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Clustering on Player Types of Students in Health Science – Trial and Data Analyses

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Abstract. Gamification has many positive effects, such as increased motivation, engagement, and well-being of users. For this purpose, a wide field of game mechanics is already available that can be used in teaching. For the development of gamified teaching methods, it's important to adapt the mechanics used to the students. There are different models that divide target groups of games and gamification into player types to understand what motivates the respective users. This paper describes a study of player types among students of health-related disciplines and analyses the data by a K-Means clustering procedure. The player types Socializer, Player and Achiever are found, and game elements for this groups are suggested. Thus, in the field of health education, game mechanics can be used, which are suitable for students of this domain.

Keywords. Gamification, Player type, Health education

1. Introduction

During their studies, students are often confronted with the challenge of acquiring extensive knowledge in a short period of time. Miller's pyramid describes four levels of competence learning. To reach the top level "Does" of competence, the lowest level "Knows" must be fulfilled first [1].

For example, in medical studies, extensive factual knowledge is therefore already required in the first semesters. The M1 exam includes 320 questions on medical factual knowledge and is administered after the 4th semester [2]. However, the way in which this basic knowledge is taught at universities is ineffective for storing the knowledge in the brain. According to Dale's cone of experience, learners can only remember 50% of the information that is conveyed visually and auditorily in a lecture [3].

As a result, lecture content should either be conveyed by other means or repeated by the students. From a motivational and learning psychology point of view, gamification can be used for this purpose. Gamification has many positive effects, such as increased motivation, engagement, and well-being of users [4–6]. For this purpose, a wide field of game mechanics is already available that can be used in teaching [7, 8].

Despite the already prevalent use of gamification in teaching, there is a lack of scientific methodology in the development of gamified teaching methods, as well as the evaluation of them [5]. For the development of gamified teaching methods, it's important to adapt the mechanics used to the students [5]. There are different models that divide

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target groups of games and gamification into player types to understand what motivates the respective users [9–11].

This paper describes a study of player types among students of health-related disciplines, and proposes a new method for evaluating them. Here, the goal is to identify the player types among the students, considering not only the strongest player type, but all player types of their personalities.

1.1. Theoretical Background and Related Work.

There are several papers that describe how gamification is used in health-related education. For example, Huber et al. [12] use an audience response system to test students, playfully. Unfortunately, the player types are often ignored.

Bartle's model is among the widely used models of player types. It defines four different player types based on two dimensions.
The first dimension deals with the relevance of the environment of the game or being surrounded by players. The second dimension extends from the preference of acting to that of reacting [9]. Critical to the model is that players in games must satisfy multiple properties of different types. Although it is often used, a player cannot be assigned exclusively to one type, but has characteristics of different types. Furthermore, the model is not based on sociologically collected data, but only on experiences and reports of players of the genre Multiuser Dungeon [8, 9].

1.1.1. The Gamification User Types Hexad Framework

To create a model that is not limited to specific game genres, but to enable the analysis of player types to a broader application group, Marczewski created the Gamification User Types Hexad Framework. The framework describes six different types, of which four (1 to 4) are intrinsically motivated, one (5) is extrinsically motivated, and one (6) is neither extrinsically nor intrinsically motivated [8, 11]:

1. Socializer: This type of player wants to interact with other players. They are interested in parts of the system that allow them to connect with other participants.
2. Free spirit: They do not want to be restricted in exploring the system or creating new things within the system. For them freedom of choice is very important.
3. Achievers: They want to use and master the system 100%. This is about improving themselves.
4. Philanthropist: This type is motivated by the feeling of being part of something bigger. Without expecting anything in return, they want to give to other players.
5. Player: This is the only extrinsic player type. These players are looking for rewards or quid pro quos from other players.
6. Disruptor: This type is neither extrinsically nor intrinsically motivated for the system. He is motivated by disrupting the system or fellow players.

1.1.2. The five player types of Gaalen et al.

Based on Bartle's model, a less genre-specific model for identifying gamer types was therefore conducted in a study among medical and dental students at the University of Groningen in the Netherlands. Subjects in the study were asked to sort a total of 49 statements regarding preferred game mechanics by providing information on whether they agreed, disagreed, or were neutral towards them. Five genre independent player types were identified [10]:

1. Social achiever: This player type prefers collaborative achievement of goals and successes in a game.
2. Explorer: Players of this player type favor exploring and changing a game world on their own.
3. Competitor: These players attach great importance to winning in a game. They look for competition with other players, but also with computer-controlled opponents.
4. Socializer: They use the activity of gaming to meet and exchange ideas with other players.
5. Troll: This type of players compensates their own lack of interest in a game by using cheats, exploiting bugs in the game to their own advantage, and annoying or harassing other players.

