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Gamification and Player Profiles in Higher Education Professors

Diego Vergara, Catholic University of Ávila, Spain*
https://orcid.org/0000-0003-3710-4818

Ana Isabel Gómez-Vallecillo, Catholic University of Ávila, Spain

Pablo Fernández-Arias, Catholic University of Ávila, Spain
https://orcid.org/0000-0002-0502-5800

Álvaro Antón-Sancho, Catholic University of Ávila, Spain
https://orcid.org/0000-0002-1901-3878

ABSTRACT

This paper conducts descriptive quantitative research of the player profile of a set of 808 university professors, and the player profiles that participants consider most suitable for learning when educational gamification is employed in higher education. It also studied the existence of influential variables in the chosen player profiles, including sociological (gender and age) and academic variables (area of knowledge). The results reveal that most professors are mostly explorers, followed by the socializers, and consider these player profiles as the most efficient for achieving learning objectives. There are no gaps based on sociological aspects or knowledge about gamification, but there are gaps based on area of knowledge. It is proposed that universities design training sessions for professors on educational gamification and further research on factors that influence the configuration of their player profile.

KEYWORDS

Faculty Training, Games, Improving Classroom Teaching, Innovative Methodologies, Motivation, Pedagogical Issues, Personalized Learning, Teacher Professional Development

INTRODUCTION

Gamification in education has been understood as a motivational resource to address school dropout and lack of student engagement in the teaching-learning process (Martí-Parreño et al., 2016; Zahedi et al., 2021). However, not all gamification applications have produced the expected positive results, either because they have failed to motivate students, or because their initial enthusiasm has gradually waned as the game novelty value faded (Domínguez et al., 2013; Williams et al., 2008; Koivisto & Hamari, 2014;

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*Corresponding Author

Dymora & Niemiec, 2019), or because of the specific training needs of the teaching staff in this area (Figg & Jaipal-Jamani, 2015). As explained by Hassenzahl et al. (2010), a growing number of studies highlight the importance of customizing the game design to meet the basic needs and personality profile of players.

Some studies, such as Denisova & Cairns (2015), claim that the full adaptation to the student's profile is not a guarantee that the game experience will be more immersive, although it increases the motivation of the students and facilitates their integration in the game. Therefore, to the extent that the immersive experience also helps to achieve the learning objectives (Subhash & Cudney, 2018; Grivokostopoulou et al., 2019), it seems necessary to distinguish between the player profiles of the game designer, the student who will be the user and the player profile that will best ensure the acquisition of learning.

A search of bibliographic resources indexed in SCOPUS with the word "Gamification" in title, abstract or keywords reveals that there are no significant works on gamification prior to 2011 but that, since that year, interest in this methodology has grown every year among researchers (Figure 1). However, if the same is done with the expression "Player profile", it is observed that, although the trend of publications is increasing, the number of studies on the player profiles of the agents involved in gamified didactic situations is very low, in relative terms, with respect to the number of papers on gamification (Figure 1). Specifically, in 2021, the most recent full year for which reference is available, there are 1879 articles on gamification, compared to only 88 that discuss player profiles, so that less than 5% of the work on gamification focuses on player profiles. Moreover, the rate of growth of the number of publications is also lower, as can be deduced from the lower slope of the curve corresponding to publications on "Player profile" with respect to the curve of "Gamification". All this occurs despite the crucial importance of matching player profiles to learner profiles, something which, as has been explained, is amply supported by the previous literature.

This article analyzes the player profile of 808 university professors and their preferences about the player profile they consider most conducive to learning. The study also analyzes the influence that certain sociological (i.e., gender and age) and academic variables (area of knowledge), exert on these preferences. The distributions of the responses to the profiles chosen within each value of the above variables are also compared. The description of the professors' player profiles in this work will allow establishing the basis for a detailed description in subsequent works of the gap between students and professors in terms of their respective player profiles. Knowledge of this gap is important, because it will allow professors to adapt more effectively the gamified didactic situations they design to the students' interests, which will help, according to the perspective of personalized learning, to increase academic performance.

