

Article

Student Player Types in Higher Education—Trial and Clustering Analyses

Lea C. Brandl*  and Andreas Schrader 

Institute of Telematics, University of Luebeck, 23562 Luebeck, Germany; andreas.schrader@uni-luebeck.de

* Correspondence: lea.brandl@uni-luebeck.de

Abstract: In the context of the ongoing transformation in education, new learning methods, as well as new technologies, and therefore new forms of interactions are challenging higher education. This challenge can be addressed through ambient learning management systems that adapt to the student in the presentation and preparation of course materials. For educational games offered in such systems, this means that the game mechanics should be adapted to the student. To narrow down the sum of mechanics to the amount that is relevant for students, player types can be identified. This paper investigates the player types among students at the University of Lübeck. The characteristics of all player types of Marczewski's Gamification User Types Hexad Framework are considered using a clustering method for the analysis. The result is three profiles with different characteristics of player types. For each of the profiles, mechanics are suggested which can be used for the respective profile. Thus, educational games can be more easily and automatically adapted to player type.

Keywords: serious gaming; player types; education



Citation: Brandl, L.C.; Schrader, A. Student Player Types in Higher Education—Trial and Clustering Analyses. *Educ. Sci.* **2024**, *14*, 352. <https://doi.org/10.3390/educsci14040352>

Academic Editor: P.G. Schrader

Received: 6 February 2024

Revised: 13 March 2024

Accepted: 23 March 2024

Published: 27 March 2024

Corrected: 6 June 2025



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Motivation

In recent years, the number of digitally provided teaching contents at universities and colleges has increased [1]. The focus has mostly been on recording lecture content or digitizing exercises and exams and making them available via a Learning Management System (LMS) [2]. Usually, these systems are online platforms that are operated via a GUI. However, like the industry, education is undergoing a transformation that not only centers on learners but also involves the adoption of new teaching methods [3–5]. Therefore, it seems reasonable to consider LMS which can adapt teaching methods to students individually. An established teaching method that can be reimaged in this context is the use of Serious Games that take place within an LMS. Due to the development of new technologies and forms of interaction, LMS and thus Serious Games can be envisioned to be embedded in the physical environment of students.

1.1. Serious Games in Education

There are many reasons for the use of educational games. Educational games have a motivating effect on students and lead them to engage with content for longer periods compared to other teaching formats [6–8]. Additionally, students are presented with extensive factual and practical knowledge throughout their studies, which forms the basis of their ability to act. Students experience pressure to perform and stress, which negatively impacts their quality of life. Stress factors include exams and difficult or extensive learning material [9,10].

When designing educational games, it must be taken into account that the content differs from course to course, and even within a course, exercises are usually offered for different content. The consequence of this is the need to create educational games that dynamically adapt to the lecture content. It should also be noted that a game should be adapted to player types in order to achieve a positive effect [11].

The vision of an adaptive learning space available as a LMS has been proposed by various authors [12,13]. A central requirement of such a system is the identification of the user and the adaptation of the content and forms of interaction to the user. This requirement is also valid for Serious Games, which are offered in the context of ambient LMS. Since there is a large number of game mechanics that can be combined arbitrarily, it seems sensible to limit the selection. Consequently, the complexity of the selection is minimized if a smaller selection of mechanics is offered, which fits the player types among the students. Once the student is identified, the combination of mechanics that fits their player type can be loaded. The requirement for this is the one-time prior questioning of the student to determine the player type and the storage of this information in the student's user profile.

1.2. Player Types

Various models exist that divide target groups of games and gamification into player types in order to understand what motivates the users. However, some of these models assume a specific genre. Furthermore, users are usually assigned to only one player type, although several types are differentially expressed among users. This paper presents a study that investigated player types across different disciplines, considering the expression of various player types among students.

Different mechanics have a motivating effect on the player depending on their player type. Mechanics refer to control mechanisms, behaviors, or actions that influence game dynamics [14]. The results of the player type analysis are then matched with mechanics sourced from the literature. Adapting serious games and their mechanics to students can positively impact motivation. Studies on game motivation have shown that using *one-size-fits-all* mechanics can promote the motivation of some players while inhibiting others [15,16]. It is presumed that adapting the mechanics can generate higher intrinsic motivation [17]. Achieving the best fit between the game and the player's personality can lead to greater enjoyment and satisfaction for the player, which, in turn, can affect productivity [18].

To aid understanding, the background is explained first, followed by the methodology used to analyze player types and link the mechanics to the results. Finally, the results are presented and discussed.

2. Background and Related Work

In the context of game development, Bartle [19] defines four different types of players. (1) Killers strive to win the game. For this group, it is important to play against other players and, if necessary, to hinder them in order to achieve victory. (2) Socializers play games because of the company. They support other players without expecting any benefit from it. For Explorers (3), it is important to discover new things in games and push their limits. Winning or losing the game is secondary for this type. (4) Achievers primarily want to accomplish something in the game. Winning points is important to them [19].

The model presented by Bartle is simple and quick to apply, but it is critical to consider that players in games fulfill several characteristics of different types. So players cannot be assigned to exactly one type. Furthermore, the model is not based on social science collected data, but only on experiences and reports of players of the genre Multi-User Dungeon [20]. In order to create a model that is not limited to specific game genres, but to enable the analysis of player types to a wider group of users, Marczewski created the Gamification User Types Hexad Framework. The framework describes six different types, four of which are intrinsically motivated, one extrinsically motivated (5), and one neither intrinsically nor extrinsically motivated (6) [20,21]:

1. Free spirits: They take advantage of the game's decision-making freedom. Exploring the game and creating new things within the game is important to them.
2. Socializers: For these players, interaction with others is important. Game elements that enable interaction with other participants motivate them.

