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Validation of the Player Personality and Dynamics Scale

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Featured Application

The Player Personality and Dynamics Scale (PPDS) can be embedded as an adaptive profiling module in any Learning Management System (LMS). After students complete the brief intake questionnaire (~1 min), the system yields five independent scores, one for each profile (Toxic, Joker, Tryhard, Aesthetic, and Coacher). These continuous scores enable the LMS and its analytics engine to perform the following: 1. Feed AI models that generate or select gamified narratives and mechanics tailored to the specific profile configuration of each learner rather than to a single dominant type. 2. Form student groups on the basis of shared or complementary play-style patterns, thereby fostering cooperation or purposeful competition and mitigating interpersonal conflict. 3. Adapt activity design and learning pathways by dynamically adjusting challenge level, feedback tone, and aesthetic presentation to the profile values of individual students or groups, thus maximizing motivation and engagement. 4. Log profile-linked learning analytics data, providing researchers and instructors with data to rigorously assess the impact of such personalized, narrative-driven gamification on academic performance and retention in forthcoming controlled studies with university cohorts and, subsequently, other educational levels. The psychometric validation reported in this article supplies the empirical foundation required to implement and evaluate these applications in future experimental research.

Abstract

This study presents the validation of the Player Personality and Dynamics Scale (PPDS), designed to identify player profiles in educational gamification contexts with narrative elements. Through a sample of 635 participants, a questionnaire was developed and applied, covering sociodemographic data, lifestyle habits, gaming practices, and a classification system of 40 items on a six-point Likert scale. The results of the factorial analysis confirm a structure of five factors: Toxic Profile, Joker Profile, Tryhard Profile, Aesthetic Profile, and Coacher Profile, with high fit and reliability indices (RMSEA = 0.06; CFI = 0.95; TLI = 0.91). The resulting classification enables the design of personalized gamified experiences that enhance learning and interaction in the classroom, highlighting the importance of understanding players' motivations to better adapt educational dynamics. Applying this scale fosters meaningful learning through the creation of narratives tailored to students' individual preferences.

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1. Introduction

Narrative-based learning environments require tools that not only capture player behavior but also explain how students construct and embody their identities in virtual worlds. Drawing on Heidegger's notion of Selbigkeit [1], understood here as the dynamic unfolding of the self through engagement with contexts rich in meaning, we conceive player identity as both a motivational and narrative construct. This "fragmentation of identity" has profound implications for how users interact in digital media such as video games, where the player can literally "be someone else," either by sheltering behind an avatar or by feeling freer to adopt behaviors they would not in a traditional setting.

This is where gamification becomes a key tool in the design of immersive educational experiences. Our goal in this project was to analyze and classify player profiles in video games based on their gameplay dynamics and personality traits in order to apply this classification to the creation of advanced narrative-driven gamification experiences.

Although classic typologies such as Bartle's player types and the BrainHex [2] model have expanded our understanding of gaming motivations, none address the specific interplay between narrative immersion and pedagogical objectives. To fill this gap, we propose the Player Personality and Dynamics Scale (PPDS), comprising five empirically grounded profiles: Tryhard, Socializer, Joker, Aesthetic, and Toxic, each reflecting distinct motivational and narrative dynamics in educational gamification. It is important to emphasize that the originality of the PPDS lies not in creating entirely novel categories, but in its pedagogical and narrative functionality: by aligning each profile with instructional-design and narrative principles, the scale provides actionable data for tailoring learning pathways in gamified environments.

In this regard, Martín-Rodríguez et al. [3] analyzed more than 2200 articles and proposed a categorization based on four dimensions: engagement with the game, social behavior, instrumental use of the game, and gameplay style. Based on these categories, the authors highlighted the need to develop an ad hoc scale that allows gamified experiences to be tailored to the individual characteristics of students, thereby optimizing their impact on learning and motivation.

These personalized narrative experiences not only foster deeper immersion in content but also enhance learning outcomes and knowledge retention. Authors such as Kalogiannakis et al. [4] have shown that the use of gamification in educational environments improves student motivation, increases engagement, and supports more meaningful and in-depth learning.

The decision to use video games as the reference context for studying player profiles rather than other recreational contexts such as board games, wargames, or team sports stems from two key factors: first, the democratization of video games, which, with their vast variety of genres and titles, have become a dominant form of entertainment among students, and second, the unique way in which video games allow users to interact both individually in virtual, fictional environments and socially enabling a deeper development of the player's identity.

Identity development within video games, enhanced by avatars and immersive settings, allows players to adopt different roles and motivations in-game. Classifying these profiles helps us better understand their gameplay dynamics and, consequently, how to design gamified experiences aligned with their preferences. Taking Bartle's classic taxonomy [5], which categorizes players as "killers," "socializers," "explorers," and "achievers" as our starting point, we recognized the need to update and expand this typology to reflect recent advances in game design and new forms of social interaction in online games [6].

One of the essential aspects of gamification, particularly in educational contexts, is that game mechanics must be adapted to the player's profile to maximize their impact. Recent studies, such as that of Vahlo et al. [7], suggest that identifying gameplay styles is crucial to tailoring motivating dynamics. For instance, players drawn to narrative or those who prefer a more competitive approach require different types of experiences. This personalization not only enhances academic performance but also fosters transversal skills such as problem-solving and teamwork [8].

In this sense, narrative-based gamification enables the creation of educational environments where players—students in this case—immerse themselves in a story that aligns with their preferences and motivations. Immersion, defined by Ermi & Mäyrä [9] as a key component of the user experience, is essential to ensure students not only enjoy themselves but also achieve meaningful learning. Furthermore, when narrative design is adapted to the player's profile, it enables a higher level of personalization, enhancing educational effectiveness [10].

To make such personalization effective, it is necessary to have tools capable of identifying the different player profiles in the classroom. Based on prior studies, we identified four major categories of players: those engaged through frequency and dedication; those who interact socially; those who use games to satisfy personal goals such as power or escapism; and those with specific gameplay styles, such as "explorers" or "completionists." Classifying players within these categories provides a solid foundation for designing gamification strategies that address the individual needs of students and maximize their learning potential.

2. Materials and Methods

2.1. Participants

The sample consisted of a total of 635 individuals: 67.4% identified as male, 31.5% as female, and 1.1% did not specify their gender. The average age was 22.13 years. Most participants were from Spain (97.3%), particularly from the Canary Islands Autonomous Community (78.3%). Among them, 62.2% were exclusively students. Regarding educational level, 41.3% were university students, with 28.3% studying Engineering and Architecture, 23.6% in Social and Legal Sciences, 15.9% in Arts and Humanities, 7.2% in Health Sciences, and 2.2% in Natural Sciences. The remaining 22.7% were not affiliated with any of these academic fields, as they were not enrolled in higher education.

To explore preliminary differences, we conducted descriptive mean comparisons of PPDS profiles by gender, educational level, and academic branch. For example, the Toxic Profile mean was 2.09 (SD = 0.98) in females versus 1.74 (SD = 0.86) in males; the Tryhard Profile had a mean of 3.81 (SD = 0.91) in university students versus 4.00 (n = 1) in vocational training. Mentor profile means ranged from 2.55 (SD = 1.18) to 2.14 (SD = 1.13) by gender and from 2.75 (SD = 1.30) to 2.50 by educational level, and varied minimally across the six academic branches ($\Delta M \leq 0.30$), suggesting relatively homogeneous performance across fields.