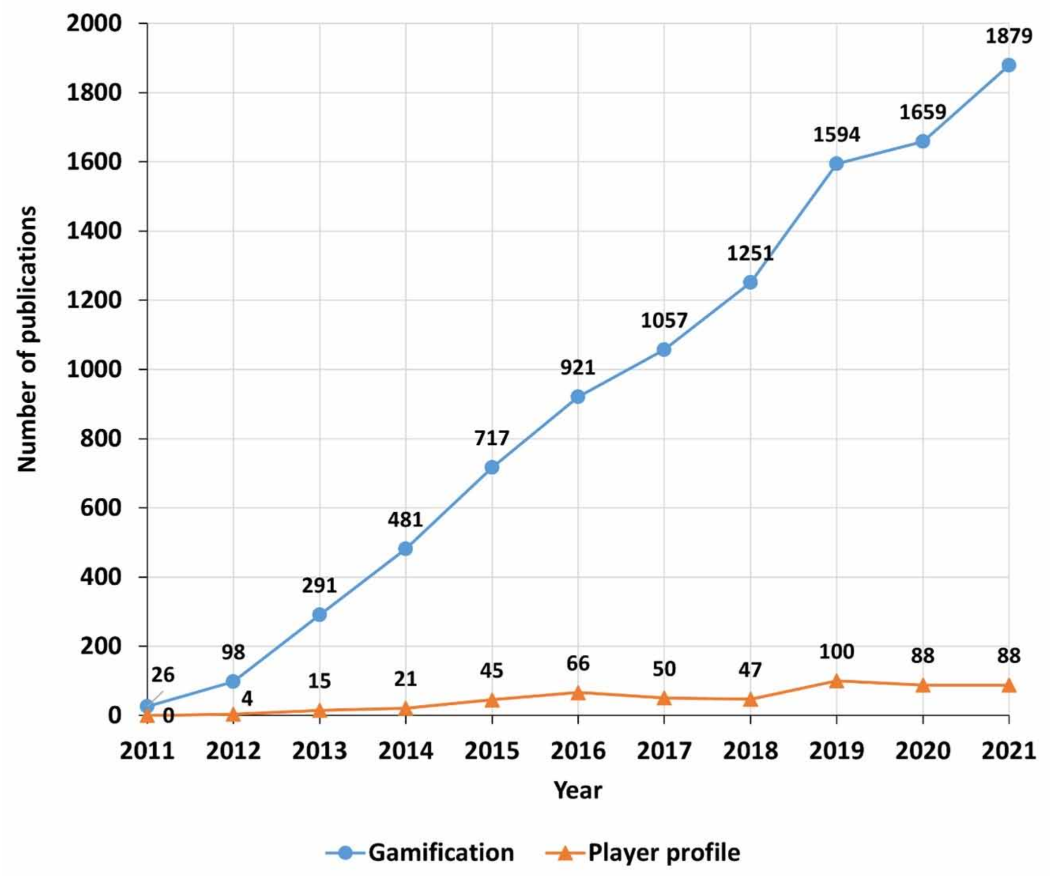
As far as it has been possible to explore, it has only been possible to find one paper that explicitly analyzes the player profiles of university professors, but only in the Engineering area (Vergara et al., 2022), whose main conclusion is the identification of a strong gap between the profiles of professors and those of students. In fact, some studies suggest that there is a divergence between the profiles chosen by professors in the design of gamified situations and the interests of the students to whom they are addressed (Kimmitt, 2017). This gap may be caused, at least partially, by the age difference between students and professors, since the preferences of player profiles change from more competitive and success-seeking to less so as age increases (Tondello et al., 2017).

LITERATURE REVIEW

Player Profiles in Game-Based Learning

There are several studies that provide a description of player types, as well as the dynamics they generate. These typologies are associated with different variables. Among the most studied, Bartle's (1996) typologies of players stand out, with four types of players (Killer, Explorer, Socializer and Achiever), and Marczewski, who extends this classification with the types: Free spirit, Philanthropist and Disruptors (De-Oliveira et al., 2020). Bartle's taxonomy was novel in the classification of player profiles when it was published and served as the foundation for all taxonomies that have followed.

Figure 1. Articles indexed in SCOPUS (decade 2012-2021) that include the expressions "gamification" or "player profile" in the title, abstract, or keywords



Bartle's original model (Bartle, 1996) used two axes of playing style (action vs. interaction and environment vs. players), to map players according to the degree of preference for acting on or interacting with the game world itself or its players. Type of players are distributed between the intersection of the two axes, which places them in a particular quadrant: Killer, Explorer, Socializer and Achiever.

Nacke et al. (2011) propose the BrainHex model inspired from four approaches: (i) neurobiological, (ii) typological, (iii) Myers-Briggs patterns of play (Conqueror, Manager, Wanderer y Participant); and (iv) the literature on game emotions. Finally, the typologies of Marczewski (De-Oliveira et al., 2020) and Tondello et al. (2016), who developed the Gamification User Types HEXAD framework based on motivation to use the system, distinguish six intrinsic motivation user types: Achiever, Disruptor, Free spirit, Philanthropist, Player y Socializer. Each of these types has corresponding associated game elements that have been mapped in Tondello et al. (2016). For further clarification of the possible player typologies, Figure 2 shows an outline of the above mentioned.

