al., 2019; Borges et al., 2020).

However, despite the increasing knowledge production in this domain, making a good game is not a trivial task. Game design is something intrinsically complex (Rozen, 2020). The study and creation of high-quality games capable of promoting engagement and achieving their purposes require knowledge and understanding of players, which leads to the need to understand their behaviors, motivations, and characteristics (Drachen et al., 2018). Comprehending the user and their behavior is an essential part of the HCI processes (Barbosa et al., 2021), and the same is true for the study and design of games (Drachen et al., 2018; MacKenzie, 2013).

Several studies have identified and classified players' traits and types according to their motivations, behavior, and emotions while playing (Bartle, 1996; Yee, 2007; Yee et al., 2011; Bateman et al., 2011; Brühlmann et al., 2020; Nacke et al., 2014). Bartle (1996) was one of the first to document specific behaviors in different types of players. Since then, many other researchers have invested efforts in detecting motivational profiles and how they impact playing. Some re-

searchers have even searched for typological classifications in other areas, such as Psychology, Anthropology, and Sociology, that can be used to understand the players' profiles (Paulin, 2013). More recently, researchers have started investigating scientifically sound approaches to identify player types, demonstrating that game effectiveness may be correlated to player types (Van Gaalen et al., 2022).

Although the literature presents several works that typify and classify players through different criteria, to the best of our knowledge, no research compares these proposals in terms of the differences and similarities of the behavioral and motivational profiles described in the several existing classifications. Thus, the present research aims to investigate the taxonomies and player typologies proposed in the literature regarding their motivations, behavior, and personality characteristics – elements directly related to the player's engagement and experience – and survey how they explore these traits comparing them.

To this end, we carried out a systematic mapping (SM) of the literature (Petersen et al., 2015), identified and analyzed 19 classifications that propose or update types of players based on the parameters mentioned above. The main contribution of this work lies in offering an overview of players' taxonomies and typologies. We compare their target genre, organization, classification strategy, and categories and map their attributes and applications. Such knowledge helps promote engagement and motivation in complementary ways and allows researchers and practitioners to look at the player with a multidimensional view of their engagement and motivations.

We highlight that our purpose is not to propose a classification, discuss the effects of games on certain types of players, or demonstrate any relationship or inferences related to types of players and their context and behavior in real life. We present a systematization of knowledge about player profiles that, although not exhaustive, can inform researchers and practitioners studying human factors in digital games, helping to form and refine concepts and identify underlying dimensions related to engagement and motivation. In addition, it also aims to assist game designers in customizing the player's experience, in making decisions for game design or even in segmenting and targeting their games to specific audiences, supporting analytical activities during the game design and evaluation process, including classifying mixed profiles, identifying player needs and associated behaviors, and mapping engagement techniques with the game's objectives and its interactive and narrative elements.

2 Background

In this section, we discuss concepts related to studying types of players and investigating their differences. We approach user engagement, a fundamental construct for the success of digital games and gamified systems, regarding the three aspects that enable the knowledge and typification of players: motivation, behavior, and personality characteristics, which together make up the focus of this work. Before, however, it is necessary to establish the difference between taxonomy and typology, two central terms for the research.

2.1 Is it a Typology or a Taxonomy?

Despite being treated as synonyms, typologies and taxonomies refer to different theoretical approaches and modes of information organization (Bailey, 1994). Part of this confusion is attributed to the fact that a typology is a theoretical approach rather than a classification system which is often misinterpreted and wrongly developed (Doty and Glick, 1994). For Bailey (1994), typologies are conceptual classification modes, which presuppose arrangements for the elements of a set in multidimensional structures (Bailey, 1994; Smith, 2002).

Units that form a typology are called types and bring together concepts. They do not have an empirical basis for their proposition and are more linked to the notion of an ideal type that models something (Weber, 1949). Hence, the proposition of a typological classification is an a priori, and deductive approach (Da Silva, 2013). Using typologies can be helpful for understanding complex scenarios and proposing generalizations as a previous step in establishing hypotheses. However, some disadvantages must be considered, such as the fact that the types are neither exhaustive nor mutually exclusive; the arbitrariness of the criteria often adopted; and its descriptive rather than explanatory or predictive character (Bailey, 1994; Smith, 2002). In the context addressed by this work, the types proposed by Nacke et al. (2014) constitute an example of typology.

Taxonomies, in turn, are empirically based ways of classification (Bailey, 1994). The taxonomy construction is done inversely compared to typology since the taxonomies derive from sample observations and measurements and an associative arrangement of the elements to be classified as possible. According to ANSI/NISO Z39.19-2005 (R2010), taxonomies consist of controlled vocabularies whose terms establish a relationship with each other and have some hierarchy level (NISO, 2010).

A taxonomy can be understood as a knowledge organization system. Its use can support one, or a combination of more than one, of these three main functions: indexing, retrieval or organization, and navigation (Hedden, 2010, p.55). Since the terms result from an observation of the general data set, one of the advantages of building and adopting a taxonomy is the consistency of the classification (Hedden, 2010). An example of a taxonomy related to player classification is in the work of Tondello et al. (2017), who proposes a taxonomy related to player preferences.

This disambiguation of terms is essential for the analysis of classificatory studies. It establishes a basis for interpreting their nature and underlying concepts, allowing the comparison of different studies. Some of the papers analyzed in this work confuse this terminology, resulting in methodological issues: sometimes, what was called a typology was, in fact, a taxonomy, for example.

The work of Bartle (1996) exemplifies the term confusion problem since it is easily observable that most of the works that reference it call their types a taxonomy, while countless others define them as typology. Once the terms typology and taxonomy are not synonymous, we use the word "classification" as an umbrella term to refer to both throughout this paper.

2.2 Study of player types

Besides being an essential tool for the design of games and gamified systems, the knowledge of specific types of players can support *game designers* and researchers. It offers a basis for the study of the player's experience, motivational factors, and specific goals, for example, learning or segmenting strategies (Fortes Tondello et al., 2018). Several researchers have made efforts over time to propose and update player models, typologies, and taxonomies – e.g., (Yee, 2006; Nacke et al., 2014; Bateman et al., 2011; Tondello et al., 2019).

The study of player types began with the work of Bartle (1996), still in 1996, who proposed what is usually considered the first typology of players based on behaviors or approaches presented during the game. He built the work from the observation of discussions of experienced MUD players¹ about motivations for playing such games. The author analyzed the players' comments and identified four distinct groups of motivations, relating them to types of players: the *achievers*, players who pursued winning points and leveling up their character in the game; the *explorers*, whose objective was to explore the game in search of understanding its mechanics and finding possible *bugs*; the *socializers*, whose interest is focused on socializing with other players; and finally, the *killers*, which mainly aim to attack other players and destroy their characters. Such types were based on four players' interests: interacting, acting, players, and game world. Each type identified was related to at least two of these interests – for example, *achievers* are interested in acting in the game world. In contrast, *socializers* are interested in interacting with other players. A weakness of Bartle's work, however, is that the assumptions adjacent to the types have not been empirically tested, which makes this an informal model (Yee, 2006; Nacke et al., 2014).

Despite the lack of validation, the Bartle model became seminal for fostering the first investigations into this field in later years, as its types became widely known and were the basis for several other studies (Nacke et al., 2014; Hamari and Tuunanen, 2014; Tondello et al., 2017). Yee (2006), for example, built quantitative measures on the foundations of Bartle's qualitative work to create an empirical model for MMORPG² which revealed ten motivation subcomponents grouped into three components: *achievement*, *social* and *immersion*. Among other relevant contributions, Yee's work made it possible to raise questions about the generalization that is usually made of Bartle's types, constructed from the comparison between specific scenarios subject to biases (Nacke et al., 2014).

Subsequently, studies were undertaken on other grounds, aiming to overcome possible limitations derived from Bartle's original work, as is the case of Tondello et al. (2017), who propose a taxonomy of player preferences based on game elements and styles to play. The correlation with per-

sonality profiles already mapped in studies in the field of psychology was also used for the categorization of players: for example, Yee et al. (2011) used the model *Big Five* (Goldberg et al., 1999) to insert the players in profiles. The model in question establishes five personality factors, with which the author relates the players, namely: extroversion, affability, conscientiousness, emotional stability and openness to experience. Through game data and questionnaires, Yee proposed a way to study them through a set of archetypes. Another strand of study makes efforts to create tools that help the automated identification of different player profiles. Although not the focus of the present work, the relevance of such research is highlighted, e.g., (Gow et al., 2012; Drachen et al., 2009).

Thus, it is possible to notice different strategies for identifying player types and profiles. However, until the conclusion of the present research, no works were identified that systematically addressed the composition of an overview of existing studies, except for the work by Klock et al. (2016), who performed an SM and identified ten classifications of players.

Although it shares similarities with the research reported here, the work of Klock et al. (2016) differs in relevant points, especially: the focus on identifying studies that *used* player classifications, while this one focuses on studies that *propose* classifications, in addition to a different focus on searches – by using a *string* and more general selection criteria, the authors admitted works with different purposes (for example, the proposition of computational clustering techniques), while we restricted the search to classifications describing different player dimensions, a perspective that seems to have expanded the scope of the results. Furthermore, Klock's work was conducted in 2016, which opens a large window for new publications. The works identified by Klock et al. that were not among our results were included in the filtering process of the present work, as reported in Section 3.

2.3 Players' engagement, motivation, and profiles

User engagement is an essential element of interaction, manifested by a range of individual states such as attention, intrinsic interest, curiosity, and motivation (Chapman, 1997; Laurel, 2013; O'Brien and Cairns, 2016). Engagement can be seen as the “emotional, cognitive and behavioral connection that exists, at any point in time and possibly over time, between a user and a resource” (Attfield et al., 2011). This construct is directly related to the level of investment someone employs to interact with a digital system - including behavioral, temporal, cognitive, and emotional investment (O'Brien and Cairns, 2016).

Thus, as a quality of user experience characterized by the depth of such investment, engagement is more than “mere” satisfaction: it is believed that the ability to engage and maintain engagement in digital environments can generate positive results. For several areas, such as citizen participation, electronic health, *e-learning* and others (O'Brien and Cairns, 2016; O'Brien et al., 2018). Thus, there is a broad understanding that designing engaging experiences are necessary for any interactive design to be considered appropriate and

¹*Multi-User Dungeons* (MUD) is a game genre that resembles a chat room in which users incorporate roles within a virtual world imagined by players.