Among the university students in the sample, 63.6% reported always attending classes unless due to force majeure, and 72.8% had never repeated an academic year. Regarding household composition, 48.8% lived alone or with their siblings and both parents. Family income data revealed that 32.1% reported a monthly income between EUR 1.201 and EUR 2.400, and 28.1% between EUR 2.401 and EUR 3.000.

In terms of health-related variables, 85.8% of participants reported not smoking, 48.8% stated that they rarely consumed alcoholic beverages, and 82.0% never used other substances. The calculated body mass index (BMI) of the sample was 23.5, indicating a normal or healthy weight range.

With respect to social/emotional indicators, 33.9% reported sometimes feeling lonely, 29.8% almost never felt lonely, and 25.4% never felt lonely. Making friends was perceived as easy or very easy by 67.3% of participants, while 32.8% found it somewhat or very difficult.

Finally, regarding participants' involvement with video games, 65.2% reported playing at least one type of eSport video game. The average length of a single gaming session was 3.29 h. In terms of self-perception of gaming skill, 43.5% identified as "good players," while 32.1% described themselves as "casual players."

The relationship between playtime and self-perceived player level is shown in Figure 1, which presents the distribution of gaming session lengths by self-assessed skill, categorizing participants as "I don't usually play video games", "Beginner", "Casual player", "Good player", and "Professional".

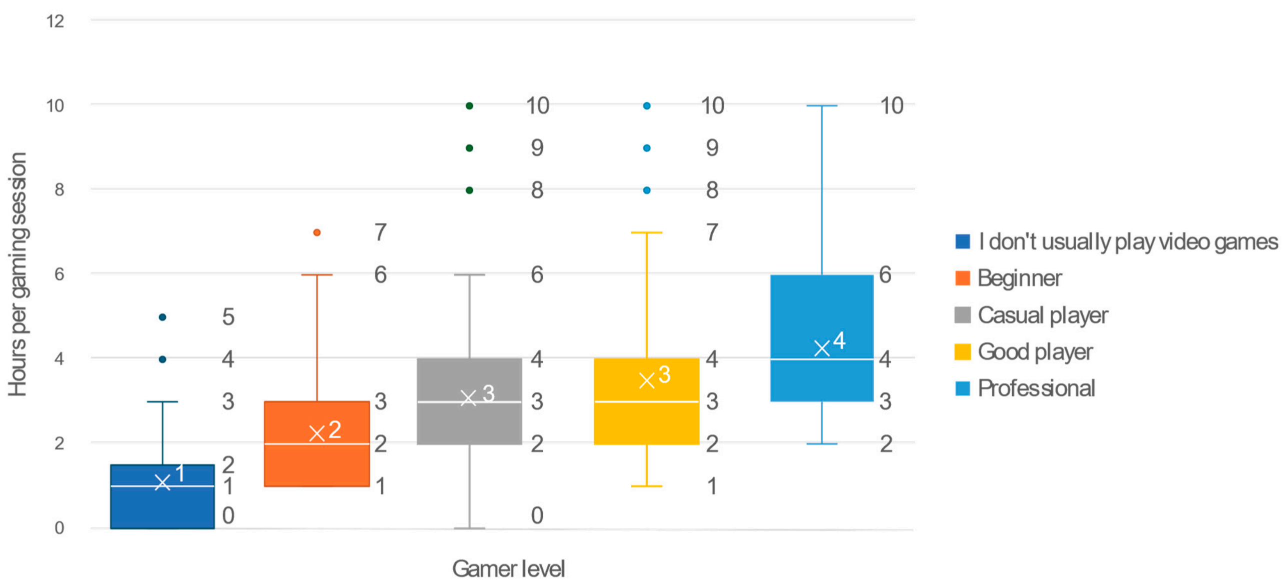

Figure 1. Box-and-whisker plot of hours per gaming session by player level.

"I don't usually play video games": This group had the lowest median playtime, with values around 1 h per session. However, there were some outliers indicating that certain individuals reported significantly longer gaming sessions.

"Beginner": At this level, a slight increase in the median was observed, with typical gaming sessions ranging between 1.5 and 3 h. The data dispersion remained moderate, although some extreme values appeared, suggesting longer sessions in certain cases.

"Casual player": The median playtime in this group increased considerably, with sessions averaging around 3–4 h. Variability was greater, with a wider interquartile range, indicating significant differences among players at this level.

"Good player": This group showed a similar median to that of casual players but with more frequent outliers. This suggests that while most players maintained moderate playtimes, some individuals greatly exceeded 6–7 h per session.

"Professional": As expected, this level had the highest median playtime, with sessions around 6–7 h. Additionally, the data dispersion was considerably broader, indicating that some players may spend up to 10 or more hours in a single session.

Overall, the trend suggests a positive correlation between self-perceived player level and time spent per gaming session, with more experienced or professional players investing the most time. Notably, outliers were present across all levels, highlighting individuals with more extreme gaming habits within each group.

2.2. Instruments

To identify different player personalities and dynamics, an ad hoc questionnaire was developed specifically for this research project. The complete instrument, together with the anonymized response data, has been deposited in Zenodo [11] to ensure transparency and facilitate replication. The instrument comprised a set of questions covering sociodemographic data, lifestyle-related aspects, information on the participant's relationship with video games, and the Player Personality and Dynamics Scale:

Sociodemographic data: Given that the study focused on young individuals and students, the sociodemographic section emphasized educational background and household structure. Variables included gender, age, level of education, place of residence (country and autonomous city or region, if in Spain), employment status, academic field, average academic performance, class attendance frequency, academic repetition, living arrangements, and monthly family income.

Lifestyle data: In light of existing stereotypes that associate gamers with unhealthy lifestyles, this section aimed to provide a broader view of participants' habits. It included items on dietary practices, body mass index (BMI) as a reference for general health, and substance use (alcohol, tobacco, and other substances).

Gaming habits: Closely aligned with the scale's focus, this section explored both the quantitative and qualitative aspects of players' relationship with video games. Variables included: time spent gaming (in hours per session), the year participants started playing video games, engagement in eSports, and self-assessed skill level.

Scale: The Player Personality and Dynamics Scale initially consisted of 40 items rated on a 6-point Likert scale measuring the frequency of specific behaviors described in each item. The first three response options reflected low or moderately low frequency (1 = Never, 2 = Almost never, 3 = Occasionally), while the next three indicated medium to high frequency (4 = Sometimes, 5 = Often, 6 = Always). The decision to adopt a six-point scale was based on findings by Lozano et al. [12], who recommended between four and seven response options for optimal reliability and validity. Using six points—rather than the more common five—helped minimize the tendency for respondents to select a neutral midpoint (typically option 3). Given that some items described undesirable or socially sensitive behaviors, this format reduced the likelihood of participants defaulting to neutrality to avoid social desirability bias.

To refine the original 40-item instrument, we applied statistical and theoretical criteria iteratively. In each round of confirmatory factor analysis performed using Mplus 8 (Muthén & Muthén, Los Angeles, CA, USA) [13], we removed items with factor loadings below 0.40 or with substantial cross-loadings on two or more factors. Additionally, any item whose content lacked narrative coherence with the other indicators of its factor, despite slightly exceeding the loading threshold, was discarded to ensure conceptual consistency within each dimension. This process yielded the final 21-item scale.

The inclusion of sociodemographic, lifestyle, and gaming habit variables was also intended to allow for future research exploring mean differences between these criterion variables and the factors extracted from the Player Personality and Dynamics Scale.