In recent years, new frameworks have been developed around the description of player profiles in gamified environments that try to overcome the closed category model of classic classifications such as Bartle's. Thus, Amy Jo Kim, for example, replaces the labels Explorer, Achiever, Socializer, and Killer in Bartle's classification with four verbs, which signify attitudes and actions: Express, Complete, Explore, and Collaborate (Kim, 2018). The paradigm shift consists in the fact that, with Kim's perspective, the door is opened so that the different profiles can coexist, in different degrees

Figure 2. Visual scheme of the existing player typologies

of presence, in the same player. The irruption of Big Data and Artificial Intelligence techniques have allowed the development of sophisticated tools to measure the levels of presence of each of the profiles in a player (Quantic Foundry, 2022).

However, the development of this type of framework for the description of player profiles is so novel that the academic literature has not yet incorporated it into its usual framework, as far as it has been possible to explore it. In addition, the application of a description such as Kim's would make data collection difficult for research such as the present one, which is why it has been chosen to follow Bartle's classic frame of reference.

For this research, it has been chosen the Bartle's typology (1996) since it has inspired profound studies on player categorization. It also has the advantage of providing a simple schematic that remains relevant in terms of motivation and players' interactions, as well as being the most widely acknowledged in literature (Williams et al., 2008; Ferro et al., 2013). Bartle's player types (1996) are featured below (Figure 3):

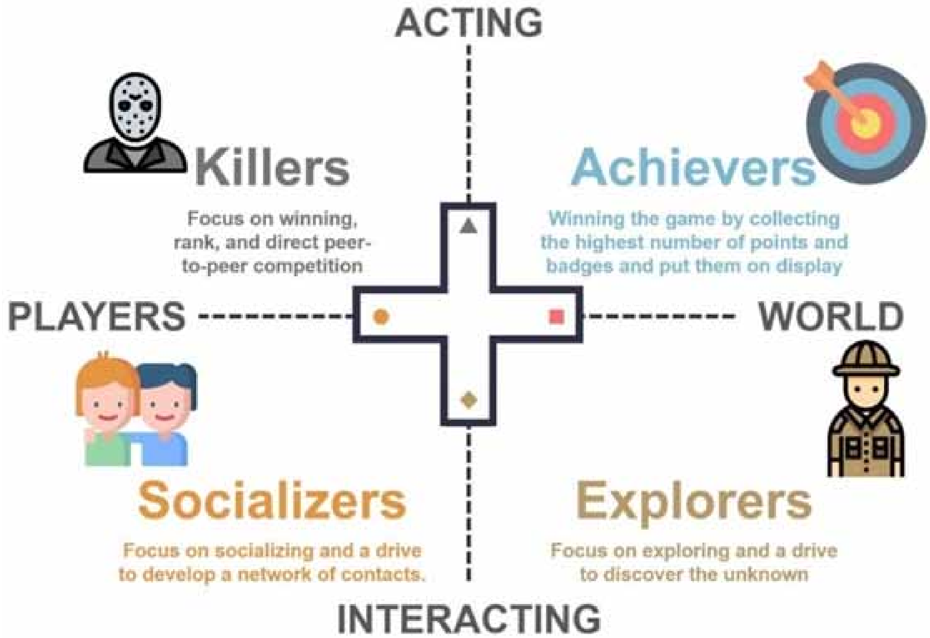
Killers, who act on other players. These players seek to win and somehow eliminate the rest of the players. They get fun from imposing themselves on other players, who are regarded just as means to an end. They want to see other people lose and rejoice when they caused them any sort of distress. Explorers, who interact with the world. They are players who prefer to discover areas, interesting features and immerse themselves in the game world, figuring out how things work. They have fun in discovery, not in interacting with the rest of the players. Socializers, who interact with other players. The game is simply a tool they use to get to know others in or outside the game. Achievers, who act on the world. Their main goal is winning the game by collecting the highest number of points and put them on display. They use any strategy that leads them to win, for instance, they socialize with other players to get information on how to earn more points.

Player Profiles of Students and Professors

The literature shows that the results of gamified didactic designs in higher education are all the better when the player profiles designed match the profile of the students participating in the situation (Andrade-Freitas et al., 2017; Krath & Von-Korflesch, 2021; Chung et al., 2022). These good results are mainly due to the influence that the connection between the player profile and the student's own profile has on the student's motivation (Reyssier et al., 2022), their academic results (Marín, 2022), and the affective components of their attitude towards learning (Su, 2022).

The specialized literature also explains that university students who participate in gamified didactic situations feel, in general, more motivated and involved in the game if they can see the evolution of their progress in the game through progress bars or know the goals achieved through achievement badges (Abramovich, 2016). Consequently, students' motivation towards learning in

Figure 3. Bartle (1996) taxonomy of player profiles



gamified situations is increased to the extent that their participation is through progress in achieving objectives. In fact, studies that explore the player profiles of university students generally attribute to them the Achiever profile, whether they work with Bartle's (Hsu et al., 2006; Yildirim et al., 2021) or Marczewski's classification (Santos et al., 2022).