3. Philanthropists: These players enjoy helping other players without expecting anything in return. It is important to them to be part of a larger picture.
4. Achievers: Achievers want to reach their full potential and constantly improve themselves.
5. Players: Players motivate themselves by being better than other players. They can be extrinsically motivated by wins or rewards.
6. Disruptors: Disruptive players compensate for the lack of motivation by disrupting the game or fellow players.

In this model, individuals never correspond to a single player type, but rather have different characteristics of the individual types. For the assessment of individuals, there is a validated questionnaire that can be used to determine how highly expressed each type is. For this purpose, four Likert scales are added up for each player type. The higher the score, the more expressed the respective type is [20,22]. In the context of this model, game mechanics are proposed which fit the player types [20–22]. Mechanics can fit to more than one player type. However, in the past, only the player type was analyzed that was most pronounced in the respective player types instead of considering the combination of different player types of the model [21,23].

Player Type Research

Based on Bartle's model, Gaalen et al. [11] conducted a study among medical and dental students using the Q-methodology. Participants were asked to sort 49 statements about gaming preferences based on their level of agreement. Of the 109 participants, 30 could be classified as Social Achiever ($n = 12$), Explorer ($n = 7$), Competitor ($n = 4$), Socializer ($n = 5$), and Troll ($n = 2$). Social Achievers are motivated by achieving goals and successes together. Explorers are excited about discovering and changing the game. Competitors seek competition with others or game opponents. Their focus is on winning. Socializers use the game as a platform to network with other players. Trolls try to break game rules or mechanics by tricking or making mistakes in the game to gain an advantage. They annoy or harass other players to compensate for their lack of interest in the game [11].

Trojanek et al. [23] used the User Types Hexad Framework along with the validated questionnaire to identify player types among students at Technical University of Dresden, Germany. Participants were assigned to the player type with the highest score. Given the same score, two of the types were considered. Among the users, the most common type was Philanthropist followed by Free Spirits and Socializing. As in analyses by Marczewski et al., the most common mixed type is Philanthropist and Socializer. Differences were found among the various disciplines. For example, there are more Players among engineers than in other disciplines, while Free Spirits are more common in the humanities and economics. Regarding gender, differences can be found among Socializers, which are more likely to occur among female participants [23].

Barata et al. [24] analyzed students in a gamified engineering course at the master's level with regard to common groups. For this purpose, they analyzed the behavior based on the rank on the leaderboard and the number of experience points collected in the game over time. Using the clustering procedure of Expectation Maximization, four clusters were found: (1) Achievers who collected all achievements in the game, (2) Regular Students who avoided challenging game content but performed well overall, (3) Halfhearted Students with little interest in the course and mostly below average performance, and (4) Underachievers who performed only enough to barely pass the course. The respective clusters were mapped to the BrainHex model, which originated in neurobiology and defines seven player types. Regular Students correspond to the player types that are motivated by achieving goals or strategically solving tasks. The latter, in addition to playing with others, also motivates the Achiever group. Halfhearted Students and Underachievers correspond to the BrainHex class, which is considered challenge-oriented [24]. The work described already analyzes students in terms of the player types they belong to. However, students are always assigned to exactly one type. The possibility that students correspond to several types with different characteristics is not taken into account. Furthermore, motivators or examples of

possible mechanics are mentioned, but an explicit assignment of mechanics to be used is not performed.

3. Methodology

There are numerous models of player types and various methods of investigating which types are present among users. Marczewski's model allows to determine the characteristics of the individual player types of a user independent of the genre [21]. Furthermore, there is already published research about game mechanics, which are proposed in relation to the player types of the model [20,22]. The validated questionnaire can be used to quickly determine the characteristics, which is why the German validated questionnaire by Krath and von Korfflesch [22] was used for this work. It is a 24-item questionnaire rated on a seven-point Likert scale. There are four items for each player type. The reliability of the instrument shows a *Cronbach's α* of 0.691 ± 0.055 . The validity is reported with $\chi^2 = 796.72$, $p < 0.01$; $RMSEA = 0.079$ and $CFI = 0.729$. Even if the instrument needs further improvement, the results support the overall validity of the HEXAD-Scale in German [22].

In contrast to the study of Marczewski et al. and Trojanek et al. [21,23], the expression of all player types is analyzed. In order to analyze the totality of students considering all expressions of player types, a clustering procedure is used to identify groups, similar to the approach of Barata [24]. Since the identified groups are defined by expressions of individual player types, they are referred as *player profiles* below.

Between 25 January 2023 and 8 February 2023, the students of the University of Lübeck, Germany [25] were invited to fill out an online questionnaire. The acquisition was performed by sending an email to the students. No incentive was offered for participation, except to find out at one's own expression at the end of the survey. In addition to the validated questions, this also included questions about gender and study area. Participants were also asked to confirm that they were completing the survey for the first time, otherwise the return was removed from the result set. The following fields of study were included:

1. Medicine and Health (MH): Occupational therapy/speech therapy, health and health care sciences, midwifery, human medicine, nursing, physical therapy;
2. Computer Science and Mathematics (CsM): entrepreneurship in digital technologies, computer science, IT security, mathematics in medicine and life sciences, media informatics, medical informatics;
3. Natural Sciences and Psychology (NP): biophysics, infection biology, medical nutrition science, molecular life science, psychology;
4. Technology (T): biomedical engineering, hearing and audiological engineering, medical microtechnology, medical engineering science, robotics and autonomous systems.