2.3. Procedure

To determine the appropriate sample size, we considered the global population of video game players. Starting with Asia—the region with the largest number of gamers—there were approximately 1.7 billion users in 2023 [14]. In contrast, the United States had 190.6 million gamers according to The 2024 Economic Impact Report by the Entertainment Software Association [15]. Latin America accounted for approximately 266 million gamers [16], and Africa, a region experiencing rapid growth in gaming, reached 186 million users [17]. Europe recorded 124.4 million gamers, with Spain alone accounting for 20.05 million—one of the highest numbers on the continent [18] (see Figure 2).

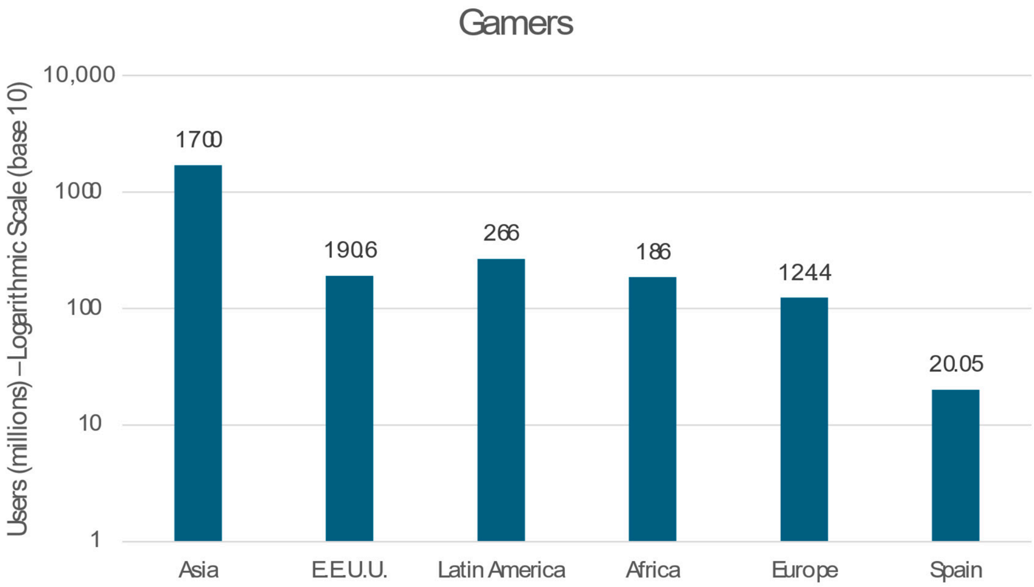

Figure 2. Distribution of video game users by region. A logarithmic scale (base 10) was used on the vertical axis to reflect the substantial differences in magnitude between the Asian market and other regions.

Based on these data, the estimated total number of video game players worldwide was approximately 2.9 billion. Due to the difficulty of accessing such a broad and dispersed population, we used **snowball sampling** [19,20]. A confidence interval of 96% and a margin of error of 4% were applied to calculate the required minimum sample size, which resulted in 601 participants [21].

Although the sample shows a high concentration in the Canary Islands (78.3%) and, more broadly, in Spain (97.3%), the validity of in-game dynamics does not appear to be substantially affected by local cultural differences. Several validation studies of motivation and gaming disorder scales have demonstrated metric and structural invariance across very different contexts:

The IGDS9-SF scale [22] for diagnosing gaming disorder in *League of Legends* exhibited factorial invariance across seven Latin American countries [23], confirming that its latent dimensions remain stable despite the region's sociocultural heterogeneity.

The 12-item shortened version of the Gamification User Types Hexad Scale (Hexad-12) [24], validated in a Chinese context, also showed an identical factor structure to the original, suggesting that basic gaming motivations transcend substantial cultural differences.

The "Trojan Player Typology" [25] revealed minimal divergences between Western and Japanese player cohorts, confirming that motivational and gameplay experiences follow universal patterns.

The questionnaire was created using Google Forms (Google LLC, Mountain View, CA, USA) to facilitate its distribution and data extraction in Excel 365 (Microsoft Corporation, Redmond, WA, USA). After designing the instrument, a pilot test was conducted with four university students from different academic years to identify any issues with item construction, measure completion time, and assess possible improvements to enhance readability, clarity, and flow.

The survey was distributed through educational institutions via school directors and faculty to ensure a heterogeneous sample, including university students, vocational training students, high school students, and secondary education students. Additionally, it was shared on international gaming forums to expand participation and gather responses from other regions of Spain, the Canary Islands, and Latin America.

The study followed the ethical guidelines of the Research Ethics Committee at Universidad del Atlántico Medio **(approval code: CEI/03-001)**. Before proceeding with the survey, participants were required to read and accept an informed consent form, which clearly explained the objectives of the study. Only after providing consent could participants access the remainder of the anonymous questionnaire.

A total of 652 responses were collected. However, any cases where participants answered "no" to a control question asking whether they played video games were excluded. This step ensured that individuals without gaming experience would not skew the scale by selecting "never" for all items. After this filtering process, the final sample consisted of 635 participants.

2.4. Data Analysis

To assess the reliability of the Player Personality and Dynamics Scale, McDonald's omega coefficient was used. This statistic is considered a superior alternative to Cronbach's alpha in many contexts, especially when alpha's assumptions are not fully met [26]. McDonald's omega accounts for the underlying factorial structure of the data, making it more suitable in cases where items are not strictly tau-equivalent (i.e., when items do not have equal variances).

Additionally, the following goodness-of-fit indices were used:

- **TLI (Tucker–Lewis Index):** This index evaluates model fit by comparing the variance explained in the proposed model to that explained in a null model. TLI values range from 0 to 1, with higher values indicating better fit. A TLI greater than 0.95 is generally considered indicative of good model fit.
- **CFI (Comparative Fit Index):** Similar to TLI, the CFI compares the fit of the proposed model against a null model. Values also range from 0 to 1, with values above 0.95 indicating good fit.
- **RMSEA (Root Mean Square Error of Approximation):** RMSEA assesses how well the model fits the data by comparing the observed covariance matrix to the expected covariance matrix. Lower values indicate better fit, with values below 0.05 suggesting a good fit, and values between 0.05 and 0.08 considered acceptable.
- **SRMR (Standardized Root Mean Square Residual):** This index measures the standardized difference between observed and expected covariances. Values below 0.08 indicate good fit.
- **CMIN (Chi-Square Minimum Discrepancy):** CMIN evaluates the sum of squared differences between observed and expected covariances. Ideally, the result should approach a value of 2 for a well-fitting model.
- **90% Percentile Confidence Interval:** This interval estimates the range within which the 90th percentile of a population parameter (e.g., the mean) is likely to fall, based on the sample. For RMSEA, a model is considered well-fitting when the upper bound of this interval remains below 0.08.

3. Results

The confirmatory factor analysis of the final 21-item instrument was performed using Mplus [13]. The five-factor solution yielded a χ^2 = 342.09 with df = 115 (p < 0.001). Although the χ^2 test was significant, expected given the large sample size, the model achieved acceptable fit according to alternative indices: RMSEA = 0.06 (90% CI [0.05, 0.06]), CFI = 0.95, TLI = 0.91, SRMR = 0.03, and CMIN = 2. Model selection followed an iterative process: we compared solutions with one to ten factors (see Table 1).

Table 1. Model fit indices for the five-factor model.