²*Massively-Multiplayer Online Role-Playing Games* player motivations, i.e., games that admit a massive number of players who assume the role of characters in a persistent virtual world in constant evolution, and can freely interact with each other.

successful (Doherty and Doherty, 2018).

In the gaming industry, engagement metrics are widely used. Large world-renowned companies have already published whitepapers on the subject. Facebook, for example, presented the results of a survey where it highlights the power of engagement to maintain the use of games and, consequently, increase revenue (Facebook IQ, 2019). Google similarly linked engagement with the “inclination to spend” in apps of this genre (Google, 2019). Activision Blizzard also highlighted that engagement means earnings for the game (Blizzard, 2021).

Engagement is a concept of interest in player-game interaction, as it contributes to different constructs related to the game and the *player experience* (Borges et al., 2020; O'Brien and Toms, 2008), being closely related to other constructs, such as immersion and presence (Cheng et al., 2015; Lessiter et al., 2001). Several researches have investigated engagement through typologies – e.g., (Brühlmann et al., 2020; Shen et al., 2020; Calegari and Celino, 2018). It is common to fraction the study of engagement to trace factors that cooperate to engage players, or that can determine how they interact and relate to a game, noting especially the player's **motivations**, his **behavior** and **personality traits or characteristics** (including preferences). Such factors – which constitute the focus of this work – stand out for cooperating individually and collectively for user engagement and can shape their experience with a game or gamified system.

O'Brien and Toms conducted a literature review and identified a certain equivalence of definitions about engagement. According to the authors, engagement is a cognitive, affective, and behavioral state of interaction with a computer application that makes the user want to be there (interacting) (O'Brien and Toms, 2010). Thus, engagement occurs in three steps: engagement point, which is the beginning of the interactional process; engagement which comprises the interaction itself; and disengagement, which comes with the end of interaction. Game designers usually seek to keep the user in the moment of engagement for large amounts of time and minimize the process of disruption (disengagement).

Although necessary for the success of a game, if abused, this resource can lead to an exaggerated engagement, which can cause serious issues such as Gaming Disorder³. Understanding engagement in the universe of digital games is important not only to avoid and denounce abusive and unethical practices in game design, but also to reveal the various parameters that guide human motivation itself, in a positive way.

The study of motivation is relevant to understand engagement because making players feel inclined to return to a game and continue playing is critical to its success (Melhart et al., 2019). Motivation – a central theme in the study of player-game interaction – is widely considered a determining factor

of player preferences and their Brühlmann et al. (2020) experience and is also related to user behaviors towards games. Thus, the study of motivation allows establishing associations between personality and behavior of users within the game – as done in the classifications of Bartle (1996) and Yee et al. (2011), for example. The first is based on motivations, and the second goes further by also relating personalities and behaviors.

The player's behavior, in turn, is directly related to what types of stimuli are presented to him during the experience (Calegari and Celino, 2018). At the same time, personality is a fraction of the engagement that strongly influences the player's involvement with the game. By identifying players' personalities and associating other factors, it is possible to design for a better and more personalized experience (O'Brien and Cairns, 2016).

Psychology studies have correlated motivation with different aspects of player profiles while engaged in gaming, including their personalities, gameplay behavior, and enjoyment (Liu et al., 2021). For example, achievement, affiliation, and power motivations – which are influential in motivation psychology – can be matched with existing player types (Liu et al., 2017). Because of that type of relationship, different works in the literature have been using a range of subjective and objective techniques for identifying player motivation, seeking to identify the profile that best describes a given player, which may impact the game design (Nacke et al., 2014).

Given the above, the present work contributes to the game user research, focusing on the overview of players' classifications according to their motivations, behavior, and personality characteristics. This perspective helps to understand the relevance and nuances of studies related to motivation and engagement in digital games, and how they can be applied to game design.

3 Methodology

To reach the proposed objective for our research – that is, to investigate and systematize the knowledge about the players' classifications proposed in the literature regarding motivations, behavior, and personality characteristics – we conducted a systematic mapping (SM) of the literature (Petersen et al., 2015). We used the PICOS characteristics (Population, Intervention, Outcome, and Study) (Stone, 2002) as eligibility criteria to help structure the review, select relevant questions and avoid unnecessary searches.

The SM consists of a secondary study method to review primary studies and build an overview of a given area of research, identifying opportunities and research gaps, for example, Petersen et al. (2015); Kitchenham et al. (2010). The SM process followed can be summarized in three phases: **planning**, **conduction** and **results reporting** (Figure 1), which are described throughout this section.

In the **planning phase**, we composed a research protocol according to the guidelines proposed by Petersen et al. (2015). The protocol comprised the study objectives, the research questions, the search string and bases, and the study selection criteria (Table 1). We listed the following research

³Gaming disorder is defined in the 11th Revision of the International Classification of Diseases (ICD-11) as a pattern of gaming behavior (“digital-gaming” or “video-gaming”) characterized by impaired control over gaming, increasing priority given to gaming over other activities to the extent that gaming takes precedence over other interests and daily activities, and continuation or escalation of gaming despite the occurrence of negative consequences. The full description is available at: <https://icd.who.int/browse11/l-m/en/http://id.who.int/icd/entity/1448597234>

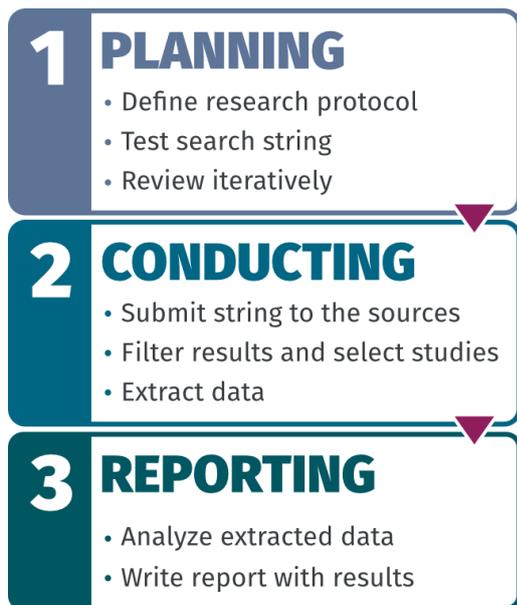


Figure 1. Summary of phases followed in this SM process

questions to be answered through the SM:

1. RQ1: What classifications (taxonomies and typologies) of player profiles are proposed in the literature?
2. RQ2: In what types of academic publications are the player profile classifications published?
3. RQ3: What types of research are conducted to propose player profile classifications?
4. RQ4: How did the studies obtain the proposed classifications?
5. RQ5: How are the classifications organized?
6. RQ6: What are the domains explored by the identified classifications?
7. RQ7: Do the proposed classifications consider elements of games? Which ones?
8. RQ8: Do the studies propose something to help others identify player types?

We specified the selection criteria for the review protocol and reviewed them among the researchers. We used a think-aloud protocol where one researcher described the reasoning of inclusion and exclusion criteria by applying them to one study. After that, we piloted the criteria and determined the level of agreement.

We used four sources to carry out searches for papers: Scopus, PubMed, Science Direct, and Web of Science. We selected these databases because together, they index the ten most relevant journals and proceedings on the topics “Game design” and “Player engagement”, according to the quality score calculated by the Microsoft Academic tool⁴. From the most relevant venues identified, we selected four control papers (Yee, 2006; Si et al., 2017; Shen et al., 2020; Kahn et al., 2015), based on their quality and relevance to our study.

To compose the search *string*, we listed keywords from terms and their synonyms identified in a set of articles relevant to the topic (Bartle, 1996; Kahn et al., 2015; Yee, 2006; Busch et al., 2016; Barata, 2014; Xu et al., 2012). These arti-

⁴The tool is part of the Microsoft Academic Services project (MAS) that offers Artificial Intelligence solutions to support researchers in conducting their research. Available at: <https://academic.microsoft.com/home>.

Table 1. Main selection criteria (inclusion and exclusion) used in the filtering process

Inclusion Criteria
The study proposes or updates a classification related to different:
<ul style="list-style-type: none"> • motivations of digital game players • personality characteristics of digital game players • behaviors of digital game players • motivations of users of gamified systems • personality characteristics of users of gamified systems • behaviors of users of gamified systems
Exclusion Criteria
<ul style="list-style-type: none"> • The full text is not available • The paper does not describe the methodology/experiment, the proposed types and/or their descriptions • The study does not propose or update a taxonomy or typology • The study does not refer to the context of games or gamified systems • The study proposes a sub-categorization restricted to a specific type of player • The study does not propose a classification, it only applies one already proposed in the literature, without modifying it

cles were defined by searches on the topic and expert recommendations. The string was iteratively tested and reviewed by three evaluators, using the control papers to ensure its quality. After the revisions, we reached the final version (Figure 2), which captured all the control papers when applied to the four selected bases.

```

(game AND player
AND
('player motivations' OR ((type OR profile)
AND (taxonomy OR classification OR typology)))
AND
(behavior OR motivation))
  
```

Figure 2. Search string submitted to the search sources

In the **conduction phase**, we submitted the search string to the four bases and obtained 397 works, including duplicates. Of these, 33 works (8.33%) came from Science Direct, four (1.01%) from PubMed, 86 (21.72%) from Web of Science, and 273 (68.94%) from Scopus. To select relevant works, we filtered the resulting set of studies in a three-step process, represented in Figure 3, applying the selection criteria established in the research protocol (Table 1). Zotero⁵ was used to organize references and remove duplicates.