Some works discuss the importance of the third person point of view (POV) when designing gamified situations (Denisova & Cairns, 2015). According to this, the immersive experience of the user does not necessarily have to be greater to the extent that the player profile matches the user's own profile. Thus, it is suggested that, at the educational level, there could be a gap between the profiles of professors and students and the profile that provides a more immersive experience to the student, which, in principle, would allow a more comprehensive experience of the game and, consequently, a better acquisition of learning. However, the previous literature does not go into this question in depth.

In addition to age, previous literature has identified gender as an influential variable in the player profile of users. Thus, males identify, in general, with active player profiles to a greater extent than females and are more motivated by the gamified situation (Tondello et al., 2017; Andrias and Sunar, 2019), although females increase academic performance to a greater extent than men through gamification (Zahedi et al., 2021). However, there are no studies that identify discriminating variables of the player profile of an academic nature, such as the area of knowledge, neither in students nor in professors. In the case of professors, the description of player profiles is, in fact, an unexplored problem in the previous literature.

MATERIALS AND METHODS

Participants

The sample consisted of 808 university professors from the region of Latin America and the Caribbean chosen by a non-probabilistic convenience sampling method (Table 1). The target population consisted of teachers attending a training session given by the authors and repeated fortnightly between January and June 2022, whose objectives were: (i) to present the basic concepts of educational gamification in virtual environments; (ii) to present Bartle's classification of player profiles. After this training session, potential participants were contacted by e-mail and sent the survey via Google Forms, explaining the research purpose of the questionnaire, the fact that no data would be collected to identify the participants, and the voluntary, free and anonymous nature of participation. All those attending the training sessions responded to the survey, and all the participants were asked to fill in the questionnaire.

The sample includes a significant majority of females (nearly double that of males). The largest proportion of respondents are between 45 and 54 years of age. The immediately preceding and following age ranges are represented by notably smaller proportions of the sample. Highest and lowest age ranges are represented by a much lower proportion, and the goodness-of-fit test statistics (Chi-square = 195.54, df = 4, p = 0.0000) show that the sample is not homogeneously distributed by age. As regards area of knowledge, each field is represented by 13% and 30% of the sample, with the exception of Computer Science, which represents only 1% of the respondents. The distribution by area of knowledge is not homogeneous (Chi-square = 78.068, df = 1, p = 0.0000).

Objectives, Variables, and Instrument

The main research objective is to describe the player profiles and the choice of player profile better for learning in the gamification process in Latin American university professors and to identify sociological or academic factors that influence their choices in this respect. Specifically, the following objectives are pursued: (i) to describe professors' player profiles and the differences with respect to the profile they consider most effective didactically; (ii) to analyze whether there are gender or age gaps in the player profiles of professors or in the profiles they choose as the best for learning; and (iii) to identify differences, in the same sense, according to the area of knowledge of the professors.

Across the sample of university professors surveyed, the three descriptive discriminant variables indicated in Table 2 are considered. The first two are intended to describe certain aspects of the sociological profile of the participants usually considered in the relevant literature (Martí-Parreño et al., 2016). The third variable is academic in nature and measures the knowledge area of the professors.

Table 1. Distribution of proportions in the sample by descriptive variables.

Variable	Value	Proportion of the Sample
Gender	Male	37%
	Female	63%
Age range	25 to 34 years old	13%
	35 to 44 years old	28%
	45 to 54 years old	33%
	55 to 64 years old	21%
	65 to 74 years old	5%
Area of knowledge	Arts and Humanities	19%
	Science	30%
	Health Sciences	13%
	Social and Legal Sciences	15%
	Computer Science	1%
	Engineering and Architecture	22%
	No	47%

Table 2. Descriptive variables

Family	Variable	Values
Sociological	Gender	Male Female
	Age range	25 to 34 years old 35 to 44 years old 45 to 54 years old 55 to 64 years old 65 to 74 years old
Academic	Area of knowledge	Arts and Humanities Science Health Science Social and Legal Sciences Computer Science Engineering and Architecture

The dependent variables are as follows: (i) Player profile with which the respondent identifies; (ii) Player profile considered most conducive to learning. Both are polytomous variables whose values are the four player profiles considered: Killer, Socializer, Explorer, and Achiever. Data were collected from a sample of university professors by means of a survey consisting of a set of six dichotomous or polytomous questions corresponding to each of the descriptive variables. The instrument consists of two polytomous questions corresponding to the dependent variables (referred to hereafter as item 1 and item 2). The participating teachers had to choose, for each of the two questions, the chosen player profile –Killer, Socializer, Achiever, or Explorer– whose respective concepts were known to the participants due to their participation in the previous training session. The Cramer's V parameter for the two items, that measure the dependence of each dependent variable with the other, is 0.0131. Therefore, there is a very weak dependence between variables.