Based on the number of students in each discipline, Cochran's formula for population-matched sampling (Equation (1)) [26] was used to calculate the required number of regressions at a 95% significance level and 10% error (compare Table 1). N is the population size and n is the sample size, z^2 is the abscissa of the normal curve corresponding to the confidence level, e is the precision level, p is the estimated proportion of an attribute present in the population. The calculation is based on the population statistics of Lübeck University in 2021 [25].

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

For the analysis, the unsupervised clustering algorithms of K-Means, Meanshift, and Agglomerative Hierarchical clustering were compared. All of these methods are characterized by grouping similar data. Distances within the groups are minimized, and distances between the groups are maximized. The optimization in the K-Means algorithm is performed by defining center points corresponding to the number of clusters. In the iterative process, center points are updated until the described optimum is reached. The result varies depending on the initial center points [27]. The algorithm used in this work selects the initial points based on a probability distribution in the data [28]. The number of clusters

can be determined based on a plot. The elbow plot shows the variance in the clusters linked to the number of clusters. The appropriate number of clusters is determined by the lowest variance compared to the lowest number of clusters [29]. The Meanshift algorithm also operates with center points. Areas with smooth density are searched for, and their mean is calculated [30]. The size of the areas to be searched is estimated by a function in this work [28]. Therefore, the number of clusters or center points does not have to be specified for this algorithm. Hierarchical clustering forms a tree structure with the data [31]. In this study, data with similarities are grouped, with the process repeated until only one cluster remains. The Euclidean distance measure between data points is used as the similarity measure, aiming to minimize the sum of squared differences. The optimum number of clusters is determined using a dendrogram, whereby the tree is cut at the point of a large distance with small branching. The comparison was conducted using the Calinski–Harabasz and Davies–Bouldin scores. Additionally, preprocessing by principal component analysis, which reduces the dimensionality of the data, was investigated in the case of K-Means. Before clustering, a standardization was used to make the expression of the player types comparable among the respondents. For both K-Means and Agglomerative Hierarchical clustering, the number of clusters was evaluated using the Silhouette score, in addition to the methods previously mentioned. This score serves as a quality measurement for clusters. The execution of the clustering, as well as the standardization and the calculation of mean, variance, and standard deviation was performed with Python 3.10.

Table 1. Description of the department and gender distribution of the sample.

Study Area	MH	CsM	NP	T	Sum
sum	190	121	111	109	531
male	56	79	32	53	220
female	132	36	74	52	294
gender queer	1	5	3	4	13
without statement	1	1	2	0	4

In the next step, the found player profiles were assigned to the game mechanics corresponding to the motivation. Game mechanics published in the context of the hexad frameworks were taken up and applied to the analyzed player profiles of the study. The player types that appear in the player profiles were weighted based on their positive expression. The most positive type received a weight of 3/6, the second strongest a weight of 2/6, and the third strongest a weight of 1/6. The less strong or negative types received no weighting. The weighting was applied to the respective mechanics. For mechanics that were related to multiple player types, the sum of the relevance values was calculated. If the relevance value was greater than 0.5, it was assumed that the mechanic was relevant for the player profile. The limit of 0.5 was chosen so that it would not be sufficient for the mechanics to correspond to only one type of player if it was not the most pronounced type.

4. Results

A total of 531 responded to the survey and were included in the result set. Enough students were canvassed for each discipline to reach the targeted significance level. The number of participants, as well as gender distribution, can be found in Table 1.

4.1. Clustering Algorithms

Standardization yielded values ranging from -2.236 to 2.122 . Regarding the number of clusters, the best Silhouette score for three clusters was obtained for the K-Means procedure with prior PCA; moreover, this combination showed the best Calinski–Harabasz and Davies–Bouldin scores (see Table 2). For this reason, the results of this cluster procedure are reported below. Each cluster corresponds to a player profile that is defined by the expressions of the player types in the cluster.

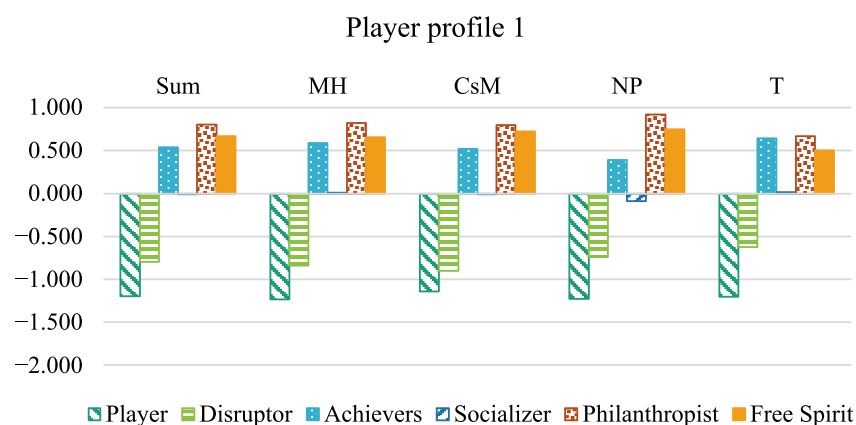
Table 2. Comparison of the algorithms using the number of clusters with the best Silhouette-score.

Algorithm	Cluster Amount	Silhouette Score	Calinski–Harabasz Score	Davies–Bouldin Score
K-Means	2	0.272	173.697	1.633
K-Means + PCA	3	0.422	448.633	0.829
Hierarchical Clustering	3	0.209	128.135	1.617
Meanshift	4	0.266	24.638	1.165

4.2. Cluster Results

The first cluster comprises a total of 137 participants. The resulting player profile is characterized by the negative expression of the Player and Disruptor types, with the Disruptor being less strongly negative and having a higher variance and standard deviation. Regarding the study directions, it is noticeable that MHs evaluate the Player type most negatively (see Figure 1).