Factor	Factor/Item	X^2	*df*	RMSEA	90%	CFI	TLI	SRMR
1	1	2883.87	189	0.15	0.15–0.16	0.40	0.34	0.12
2	2	1560.30	169	0.11	0.11–0.12	0.70	0.62	0.07
3	3	1045.74	150	0.097	0.09–0.10	0.80	0.72	0.06
4	4	677.314	132	0.08	0.08–0.09	0.88	0.81	0.04
5	**5**	**342.09**	**115**	**0.06**	**0.05–0.06**	**0.95**	**0.91**	**0.03**
6	5	238.13	99	0.05	0.04–0.06	0.97	0.94	0.02
7	5	170.82	84	0.04	0.03–0.05	0.98	0.95	0.02
8	5	124.10	70	0.04	0.03–0.05	0.99	0.97	0.02
9	5	87.31	57	0.03	0.02–0.04	0.99	0.98	0.01
10	6	64.08	45	0.03	0.01–0.04	0.99	0.98	0.01

These optimal fit indices were obtained using a five-factor factorial structure, after testing multiple solutions ranging from one to ten factors. A summary visualization of the RMSEA, CFI, and TLI values across models with one to ten factors is provided in Figure 3, highlighting the inflection point at five factors. The final structure consisted of 21 items with factor loadings ranging from 0.436 to 0.801. Only items with loadings above 0.40 were retained. According to McDonald's omega, the overall reliability of the scale was **ω = 0.93**.

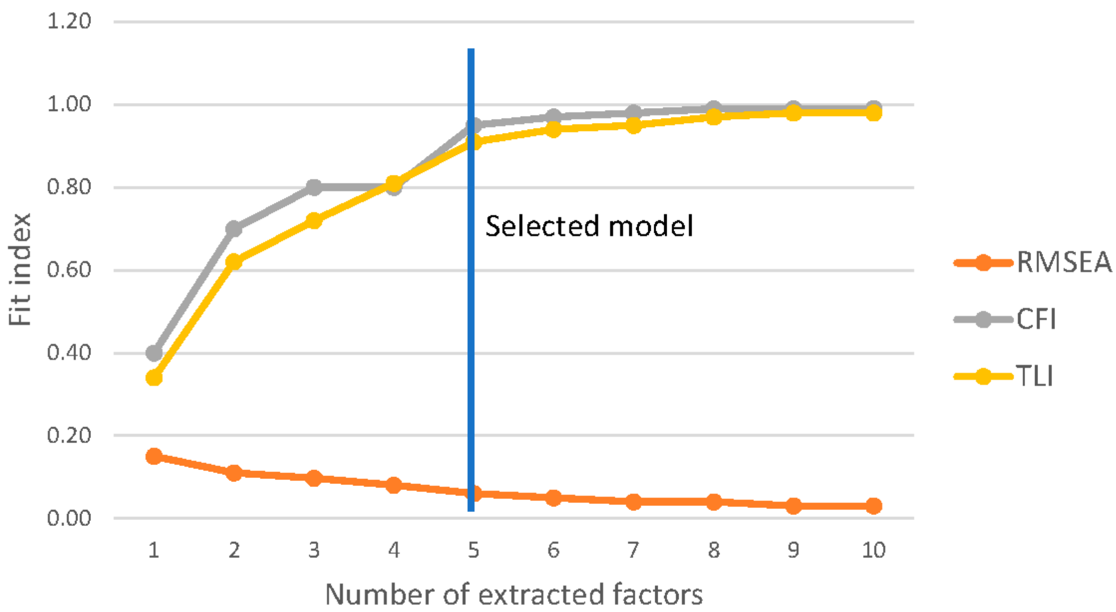

Figure 3. Fit indices (RMSEA, CFI, TLI) across models with 1 to 10 factors. The selected model (k = 5) is marked with a vertical line.

The five factors extracted from the confirmatory factor analysis were as follows: **Toxic Profile** (ω = 0.81), 5 items; **Joker Profile** (ω = 0.66), 4 items; **Tryhard Profile** (ω = 0.68), 5 items; **Aesthetic Profile** (ω = 0.62), 3 items; **Coacher Profile** (ω = 0.78), 4 items.

A detailed list of the 19 excluded items, their initial profile assignment, and the primary reason for exclusion is provided in Table A2.

While conventional guidelines suggest McDonald's omega values of 0.70 or higher for well-established scales, the Joker (Ω = 0.66) and Aesthetic (Ω = 0.62) subscales of the PPDS remain in the final model for several reasons. First, each subscale is composed of only four items; shorter scales inherently yield lower reliability coefficients, yet they can still capture coherent and meaningful constructs when their content validity is robust. Second, the PPDS is in an exploratory validation phase: values above 0.60 are generally deemed acceptable at this stage, particularly when theoretical justification supports the construct's inclusion [27]. Third, both subscales address motivational–narrative dynamics that are central to educational gamification: playful creativity (Aesthetic) and strategic unpredictability (Joker). Excluding them would omit important pedagogical levers.

The factorial structure of the Player Personality and Dynamics Scale is shown in the Table 2.

Table 2. Factor structure of the Player Personality and Dynamics Scale. (F1: Factor 1, F2: Factor 2, F3: Factor 3, F4: Factor 4, and F5: Factor 5).

Item Description	F1	F2	F3	F4	F5
			F1: Toxic Profile		
18. People often tell me to calm down when playing with me	0.716	−0.005	−0.138	0.114	0.166
27. I often end up damaging my peripherals (mouse, keyboard, controller, etc.) due to frustration with certain games27	0.712	0.068	−0.171	0.001	0.138
28. I have been banned or penalized in a game for inappropriate behavior in the chat	0.703	0.001	0.266	−0.174	−0.057
16. My family or people around me have complained that I yell while playing	0.674	−0.081	0.238	0.005	0.007
04. I have been banned or penalized in a game for leaving a match	0.598	0.111	−0.019	−0.025	−0.034
			F2: Joker Profile		
06. I usually design characters in the most ridiculous way possible	−0.01	0.706	−0.046	−0.021	0.113
32. I give ridiculous nicknames to my avatars or characters in games	0.096	0.678	0.078	0.017	−0.022
09. I usually enjoy playing pranks on other players	0.252	0.467	0.275	−0.071	0.014
03. I tend to not take video games seriously	−0.14	0.44	−0.267	0.053	−0.1
			F3: Tryhard Profile		
29. I pay attention to how polished the game mechanics and dynamics are (hitboxes, damage areas, collisions, particles, etc.)	−0.03	−0.078	0.758	0.026	0.156
05. When I play, I do it on the hardest difficulty available	−0.019	0.043	0.534	−0.165	0.163
19. I tend to notice and take advantage of bugs, glitches, and exploits (programming flaws)	0.201	0.088	0.513	0.089	−0.03
33. I usually enjoy interacting with other players	0	0.174	0.5	0.05	0.055
02. I value games that allow me to customize everything possible: clothing, physical appearance, weapons, etc.	−0.06	0.004	0.436	0.24	−0.08
			F4: Aesthetic Profile		
20. When choosing a game, I consider the aesthetic and narrative aspects (storyline) to be important	0	−0.042	0.347	0.68	−0.06
21. I usually prioritize the aesthetics and narrative of a character over being stronger or easier to use	0.021	0.12	−0.024	0.624	0.193
17. In games where I can choose a character, I tend to pick the one with the most appealing lore or backstory	−0.03	0	0.369	0.489	0.036
			F5: Coacher Profile		
37. I usually study the matches of friends or teammates to help them improve	−0.041	0.005	−0.001	−0.016	0.801
39. I spend time extracting gameplay statistics to get better (my scores, times, damage, builds, etc.)	0	0.009	0.122	−0.051	0.774
35. I analyze matches after playing	0.099	−0.049	0.019	0.046	0.739
22. I've tried beating a game with no hits (without taking a single hit) or speedrunning it	0.097	0.248	−0.016	0.024	0.442