Among the 109 participants, 30 were assigned to a type. 12 Social Achievers, seven Explorers, four Competitors, five Socializers and two Trolls were identified [10].

2. Methods

In order to identify the types of players, the students of the University of Lübeck were asked by e-mail to fill out an online survey between 25.01.23 and 08.02.23. . From the field of health sciences this concerns students of occupational therapy/logopedics, health and care research, midwifery, human medicine, nursing, and physiotherapy 3]. These were included in the study. There was no reward offered to the students, other than the fact at the end of the survey to know their own player type. All participants confirmed that they had not already completed the survey, otherwise the data set was excluded from the analysis.

2.1. Sample size calculation

The sample size calculation was based on the University of Lübeck's 2021 university figures. According to these, 2098 students are enrolled in the previously listed degree programs 3]. Based on Cochran's formula for population-adjusted sample size 4] (see Eq. (1)) 92 responses are required for a representative sample, assuming a significance level of 95% and an error of 10%.

$$n = \frac{n_0}{1+(\frac{n_0-1}{N})} \text{ with } n_0 = \frac{z^2 p(1-p)}{e^2} \tag{1}$$

2.2. Measuring instrument

Tondello et al. developed and validated a questionnaire that identifies player types according to the Hexad Framework. The questionnaire includes 24 items, which are answered on a 7-point Likert scale. Each player type is assigned four items [8]. This was translated into German and validated by Krath and von Korflesch [7]. Compared to the instrument used by Gaalen et al., it can be completed in a shorter time. In addition, a simple evaluation of all expressions is possible. For the evaluation of the measuring instrument, the items of the respective characteristics are added up [8]. It is suggested to assign the player type whose proficiency is the highest. Since the proficiencies of other player types among the respondents are not considered, the data in this paper were evaluated using a cluster procedure that takes all proficiencies into account. To ensure the comparability of the data sets and to consider only the proficiency of the player types, the data were standardized before the cluster procedure. Three cluster procedures were compared using the Calinski-Harabasz [15] and Davies-Bouldin scores [16]. The unsupervised clustering algorithms K-Means, Meanshift, and agglomerative hierarchical clustering (Euclidean distance, ward linkage) were compared to analyze the data. In addition, preprocessing by PCA for K-Means was analyzed. The number of clusters was evaluated using the Silhouette score as well as the Elbow plot or a histogram. The clustering and the analyses were realized with python (v. 3.10).

The Hexad framework was used to assign individual game mechanics to the identified clusters.

3. Results

There were 190 students participating in the survey. The standardization resulted in values between -2.236 and 2.122. The best values were obtained for clustering with three clusters in the K-Means and hierarchical procedure and four clusters in the Meanshift procedure. For the latter, the estimator of Comaniciu and Meer [17] was used.

3.1. Clusters

The best results are obtained with K-Means clustering and previous PCA with two axes (see Table 1). The Silhouette score for three clusters is 0.44.

Table 1. Comparison of the clustering algorithms K-Means, Meanshift and agglomerative hierarchical clustering (Euclidean distance, ward linkage) using the Calinski-Harabasz score and the Davies-Bouldin score.

Algorithm	Calinski-Harabasz score	Davies-Bouldin score
K-Means	66.617	1.314
K-Means + PCA	164.127	0.796
Hierarchical Clustering	60.119	1.343
Meanshift	24.638	1.165

Table 2. Description of the clusters by mean, variance and standard deviation of the manifestations.

Cluster		Socializer	Free spirit	Achievers	Philanthropist	Player	Disruptor
1 (n=94)	Mean	0.726	0.022	0.285	0.762	0.063	-1.858
	Std	0.424	0.536	0.541	0.434	0.514	0.396
	Var	0.180	0.287	0.292	0.188	0.265	0.157
2 (n=52)	Mean	-0.889	0.361	0.746	0.340	0.730	-1.289
	Std	0.643	0.587	0.583	0.636	0.491	0.716
	Var	0.405	0.345	0.340	0.409	0.240	0.513
3 (n=44)	Mean	0.012	0.659	0.586	0.821	-1.235	-0.841
	Std	0.808	0.610	0.604	0.612	0.383	0.681
	Var	0.652	0.371	0.364	0.374	0.147	0.464