The first filter (F1) consisted of removing duplicates, which reduced the set of 397 works to 309 (77.83%) – Zotero automatically identified 83 works, and we manually removed another five, totaling 88 duplicate items (22.17% of the total). Then, three independent researchers performed the second filter (F2), applying the inclusion and exclusion criteria after

⁵<https://www.zotero.org/>

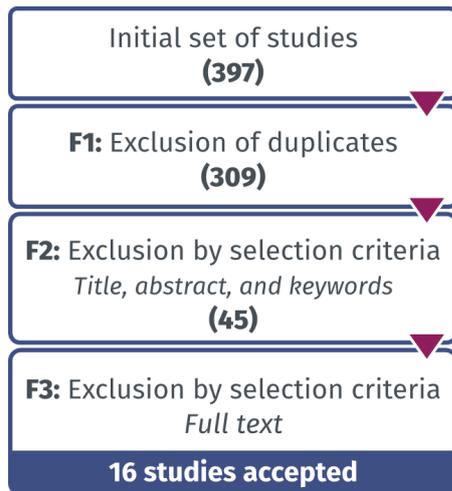


Figure 3. Filtering process followed in the systematic mapping conduction, consisting of three filters: F1, F2 and F3.

reading the title, abstract, and keywords of the 309 remaining studies. This resulted in the exclusion of 264 (66.5%) works. In addition to the exclusion criteria listed in Table 1, we excluded (i) secondary or tertiary studies, (ii) works that were not written in English or Portuguese, (iii) works that had three pages or less, and (iv) works that were not published in peer-reviewed venues – here one should note that the work of Bartle Bartle (1996), despite being widely used in several studies, were excluded from this mapping because it did not meet this last requirement.

Aiming to verify the reliability of the filtering process, we randomly selected a sample of 40 works (10.1% of the total). We asked three other researchers to analyze them independently, applying the inclusion and exclusion criteria. We then calculated the level of agreement between the three evaluators and between these evaluators and the initial score. We used the Pearson's correlation coefficient (PCC)⁶, and all tests showed a strong positive agreement between raters, with r ranging from 0.408 to 0.720 between raters ($p \leq 0.05$).

Once attested the reliability of the filtering process, we performed the third filter (F3) in 45 (11.33%) studies, which consisted of reading the full text of these articles and reapplying the selection criteria. In this step, two evaluators independently analyzed the works and later discussed and consolidated their evaluations. In cases where the evaluators did not reach a consensus (six works), a third evaluator analyzed them separately to validate the applied criteria. Thus, we excluded 29 (7.3%) studies in this filter, which resulted in the final set of 16 accepted articles, namely: Bontchev et al. (2018); Kahn et al. (2015); Shen et al. (2020); Fortes Tondello et al. (2018); Nacke et al. (2014); Si et al. (2017); Rodrigues and Brancher (2018); Chandra et al. (2019); Benlamine et al. (2017); Calegari and Celino (2018); Brühlmann et al. (2020); Yee (2006); Tondello et al. (2017); Vahlo et al. (2017); Tondello et al. (2019); Bicalho et al. (2019). Of these, five (31.25%) studies came from Science Direct, two (12.5%) from Web of Science, and nine (56.25%) from Scopus.

Seven additional studies were analyzed using the same fil-

ters. They were selected not from the basis but from the only related literature review identified in F2 (Klock et al., 2016), as the present research did not include secondary studies. That work is an SM on player classifications, as discussed in Section 2. We then performed filters F2 and F3 on them. Four of the seven additional works did not meet our inclusion criteria and, therefore, were excluded. This procedure resulted in the inclusion of three new papers (Bateman et al., 2011; Schuurman et al., 2008; Drachen et al., 2009), totaling our final set of 19 studies for the data extraction stage.

Finally, three evaluators extracted the data from the selected works, using a form prepared with the Google Forms tool, containing questions elaborated according to our research protocol. According to the respective authors' perspective, the extraction form allowed the identification of various quali-quantitative information about each article. The extraction form items included: basic information about the article, such as its reference and type, year and place of publication; information about the classification, including whether the proposed classification is a typology or taxonomy, its name, description, organization criteria, quantity, levels, and list of taxonomic categories, scope and target game genre; previous classifications used as a basis (if any); characterization of the methodology to propose the classification; ways to apply the classification and additional observations about the work.

The data were organized in spreadsheets and analyzed quantitatively and qualitatively, considering the research questions. In the following section, we conclude the **reporting phase**.

4 Results

In this section, we present the results obtained by analyzing the data extracted from the accepted studies as answers to the research questions (RQ) listed in Section 3.

4.1 Classifications of player profiles (RQ1)

The accepted works propose or update classifications of players' profiles in games or gamified systems, using their motivations, behaviors, personality characteristics, or preferences as a parameter. Fifteen (78.9%) of the 19 works propose new classifications, and four (21.1%) update or modify an existing classification in the literature. Eighteen (94.74%) classifications focus on games and one (5.26%) on gamified systems, more precisely, on applications for gamified travels (Shen et al., 2020).

Regarding the entities or objects of classification explored in the works, we observed that most classifications deal with behavior (7 works – 36.84%), and the least explored entity is personality characteristics, with two (10.53%) works only (Bateman et al., 2011; Nacke et al., 2014) – as shown in Figure 4. Considering the difference between typology and taxonomy (as discussed in Section 2), it is worth noting that all 19 studies accepted present taxonomies once they all used empirical methods to gather data to ground the proposed profiles. Table 2 presents a summary of the identified classifications.

⁶<https://www.statisticshowto.com/probability-and-statistics/correlation-coefficient-formula/#definition> (Last access in October, 2022).

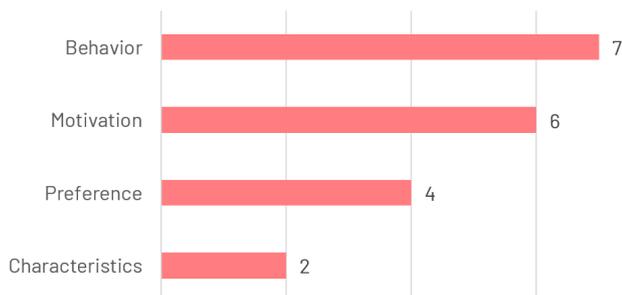


Figure 4. Identified classification entities

In general, the analysis of the 19 articles revealed the existence of three types of player classification: (1) specific to a game, (2) specific to a game genre or mechanics, and (3) generic.

In the first case, **game-specific**, the classification refers exclusively to the context of a specific game, not corresponding to a broader generalization beyond it, due to the absence of evidence to prove this. An example of this type is the work of Rodrigues and Brancher (2018), in which both the classification and the used data relate only to the game “Space Math”.

In the second, **specific to a genre or mechanics**, the definition of each player profile can be extended to an entire genre or game mechanic. A good example of this type of work is (Chandra et al., 2019), which explicitly covers the exploratory process of virtual environments, classifying players based on their behavior towards this type of mechanics. Another work that exemplifies this type of classification is the one presented by Shen et al. (2020), which typifies the behavior of participants in gamified travel.

Finally, the **generic classifications** apply to human behavior patterns and human preferences regarding games and are not limited to a specific game or genre. An example is “The Trojan Player Typology” by Kahn et al. (2015), which is broadly based on a player’s preferences. Another example would be Tondello et al.’s taxonomy (Tondello et al., 2017), which, similarly to the previous one, considers the preferences of individuals in the classification.

4.2 Publication types (RQ2)

We observed that the year of publication of the obtained works varies from 2006 to 2020, with 2017 and 2018 being the years with the highest number of publications (four works, or 21.05%, in each), as shown in Figure 5. No works published from 2007, 2010, 2012, 2014, and 2016 were identified. We highlight that we did not include Bartle’s work in the results because it did not meet the selection criteria. Hence, the oldest work was Yee (2006), published in 2006, and which builds its proposal on the work of Bartle when exploring quantitative measures to analyze the original types – a study that provided the basis for only three of the four motivations originally pointed out (*achievement*, *social* and *immersion*), allowing to check the type *killer* proposed by Bartle.

Regarding the publication types, 10 (52.6%) classifications were published in proceedings, while nine (47.4%) were published in journals, as indicated in Table 2. The journals *Computers in Human Behavior* and *Entertainment Com-*

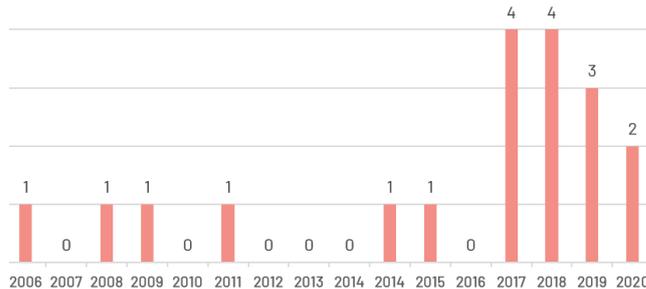


Figure 5. Number of classification published per year

puting stood out for having published two classifications each. The *Brazilian Symposium on Games and Digital Entertainment (SBGames)* also had two publications. Figure 6 relates the types of venues with the years of publication.

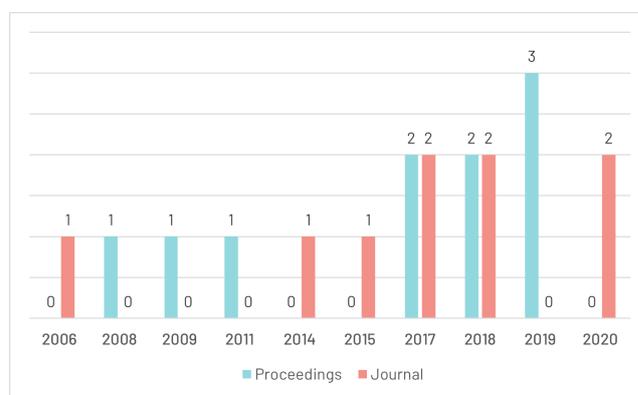


Figure 6. Studies per year and type of publication venue

4.3 How classifications are proposed (RQ3)

The SM we conducted aims to bring light to the application of existing classifications for the design and study of digital games and to outline a characterization of the research that gave rise to the classifications analyzed. In that regard, all the papers reported employing applied research. Most of them relied on quantitative approaches – 12 (63.16%). One (5.26%) study focused on qualitative research, and six (31.58%) others followed mixed approaches, combining quantitative and qualitative measures to deepen and enrich their results.

All studies report descriptive research. However, some of them also describe exploratory activities, such as (Tondello et al., 2017) and (Tondello et al., 2017). The most used method was surveying, applied in nine (47.37%) studies. In most cases, the surveys generated data to identify and extract player profiles through advanced statistical analysis techniques or machine learning. Another common approach was game metrics, such as hours played, number of wins and losses, and areas of the map most explored. Six (31.58%) studies analyzed this data type to extract their proposed classifications. Some works relied heavily on bibliographic research, building and complementing their classifications from related theories, as did Fortes Tondello et al. (2018), whose research also stands out for having an explanatory bias. Some studies have combined the three types of research in complementary phases or steps.