The **Toxic Profile** comprises the following items: "People often tell me to calm down when playing with me," "I often end up damaging my peripherals (mouse, keyboard, controller, etc.) due to frustration with certain games," "I have been banned or penalized in a game for inappropriate behavior in the chat," "My family or those around me have complained that I yell while playing," and "I have been banned or penalized in a game for leaving a match." This factor is defined by high emotional reactivity and disruptive behavior during gameplay. Players who score high on this factor tend to express frustration, anger, and negative attitudes that impact both their in-game environment and the people around them, such as teammates or family members. This profile typically involves manifestations of verbal aggression, lack of self-control, and behaviors that are sanctioned within the game itself. A high score on this profile clearly indicates a strong tendency to behave in a reactive and disruptive manner. Players with this profile have difficulty managing their emotions during gameplay, which often results in intense frustration and impulsive behavior, both verbal and physical. These behaviors often result in in-game sanctions and can lead to interpersonal conflict in the player's real-world environment. Because of its connection to interactions with others, a high score in this profile may deteriorate the gaming experience for teammates, generating tension and hostility. Conversely, a low score in this factor reflects strong emotional control, contributing to a more positive and cooperative gaming environment and avoiding actions that might negatively affect others or the physical space. Players who score low tend to foster a good atmosphere and demonstrate a high level of frustration tolerance.

The **Joker Profile** includes the following items: "I tend to design characters in the most ridiculous way possible," "I use ridiculous nicknames for my avatars or characters in games," "I usually enjoy playing pranks on other players," and "I tend to not take video games seriously." This profile refers to players who adopt a humorous and carefree attitude within the game environment. The profile is characterized by a playful and laid-back style in which humor is used as a means of personal and social entertainment. Players scoring high in this profile tend to create absurd avatars, use extravagant nicknames, and play pranks on other participants, which can either contribute to a relaxed and fun atmosphere or, if disruptive, hinder the gameplay for those who take it more seriously. Joker Profiles do not show signs of competitiveness or a strong desire to achieve high performance. Rather, they focus on fun and creativity. This profile is not inherently positive or negative; its interpretation depends on the gaming context, whether the pranks are performed in competitive settings, and the player's personality. High scores indicate a preference for creativity and amusement, often through nicknames or humorous behaviors. Joker players generally display a relaxed attitude toward the game, prioritizing fun and entertainment over competition and achievement. They enjoy making others laugh and tend to playfully challenge the rules in friendly environments. These players are driven by social interaction and entertainment and are less likely to take game challenges seriously, which can be frustrating for other players—especially in competitive formats. Conversely, low scores indicate a more serious and goal-oriented player who does not use humor or pranks as a form of entertainment. These players usually adopt a more structured, performance-focused approach.

The **Tryhard Profile** comprises the following items: "I pay attention to the precision of game mechanics and dynamics (hitboxes, damage areas, collisions, particles, etc.)," "I play on the hardest difficulty mode possible," "I tend to exploit bugs, glitches, or programming flaws in the game to gain advantage," "I enjoy interacting with other players," and "I value games that allow for full customization of elements such as clothing, physical appearance, weapons, etc." This profile groups players who approach the game seriously and with a high level of commitment, appreciating the technical quality of the gaming experience. These players value challenge and difficulty and tend to measure their skills against others, often within competitive environments. Tryhard Profile players seek to optimize their performance in-game by identifying and using the META (Most Effective Tactic Available), i.e., strategies and mechanics that offer significantly greater effectiveness. Often, they are aware of and exploit bugs or glitches—programming errors that allow players to perform actions that would otherwise be impossible—until such exploits are patched by developers. Additionally, they are highly inclined to participate in community challenges and favor games that require skill and precision. A high score on this factor indicates a highly competitive player who devotes considerable time to gaming and treats it as more than mere entertainment. In contrast, a low score reflects a more casual player—someone who plays occasionally and with little interest in improvement or optimization.

The term **Aesthetic Profile** is inspired by a concept popularized in Gen Z culture, referring to a visually or atmospherically appealing style associated with art, fashion, and lifestyle. It is essentially a reinterpretation of the traditional term, enriched with new meanings to reflect emerging cultural phenomena [28]. In the context of video games, this factor translates into a preference for visually striking experiences, artistic design, and immersive narratives. It comprises three items: “When choosing a game, I consider aesthetic and narrative aspects important (storyline),” “I tend to prioritize the aesthetics and narrative of a character over their strength or ease of use,” and “In games where I can choose a character, I usually pick the one with the most interesting lore or backstory.” These players prioritize visual and narrative aspects, including the game’s story, lore, world-building, and artistic direction. This type of player prefers to experience games aesthetically rather than functionally and tends to choose visually appealing elements regardless of their in-game effectiveness. A high score on this factor indicates a strong appreciation for audiovisual and narrative immersion, and a tendency to choose games that offer such experiences. Conversely, a low score suggests that the player is not particularly motivated by graphics, visual design, or storyline elements.

The **Coacher Profile** is defined by in-depth study of the game, including statistical analysis and performance metrics. It includes the following items: “I tend to study my friends’ or teammates’ matches to help them improve,” “I invest time in extracting game statistics to improve (scores, timing, damage, builds, etc.),” “I analyze matches after playing,” and “I’ve tried beating a game with no hits (not taking a single hit) or in a speedrun (completing the game as fast as possible).” This profile describes players who find purpose beyond gameplay itself, often dedicating more time to studying the game than playing it. Their goal is to serve as a reference and assist others through coaching or by creating online content, such as streaming. These players often share their own matches and engage in challenges that showcase the knowledge that makes them mentors and analysts. Common activities include speedruns—completing a game in record time—no-hit runs, and ranked matches in eSports or other competitive formats. A high score on this factor reflects deep involvement in analytical processes and a tendency toward competitive and educational challenges. In contrast, a low score suggests a player who does not engage in teaching or sharing their knowledge, and instead focuses solely on their own gameplay experience.

Once the factors were extracted, we calculated their mean scores to determine which profiles scored highest and lowest. The results are shown in the Table 3 and Figure 4:

Table 3. Mean scores for the Player Personality and Dynamics Scale factors.