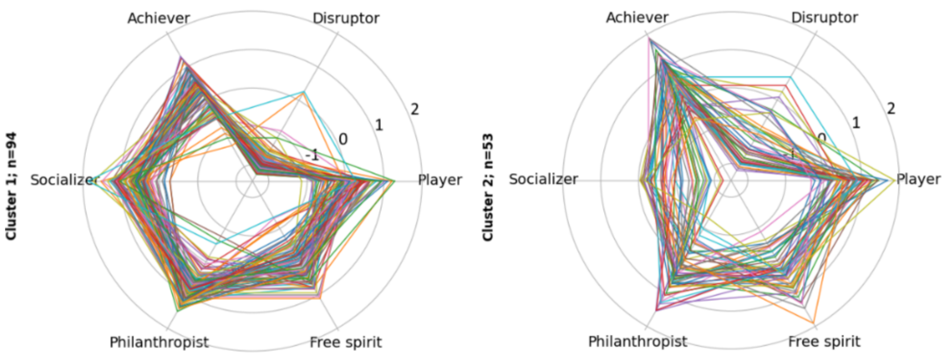

Figure 1. Polar plot of cluster 1 (left) and 2 (right).

The results of the clustering process can be seen in Table 2. The first cluster includes 94 subjects. The low expression of the player type Disruptor and the strong expression of the Socializer and the Philanthropist is noteworthy. The other types are on average less strong to neutral in their expression, see figure 1 (left).

The second cluster consists of 52 subjects. In contrast to the first cluster, the Socializer player type is weak to neutral, as is the Disruptor type. In comparison, the Achiever and the Player types are remarkably strong, see figure 1 (right).

The last cluster comprises 44 subjects. The only striking feature of this cluster is the very weak expression of the Player type. The other types within this cluster show a high variance, shown in table 2 and figure 2, which is why no statement can be made here.

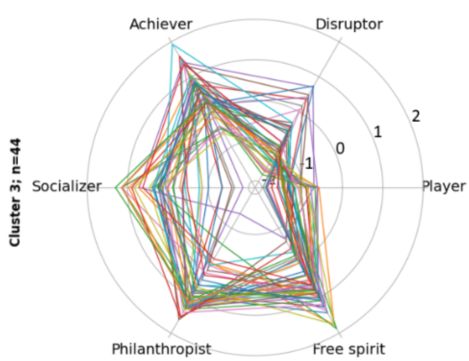

Figure 2. Polar plot of cluster 3.

3.2. Game elements

Since the player type Disruptor is found to be notably weak in the clusters and not notably absent in other clusters, this type can be neglected when selecting game mechanics. Socializers, and Achievers, on the other hand, should receive more attention. Due to the high level of the Player in cluster 2, it should be considered to include elements for this type. Also, elements to support the Philanthropist and Free Spirit types can also be incorporated. Based on Tondello et al. [8] and Karth and von Korflesch [7], the use of challenges or quests that are to be solved together is particularly suitable for Achievers and Socializers. For example, teams that compete against each other. For Players, rewarding elements such as points, or achievements represent an opportunity. Easter Eggs for Free Spirits and administrative roles for Philanthropists can be integrated also.

4. Discussion

The choice of possible game mechanics is large and should be adapted to the students. For example, in the case of Huber et. al. [12] the mechanics used match partly not the player types evaluated in this work and other mechanics could further amplify the measured effects. Compared to the results of Gaalen et al. no clear differences can be seen, if only the most expressed player types are considered. But this paper extends previous evaluations by clustering them to account for all characteristics of player types. Based on this, it shows which mechanics are most suitable for students in the healthcare sector.

The sample size is significant for the population studied and a silhouette score of 0.44 could be obtained, showing a weak cluster strength. The clustering procedure could probably be further improved by a larger sample and stronger clusters could be achieved. Also, bootstrap methods could be used to compensate for uncertainties regarding cluster properties. Since only students from the University of Lübeck were surveyed, the study should be repeated with the inclusion of additional institutions.

Furthermore, it should be noted that in a survey with voluntary participation, a self-selection bias can be assumed, which may have had an influence on the characteristics of the player types.

Declarations

Conflicts of Interest: None declared.

Contributions of the authors: LB, AS: conception of the study, LB: conduct of the study, data collection, data analysis and interpretation; LB: writing of the manuscript, AS substantial revision of the manuscript. All authors have approved the manuscript as submitted and accept responsibility for the scientific integrity of the work.

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