Table 2. Summary of the 19 identified classifications

REF	PUBLICATION	TYPE	YEAR	GENRE	ORGANIZATION				CLASSIFICATION			Qty	CATEGORIES
					D	G	P	B	Behavior	Motivation	Character.		
<i>PROPOSALS</i>													
Yee (2006)	Cyberpsychology & Behavior	Journal	2006	RPG			✓			✓		3	Achievement, Social, Immersion
Schuurman et al. (2008)	ACM DIMEA	Proceedings	2008	General			✓	✓		✓		4	Fanboys, Competers, Escapists, Time-Killers
Drachen et al. (2009)	IEEE CIG	Proceedings	2009	Puzzle and strategy				✓	✓			4	Veterans, Solvers, Pacifists, Runners
Bateman et al. (2011)	DiGRA	Proceedings	2011	General	✓		✓	✓	✓		✓	4	Tactical, Logical, Strategic, Diplomatic
Nacke et al. (2014)	Entertainment Computing	Journal	2014	General	✓	✓	✓	✓		✓		7	Seeker, Survivor, Daredevil, Mastermind, Conqueror, Socialiser, Achiever
Kahn et al. (2015)	Computers in Human Behavior	Journal	2015	MOBA / MMO			✓	✓	✓	✓		6	Socializer, Story-driven, Escapist, Completionist, Smarty-pants, Competitor
Benlamine et al. (2017)	Springer LNCS	Proceedings	2017	Action	✓		✓	✓		✓		4	Mastery-Approach, Mastery-Avoidance, Performance-Approach, Performance-Avoidance
Si et al. (2017)	Entertainment Computing	Journal	2017	RTS				✓	✓			4	Wanderers, Seers, Pathers, Targets
Tondello et al. (2017)	ACM CHI Play	Proceedings	2017	General	✓		✓			✓		14	Elements: Strategic resource management, Puzzle, Artistic movement, Sports and Cards, Role-playing, Virtual goods, Simulation, Action, Progression Game Playing Styles: Multiplayer, Abstract interaction, Solo play, Competitive community, Casual play
Vahlo et al. (2017)	JCMC	Journal	2017	General	✓	✓	✓				✓	7	The Mercenary, The Adventurer, The Commander, The Daredevil, The Companion, The Patterner, The Explorer
Calegari and Celino (2018)	Springer LNCS	Proceedings	2018	GWAP				✓	✓			4	Beginners, Snipers, Champions, Trolls
Rodrigues and Brancher (2018)	SBGAMES	Proceedings	2018	Serious	✓			✓	✓			4	Advanced, Skilled, Beginner, Intermediate
Chandra et al. (2019)	IEEE/ACM ASONAM	Proceedings	2019	RPG				✓	✓			4	Lone Wolf, Small Pack Wolf, Large Pack Wolf, Social Butterfly
Shen et al. (2020)	Tourism Management	Journal	2020	N/A			✓			✓	✓	6	Knowledge collectors, Reward seekers, Explorers, Curiosity seekers, Sensation seekers, Flow experiencers
Brühlmann et al. (2020)	Frontiers in Psychology	Journal	2020	MOBA	✓		✓	✓		✓		4	Amotivated, External, Intrinsic, Autonomous
<i>UPDATES</i>													
Bontchev et al. (2018)	Computers in Human Behavior	Journal	2018	General	✓			✓	✓			4	Competitor, Dreamer, Logician, Strategist
Fortes Tondello et al. (2018)	IJHCI	Journal	2018	General	✓	✓	✓			✓		3	Action Oriented, Esthetic Oriented, Goal Oriented
Bicalho et al. (2019)	SBGAMES	Proceedings	2019	Shooter			✓	✓	✓			8	Casual Killer, Casual Achiever, Casual Socializer, Casual Explorer, Hardcore Killer, Hardcore Achiever, Hardcore Socializer, Hardcore Explorer
Tondello et al. (2019)	IFIP INTERACT	Proceedings	2019	General	✓	✓	✓	✓	✓	✓		5	Aesthetic orientation, Narrative orientation, Goal orientation, Social orientation, Challenge orientation

Under ORGANIZATION, read D = Demographic, G = Geographic, P = Psychographic, and B = Behavioral.

4.4 Strategies to obtain classifications (RQ4)

We also searched for information on methods used by researchers to identify the players' profiles and propose their classifications. We observed that all studies rely on empirical research, showing that all analyzed studies aimed to propose taxonomies. Most studies (15 - 78,94%) used surveys with players as the primary way to gather data to identify patterns and group players in profiles according to each study's focus. Four (21,05%) works used other methodologies involving clustering of game metrics. Besides the studies that used surveys, the work of Shen et al. stands out for using a specific methodology, called Q Methodology, to identify their players' profiles (Shen et al., 2020).

According to the authors, the Q methodology is a qualitative research approach developed in 1935 that combines qualitative explanation with quantitative statistical analysis and overcomes some drawbacks of exploratory factor analysis. In the words of Shen and coauthors, the Q methodology reveals groups of individuals who have ranked statements in the same order and categorizes them under each factor. Hence, it changes the focus from variables to respondents to explore subjectivity (Shen et al., 2020). Brühlmann et al. (2020) and Si et al. (2017) combined surveys and game metrics – Si et al. (2017) also conducted interviews with players. The work of Benlamine et al. (2017) was the only study that also analyzed eye-tracking and physiological data. This work stands out because the authors collected multimodal data from the player's body and face (visual and physiological signals) to analyze their affective and mental states and produce a machine learning model to predict players' motivational goal orientations.

Once all works report empirical research, user participation is a constant in their methodologies. As mentioned above, all studies report using data from players but with different origins. Some studies collect in-game data from players (sometimes in retrospect, as in (Drachen et al., 2009)'s work, that studied patterns of playing behavior in the commercial game *Tomb Raider: Underworld*), others conduct surveys or interviews.

Regarding the sample size in the analyzed works, we observed the number of participants varying from 21 (Benlamine et al., 2017) to over 50,000 players (Fortes Tondello et al., 2018; Nacke et al., 2014). For the sake of organization, we grouped the studies in zones according to the sample size, being:

- **Strict user participation ($n < 50$):** three studies fit this category (Bicalho et al., 2019; Benlamine et al., 2017; Si et al., 2017). These studies offer an initial understanding or more general models of players' behaviors or motivations, but the limited user participation compromises these proposals' generalization.
- **Wide user participation ($50 \geq n \leq 1000$):** Seven studies (Bontchev et al., 2018; Shen et al., 2020; Rodrigues and Brancher, 2018; Brühlmann et al., 2020; Calegari and Celino, 2018; Tondello et al., 2017, 2019) fit this range of participants. Interestingly, only two studies had national samples (i.e., they did not compose their sample with people of different nationalities). This sample

heterogeneity contributes positively to generating more comprehensive models and classifications.

- **Massive user participation ($1000 \leq n$):** Nine studies fit here (Kahn et al., 2015; Fortes Tondello et al., 2018; Nacke et al., 2014; Chandra et al., 2019; Yee, 2006; Vahlo et al., 2017; Bateman et al., 2011; Schuurman et al., 2008; Drachen et al., 2009). The two works (Fortes Tondello et al., 2018; Nacke et al., 2014) that presented the most extensive sample (50,423 participants) performed tests on a base test of the game *EverQuest II* – both shared the same database. Five of these studies in this range recruited participants, and the four performed their tests based on existing databases.

4.5 Organization of the classifications (RQ5)

To better understand the proposed classifications, we noted which criteria were used to classify players into types and organize them. For this, we used the work of Hamari and Tuunanen (2014), which lists four organization criteria: *geographic* (i.e., divides players into groups based on where they live); *demographic* (i.e. the organization is based on descriptive characteristics such as age, gender, education or social status); *psychographic* (i.e., grouping players based on their attitudes, interests, values and lifestyles) and *behavioral* (ie, grouping based on patterns of behavior with or in relation to the game). Sometimes, the organization may involve more than one criterion, combining them to generate more "detailed" types.

Thus, it is more appropriate to indicate what seems to be the main criterion used without discarding the others. The criteria *behavioral* (12 papers - 63.16%) and *psychographic* (7 papers - 36.84%) were the main criteria used. As shown in Table 2, many studies also considered demographic factors to investigate whether descriptive characteristics such as gender, age, or even education significantly affect the types identified, as done by Rodrigues and Brancher (2018).

The categories used in the analyzed classifications are listed in Table 2. The number of categories proposed in each work – an indication of the granularity of each classification – varies from three to 14 categories, as shown in Figure 7. The works with the fewest categories are Yee (2006) and Fortes Tondello et al. (2018), with three categories each. The most frequent number of categories among the analyzed group was four, observed in 10 works.

Furthermore, the work of Tondello et al. (2017) stood out for having the largest number of categories, 14. However, this "leap" is explained by the authors using a different perspective to compose their taxonomy, which is the combination of nine game elements preferred by players and four "play styles". Only three classifications have sub-levels for the identified types: (Yee, 2006), (Calegari and Celino, 2018) and (Tondello et al., 2017). The Table 2, presented above, indicates the number of categories for each work and lists each one of them.

4.6 Domains of the classifications (RQ6)

Almost all the classifications analyzed focus on game studies (18 out of 19, i.e., 94.74%), and only the work by Shen

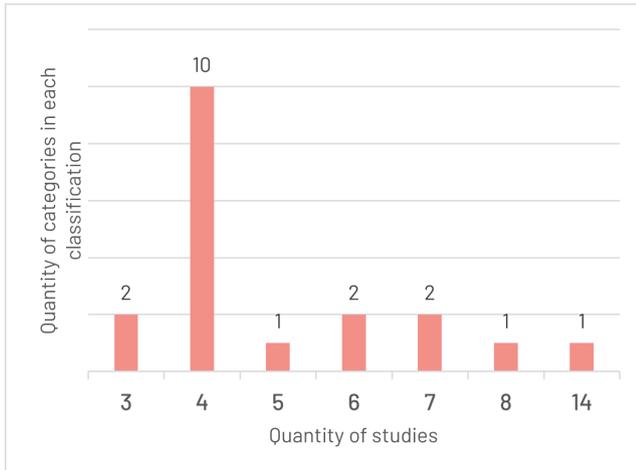


Figure 7. Number of taxonomic/typological categories per classification

et al. (2020) covered gamified systems. Following the same proportions, 18 (94.74%) focused on overall digital media. Again, the classification proposed by Shen et al. stands out for studying pervasive systems, i.e., that blend the boundaries between the real and virtual world, which allows us to consider them mixed media.