Factor	*N*	Minimum	Maximum	*Mean*	*SD* (σ)
Toxic Profile	635	1	6	1.99	0.97
Joker Profile	635	1	6	3.14	1.08
Tryhard Profile	635	1	6	3.77	0.93
Aesthetic Profile	635	1	6	3.95	1.19
Coacher Profile	635	1	6	2.44	1.19

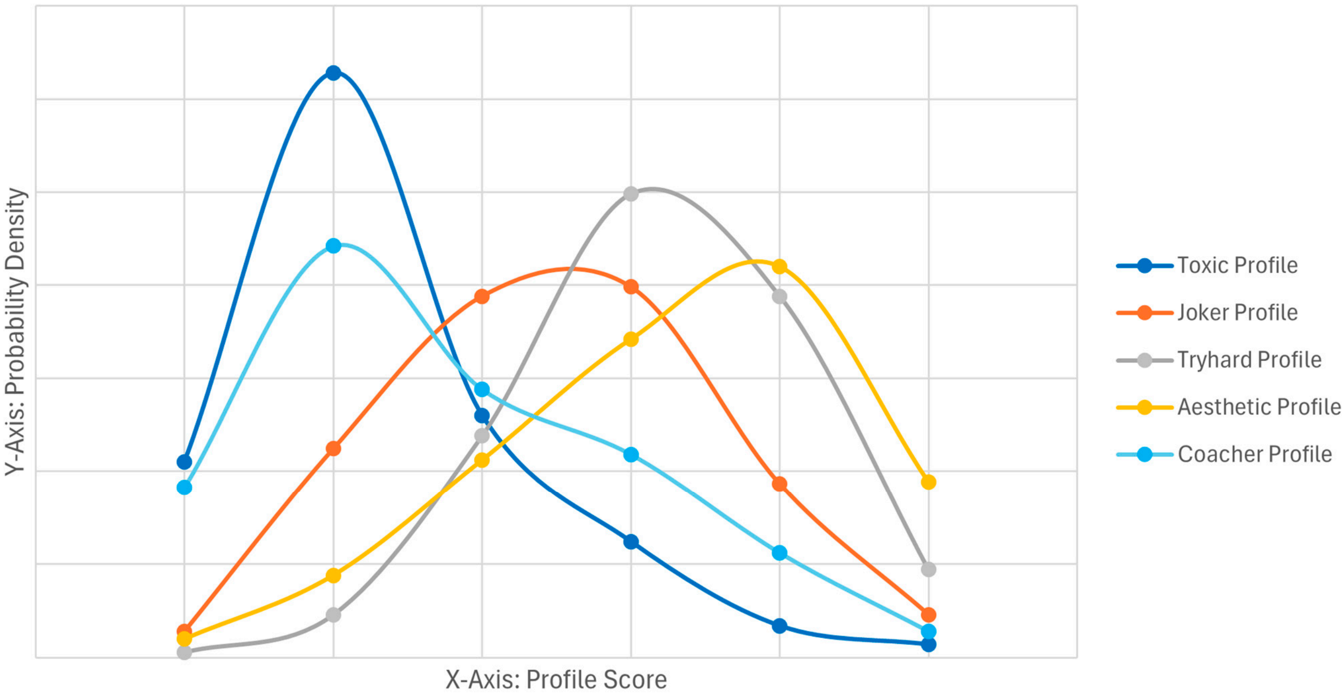

Figure 4. Normal distribution of the profiles.

As shown in the table, the highest scoring profile is the Aesthetic Profile, with a mean of 3.95, closely followed by the Tryhard Profile, with a mean score of 3.77. In contrast, the lowest scoring profile is the Toxic Profile, with a mean of 1.99, followed by the Coacher Profile, with a mean of 2.44. The Joker Profile falls in the mid-range, with an average score of 3.14 on a scale from 1 to 6.

These results suggest that video game players tend to identify more strongly with profiles that reflect an appreciation for the aesthetic and narrative qualities of games (Aesthetic Profile), while also taking gameplay seriously, striving for high performance and difficult achievements (Tryhard Profile). On the other hand, fewer participants identify with the Toxic Profile and the Coacher Profile—both more specialized in their relationship with gameplay. The former implies an explicitly negative interaction with little room for interpretative flexibility, and the latter reflects thorough out-of-game study, focused on analysis and coaching.

This relationship between profile specificity and polarization is especially clear in the case of the Joker Profile, which—as previously discussed—has a "dual face": either a laid-back, humorous, and socially engaging presence, or, conversely, a lack of seriousness in competitive environments, with a tendency toward disruptive or bothersome humor.

The following graph (Figure 5) illustrates the differences between the corresponding factors.

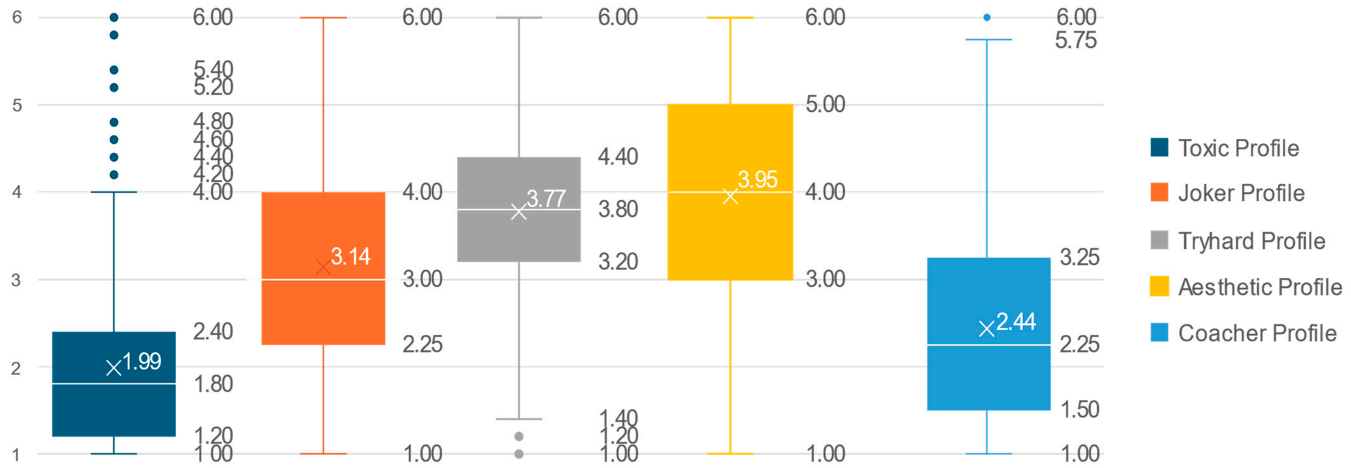

Figure 5. Representation of the Player Personality and Dynamics Scale factors.

Below we provide a set of descriptive statistics (mean and standard deviation) for all five PPDS profiles, broken down by three key demographic variables: gender, educational level, and academic branch. These figures, as shown in Tables 4–6 offer a preliminary view of how player profiles are distributed across these dimensions.

Table 4. Descriptive statistics of PPDS profiles by gender.

Gender	N	Toxic M (SD)	Joker M (SD)	Tryhard M (SD)	Aesthetic M (SD)	Coacher M (SD)
Male	428	2.09 (0.98)	3.15 (1.06)	3.96 (0.88)	3.94 (1.18)	2.55 (1.18)
Female	200	1.74 (0.86)	3.06 (1.10)	3.36 (0.90)	3.97 (1.21)	2.14 (1.13)
Other	7	2.94 (1.57)	4.43 (0.86)	4.51 (1.01)	4.14 (1.20)	3.82 (1.53)

Table 5. Descriptive statistics of PPDS profiles by academic branch.