Positively pronounced in this player profile is the Philanthropist type. This is strikingly expressed in NP, whereas in T the Achiever type is equally expressed. In the latter case, both values show a high variance and standard deviation compared to other values (see Row 1 of Table S5 in the Supplementary Material).

**Figure 1.** Results of the clustering process. First player profile in the different disciplines.

The second cluster, with $n = 134$, is similar in size to Cluster 1. The player profile resulting from the cluster also reveals a negative expression of the player type Disruptor. These values are less expressed in NP and T, but have a higher standard deviation and variance (see Row 2 in Tables S4 and S5 in Supplementary Material). It is also noticeable in these study areas that the negative expression of the Socializer type is stronger than in the Disruptor type and the other study areas. The lowest expression of the Socializer is in the CsM study area, where deviation and scattering can be seen. In this cluster, the Player and Achiever types find the strongest positive expression. The latter is more pronounced in CsM than in the entire group (see Figure 2). The former is less pronounced in NP.

The last cluster comprises 260 participants and is thus significantly larger than the other two. In this player profile, the Disruptor again attains a strong negative expression. The Philanthropist type finds the strongest positive expression. This is most pronounced in CsM followed by NP (see Figure 3). In the case of MH, the Socializer is remarkably positive in this cluster (see Figure 3).

The whole results of the clustering process can be seen in Tables S1–S5 in Supplementary Material.

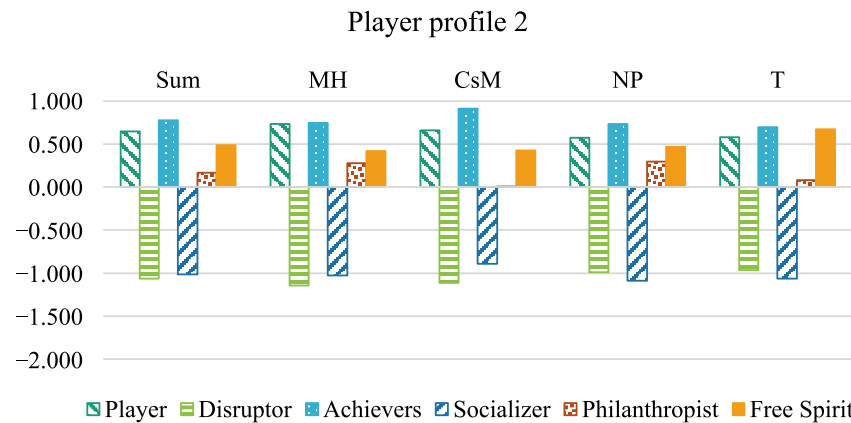


Figure 2. Results of the clustering process. Second player profile in the different disciplines.

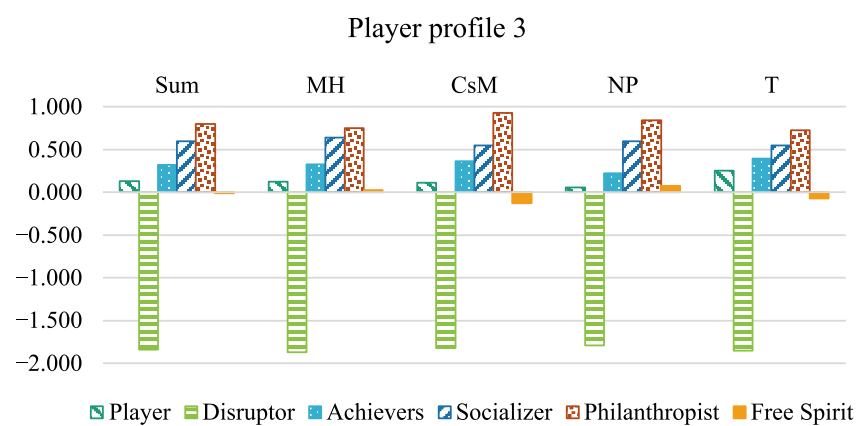


Figure 3. Results of the clustering process. Third player profile in the different disciplines.

4.3. Gender Comparison

Comparing the genders, it is noticeable that a conspicuously large number of female participants belong to cluster three, while the male population is evenly distributed among all three clusters (see Table 3).

An exception here are the students of department T, since here, the male participants also correspond more frequently to the type of the third cluster. In the case of queer participants, it is noticeable that the majority is represented in Cluster 1, although this is negligible given that this group has a small n and Cluster 3 is the largest of the clusters. This also applies to the group that did not specify their gender.

Table 3. Comparison of gender distribution on clusters.

	Female	Male	Gender Queer	Without Statement
Cluster 1	63 (21.429%)	66 (30.000%)	8 (61.538%)	0 (0.000%)
Cluster 2	60 (20.408%)	71 (32.273%)	3 (23.077%)	0 (0.000%)
Cluster 3	171 (58.163%)	83 (37.727%)	2 (15.385%)	4 (100.000%)

4.4. Game Mechanics

The mechanics known from the literature were analyzed as described in Section 3. This resulted in 21 mechanics that have different relevance for the respective player profiles. These can be seen in Figure 4. The non-relevant mechanics are not listed. The middle column of the figure shows which weights the player types have for the respective profiles. The total length represents the maximum sum of all weights. Solid connections on the right side indicate positive expressions of the player types in the player profiles. The thicker the line, the stronger the expression. Red dashed lines show negative expressions. The left

column shows the sum of the weights of the respective mechanics. The sum results from the weights of the player types, if they are relevant for the player type according to the literature. The solid lines on the left indicate the mechanics for player types proposed by Marcewski [21], the dotted lines the associations identified in [20,22].