In the 18 works that focused on games, 12 (66.67%) classifications aim to cover the domain in general without pointing out distinctions between types or genres of games. Four (22.22%) works have a more restricted scope, as they were developed for specific games or types of games (Drachen et al., 2009; Brühlmann et al., 2020; Calegari and Celino, 2018; Rodrigues and Brancher, 2018). Drachen et al. (2009) and Brühlmann et al. (2020) focused on classifying players of specific games, the first on Tomb Raider: Underworld, and the second on League of Legends. Calegari and Celino (2018) focused on games with a purpose or GWAP (Games With A Purpose), which are games that encourage users to perform tasks with an entertainment reward. Rodrigues and Brancher (2018) focused on a classification for educational games.

Some works, however, make distinctions between “segments” of games, for example, *multiplayer* and online, as is the case with Yee (2006) and Chandra et al. (2019) who built their rankings by focusing on MMORPG games. Regarding the genres of the games targeted by the classifications, most works (eight – 44.44%) were not tied to a specific genre. In contrast, the others were equally divided among other genres, as shown in Figure 8.

The work of Kahn et al. (2015) stood out for targeting two genres, MMO⁷, and MOBA⁸. The definition of genres and types of games is a frequent cause of confusion and disagreement, and there is no standard followed in the industry, and the studies of games (Grace, 2005). Therefore, the division used here was based on the complementary views of Grace (2005) and Apperley (2006).

Regarding their purpose, most of the papers focused on games for entertainment, as shown in Figure 9. The work of Nacke et al. (2014) stands out for embracing games for all purposes, which seeks broad applicability of the typology.

⁷Massively Multiplayer Online Game – games capable of supporting large numbers of players simultaneously and connected

⁸Multiplayer Online Battle Arena – a type of game in which the player controls a character in a battle between two teams, to defeat the enemy base

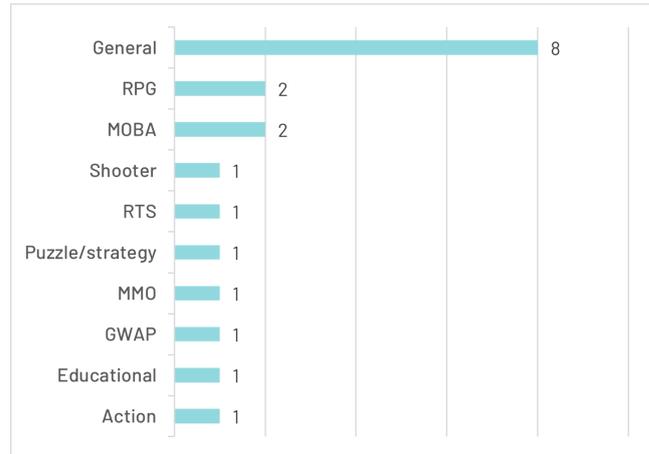


Figure 8. Game genres covered by the classifications

Calegari and Celino (2018) work with GWAPs, which may have varied purposes within the spectrum of games that aim to get player collaboration on something.

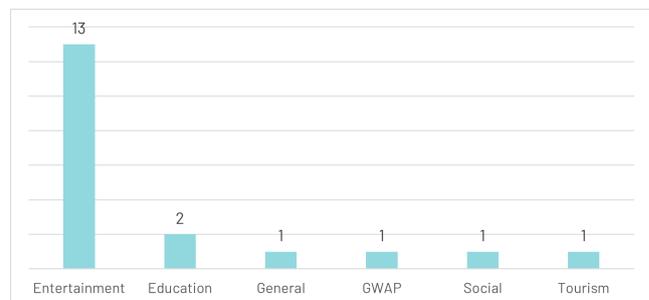


Figure 9. Purposes of games addressed by the classifications

4.7 Use of game elements in the classifications (RQ7)

We observed if and how the studies considered game design elements to compose their classifications to gain perspective on how they explore games' particularities. We noted that only two (10,53%) of the 19 works do not directly incorporate game elements in their classifications (Benlamine et al., 2017; Bateman et al., 2011). That can be explained by the fact that Bateman et al.'s work offers a view centered more on players' subjectiveness, focusing on players' personality factors and play styles.

However, the work conclusions inspired a new player satisfaction model, the BrainHex (Nacke et al., 2014), based on game elements. Regarding the work of Benlamine et al. (2017), this study used a different approach to obtain data to compose their classification (monitoring players' visual and physiological signals) and thus explored game elements indirectly, in the form of game scenes and how they affect players' motivations.

Considering the other 17 studies, we noted that we could group the game design elements considered by the classifications into two types: *conceptual* and *parametric*. We considered conceptual elements as the qualitative aspects extracted from theories or mechanics that make up conceptual aspects of games – for example, game genres, mechanics (e.g., cards, strategic management, roleplaying or puzzles),

and motivations (e.g., surprise, socialization, progression, accumulation).

Fourteen (73,68%) works explored this type of elements: Bontchev et al. (2018); Kahn et al. (2015); Shen et al. (2020); Fortes Tondello et al. (2018); Nacke et al. (2014); Si et al. (2017); Rodrigues and Brancher (2018); Yee (2006); Tondello et al. (2017); Vahlo et al. (2017); Tondello et al. (2019); Bicalho et al. (2019); Bateman et al. (2011); Schuurman et al. (2008). The percentage of studies in this group suggests a slight preference for exploring this element type.

On the other hand, parametric elements would be the quantitative elements used to detect players' behavior patterns – we can point as an example of these quantifiable elements: game time, win rate, score, number of shots, and lives, among others. Nine studies (47,37%) considered this type of element to determine their profiles: Bontchev et al. (2018); Fortes Tondello et al. (2018); Nacke et al. (2014); Rodrigues and Brancher (2018); Chandra et al. (2019); Calegari and Celino (2018); Brühlmann et al. (2020); Bicalho et al. (2019); Drachen et al. (2009).

The works that used neural networks for clustering (Rodrigues and Brancher, 2018; Chandra et al., 2019; Calegari and Celino, 2018; Drachen et al., 2009) relied heavily on this type of element to perform their analysis and identify patterns. It is also worth noticing that Bontchev et al. (2018); Fortes Tondello et al. (2018); Rodrigues and Brancher (2018); Nacke et al. (2014); Bicalho et al. (2019) stood out for considering both types of elements in their research.

4.8 Tools proposed to identify players profiles (RQ8)

Aiming to offer some additional information that could help other researchers and practitioners use the classifications identified here, we noted which studies proposed tools to help other researchers apply their classifications to identify which profile fits a specific player or group of players. Eight (42,10%) papers present, besides a classification, an instrument to this end (Bontchev et al., 2018; Shen et al., 2020; Benlamine et al., 2017; Vahlo et al., 2017; Tondello et al., 2019; Bicalho et al., 2019; Bateman et al., 2011; Kahn et al., 2015).

In general, the proposed instruments were derived from studies that used surveys to gather data on players' traits. It generated self-report tools (questionnaires or scales) that present a set of questions that help to relate players with profiles regarding behavior, preferences, and motivations. Table 3 indicates these studies, specifying the entity their instrument address, the types they identify, and the number of items/questions each one presents. It is worth noticing that not all of the instruments are validated, and, in some cases, they still need further studies to prove them.

One of the other works (Shen et al., 2020) that do not propose a specific instrument gives clear recommendations on using the methodology used in the study to obtain their classification (the Q methodology) to identify other players' profiles. This methodology, briefly discussed above, is widely used in the social sciences and humanities to seek a more quantitative bias to investigate beliefs, attitudes, behaviors,

Table 3. Studies that proposed instruments to help identify players' profiles

Ref.	Entity	Types/Profiles	No. Items
Bontchev et al. (2018)	Preference	Competitor, Dreamer, Logician, Strategist	40
Kahn et al. (2015)	Motivation	Socializers, Completionists, Competitors, Escapists, Story-driven, Smarty-pants	15
Benlamine et al. (2017)	Motivation	Mastery-Approach, Mastery-Avoidance, Performance-Approach, Performance-Avoidance	14
Vahlo et al. (2017)	Preference	The Mercenary, The Adventurer, The Commander, The Daredevil, The Companion, The Patterner, The Explorer	33
Tondello et al. (2019)	Preference	Aesthetic orientation, Narrative orientation, Goal orientation, Social orientation, Challenge orientation	50
Bicalho et al. (2019)	Behavior	Casual Killer, Casual Achiever, Casual Socializer, Casual Explorer, Hardcore Killer, Hardcore Achiever, Hardcore Socializer, Hardcore Explorer	10 + 15
Bateman et al. (2011)	Behavior	Tactical, Logical, Strategic, Diplomatic	5 + 5 + 5
Schuurman et al. (2008)	Motivation	Fanboys, Competers, Escapists, Time-Killers	11

and opinions (Herrington and Coogan, 2011). Applying this methodology to identify players' profiles is a differential of this work and shows an alternative path to others who want to explore another perspective to this process.

Regarding the studies that relied on game metrics clustering with machine learning techniques, it was unclear if some proposed, in fact, a tool or algorithm for general use to identify profiles given other datasets. However, the description of their methodologies, processes, and lessons can undoubtedly support other studies that aim to do the same.

5 Discussion

The analysis of the results allowed us to draw an overview of the players' classifications available in the literature and highlighted relevant points to be considered in the mission to make these results more beneficial for the design and evaluation of games. Therefore, in this section, some *insights* and concerns that emerged during the conduction of the research are discussed, aiming to provoke reflections and contribute to game studies.

5.1 Lack of coherence in the use of terms

In games research, the same phenomenon previously described by Doty and Glick (1994) occurs: many works use the terms typology and taxonomy interchangeably, although they are not synonymous. We agree with Doty and Glick that such confusion of terminology can impact the work methodology.