Academic Branch	N	Toxic M (SD)	Joker M (SD)	Tryhard M (SD)	Aesthetic M (SD)	Coacher M (SD)
None	144	2.18 (1.08)	3.20 (1.09)	3.69 (0.98)	3.74 (1.26)	2.61 (1.22)
Arts and Humanities	101	1.76 (0.76)	2.90 (1.00)	3.85 (0.76)	4.35 (1.05)	2.23 (1.06)
Sciences	14	2.51 (0.81)	3.93 (0.72)	4.23 (0.53)	3.81 (1.09)	2.82 (0.96)
Health Sciences	46	1.60 (0.80)	2.90 (1.10)	3.60 (1.06)	3.65 (1.31)	2.53 (1.40)
Social and Legal Sciences	150	1.92 (0.92)	3.14 (1.11)	3.58 (0.90)	3.99 (1.17)	2.26 (1.13)
Architecture and Engineering	180	2.08 (1.00)	3.23 (1.07)	3.97 (0.95)	3.96 (1.15)	2.51 (1.22)

Table 6. Descriptive statistics of PPDS profiles by educational level.

Educational Level	N	Toxic M (SD)	Joker M (SD)	Tryhard M (SD)	Aesthetic M (SD)	Coacher M (SD)
No formal education	1	3.20 (–)	5.25 (–)	4.80 (–)	4.00 (–)	2.50 (–)
Primary education	136	2.18 (1.13)	3.50 (1.06)	3.80 (0.91)	3.81 (1.14)	2.75 (1.30)
Secondary education	51	2.39 (0.98)	3.07 (0.98)	3.66 (0.95)	3.63 (1.27)	2.75 (1.12)
High school	73	1.73 (0.69)	2.97 (1.14)	3.86 (0.94)	4.11 (1.15)	2.11 (1.05)
Vocational training	112	2.19 (1.05)	3.29 (1.00)	3.86 (1.01)	3.88 (1.26)	2.49 (1.26)
Higher education	262	1.79 (0.82)	2.94 (1.07)	3.72 (0.90)	4.08 (1.17)	2.29 (1.11)

4. Discussion

The identification of profiles provided by the Player Personality and Dynamics Scale in the context of narrative-based gamification offers a significant strategic advantage when designing personalized educational experiences and collaborative work dynamics. Gamification relies on motivating students through mechanics and narratives that capture their interest, and the identification of these profiles allows for the experience to be adjusted in ways that improve both learning outcomes and group interaction.

The creation of a player profile scale for narrative gamification in educational settings is grounded in a thorough review of previous player typology models, such as the Trojan Player Typology [25], and Bartle's model [5]; other lesser-known scales like BrainHex [2], the Online Player Type Scale (OTPS) [29], and the Gameplay Activity Inventory GAIN [30]; and more recent studies that expand the classical understanding of player motivations, behaviors, and styles—factors that directly influence the structure and effectiveness of narrative-based gamification in the classroom.

The Player Personality and Dynamics Scale introduces five profiles, each designed to capture the diversity of player interactions and motivations within educational gamification environments. When compared with previously cited scales, we find both points of convergence and expansions upon earlier classifications. For instance, the Tryhard Profile shares similarities with Bartle's "Achievers," as both emphasize overcoming challenges and pursuing high performance. However, the Tryhard Profile broadens this perspective by including the exploitation of system flaws to optimize one's experience. Similarly, the Aesthetic Profile, with its focus on design and storytelling, mirrors Bartle's "Explorer" and the "Narrative" category in BrainHex, but goes further by emphasizing the visual immersion and lore as key motivational components.

On the other hand, the Toxic Profile and Joker Profile reflect dimensions that are less frequently addressed in previous scales. While the Trojan Player Typology refers to intense competitive behaviors, the Toxic Profile in our scale specifically defines emotional reactivity and disruptive conduct during gameplay, offering a lens that can be especially useful for managing behavior in educational contexts. Rather than functioning as rigid behavioral labels, the Toxic and Joker Profiles are designed as narrative and pedagogical tools. The Toxic Profile does not imply a clinical or pathological category but rather flags high emotional reactivity, which can be addressed through story-based self-regulation strategies. The Joker Profile, often misunderstood as merely chaotic, can be reimagined as a creative and socializing agent when aligned with roles that encourage comic relief or imaginative expression. In this sense, both profiles serve as adaptive levers for tailoring narrative arcs and team roles within gamified learning environments. The Coacher Profile shares elements with Bartle's "Socializer" and the collaborative, strategy-focused profiles in the OTPS, but it adds a distinct layer of mentorship and performance optimization, highlighting the importance of helping others and conducting post-game analysis. This unique focus on development and support within gamified learning environments positions the Player Personality and Dynamics Scale as a robust tool for personalizing classroom dynamics, addressing both individual performance and social interaction.

At this point, a key question arises: how can the profiles identified by the Player Personality and Dynamics Scale be applied to narrative gamification?

Identifying students with a Toxic Profile allows for the implementation of narrative elements that redirect their energy toward more constructive activities—an approach that contrasts with more traditional scales, which tend to classify players based on motivation or social role. Narrative gamification design must include mechanisms for managing interaction and preventing disruptive behavior. In this sense, the narrative can include conflict-resolution scenarios that promote self-regulation and moderation within the game.

Students with a Joker Profile would incorporate humor and creativity into their activities, fostering a more relaxed and motivating play environment. Models such as GAIN and BrainTex highlight the motivational power of enjoyment and humor, yet they often fall short in detailing how these traits can be integrated into educational narratives. Introducing comic roles or characters would allow these players to express their creativity, thereby helping to create a more engaging and accessible learning experience.

Tryhard Profile players require skill and precision. The GAIN and BrainTex scales describe these individuals as players who seek challenges and strive for self-improvement. In an educational narrative, this motivation can be translated into complex missions and tasks that test their abilities. The narrative should be designed with a strong emphasis on competition and performance optimization to cater to this profile.

Players with an Aesthetic Profile consider immersion and fantasy as fundamental elements. These players bring a unique perspective by valuing visual design and character backstories, which can inform the construction of visually rich and narratively compelling educational content.

Finally, the Coacher Profile has its equivalent in the GAIN and OTPS as players characterized by their willingness to help others and optimize resources. In an educational context, narratives can incorporate leadership and mentorship roles, which these profiles will eagerly assume, thereby helping others and contributing to a reflective and meaningful learning environment.

In the classroom, forming workgroups based on these player profiles enables balanced, collaborative dynamics that enhance learning and reduce conflict. Students with a Toxic Profile, who may display intense or disruptive behaviors, should be paired with more collaborative peers—such as those with Joker or Coacher Profiles—who can support self-regulation and promote a positive working atmosphere. This combination reduces the likelihood of confrontation and allows more impulsive students to channel their energy constructively, facilitating both self-control and shared learning.

Joker Profile students can play a crucial role in easing tension and creating a relaxed working environment. When included in teams with more technically oriented students—such as those with Tryhard or Coacher Profiles—their humor and creativity can complement the team's structure and discipline, promoting a balance between seriousness and enjoyment in the learning process. This interaction helps reduce stress and fosters group cohesion, allowing students to feel more comfortable and motivated to participate actively.

Students with a Tryhard Profile and an Aesthetic Profile can assume complementary roles within the group. While Tryhards bring precision and rigor to technical tasks, Aesthetic players contribute an artistic and narrative dimension that enriches the final product. Alongside Coacher students—who support organization and promote workflow optimization—these profiles form teams with diverse skills, combining efficiency, creativity, and collaborative learning. The presence of these different profiles in the classroom enables a balanced learning environment, where each student contributes their strengths to foster a dynamic and adaptive educational experience.