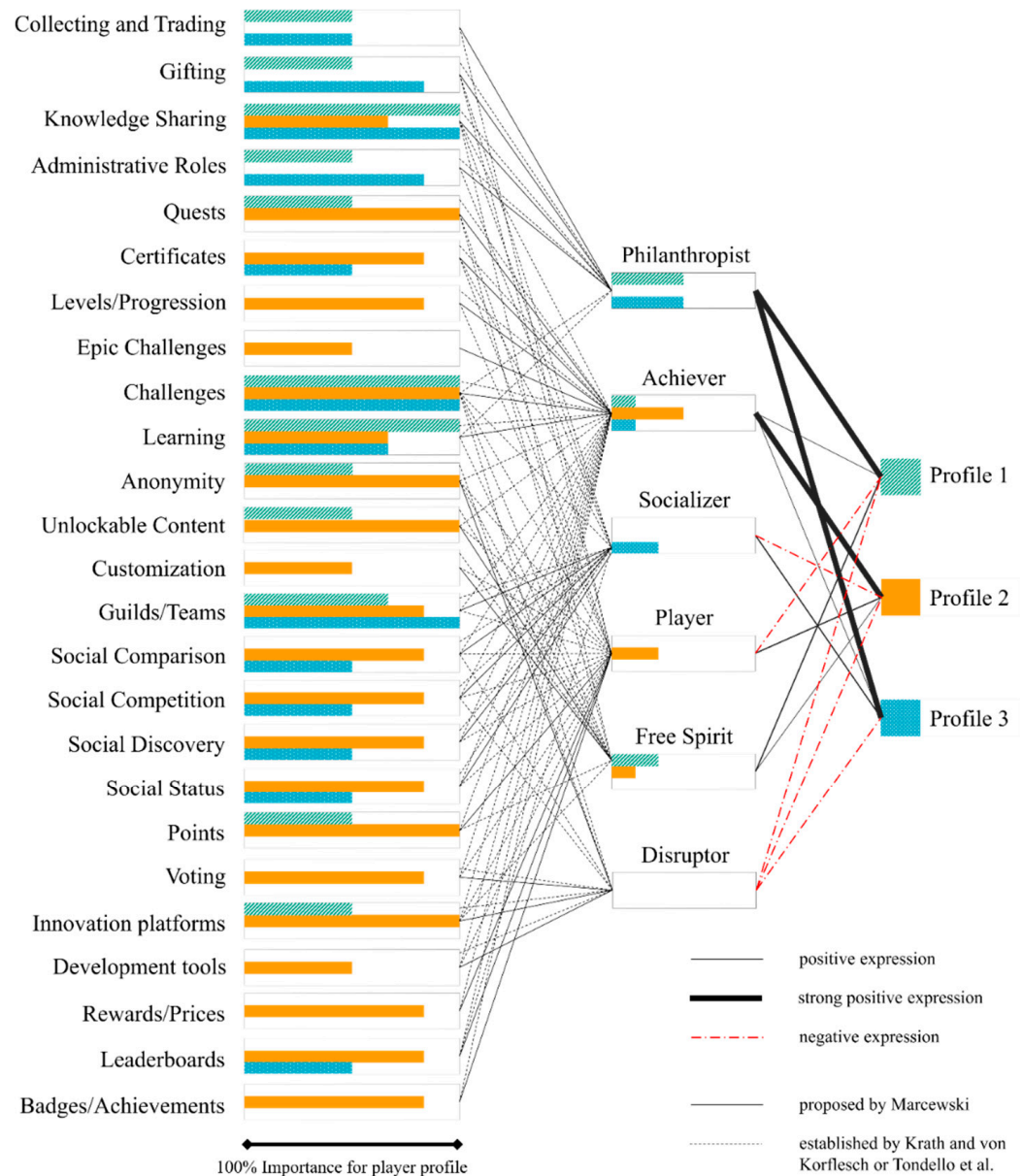


Figure 4. Player profiles assigned player types and the associated game mechanics. Solid lines between mechanics are proposed relationships by Marcewski [21], dotted lines are relationships established by Krath and von Korflesch [22] or Tondello et al. [20].

It is noticeable that the *Challenges* mechanic has the highest relevance for all player profiles. *Knowledge Sharing*, *Guilds or Teams* and *Learning* are also relevant for all player profiles. For the third and largest cluster, *Collecting and Trading*, *Gifting*, *Administrative Roles*, *Certificates*, *Leaderboards*, *Social Comparison*, *Social Competition*, *Social Status* and *Social Discovery* are also relevant. The first three are also relevant for Player Profile 1 and the last six of these mechanics for Player Profile 2. This Profile has the peculiarity of some mechanics only being relevant for this player profile. *Levels or Progression*, *Customization*, *Rewards or Prices*, *Voting*, *Development Tools*, *Epic Challenges* and *Badges or Achievements* can be used explicitly for players who match Player Profile 2. *Quests*, *Anonymity*, *Unlockable Content*,

Innovation Platforms, and *Points* can be used for Player Profiles 1 and 2. Due to the negative expression of the Disruptor in all player profiles, only one associated mechanic is relevant. The mechanic of *Challenges* is relevant to all three player profiles due to its association with the Philanthropist, Achiever, as well as Free Spirit type, and according to Tondello et al. [20] there is also a correlation to the Disruptor type. For Profile 1 and 2 *Innovation Platforms* seems appropriate. Regarding the differences in the player profiles between the study programs, adjustments can now be made by giving preference to mechanics that do or do not have associations with player type. For example, the group of MH students of Player Profiles 2 and 3 can benefit more from the use of *Social Comparison*, *Social Competition*, *Social Status* and *Social Discovery* than the other groups, since they have the strongest expression of the Socializer indicator.