Design

In this research, a quantitative study has been carried out by means of a questionnaire designed by the authors, and collected from a sample of university professors, containing questions about their sociological and academic profile, and their preferences in terms of players types. The participants answered the questionnaire voluntarily, freely and anonymously, were previously informed of the research purposes of the questionnaire and gave their consent to participate under the aforementioned conditions. The authors ensured that the study complied with ethical and legal requirements. In particular, no vulnerable population (e.g., children) was surveyed, nor did the research participants suffer any physical or psychological harm. The validation of the questionnaire was based on the analysis of the correlations between the different items of which the survey is composed and of each of these items with regard to the overall questionnaire.

The results obtained have been analyzed in a statistical-descriptive manner. Pearson's Chi-square tests of independence were conducted to study the behavior of the distributions of profile elections within each value of the sociological and academic aspects, and to analyze the degree of dependence of the chosen player profile in each of the items under study with regard to the descriptive variables values. All tests were performed with a significance level of 0.05.

RESULTS

Table 3 shows the relative frequencies of the profiles chosen in item 1 (profile they identify with) according to the responses for item 2 (profile considered as most suitable for learning). Abbreviations

DK/NA correspond to don't know/no answer. The player type with which respondents most frequently identify themselves is that of Explorer, followed by Socializer, more than nine points behind the former. The least frequent profiles are Killer and Achiever, far behind Explorer. The differences between the proportions of responses are significant, as shown by the statistics of the goodness-of-fit tests to a homogeneous distribution, for item 1 (Chi-square=458.19, p-value=0.0000) and for item 2 (Chi-square=620.06, p-value=0.0000).

The relative frequencies of the responses to each of the two items studied, when differentiating the sample by gender, are shown in Table 4. The Explorer and Socializer profiles are in this order the most frequent options in both items and genders. Females concentrate their choice on the Explorer and Socializer profiles more than males, to the detriment of the other profiles. However, it can be assumed that the distribution of response proportions is not statistically significantly dependent on the gender variable, for either of the two items studied, as supported by the statistics of Pearson test of independence with four degrees of freedom (Table 4).

Although Explorer is the most chosen profile in both items, there is a certain proportion of respondents who choose it as the most suitable for learning, but they do not identify themselves with it (in a higher proportion of females than males). This indicates that females recognize the educational benefits of the Explorer profile to a greater extent than they identify with it. The data in Table 5 suggest that there is a certain statistically significant proportion of females who identify with the Socializer

Table 3. Relative frequencies of responses to each item with respect to the other

		Item 2					
		Killer	Explorer	Socializer	Achiever	DK/NA	Total
Item 1	Killer	6.2%	7.5%	3.2%	1.1%	0.0%	18.1%
	Explorer	6.1%	25.1%	9.0%	0.7%	0.5%	41.5%
	Socializer	5.3%	14.0%	10.4%	2.0%	0.4%	32.1%
	Achiever	1.6%	3.5%	1.8%	1.0%	0.0%	7.8%
	DK/NA	0.1%	0.2%	0.1%	0.0%	0.1%	0.6%
	TOTAL	19.3%	50.4%	24.5%	4.8%	1.0%	100%

Table 4. Distribution of the relative frequencies of responses differentiated by gender and the Pearson test of independence statistics

	Profile	Male	Female	Chi-sq.	p-Value
Item 1	Killer	20.7%	16.5%	7.8922	0.0956
	Explorer	39.0%	42.9%		
	Socializer	29.7%	33.5%		
	Achiever	10.3%	6.3%		
	DK/NA	0.3%	0.8%		
Item 2	Killer	19.3%	19.3%	9.4380	0.0510
	Explorer	45.0%	53.5%		
	Socializer	28.3%	22.2%		
	Achiever	6.7%	3.7%		
	DK/NA	0.7%	1.2%		

profile but who opt for Explorer when it comes to assessing suitability for learning. This also occurs, although to a lesser extent, in males. The differences between proportions are statistically significant. Pearson's Chi-square tests of independence of distributions (Table 5) show that, for both genders, there is a significant dependence between the profile with which respondents identify themselves and the most conducive to learning.

The frequencies of player profiles chosen for each item differentiated by age range are shown in Table 6. Respondents under the age of 55 years identify themselves mostly with the Explorer profile, followed by the Socializer. In those over 55 years of age, the Socializer profile is more frequent, by almost 3% in the 55 to 64 age range, and by slightly more than 2% in the 65 to 74 age range.