5. Conclusions

Validating the Player Personality and Dynamics Scale (PPDS) has proved both necessary and timely. By grounding its five profiles (Tryhard, Coacher, Joker, Aesthetic, and Toxic) in robust theory and rigorous factor-analytic methods, we now possess a tool capable of revealing how learners enact identity and motivation within narrative-based gamified environments. Our results confirm that the 21-item, five-factor structure fits the data well and demonstrates high internal consistency, while its profiles align meaningfully with instructional-design principles. In essence, the PPDS bridges a gap left by earlier player typologies: it does not simply catalog gamer types, it translates those types into pedagogical levers, offering educators clear, actionable insights for tailoring challenges, feedback, and narrative arcs to distinct learner/player motivations.

6. Limitations and Future Directions

Our snowball sampling, heavily weighted toward the Canary Islands (78.3% of participants) and Spain overall (97.3%), raises legitimate questions about cultural generalizability. Although comparable gaming motivation instruments have shown structural invariance across Latin America, China, and even between Western and Japanese cohorts, we acknowledge that local educational norms and gaming cultures may yet shape subtle response patterns. Future research should therefore extend the PPDS to diverse linguistic and sociocultural contexts, both to confirm its metric invariance and to refine item wording where nuances emerge.

The reduction from 40 to 21 items, driven by statistical thresholds and narrative coherence, represents a strength in parsimony but also a constraint: there may remain facets of player motivation that our pruning overlooked. Moreover, without cross-validation on an independent sample or test–retest data, the temporal stability of profiles remains an open question.

Looking ahead, the PPDS enables us to design gamified learning sequences that honor the diversity of learner motivations. Consider a module with an engaging theme based on fantasy literature where a class of 100 students completes the PPDS and yields roughly 30% Tryhards, 25% Aesthetics, 20% Coachers, 15% Jokers, and 10% Toxics. The module unfolds through a coherent storyline, with each profile group receiving tailored tasks. Tryhards tackle multi-phase logic puzzles and complex problem sets; aesthetics enrich the experience by creating visual annotations and brief narrative reflections; mentors facilitate peer-led workshops or strategy sessions that deepen understanding; jokers inject creative twists or humorous scenarios that unlock bonus content; and students with a Toxic Profile are guided toward structured debates or competitive mini-games designed to channel critical thinking and assertiveness constructively. All contributions earn "insight points" that open interdisciplinary side activities, such as collaboratively mapping narrative elements or composing reflective journals. By blending structured challenges with opportunities for creative, social, and leadership engagement, this PPDS-informed design respects each profile's motivations and offers a practical setting to observe how tailored gamification deepens engagement, enhances collaboration, and elevates the overall educational experience.

To strengthen the generalizability of the PPDS, future studies should prioritize two tasks: first, administering the PPDS to culturally and linguistically diverse populations to test for metric invariance and semantic equivalence, and second, implementing cross-validation and test–retest analyses to examine temporal stability. Both are essential steps to move from exploratory validation to a fully generalizable and robust profiling tool.

For future studies, it will be essential not only to conduct empirical evaluations of PPDS-guided interventions but also to explore effective strategies for balancing profile distributions, especially when disruptive profiles emerge, to ensure cohesive group dynamics and equitable learning opportunities.

In addition, future analyses should investigate the extent of semantic overlap between profiles and the possibility that certain behaviors may involve multidimensional trait activation. While the current factor structure avoids cross-loadings for clarity and parsimony, this analytical decision may mask subtler interplays between profiles, particularly in emotionally or contextually charged behaviors.

Finally, future research should take advantage of the external variables already collected in the dataset—such as gaming session length, academic background, or body mass index (BMI)—to explore correlations with the PPDS profiles. These analyses were beyond the scope of this psychometric validation but are essential to deepen the explanatory power of the model and understand how player traits interact with broader lifestyle and academic factors.

As a next phase of this research, we will implement the PPDS in real educational contexts using a pre-test/post-test design. This pilot will gather both quantitative (motivation, performance, and response times) and qualitative (user feedback) data to evaluate operational feasibility and educational impact, and we plan to extend this validation by conducting exploratory correlation analyses between PPDS scores and available external variables, which will further inform the scale's practical applicability.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
BMI	Body Mass Index
CFI	Comparative Fit Index
CI	Confidence Interval (90% CI)
CMIN	Chi-Square Minimum Discrepancy
EDM	Educational Data Mining
GAIN	Gameplay Activity Inventory
LA	Learning Analytics
LMS	Learning Management System
META	Most Effective Tactic Available
OTPS	Online Player Type Scale
PPDS	Player Personality and Dynamics Scale
RMSEA	Root Mean Square Error of Approximation
SD	Standard Deviation
SRMR	Standardized Root Mean Square Residual
TLI	Tucker–Lewis Index

Appendix A

Player Personality and Dynamics Scale

Table A1. Player Personality and Dynamics Scale.

Toxic Profile
People often tell me to calm down when playing with me I often end up damaging my peripherals (mouse, keyboard, controller, etc.) due to frustration with certain games I have been banned or penalized in a game for inappropriate behavior in the chat My family or people around me have complained that I yell while playing I have been banned or penalized in a game for leaving a match
Joker Profile
I usually design characters in the most ridiculous way possible I give ridiculous nicknames to my avatars or characters in games I usually enjoy playing pranks on other players I tend to not take video games seriously
Tryhard Profile
I pay attention to how polished the game mechanics and dynamics are (hitboxes, damage areas, collisions, particles, etc.) When I play, I do it on the hardest difficulty available I tend to notice and take advantage of bugs, glitches, and exploits (programming flaws in the game) I usually enjoy interacting with other players I value games that allow me to customize everything possible: clothing, physical appearance, weapons, etc.
Aesthetic Profile
When choosing a game, I consider the aesthetic and narrative aspects (the game's story) to be important I usually prioritize the aesthetics and narrative of a character over being stronger or easier to use In a game where I can choose a character, I tend to pick the one with the most appealing lore or backstory
Coacher Profile
I usually study the matches of friends or teammates to help them improve I spend time extracting gameplay statistics to get better (my scores, times, damage, builds, etc.) I analyze matches after playing I've tried beating a game with no hits (without taking a single hit) or speedrunning it (completing the game as fast as possible)

Appendix B

Excluded Items and Exclusion

Table A2. Excluded items and exclusion criteria.

Item No.	**Exclusion Criteria**	**Item Statement**
30 36	Has very little theoretical connection with the other items in the factor	I typically purchase games in special or collector's editions. I typically purchase merchandise related to the games I enjoy.
11 23 24 25	Factor loading very similar on two factors	When playing, I limit myself to using only the most basic controls. When playing with others, I tend to alleviate tension if it arises. I often purchase skins in games that allow such customization. I tend to make microtransactions (small expenditures) to obtain loot boxes and similar items.
1 7 8 10 12 13 14 15 26 31 34 38 40	Factor loading below 0.40	I am indifferent to customizing the main character in a video game. I tend to acknowledge an opponent's skill when they have defeated me. I place importance on the community surrounding a video game. I tend to replay video games to obtain all achievements or improve my scores. I take into account my gaming setup (peripherals, chair, lighting, equipment, etc.) when playing. If a game includes a level, ranking, or leaderboard, I strive to ascend as much as possible. I am often influenced by a video game's cover art when making a purchase decision. I find it burdensome to decide among numerous options in a game. I generally read only the basic information about a game without exploring further. I generally play simple video games. Playing typically means being in the company of others for me. I often purchase video games even though I seldom play them afterwards. Even in competitive video games, I tend to play as casually as possible.

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