However, we also observed that this misinterpretation makes understanding the classification and its application in

game design and evaluation challenging. In addition, the incoherent use of terms makes an objective comparison of the classifications difficult since it becomes hard to identify, and it is necessary to analyze the terms used in the context of each work.

In game studies, this issue goes beyond the scope of the discussion about the common confusion between typology and taxonomy. The works analyzed employ many terms with different meanings but are treated as having similar natures. For example, at least seven different terms were identified in the analyzed works: typology (Kahn et al., 2015; Shen et al., 2020; Nacke et al., 2014; Bateman et al., 2011; Schurman et al., 2008); taxonomy (Tondello et al., 2017; Vahlo et al., 2017; Bicalho et al., 2019); model (Fortes Tondello et al., 2018; Benlamine et al., 2017; Yee, 2006; Drachen et al., 2009); profiles (Rodrigues and Brancher, 2018; Calegari and Celino, 2018; Brühlmann et al., 2020); types (Chandra et al., 2019; Drachen et al., 2009); styles (Bontchev et al., 2018); and archetypes (Si et al., 2017). In some cases, more than one term is used to describe the same classification.

This issue echos the analysis of Kultima who affirms that the lack of conversation between game studies and general design research is visible yet historically explainable (Kultima, 2015). We also agree with the author when she states that, considering the field's maturity, incorporating more sound design research frameworks could alleviate this epistemic gap, which we find to be not only between the practice and academia but also inside game theoretical research.

The lack of standardization in using these terms makes it difficult to correctly identify the proposed classifications and the possibility of applying the terminologies for subsequent studies. This issue may come from the growing effort to solidify the theoretical framework on games, which is also manifested in the debate and adequacy of using different terms in this area. For example, Darin and Carneiro (2020) and Borges et al. (2020) discuss the lack of consensus on what the term "player experience" means, what dimensions it encompasses, and which human characteristics and market practices it impacts.

We highlight that the use of technical and scientific terms must be done carefully, as it can generate confusion and inconsistencies in research, design, and game evaluation. The misuse of terms makes it difficult to systematize and develop mature research on human factors in games and diffuse poorly founded knowledge. Thus, it is necessary to discuss and identify ambiguities about terms and concepts related to player behavior and game elements, aiming to solidify them, contributing to the maturation of practices and research in games and interfaces.

5.2 Relationship between different player classifications

When surveying the different classifications of players, one could think that seeking a correlation between the elements of the classifications towards a unified model would be desirable. However, in this work, we did not look for those relationships. As we see it, one needs to recognize that classifications are an abstraction of the complexity of human behavior,

emphasizing some characteristics, to the detriment of others, to group individuals into types.

A unified model would look for similarities between abstractions. Therefore, a new abstraction must be created, looking for characteristics between different classifications. That "abstraction of previous abstractions" increasingly diminishes the ability to represent the complexity of human behavior, which is likely to move further and further away from the real motivations of individuals.

We demonstrate our point by analyzing the attempt at unification by Stewart (2011), in which the author proposes a unified model for personality and play styles. The work begins by approximating the four types of players proposed by Bartle (1996) with the four types of temperaments by Keirsey (1998). Based on each author's descriptions of types, Stewart (2011) proposes that Keirsey types are supersets of Bartle types and correlate the models. After defining the four types of players from the union of the theories of those two researchers, the author uses different known classifications, relating their types to the now unified elements.

In the approximation created between the Killer type (Bartle) and the Artisan type (Keirsey), the author emphasizes the common characteristic between the types as manipulation (the author prefers to call the Killer type Manipulator). When describing the Killer, the author points out the player's main characteristics: the desire to impose themselves on other players and demonstrate their superiority over others. As for Artisan, the author emphasizes the player's desire to have power over everything in their world.

Stewart then presents some expressions from the original works related to their types to determine that correlation. If we tabulate and observe the terms the author uses to correlate the two classifications (Table 4), one can realize that some elements can be directly related. Still, many others do not have correspondence or would need a greater abstraction to be associated, removing a type's characteristic so it can relate to the other one.

Table 4. Summary of analysis of correlation between characteristics of the Artisan (Keirsey, 1998) and the Killer (Bartle, 1996) types

Artisan (Keirsey, 1998)	Killer (Bartle, 1996)
tactical	-
fun-loving	juicy fun
realistic	-
unconventional	-
spontaneous	-
seek stimulation	adrenalin-shooting
prize freedom	-
-	imposition upon others
-	cause distress
-	thrill of the chase
-	reputation

Thus, a unified model becomes a new abstraction. The sense that it more comprehensively represents players' motivations turns out to be just a new way of classifying them – perhaps even less representative because it is an abstraction of several abstractions. However, executing a unification is not unproductive since it makes us reflect on the characteris-

tics of the types of each classification.

Still, we believe that it is more productive for designers, game creators, and researchers to have a broader knowledge of the possibilities of organizing players' motivations. Then they can select the one that best helps in developing a specific project, considering the criteria used for the classification organization. For that, we believe that this mapping can contribute to this choice.

5.3 Players profiles and game elements

The players' profiles and motivations can impact how a group engages with a game. Hence, the analysis of player motivations can inform game designers and researchers on the behavioral patterns of game players, and they may use those behavioral patterns to drive eventual player engagement through game elements. For example, achiever players engage with tangible rewards for achievement, like coins and badges, while explorer players engage by exploring the rules and bounds of the game environment (Stefan et al., 2017).

However, our analysis showed that classifications that seek to explain the behavior and motivations of different player profiles – in most cases – do not directly relate the identified types to specific game elements. In the context of games, the term “element” can represent different ways of dividing or understanding the parts of a game. Such elements have been identified in the game design literature at different levels of abstraction. Schell, for example, defends four elements: mechanics, narrative, aesthetics, and technology (Schell, 2020).

Another famous approach is the framework MDA, which proposes the division into mechanics, dynamics, and aesthetics (Hunicke et al., 2004). The possibilities are endless since the elements that make up the games can still be grouped in terms of components, environment, players, context, rules, mechanics, theme, interface, and information (Järvinen, 2009). Or – as Bjork and Holopainen present – can be defined by design patterns exceeding 100 (Bjork and Holopainen, 2004).

Although this diversity in understanding the elements that make up a game derives from seeing which characteristics are essential to be observed, depending on the purpose, it is not easily comparable – and the same happens to players' classifications. One can perceive the different perspectives on game elements in how they are delimited by different definitions, in different levels of granularity, views, and forms, making it difficult to compare which game elements from one work relate to the elements from another. The same happens to how players' profiles can relate to the different categories of game elements, ultimately confusing their application in practice.

However, the work of Tondello et al. (2019) stands out in discussing that analyzing player types in a way that is directly related to game elements makes the application of types more direct and practicable. The authors translate the game elements into activities that players engage in while gaming, such as progression, action and role-playing, resource management, exploration, or combat.

In the present work, we confirmed this perspective by identifying that most approaches to studying player types seem

to ignore the relationship between such types and game elements. We agree with the authors that much work focuses on higher-level factors such as immersion or achievement, making applying such classifications difficult. Although we identified some preliminary initiatives to relate the behavioral profiles of players with the components of games (Paulin, 2013), it is necessary to deepen the study of these elements and their correlation with the motivational and behavioral profiles of players.

5.4 Gaps and research opportunities

As detailed above, the results of this SM indicate a research gap for carrying out experimental studies that map game elements to player profiles. Our findings also indicated the need to investigate personality characteristics further – an essential factor for engagement but still little explored. Furthermore, some expanding domains, such as serious games and gamified systems, were timidly addressed in the classifications (only in one work each).

As recent research indicates, the effectiveness of serious games appears to be correlated to the degree to which players like the game (Van Gaalen et al., 2022). Hence, using a player classification in the games user research can help game designers to identify more clearly interpretable patterns and show how players perceive play to design more compelling games.

It is also necessary to highlight the scarcity of Brazilian research on the subject – in formal and informal searches, only two works (Rodrigues and Brancher, 2018; Bicalho et al., 2019) were identified in a national event. There is an opportunity of developing more research that seeks to investigate the profiles of Brazilian players and users, aiming to understand cultural particularities.

In this sense, we agree with the conclusions drawn in the work of Miranda et al. (2021) when they question the use of game research tools made from and for other cultural and social characteristics, which are only assumed to be valid for local users. We underline the work of Kahn et al. (2015) which stood out for validating its typology in two different cultural contexts (with American players and, in other ways, with the Chinese audience), which is an excellent example to be followed in future research.

Finally, it is necessary to emphasize that there is still a wide range of games to be examined. Works that explore online games and their direct variations (such as MMO, MMORPG, and MOBA, among others) are common, while few works deal with offline or single-player games, for example. As pointed out in the work of Fortes Tondello et al. (2018), we also identified that research on player classifications has tended to fall into the same group. Observing our findings, we have the same understanding as Hamari and Tuunanen (2014) when their work suggests that it can compromise the generalizability of the results.

6 Research Limitations

Apart from the contributions to the literature in this domain, this study is not free from limitations characteristic of most

systematic reviews and mappings. First, due to the nature of the process of selecting, filtering, and extracting data from articles, it is possible that relevant studies have not been analyzed. In addition, only four bases were selected. Although evaluating the bases' quality was decisive in the choice of these four as representative of the research scenario in national and international games, the authors understand that there may be works that are relevant to the objectives of this research that are not indexed in them.

Furthermore, another limitation can be found in the fact that the searches did not capture some relevant works due to the wide variety of terms papers use for classifications (which are not always synonymous, as discussed in Section 5). Such lack of standardization makes it difficult to build a complete and far-reaching search *strings*. To mitigate such limitations, relevant works identified in another SM were manually included and properly filtered and analyzed, as described in Section 3.

7 Conclusion

Although the literature is rich in works that typify and classify players, the lack of an objective analysis can make it difficult for researchers and practitioners to decide how to employ them to support game user research and game design. Thus, this research investigates players' taxonomies and typologies regarding their motivations, behavior, and personality characteristics, analyzing how they explore these traits.

Our results indicated various categories to describe players, different ways to propose and validate such categorizations, and tools to assist researchers and practitioners in identifying players' profiles. They can be used to help customize the player's experience and increase the engagement and motivation of specific groups with the interactive and narrative elements most suitable to them. They can also be employed in experimental studies that analyze physical, psychological, and social factors impact on player profiles.