It is also the Explorer profile the most frequently chosen as suitable for learning in all age ranges, followed by the Socializer. This preference decreases, however, as the age range increases. The opposite is true for the Socializer profile. The Killer profile presents frequencies always slightly below the Socializer. In contrast, the Achiever profile is well below the Explorer in all age ranges, with the most notable difference in the youngest segment of participants (a difference of 57%), and the oldest age range where the difference is smaller (slightly more than 36%). As higher age ranges are considered, an increase in the choice of the Socializer profile as the most conducive to learning is perceived. However, Pearson's Chi-square test statistics (Table 6) show that there is no statistically significant gap between the response proportions to either item when differentiated by age ranges, in the sense that the distribution of profile choice is independent of the respondent's age.

Across all age ranges there are respondents who identify with the Socializer, but do not consider it the most suitable for learning, and there are respondents who do not identify with the Explorer, but consider it the best for learning. These differences between proportions are notably greater among younger respondents. Pearson's Chi-square test statistics (Table 7) reveal that for the youngest age group, both preferred profiles are independently distributed. This indicates that player types concept is not adequately formed in the younger age group. Thus, there is a condition of cognitive maturity,

Table 5. Pearson's chi-square test of independence differentiating by responses to the two items, within each gender

Gender	Chi-sq.	df	p-Value
Male	188.76	16	0.0000*
Female	30.732	16	0.0146*

*p<0.05

Table 6. Distribution of the relative frequencies of responses differentiated by age

	Profile	25 to 34	35 to 44	45 to 54	55 to 64	65 to 74	Chi-sq.	p-Value
Item 1	Killer	24.3%	20.2%	13.6%	19.8%	13.3%	20.060	0.2175
	Explorer	38.8%	42.2%	47.2%	34.3%	37.8%		
	Socializer	30.1%	30.0%	29.8%	37.2%	40.0%		
	Achiever	5.8%	6.7%	9.4%	8.1%	6.7%		
	DK/NA	1.0%	0.9%	0.0%	0.6%	2.2%		
Item 2	Killer	17.5%	21.1%	18.9%	19.8%	15.6%	12.922	0.6784
	Explorer	60.2%	52.9%	48.7%	45.9%	42.2%		
	Socializer	17.5%	20.6%	26.0%	29.1%	33.3%		
	Achiever	3.9%	4.5%	5.3%	4.7%	6.7%		
	DK/NA	1.0%	0.9%	1.1%	0.6%	2.2%		

associated to the age of the individual, which influences the formation of his or her player type self-concept. In addition, profile choices among those over 35 years of age show that participants express a significant gap between their self-concept (mostly Socializer) and the most suitable type for learning (Explorer).

The most chosen profile in all knowledge areas is that of Explorer, followed by that of Socializer (Table 8), except for the area of Social and Legal Sciences, in which individuals mostly identify with the Socializer, although they are very much of the opinion that the profile of Explorer is more conducive to learning; and the area of Computer Science, in which respondents identify with the Explorer, but believe that the most appropriate profile for learning is that of Killer. Regarding item 1, the difference between the Explorers and Socializers is greater in the scientific-technical areas than in the humanistic-social areas. In fact, the highest frequencies of the Explorer with respect to item 1 are reached in the scientific-technical areas, while the highest frequencies of the Socializer are reached in the humanistic-social areas. Regarding item 2, the largest gap between the Explorer and Socializer profiles is found in the Engineering and Architecture (hereinafter called Engineering) area, with a difference of 30.5%. The smallest gap (except for Computer Science, where the two profiles are equal) is in the Social Sciences and Health Sciences areas, with a difference of around 15%.

The distribution of responses to item 1 is independent of the area of knowledge, since the p-value of Pearson's test of independence is greater than the significance level. However, the distribution of responses to item 2 depends significantly on the area of knowledge. Regarding item 2, there is a

Table 7. Pearson's chi-square test statistics of independence differentiating by responses to the two items, within each age range

Age range	Chi-sq.	df	p-Value
25 to 34 years	20.754	16	0.1882
35 to 44 years	31.629	16	0.0112*
45 to 54 years	38.825	12	0.0001*
55 to 64 years	28.082	16	0.0309*
65 to 74 years	58.97	16	0.0000*

*p<0.05

Table 8. Relative frequencies of responses differentiated by area of knowledge

	Profile	Arts.	Sci.	Health	Soc.	Comp.	Engin.	Chi-sq.	p-Value
Item 1	Killer	12.4%	17.0%	20.0%	19.8%	25.0%	19.6%	27.736	0.1158
	Explorer	47.1%	48.1%	45.0%	33.5%	50.0%	40.8%		
	Socializer	35.3%	23.6%	30.0%	37.2%	25.0%	29.1%		
	Achiever	4.6%	10.4%	5.0%	9.5%	0.0%	8.9%		
	DK/NA	0.7%	0.9%	0.0%	0.0%	0.0%	1.7%		
Item 2	Killer	9.8%	20.8%	20.8%	20.2%	37.5%	23.5%	43.996	0.0015*
	Explorer	57.5%	51.9%	44.2%	45.9%	25.0%	54.7%		
	Socializer	26.1%	20.8%	29.2%	30.2%	25.0%	14.5%		
	Achiever	5.9%	5.7%	4.2%	2.9%	0.0%	6.7%		
	DK/NA	0.7%	0.9%	1.7%	0.8%	12.5%	0.6%		