5. Discussion

The paper presents a comprehensive analysis of the expression of individual player types in various fields of study. Not only player types that are particularly pronounced were considered, but also those that appear to be weakly pronounced. Only minor differences between the fields of study were found, although the use of some mechanics in certain fields of study seems to make sense as they cover combinations of player types that stand out in the comparison of the groups. Also noticeable is that female students are more likely to fall into a cluster in which the Philanthropist and Socializer types are positively expressed and the Disruptor type is negatively expressed. One possible factor could be the influence of the proportion of female students in relation to the field of study. More female than male students take part in the MH and NO fields. It could be assumed, therefore, that more female students in these fields would be assigned to the third profile. However, this is not evident in the distribution of clusters when considering individual study disciplines or in the comparison of study disciplines with each other. There are studies on game mechanics that could be better suited for women than for men. Proposed mechanics include *Customization*, *Badges*, *Levels*, *Guilds*, *Points*, *Social Status*, *Competition*, *Consequences*, *Feedback*, and *Signposting* [32]. While *Customization*, *Badges*, *Levels*, and *Points* are not associated with Profile 3 in our results, a few of these mechanics are. For instance, *Guilds*, *Leaderboards*, *Social Status* and *Social Competition* are associated with the profile. The remaining mechanics are not directly comparable to those listed in the study. Therefore, the results seem to contradict previous studies, and further research is needed regarding gender-specific suitable mechanics. On the other hand, our results are in line with the results of Trojanek et al. [23]. Basically, as in their populations, there are differences in the types of players between different courses of study and genders, with the recorded gender difference being more significant. Looking at the characteristics within the clusters and comparing them with the results of Trojanek et al., it is noticeable that mechanics for the Philanthropist, the Achiever, and the Free Spirit are particularly suitable for the participants of this survey, as they are especially represented in the clusters. There is a difference here, since Trojanek also identifies the Philanthropist as frequent, but in second place is the Socializer type [23]. This discrepancy can be attributed to disparities in study populations. The Technical University of Dresden offers humanities and social sciences, as well as teaching subjects. In the results of this survey, it can be seen that NP students in Cluster 1 correspond less to the type of Socializer than students of other disciplines.

Furthermore, the deviation can be explained by the use of the cluster method in the analysis. By considering all types of players, the Socializer is less important than when calculating the types of players by summing them up. In this case, the Socializer is more important, since other less pronounced types are not considered.

5.1. Implications and Examples for Higher-Education Teaching

For the use of Serious Games in teaching, these results can facilitate the choice of the implemented game mechanics, since some mechanics are particularly suitable for the investigated group. The results of the analysis allow for a prioritization due to the positive

expression in several player profiles. Noteworthy is that the Disruptor appears in all player profiles with negative expression, but this player type can influence other players. In the case of multi-user games, the Disruptor should be prevented from negatively influencing others [21]. Regarding the effect of individually utilized mechanics described in the introduction, the results allow for two possibilities in practice. Firstly, the implementation of games with mechanics tailored to the player type, as advocated by Bakkes et al. [18]. This work provides the added value of reducing the range of suitable mechanics by classifying students to one of three player profiles with suggested appropriate mechanics. Based on the presented data, students whose player type is captured by the instrument of Krath and on Kornflesch [22] or another translation of the instrument can be assigned to a player profile. Secondly, the possibility of a one-size-fits-all approach remains, using the mechanics that seem to be suitable for all player profiles in the study. In the following, some examples of serious games for different player types are described. Let us assume that the learning content of a programming course is in focus. The one-fits-all approach could be an escape game, as solving a puzzle could be seen as a challenge to unlock further content. The games convey learning content by presenting the challenge of solving the puzzles. The game is designed for a multi-player mode so that knowledge exchange between students is helpful or necessary. Puzzles that build on each other encourage the *Learning* mechanics. A game design that can appeal to players of the first profile is an adventure. It includes earning a kind of in-game currency by solving programming tasks. Using this currency, players can progress in the in-game *Epic Challenge*. Furthermore, it is conceivable to earn currency by *Knowledge Sharing* or *Trading* with the currency or purchased goods and complete tasks within the game story. The latter can also come from the field of programming lectures. A quiz seems to be a good option for the second profile, as players of this profile are motivated by *Points*, *Prizes*, *Leaderboards*, or *Achievements*. Therefore, a game that sets programming tasks rated with points is possible. These tasks can be grouped, and a reward can be awarded when a certain number of points is reached. This can be combined with a *Level* system in which rewards lead to advancement would support the profile. For players of the third profile, multiplayer games where *Teams* work together are necessary. Here, designing a game about solving programming tasks cooperatively in teams is imaginable. By solving the tasks, the teams can receive *Certificates* that present their status to the outside world. To support *Gifting* and *Collecting and Trading*, collecting different certificates entitles teams to help others to gain new status symbols. All three games teach the same content and implement it partially or completely in the same tasks. According to the literature [15–18], the motivation and satisfaction of the students can be increased by embedding them in three different games. The examples described are only rough sketches conceivable for any lecture topic. As the implementation of each example requires a lot of effort, consideration should be given to the automated creation of serious games.

5.2. Automated Generation and Further Research

If the results are used as the basis for a system for the automated generation of Serious Games, this has the advantage that users no longer have to be reduced to one player type but can be assigned to one of three player profiles. Thus, more than one type can influence the mechanics used. The combination of six player types to three profiles reduces the number of mechanisms to be provided and could thus speed up the calculation process. It also facilitates the calculation of multi-user players, since fewer combinations are possible here as well. Apart from an automated creation of games, the results of the paper offer lecturers the possibility to select mechanics for Serious Games or gamification more specifically, insofar as the students resemble the population of the study.