Our future work focuses on analyzing the relationship between different interface and interaction elements in games with the level of motivation and engagement of different player profiles. Attempts were made to relate players' behavioral profiles with game components, but still, superficially (Paulin, 2013). Research on game resources is pretty fragmented, and experimental studies are needed to map game resources to player engagement (Boyle et al., 2016), relating them to their motivational and behavioral profiles. Thus, in the future, this research will address the search for a relationship between player profiles and their level of engagement with the game, given specific elements of digital games.

References

- Adisusilo, A. K., Hariadi, M., Yuniarno, E. M., and Purwantana, B. (2020). Optimizing player engagement in an immersive serious game for soil tillage base on pareto optimal strategies. *Heliyon*, 6(3):e03613.
- Aksakal, N. (2015). Theoretical view to the approach of the edutainment. *Procedia-Social and Behavioral Sciences*, 186:1232–1239.
- Alankus, G., Lazar, A., May, M., and Kelleher, C. (2010). Towards customizable games for stroke rehabilitation. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 2113–2122.
- Apperley, T. H. (2006). Genre and game studies: Toward a critical approach to video game genres. *Simulation & Gaming*, 37(1):6–23.
- Attfield, S., Kazai, G., Lalmas, M., and Piwowarski, B. (2011). Towards a science of user engagement (position paper). In *WSDM workshop on user modelling for Web applications*, pages 9–12.
- Bahrini, M., Zargham, N., Pfau, J., Lemke, S., Sohr, K., and Malaka, R. (2020). Good vs. evil: Investigating the effect of game premise in a smart home security educational game. In *Extended Abstracts of the 2020 Annual Symposium on Computer-Human Interaction in Play*, pages 182–187.
- Bailey, K. D. (1994). *Typologies and taxonomies: An introduction to classification techniques*, volume 102. Sage.
- Barata, G., G. S. (2014). Relating gaming habits with student performance in a gamified learning experience. *Proceedings of the first ACM SIGCHI annual symposium on Computer-human interaction in play*, page 17–25.
- Barbosa, S. D. J., Silva, B. S. d., Silveira, M. S., Gasparini, I., Darin, T., and Barbosa, G. D. J. (2021). *Interação Humano-Computador e Experiência do Usuário*. Autopublicação.
- Bartle, R. (1996). Hearts, clubs, diamonds, spades: Players who suit muds. *Journal of MUD research*, 1(1):19.
- Bateman, C., Lowenhaupt, R., Nacke, L. E., et al. (2011). Player typology in theory and practice. In *DiGRA Conference*.
- Benlamine, M. S., Dombouya, R., Dufresne, A., and Frasson, C. (2017). Game experience and brain based assessment of motivational goal orientations in video games. In *International Conference on Brain Function Assessment in Learning*, pages 118–132. Springer.
- Bicalho, L. F., Baffa, A., and Feijó, B. (2019). A game analytics model to identify player profiles in singleplayer games. In *2019 18th Brazilian Symposium on Computer Games and Digital Entertainment (SBGames)*, pages 11–20. IEEE.
- Bitrián, P., Buil, I., and Catalán, S. (2021). Enhancing user engagement: The role of gamification in mobile apps. *Journal of Business Research*, 132:170–185.
- Bjork, S. and Holopainen, J. (2004). *Patterns in game design (game development series)*. Charles River Media, Inc.
- Blizzard, A. (2021). Social connection in a virtual world. <https://www.activisionblizzard.com/newsroom/2021/10/social-connection-in-a-virtual-world> (Accessed in 12/20/2021).
- Bontchev, B., Vassileva, D., Aleksieva-Petrova, A., and Petrov, M. (2018). Playing styles based on experiential learning theory. *Computers in Human Behavior*, 85:319–328.
- Borges, J. B., Juy, C. L., de Andrade Matos, I. S., Silveira,

- P. V. A., and Darin, T. d. G. R. (2020). Player experience evaluation: Which instrument should i use? *Journal on Interactive Systems*, 11(1):74–91.
- Boyle, E. A., Hainey, T., Connolly, T. M., Gray, G., Earp, J., Ott, M., Lim, T., Ninaus, M., Ribeiro, C., and Pereira, J. (2016). An update to the systematic literature review of empirical evidence of the impacts and outcomes of computer games and serious games. *Computers & Education*, 94:178–192.
- Brühlmann, F., Baumgartner, P., Wallner, G., Kriglstein, S., and Mekler, E. D. (2020). Motivational profiling of league of legends players. *Frontiers in Psychology*, 11:1307.
- Busch, M., Mattheiss, E. E., Hochleitner, W., Hochleitner, C., Lankes, M., Fröhlich, P., Orji, R., and Tscheligi, M. (2016). Using player type models for personalized game design—an empirical investigation. *IXD&A*, 28:145–163.
- Cairns, P. (2016). *Engagement in Digital Games*, pages 81–104. Springer International Publishing, Cham.
- Calegari, G. R. and Celino, I. (2018). Interplay of game incentives, player profiles and task difficulty in games with a purpose. In *European Knowledge Acquisition Workshop*, pages 306–321. Springer.
- Carneiro, N., Darin, T., and Viana, W. (2019). What are we talking about when we talk about location-based games evaluation? a systematic mapping study. In *Proceedings of the 18th Brazilian Symposium on Human Factors in Computing Systems*, pages 1–13.
- Chandra, A., Borbora, Z., Kumaraguru, P., and Srivastava, J. (2019). Finding your social space: empirical study of social exploration in multiplayer online games. In *2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pages 1072–1080. IEEE.
- Chapman, P. M. (1997). *Models of engagement: Intrinsically motivated interaction with multimedia learning software*. PhD thesis, University of Waterloo.
- Cheng, M.-T., She, H.-C., and Annetta, L. A. (2015). Game immersion experience: its hierarchical structure and impact on game-based science learning. *Journal of computer assisted learning*, 31(3):232–253.
- Da Silva, R. B. (2013). Taxonomie et typologie: est-ce vraiment des synonymes? *Santé publique*, 25(5):633–637.
- Darin, T. and Carneiro, N. (2020). Avaliação de fatores humanos na interação com jogos digitais. In *2020 19th Brazilian Symposium on Computer Games and Digital Entertainment (SBGames)*, pages 1120–1123. SBC – Proceedings of SBGames 2020 — ISSN: 2179-2259.
- de Souza Filho, J. C., Sampaio, A. L., Monteiro, I. T., and Jucá, P. M. (2019). Exploring how expert and novice evaluators perceive g4h to consolidate heuristic evaluation. In *Proceedings of the 18th Brazilian Symposium on Human Factors in Computing Systems, IHC '19*, New York, NY, USA. Association for Computing Machinery.
- Doherty, K. and Doherty, G. (2018). Engagement in hci: conception, theory and measurement. *ACM Computing Surveys (CSUR)*, 51(5):1–39.
- Doty, D. H. and Glick, W. H. (1994). Typologies as a unique form of theory building: Toward improved understanding and modeling. *Academy of management review*, 19(2):230–251.
- Drachen, A., Canossa, A., and Yannakakis, G. N. (2009). Player modeling using self-organization in tomb raider: Underworld. In *2009 IEEE symposium on computational intelligence and games*, pages 1–8. IEEE.
- Drachen, A., Mirza-Babaei, P., and Nacke, L. E. (2018). *Games user research*. Oxford University Press.
- Evelin, A. D., da Silva, K. C., Neves, O. F., Ishitani, L., and Nobre, C. N. (2016). Emotional experience of older adults with digital games for smartphones—a case study of the brazilian game viajando pelo mundo. In *Proceedings of the 15th Brazilian Symposium on Human Factors in Computing Systems*, pages 1–9.
- Facebook IQ, M. (2019). Strategic considerations for mobile gaming engagement campaigns. <https://www.facebook.com/business/news/insights/strategic-considerations-for-mobile-gaming-engagement-campaigns> (Accessed in 12/20/2021).
- Fortes Tondello, G., Valtchanov, D., Reetz, A., Wehbe, R. R., Orji, R., and Nacke, L. E. (2018). Towards a trait model of video game preferences. *International Journal of Human-Computer Interaction*, 34(8):732–748.
- Gee, J. P. (2005). Pleasure, learning, video games, and life: The projective stance. *E-Learning and Digital Media*, 2(3):211–223.
- Goldberg, L. R. et al. (1999). A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. *Personality psychology in Europe*, 7(1):7–28.
- Google (2019). Change the game: Driving inclusivity and belonging in gaming. <https://static.googleusercontent.com/media/play.google.com/pt-BR//about/changethegame/assets/static/pdf/white-paper-2019.pdf> (Accessed in 12/20/2021).
- Gow, J., Baumgarten, R., Cairns, P., Colton, S., and Miller, P. (2012). Unsupervised modeling of player style with lda. *IEEE Transactions on Computational Intelligence and AI in Games*, 4(3):152–166.
- Grace, L. (2005). Game type and game genre. *Retrieved February*, 22(2009):8.
- Hamari, J. and Tuunanen, J. (2014). Player types: A meta-synthesis.
- Hedden, H. (2010). The accidental taxonomist.
- Herrington, N. and Coogan, J. (2011). Q methodology: an overview. *Research in Teacher Education*, 1(2):24–28.
- Hookham, G. and Nesbitt, K. (2019). A systematic review of the definition and measurement of engagement in serious games. In *Proceedings of the Australasian Computer Science Week Multiconference*, pages 1–10.
- Hunicke, R., LeBlanc, M., and Zubek, R. (2004). Mda: A formal approach to game design and game research. In *Proceedings of the AAAI Workshop on Challenges in Game AI*, volume 4, page 1722. San Jose, CA.
- Järvinen, A. (2009). *Games without frontiers: methods for game studies and design*. VDM, Verlag Dr. Müller.
- Kahn, A. S., Shen, C., Lu, L., Ratan, R. A., Coary, S., Hou, J., Meng, J., Osborn, J., and Williams, D. (2015). The