*p<0.05

predominance of the Explorer profile in all areas except in Computer Science, which opts for the Killer profile. It is precisely the area of Computer Science that presents the highest level of abstentionist responses to this item. There is a lower frequency of preference for the Killer profile in Arts and Humanities (hereinafter called Humanities). Likewise, in the areas of Sciences and Engineering, the preference for the Explorer profile differs more than in other areas from that of Socializer. It can be concluded that there is a significant difference in the area of Computer Science compared to the rest of the areas regarding the most suitable profile for learning. Specifically, there is a certain opposition, in terms of the relative frequencies of the profile responses, between Computer Science and Humanities, and a certain homogeneity in the rest of the areas.

In Engineering and Social Sciences, the distributions of player profile choice in the two items studied are statistically dependent, as follows from the Pearson test statistics in Table 9. This means that participants identify the Explorer profile as the most conducive to learning but they do not perceive themselves as such. Assuming that these areas have the most hands-on application, it is deduced that there is a significant correlation between the degree of training in the player types concept and the hands-on nature of the participant's area of knowledge.

DISCUSSION

According to the results, university professors are, for the most part, Explorers and Socializers. These player profiles are also generally considered to be the most conducive to learning. There are no previous studies in the literature describing the player profiles of higher education professors, but compared to the case of students, it can be concluded that there is a gap in this sense, because students are mostly Achievers (Hsu et al., 2006; Yildirim et al., 2021; Santos et al., 2022; Vergara et al., 2022). Moreover, these results are somewhat in line with previous work attributing less competitive player profiles to older users (Tondello et al., 2017).

The results also show a clear difference between the profile of the professors and the profile they consider most appropriate for learning (Table 3). In this sense, the participants value the Explorer and Socializer profiles as more appropriate for learning. These player profiles are also the most frequent among professors. However, the proportion of Explorer professors is smaller than that of those who consider it the best player profile for learning. On the other hand, there is a certain proportion of Socializer professors who, on the other hand, do not consider this player profile to be the most didactically effective. A similar phenomenon occurs with the Achiever profile. In fact, the data show that there are slightly more than 10% of professors who, while considering themselves Socializers or Achievers, nevertheless believe that the most didactic player profile is that of Explorer or Killer –the latter to a lesser extent– (Table 3). Although the literature has not described these types of gaps comprehensively so far, the opinions expressed by professors are in line with Denisova and Cairns

Table 9. Pearson's chi-square test statistics of independence differentiating by responses to the two items, within each area of knowledge

Area of Knowledge	Chi-sq.	df	p-Value
Arts and Humanities	23.946	16	0.0907
Science	14.012	16	0.5978
Health Science	10.456	12	0.5760
Social and Legal Sciences	43.654	12	0.0000*
Computer Science	3.3333	6	0.7660
Engineering and Architecture	77.422	16	0.0000*

*p<0.05

(2015), who suggests the existence of significant differences between the own player profile and the most appropriate player profile to ensure the most immersive gaming experience possible.

The statistical analysis reveals no significant gap in the choice of player profile by gender or age. These findings support the results of Martí-Parreño et al. (2016), who find no differences in the use and perception of gamification as a didactic resource based on these same variables. In addition, the conclusions of other studies, focused on the students' vision, in which gender is identified as a neutral variable in the didactic assessment of gamification, are extended to the choice of player profile, to the faculty's perspective and to all areas of knowledge (Martí-Parreño et al., 2016; Zahedi et al., 2021). However, the results are in contradiction with some studies that analyze profile preferences in a more general population. For example, Tondello et al. (2017) find gaps by gender and age, but the population under study was both academic and non-academic. Therefore, it can be concluded that, in the population of university professors, such gaps are blurred.

This study also identifies the area of knowledge as a variable that significantly discriminates the preference of the player profile. Indeed, there is a significant gap by area of knowledge in the choice of the most conducive profile to learning. The preferred profile is Explorer in all areas except Computer Science, which opts for Killer. This is a novel result since, to the best of our knowledge, specialized literature has not studied this variable with regard to the player profile. It may be because gamification is often linked to computing environments (Saleem et al., 2022) and, in this area, it is reasonable that computer science professors feel closer towards more active profiles.

Among Social Sciences professors, Socializer is the more frequent profile, followed by Explorer, in contrast to the rest of the fields. Participants identify themselves with the Socializer profile to a greater extent than they value it as the most effective for learning.