A silhouette score of 0.42 was achieved, indicating at least a weak cluster correlation. A higher value could possibly be achieved by a larger sample. The number of participants surveyed reached a significance level of 95%. However, the survey was only conducted among students at the University of Lübeck, and due to acquisition via mail, a selection bias can also be assumed. Further research is conceivable to gather additional data. This should

be performed across locations to exclude biases due to offered fields of study or other local distortions. The method described in this work is easy to replicate with current tools and can be repeated with additional data due to the description provided. The instrument used is validated in various languages and can be implemented in an online questionnaire. By collecting additional data and conducting investigations regarding gender distribution, further results can simplify the selection of game mechanics and customization for individuals. Since adaptive Serious Games align with the current transformation in education [33], the idea of implementing such games appears desirable. This publication presents possible approaches and ideas for implementing adapted Serious Games. From a research perspective, it is interesting to explore how adapted games can be implemented and perceived by students. In addition to acceptance, outcomes such as motivation, player satisfaction, and learning effects are of interest. These could substantiate previous findings and psychological theories through empirical results. Therefore, we advocate for investigating games in line with this work compared to unadapted games to expand the research landscape.

In the next steps, we plan to design automatically generated adaptive games in a co-creation process. They will be finalized with suitable mechanics for the profile of the student, by an automatic calculation. Furthermore, the context in which adaptive LMS and thus Serious Games are used and accepted by lecturers and students will be investigated. After a comprehensive context, task and user analysis, a prototype will be built. Based on this prototype, it will be evaluated whether it is possible for users to play adaptive Serious Games automatically and independently from the learning content.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/educsci14040352/s1>, Tables S1–S5 show the results of the K-Means Clustering with PCA reported with standard deviation and variance of all students and for each group in particular.

Author Contributions: Conceptualization, A.S. and L.C.B.; Methodology, L.C.B.; Software, L.C.B.; Validation, L.C.B.; Formal Analysis, L.C.B.; Investigation, L.C.B.; Resources, L.C.B.; Data Curation, L.C.B.; Writing—Original Draft Preparation, L.C.B.; Writing—Review & Editing, A.S. and L.C.B.; Visualization, A.S. and L.C.B.; Supervision, A.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki. Ethical review and approval were waived for this study due to anonymously data collection and the informed consent of all participants to the processing and publication of the data. No personal data were collected at any time. The survey was conducted exclusively by presenting questions in an online questionnaire. The participants received no incentive to answer the survey except the result of the validated questionnaire on their player type.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The datasets generated by the survey research during and/or analyzed during the current study are available in the Zenodo repository, <https://zenodo.org/records/10477769> accessed on 5 February 2024.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Kumar Basak, S.; Wotto, M.; Bélanger, P. E-learning, M-learning and D-learning: Conceptual definition and comparative analysis. *E-Learn. Digit. Media* **2018**, *15*, 191–216. [\[CrossRef\]](#)
2. Cavus, N. Distance Learning and Learning Management Systems. *Procedia-Soc. Behav. Sci.* **2015**, *191*, 872–877. [\[CrossRef\]](#)
3. Miranda, J.; Navarrete, C.; Noguez, J.; Molina-Espinosa, J.M.; Ramírez-Montoya, M.S.; Navarro-Tuch, S.A.; Bustamante-Bello, M.R.; Rosas-Fernández, J.B.; Molina, A. The Core Components of Education 4.0 in Higher Education: Three Case Studies in Engineering Education. *Comput. Electr. Eng.* **2021**, *93*, 107278. [\[CrossRef\]](#)
4. Ramírez-Montoya, M.S.; Castillo-Martínez, I.M.; Sanabria-Z, J.; Miranda, J. Complex Thinking in the Framework of Education 4.0 and Open Innovation—A Systematic Literature Review. *J. Open Innov. Technol. Mark. Complex.* **2022**, *8*, 4. [\[CrossRef\]](#)