- trojan player typology: A cross-genre, cross-cultural, behaviorally validated scale of video game play motivations. *Computers in Human Behavior*, 49:354–361.
- Keirse, D. (1998). *Please understand me II: Temperament, character, intelligence*. Prometheus Nemesis Book Company.
- Kitchenham, B. A., Budgen, D., and Brereton, O. P. (2010). The value of mapping studies—a participant-observer case study. In *EASE*, volume 10, pages 25–33.
- Klock, A. C. T., Flores, T. H., Gasparini, I., and da Silva Hounsell, M. (2016). Classificação de jogadores: um mapeamento sistemático da literatura. *Anais do Simpósio Brasileiro de Jogos e Entretenimento Digital*. Porto Alegre: SBC.
- Kultima, A. (2015). Game design research. In *Proceedings of the 19th International Academic Mindtrek Conference*, pages 18–25.
- Laurel, B. (2013). *Computers as theatre*. Addison-Wesley, 2. edition.
- Lessiter, J., Freeman, J., Keogh, E., and Davidoff, J. (2001). A cross-media presence questionnaire: The itc-sense of presence inventory. *Presence: Teleoperators & Virtual Environments*, 10(3):282–297.
- Liu, X., Kasmarik, K., and Abbass, H. (2021). Assessing player profiles of achievement, affiliation, and power motivation using electroencephalography. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*.
- Liu, X., Merrick, K., and Abbass, H. (2017). Toward electroencephalographic profiling of player motivation: A survey. *IEEE Transactions on Cognitive and Developmental Systems*, 10(3):499–513.
- MacKenzie, I. S. (2013). *Human-Computer Interaction: An Empirical Research Perspective*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1st edition.
- Martins, G., Gomes, G., Conceição, J. L., Marques, L., Silva, D. d., Castro, T., Gadelha, B., and de Freitas, R. (2020). Enhanced interaction: Audience engagement in entertainment events through the bumbometer app. In *Proceedings of the 19th Brazilian Symposium on Human Factors in Computing Systems, IHC '20*, New York, NY, USA. Association for Computing Machinery.
- Melhart, D., Azadvar, A., Canossa, A., Liapis, A., and Yanakakis, G. N. (2019). Your gameplay says it all: modelling motivation in tom clancy's the division. In *2019 IEEE Conference on Games (CoG)*, pages 1–8. IEEE.
- Mendoza, Y. L. M. and Baranauskas, M. C. C. (2019). Tangitime: designing a (socio) enactive experience for deep time in an educational exhibit. In *Proceedings of the 18th Brazilian Symposium on Human Factors in Computing Systems*, pages 1–11.
- Miranda, D., Li, C., and Darin, T. (2021). Ues-br: Translation and cross-cultural adaptation of the user engagement scale for brazilian portuguese. *Proceedings of the ACM on Human-Computer Interaction*, 5(CHI PLAY):1–22.
- Miranda, P., Viana, J., Nascimento, E., and Portela, C. (2019). O uso de estratégias de gamificação em uma disciplina de ihc: Um relato de experiência. In *Anais Estendidos do XVIII Simpósio Brasileiro sobre Fatores Humanos em Sistemas Computacionais*, pages 94–99. SBC.
- Nacke, L. E., Bateman, C., and Mandryk, R. L. (2014). Brainhex: A neurobiological gamer typology survey. *Entertainment computing*, 5(1):55–62.
- NISO, N. I. S. O. (2010). *Guidelines for the construction, format, and management of monolingual controlled vocabularies*. NISO Press, Baltimore, Maryland.
- O'Brien, H. and Cairns, P. (2016). *Why engagement matters: Cross-disciplinary perspectives of user engagement in digital media*. Springer.
- O'Brien, H. L. and Toms, E. G. (2008). What is user engagement? a conceptual framework for defining user engagement with technology. *Journal of the American Society for Information Science and Technology*, 59(6):938–955.
- O'Brien, H. L. and Toms, E. G. (2010). The development and evaluation of a survey to measure user engagement. *Journal of the American Society for Information Science and Technology*, 61(1):50–69.
- Orhan Gökşün, D. and Gürsoy, G. (2019). Comparing success and engagement in gamified learning experiences via kahoot and quizzz. *Computers Education*, 135:15–29.
- Orji, R., Nacke, L. E., and Di Marco, C. (2017). Towards personality-driven persuasive health games and gamified systems. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 1015–1027.
- O'Brien, H. L., Cairns, P., and Hall, M. (2018). A practical approach to measuring user engagement with the refined user engagement scale (ues) and new ues short form. *International Journal of Human-Computer Studies*, 112:28–39.
- Paulin, R. E. (2013). Mapeamento das relações entre perfis de jogadores, tipos psicológicos, emoções e componentes de jogos eletrônicos.
- Petersen, K., Vakkalanka, S., and Kuzniarz, L. (2015). Guidelines for conducting systematic mapping studies in software engineering: An update. *Information and Software Technology*, 64:1–18.
- Rodrigues, L. A. and Brancher, J. D. (2018). Improving players' profiles clustering from game data through feature extraction. In *2018 17th Brazilian Symposium on Computer Games and Digital Entertainment (SBGames)*, pages 177–17709. IEEE.
- Rozen, R. V. (2020). Languages of games and play: A systematic mapping study. *ACM Computing Surveys (CSUR)*, 53(6):1–37.
- Santos, C. Q., Müller, L., Ziesemer, A. C., Espindola, L. S., Pires, P. A., and Silveira, M. S. (2015). How can i help you? preliminary studies about user strategies and preferences during a game. In *Proceedings of the 14th Brazilian Symposium on Human Factors in Computing Systems*, pages 1–4.
- Schell, J. (2020). *The art of game design: a book of lenses*.
- Schuurman, D., De Moor, K., De Marez, L., and Van Looy, J. (2008). Fanboys, competitors, escapists and time-killers: a typology based on gamers' motivations for playing video games. In *Proceedings of the 3rd international conference on Digital Interactive Media in Entertainment and Arts*, pages 46–50.
- Shen, Y. S., Choi, H. C., Joppe, M., and Yi, S. (2020). What motivates visitors to participate in a gamified trip? a player typology using q methodology. *Tourism Management*,

- 78:104074.
- Si, C., Pisan, Y., Tan, C. T., and Shen, S. (2017). An initial understanding of how game users explore virtual environments. *Entertainment Computing*, 19:13–27.
- Silva, A. J., Romeiro, T. V., and Nobre, C. N. (2020). Evaluation of digital games for autistic children using heuristics and observation tests. In *Proceedings of the 19th Brazilian Symposium on Human Factors in Computing Systems*, pages 1–10.
- Smith, K. B. (2002). Typologies, taxonomies, and the benefits of policy classification. *Policy Studies Journal*, 30(3):379–395.
- Stefan, S., Alex, B., Shimin, K., and Valerie, S. (2017). A typology of players in the game physics playground. In *DiGRA & #3917 - Proceedings of the 2017 DiGRA International Conference*, Melbourne, Australia. Digital Games Research Association.
- Stewart, B. (2011). Personality and play styles: A unified model. *Gamasutra*, September, 1.
- Stone, P. (2002). Popping the (pico) question in research and evidence-based practice. *Nurs Res*, 15(3):197–198.
- Toda, A., Klock, A. C. T., Palomino, P. T., Rodrigues, L., Oliveira, W., Stewart, C., Cristea, A. I., Gasparini, I., and Isotani, S. (2020). Gamicism: relating education, culture and gamification—a link between worlds. In *Proceedings of the 19th Brazilian Symposium on Human Factors in Computing Systems*, pages 1–10.
- Tondello, G. F., Arrambide, K., Ribeiro, G., Cen, A. J.-I., and Nacke, L. E. (2019). “i don’t fit into a single type”: A trait model and scale of game playing preferences. In *IFIP Conference on Human-Computer Interaction*, pages 375–395. Springer.
- Tondello, G. F., Wehbe, R. R., Orji, R., Ribeiro, G., and Nacke, L. E. (2017). A framework and taxonomy of videogame playing preferences. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, pages 329–340.
- Vahlo, J., Kaakinen, J. K., Holm, S. K., and Koponen, A. (2017). Digital game dynamics preferences and player types. *Journal of Computer-Mediated Communication*, 22(2):88–103.
- Van Gaalen, A. E. J., Schönrock-Adema, J., Renken, R. J., Jaarsma, A. D. C., and Georgiadis, J. R. (2022). Identifying player types to tailor game-based learning design to learners: Cross-sectional survey using q methodology. *JMIR Serious Games*, 10(2):e30464.
- Vasconcelos, V., Amazonas, M., Castro, T., Freitas, R., and Gadelha, B. (2018). Watch or immerse? redefining your role in big shows. In *Proceedings of the 17th Brazilian Symposium on Human Factors in Computing Systems, IHC 2018*, New York, NY, USA. Association for Computing Machinery.
- Voulgari, I. and Komis, V. (2010). ‘elven elder lvl59 lf p/rb. please pm me’: immersion, collaborative tasks and problem solving in massively multiplayer online games. *Learning, Media and Technology*, 35(2):171–202.
- Wang, M. and Nunes, M. B. (2020). A design research approach for iot gamification of museum visiting experiences. In *20th European Conference on Research Methodology for Business and Management Studies: ECRM 2020*, page 309. Academic Conferences and publishing limited.
- Weber, M. (1949). The methodology of the social sciences (e. schills & h. finch, trans.). *Illinois: The Free Press of Glencoe*.
- Wiebe, E. N., Lamb, A., Hardy, M., and Sharek, D. (2014). Measuring engagement in video game-based environments: Investigation of the user engagement scale. *Computers in Human Behavior*, 32:123–132.
- Xu, Y., Poole, E. S., Miller, A. D., Eiriksdottir, E., Kestranek, D., Catrambone, R., and Mynatt, E. D. (2012). This is not a one-horse race: understanding player types in multiplayer pervasive health games for youth. *Proceedings of the ACM 2012 conference on computer supported cooperative work*, pages 843–852.
- Yee, N. (2006). Motivations for play in online games. *CyberPsychology & behavior*, 9(6):772–775.
- Yee, N. (2007). Motivations of play in online games. *Journal of CyberPsychology and Behavior*, pages 772–775.
- Yee, N., Ducheneaut, N., Nelson, L., and Likarish, P. (2011). Introverted elves & conscientious gnomes: the expression of personality in world of warcraft. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 753–762.