Based on the results, it is suggested, following Figg and Jaipal-Jamani (2015), that the universities design training sessions for professors on educational gamification. This training should follow the following aspects: (i) the pedagogical orientation of the design of gamified situations should be worked on, which should also be done according to the specific area of knowledge in question; and (ii) the design of the player profiles should consider the characteristics and interests of the students, which generally differ from those of the professors who design the games, or perhaps lead students to player profiles that, although different from their own, allow them to learn more.

As future lines of research, it is proposed to carry out a study analogous to the one conducted here, but with a sample that is homogeneously distributed by gender, age ranges and areas of knowledge, with the aim of contrasting the results obtained here, avoiding possible biases. In addition, it would be interesting to complete this study with qualitative research that would allow to identify the reasons behind professors' choices of player profile. Finally, it would be useful to carry out comparative and differential studies between different geographical regions and between professors and students, the latter aimed at corroborating the gap between professors and students with respect to the player profile and describing it in more detail.

CONCLUSION

It has been found that the valuation of educational gamification by the surveyed professors is high, even though the training they have received is moderate. Professors identify themselves to a greater extent with the profiles of Explorer and Socializer and consider these profiles as the most suitable for learning. Specifically, one of the most notable findings is that there is a significant proportion of professors who choose the Explorer profile as the most conducive to learning and yet do not identify with it (they usually identify with the Socializer profile). There is, therefore, a certain gap between the profile with which professors identify and the one considered most conducive to learning. This implies that there are dimensions that are not strictly didactic that affect professors' user preference. In future work, it would be interesting to further explore the identification of these dimensions.

There are no gender or age gaps in university professors, contrary to what occurs with students. The most influential variable in player profile choices is the area of knowledge. While in the more technical areas (Engineering and Computer Sciences) respondents identify with more active profiles such as Killer (which might indicate a more competitive nature of the higher education professors in these areas of knowledge), in the rest of the areas participants identify more strongly with the Explorer profile (or Socializer, in the case of Social Sciences).

The main implications of the results obtained here refer to the training of professors in educational innovation and, particularly, gamification, by their respective universities. In the first place, this training should be increased, adapted to the requirements of each area of knowledge and attend to the different needs of professors, especially those derived from their age, in order to overcome the corresponding gap. In addition, professors should be specifically trained on the preferences of students in terms of player profile, since it has been found that there is a gap in this respect between professors and students. Following the personalized learning perspective, it is clear that, in order to be more effective in the design of gamified training actions in virtual environments, professors need to know what their own player profile is and what their students' preference is in this respect, so that they are aware of the gap in this regard and have the tools to overcome it. In this sense, the design of gamified situations oriented to the training of university professors must be specific and different from the design of situations for students.

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Diego Vergara is an Associate Professor in the Department of Mechanical Engineering at the Catholic University of Avila (Spain). He completed his Ph.D. studies at the University of Salamanca, where he also obtained the degrees in both Civil Engineering and Materials Engineering. He has participated as co-author in more than 200 papers published in recognized international conferences and journals, as well as in several research projects. It is worth mentioning his activity as a reviewer of prestigious journals.

Ana Isabel Gómez-Vallecillo has a PhD degree in English Philology from the University of Extremadura (Spain). Lecturer and researcher at the Catholic University of Avila (UCAV), Spain. She is a member of the Centre for Innovation and Teacher Training Studies of the UCAV and a member of the Training and Innovation Commission of the UCAV. Coordinator and member of the scientific committee of the Teaching Innovation Conference of the UCAV.

Pablo Fernández-Arias holds a degree in Industrial Engineering from the University of Salamanca and Industrial Engineering from the University Alfonso X el Sabio. He later obtained his PhD degree from the University of Salamanca, in the PhD program in Social Studies of Science and Technology. He has more than 10 years of professional experience in the energy sector. He has had different professional profiles, including Nuclear Power Plant Operation Instructor, Technological Development and Innovation Manager and Technological Leader. Expert in new educational environments, disruptive technologies for training and active learning methodologies. Since 2019, he has been working as a Teacher and Researcher at the Catholic University of Avila (Spain).

Álvaro Antón-Sancho is a Researcher and Teacher at the Department of Mathematics of the Fray Luis de Leon University College of Education (Spain) and at the Catholic University of Avila (Spain). He completed his Ph.D. in Mathematics at the Spanish National Research Council and at the Complutense University of Madrid. He has published numerous research articles in recognized journals on algebraic geometry, educational technologies, and didactic methodologies. In addition, he has been a visitor in several foreign universities, participated in different research projects, and organized some research events. He is currently a member of Technology, Instruction and Design in Engineering and Education Research Group (TiDEE.rg).