5. Tang, S.; Long, M.; Tong, F.; Wang, Z.; Zhang, H.; Sutton-Jones, K.L. A Comparative Study of Problem-Based Learning and Traditional Approaches in College English Classrooms: Analyzing Pedagogical Behaviors Via Classroom Observation. *Behav. Sci.* **2020**, *10*, 105. [CrossRef] [PubMed]
6. Faiella, F.; Ricciardi, M. Gamification and learning: A review of issues and research. *J. E-Learn. Knowl. Soc.* **2015**, *11*, 13–21. [CrossRef]
7. Susi, T.; Johannesson, M.; Backlund, P. *Serious Games—An Overview*; Technical Report HS- IKI -TR-07-001 School of Humanities and Informatics; University of Skövde: Skövde, Sweden, 2007; p. 28.
8. Boeker, M.; Andel, P.; Vach, W.; Frankenschmidt, A. Game-Based E-Learning Is More Effective than a Conventional Instructional Method: A Randomized Controlled Trial with Third-Year Medical Students. *PLoS ONE* **2013**, *8*, e82328. [CrossRef] [PubMed]
9. Cordova, D.I.; Lepper, M.R. Intrinsic motivation and the process of learning: Beneficial effects of contextualization, personalization, and choice. *J. Educ. Psychol.* **1996**, *88*, 715–730. [CrossRef]
10. Froiland, J.M.; Worrell, F.C. Intrinsic Motivation, Learning Goals, Engagement, and Achievement in a Diverse High School. *Psychol. Sch.* **2016**, *53*, 321–336. [CrossRef]
11. Gaalen, A.E.J.V.; Schönrock-Adema, J.; Renken, R.J.; Jaarsma, A.D.C.; Georgiadis, J.R. Identifying Player Types to Tailor Game-Based Learning Design to Learners: Cross-sectional Survey using Q Methodology. *JMIR Serious Games* **2022**, *10*, e30464. [CrossRef] [PubMed]
12. Rahimi, I.D. Ambient Intelligence in Learning Management System (LMS). In Proceedings of the 2022 Computing Conference, London, UK, 14–15 July 2022; Arai, K., Ed.; Springer: Cham, Switzerland, 2022; pp. 379–387. [CrossRef]
13. Olsevicova, K.; Mikulecky, P. Learning management systems as an ambient intelligence playground. *Int. J. Web Based Communities* **2008**, *4*, 348–358. [CrossRef]
14. Hunicke, R.; LeBlanc, M.; Zubeck, R. MDA: A formal approach to game design and game research. In Proceedings of the AAAI Workshop on Challenges in Game AI, San Jose, CA, USA, 25–26 July 2004; Volume 4, p. 1722.
15. Orji, R.; Mandryk, R.L.; Vassileva, J.; Gerling, K.M. Tailoring Persuasive Health Games to Gamer Type. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, New York, NY, USA, 27 April–2 May 2013; CHI '13; pp. 2467–2476. [CrossRef]
16. Orji, R.; Vassileva, J.; Mandryk, R.L. Modeling the Efficacy of Persuasive Strategies for Different Gamer Types in Serious Games for Health. *User Model. User-Adapt. Interact.* **2014**, *24*, 453–498. [CrossRef]
17. Ferro, L.S.; Walz, S.P.; Greuter, S. Towards Personalised, Gamified Systems: An Investigation into Game Design, Personality and Player Typologies. In Proceedings of the 9th Australasian Conference on Interactive Entertainment: Matters of Life and Death, New York, NY, USA, 30 September–1 October 2013; IE '13; pp. 1–6. [CrossRef]
18. Bakkes, S.; Tan, C.T.; Pisan, Y. Personalised Gaming: A Motivation and Overview of Literature. In Proceedings of the 8th Australasian Conference on Interactive Entertainment: Playing the System, Auckland, New Zealand, 21–22 July 2012; pp. 1–10. [CrossRef]
19. Bartle, R. Hearts, Clubs, Diamonds, Spades: Playery Who Suit MUDS. *J. MUD Res.* **1996**, *1*, 19.
20. Tondello, G.F.; Wehbe, R.R.; Diamond, L.; Busch, M.; Marczewski, A.; Nacke, L.E. The Gamification User Types Hexad Scale. In Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play, Austin, TX, USA, 16–19 October 2016; pp. 229–243. [CrossRef]
21. Marczewski, A. *Even Ninja Monkeys Like to Play: Gamification, Game Thinking and Motivational Design*; CreateSpace Independent Publishing Platform: North Charleston, SC, USA, 2015.
22. Krath, J.; von Korfflesch, H.F.O. Player Types and Game Element Preferences: Investigating the Relationship with the Gamification User Types HEXAD Scale. In Proceedings of the HCI in Games: Experience Design and Game Mechanics, Virtual Event, 24–29 July 2021; Springer: Cham, Switzerland, 2021; pp. 219–238. [CrossRef]
23. Trojanek, A.; Fischer, H.; Heinz, M. Auf die Typen kommt es an. Eine empirische Analyse studentischer Spielertypen. In Proceedings of the Workshop Gemeinschaften in Neuen Medien (GeNeMe) 2017, Dresden, Germany, 18–20 October 2017; pp. 137–144.
24. Barata, G.; Gama, S.; Jorge, J.A.; Gonçalves, D.J. Relating gaming habits with student performance in a gamified learning experience. In Proceedings of the First ACM Symposium on Computer-Human Interaction in Play, New York, NY, USA, 19–21 October 2014; CHI PLAY '14. [CrossRef]
25. Gillessen-Kaesbach, G.; Münte, T.; Hartmann, E.; Fischer, S. Universitätskennzahlen 2021, 2022. Available online: https://www.uni-luebeck.de/fileadmin/uzl_qm/PDF/Universitaetskennzahlen/Unikennzahlen2021_Web.pdf (accessed on 21 March 2024).
26. Israel, G. Determining sample size. *PEOD* **2009**, *6*, 1–7.
27. Likas, A.; Vlassis, N.; Verbeek, J. The Global K-Means Clust. Algorithm. *Pattern Recognit.* **2003**, *36*, 451–461. [CrossRef]
28. 2.3. Clustering (Python Online Documentation). Available online: <https://scikit-learn.org/stable/modules/clustering.html> (accessed on 6 March 2024).
29. Thorndike, R.L. Who Belongs in the Family? *Psychometrika* **1953**, *18*, 267–276. [CrossRef]
30. Comaniciu, D.; Meer, P. Mean Shift: A Robust Approach toward Feature Space Analysis. *IEEE Trans. Pattern Anal. Mach. Intell.* **2002**, *24*, 603–619. [CrossRef]
31. Nielsen, F. Hierarchical Clustering. In *Introduction to HPC with MPI for Data Science*; Nielsen, F., Ed.; Undergraduate Topics in Computer Science; Springer International Publishing: Cham, Switzerland, 2016; pp. 195–211. [CrossRef]

32. Klock, A.C.T.; Gasparini, I.; Pimenta, M.S.; Hamari, J. Tailored Gamification: A Review of Literature. *Int. J. Hum.-Comput. Stud.* **2020**, *144*, 102495. [[CrossRef](#)]
33. Brandl, L.C.; Schrader, A. Serious Games in Higher Education in the Transforming Process to Education 4.0—Systematized Review. *Educ. Sci.* **2024**, *14*, 281. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.