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Article

Using Serious Game Techniques with Health Sciences and Biomedical Engineering Students: An Analysis Using Machine Learning Techniques

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Abstract: The use of serious games on virtual learning platforms as a learning support resource is increasingly common. They are especially effective in helping students acquire mainly applied curricular content. However, a process is required to monitor the effectiveness and students' perceived satisfaction. The objectives of this study were to (1) identify the most significant characteristics; (2) determine the most relevant predictors of learning outcomes; (3) identify groupings with respect to the different serious game activities; and (4) to determine students' perceptions of the usefulness of the simple and complex serious game activities. We worked with a sample of 130 university students studying health sciences and biomedical engineering. The serious game activities were applied in a Moodle environment, UBUVirtual, and monitored using the UBUMonitor tool. The degree type and the type of serious game explained differing percentages of the variance in the learning results in the assessment tests (34.4%—multiple choice tests [individual assessment]; 11.2%—project performance [group assessment]; 25.6%—project presentation [group assessment]). Different clusters were found depending on the group of students and the algorithm applied. The Adjusted Rang Index was applied to determine the most appropriate algorithm in each case. The student satisfaction was high in all the cases. However, they indicated complex serious games as being more useful than simple serious games as learning resources for the practical content in both health sciences and biomedical engineering degrees.

Keywords: serious games; machine learning; learning monitoring; branching scenario

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1. Introduction

Digitalisation in the educational context is one of the needs and challenges of 21st-century society, and one that has only been accelerated by the SARS-CoV-2 pandemic, especially in higher education [1]. More specifically, the use of technological resources applied to teaching in courses that include practical training, such as health sciences and biomedical engineering degrees, has become a very effective tool [2–5]. One of the most effective tools for clinical and engineering practicals has been shown to be virtual simulation laboratories (or labs) [6]. One important resource in this area is the H5P tool (Hyper Text Markup Language 5 Package) within Learning Management Systems (LMS) platforms such as the Modular Object-oriented Dynamic Learning Environment (Moodle), Canvas, Brightspace, Blackboard, etc. This is because it offers a variety of options, has zero cost (it offers free access), and allows the re-use of any elements created. This makes H5P a sustainable and easily accessible tool [7,8]. However, within this framework, the teacher or researcher is faced with the problem of data pre-processing, analysis, and interpretation, as a huge amount of data are recorded in these learning spaces (LMS) [9]. Therefore, to address this issue, the user has to apply machine learning techniques within educational data mining (EDM). These points are discussed in more detail below.

1.1. Background

1.1.1. Virtual Simulation Through Serious Game Resources

The use of simulation-based learning practices in virtual laboratories has been shown to be an important support for teaching in health sciences degrees [2]. Virtual simulation scenarios contribute to increased deductive reasoning, cognitive and metacognitive knowledge, and self-efficacy, as well as student engagement [6]. In this framework, virtual simulation environments applying serious games play an important role, especially in learning that guides clinical practice in health science disciplines (medicine, psychology, nursing, occupational therapy, physiotherapy, etc.). These serious game environments facilitate the creation of virtual simulation activities. They also provide real-time feedback to the learner, facilitating self-reflection [3]. Although the design of these simulation spaces is initially costly, it later significantly reduces the teacher's work without reducing the quality of teaching [4].

Virtual simulation techniques have been shown to be very effective in engineering degrees. Engineering requires a structured, hierarchical, step-by-step approach to solving processes [10]. In this framework, using H5P tools promotes a powerful learning environment that increases student motivation and engagement [5]. Other studies have examined the relationship between the participation in serious game activities that apply interactive videos and learning outcomes [11]. Students who have worked in these environments achieve better learning outcomes [7]. Although at the beginning, students see participation in serious game activities as additional effort, once they have completed the gamified practical, their levels of satisfaction are higher [3]. Teacher satisfaction is also perceived to be high, although the process of evaluation and redesign is continuous [3].

Furthermore, digitisation of the teaching–learning process in these disciplines guides evidence-based teaching, and the design of virtual scenarios is a fundamental part of this [6,12]. More specifically, designing e-learning scenarios that include self-regulated learning (SRL) facilitates learning by doing and increases student motivation [13–17]. Using virtual reality resources in particular facilitates information retention [18]. Clinical simulation supports teaching–learning processes in health sciences and biomedical engineering degrees, and is having a significant impact on future graduates' education [19].

It is important to try and clarify the distinction between gamification and serious games. The two terms are related but are not synonymous. Gamification refers to using fun elements to improve learning in whichever knowledge area [20] and usually includes some reward system based on badges or points. In contrast, serious games are more focused on specific learning objectives and goals that promote better engagement, and they do not normally use rewards [21].

In summary, facilitating effective and motivating learning through using tools such as the H5P environment has been shown to be a key goal for increasing the learning outcomes and student engagement [21].

1.1.2. Application of H5P Resources in Serious Game Practice

As mentioned above, H5P is an open-source, JavaScript-based environment that can be used in LMSs. This environment facilitates the development and reuse of collaborative content [7]. Moodle, among other platforms, supports the integration of this content, facilitating interactivity [22]. In short, H5P is a versatile, powerful tool that can help to reinforce effective learning in blended learning (b-Learning) or electronic learning (e-Learning) environments. More specifically, students can improve their critical thinking, problem solving, and understanding of content [23]. In recent years, interactive activities based on H5P have been incorporated into e-learning environments, and the research results indicate that they are more effective for learning outcomes and increasing student motivation than other types of activities [22–25].

The H5P interactive activities are suited to allowing the learner to learn at their own pace, which leads to greater engagement with more autonomous, self-directed learning [26,27]. In addition, the participants often perceive H5P interactive activities as more accessible, which increases their motivation [25]. The H5P environment allows teachers to develop gamified scenarios and to apply debriefing techniques with learners afterwards. These debriefs help students reflect on their learning experiences, which is essential in health science subjects [2]. Interactive videos are one of the possible resources that can be developed on the H5P platform, which seem to be very useful, as they increase students' understanding of content and engagement [22,28]. In addition, using 360° video plays an important role in creating realistic virtual tour experiences [10,29–31], and using H5P resources such as branching scenarios involving interactive 360° videos and comprehension questions [30] seems to increase students' hypothetical deductive reasoning and scientific explanation skills [31].

However, the usefulness of these activities has to be tested to determine how effective they are in the learning process [32,33]. The influence of other variables, such as the type of activity design (simple vs. complex serious game activities) [34] and individual student variables (type of degree, academic year, learning style, etc.) [22], should also be studied, as well as students' perceptions of usefulness [35]. The ultimate aim is to test whether H5P-based activities particularly facilitate the personalisation of learning [11]. Finally, it is worth noting the reusability of the materials which can be used again after being tested [34].

1.1.3. Data Analysis Using Data Mining and Artificial Intelligence Techniques

Using multimedia technology together with artificial intelligence resources opens up a new scenario in the field of educational instruction in the 21st century. Within this framework, one of the greatest challenges is related to the design of virtual simulated learning scenarios, an aspect addressed in the previous section. However, once these environments have been designed, their usefulness must be tested [32,33,35].

Effectiveness studies, in addition to requiring records of user interactivity in LMSs, need to consider variables such as the level of prior knowledge, motivation towards the object of learning, cognitive load experienced with respect to the tasks, and the perceived level of anxiety [36]. In other words, it is necessary to analyse the explainability of the results in order to obtain the best possible interpretability. Achieving this needs models to be designed that apply machine learning algorithms [37], notably the creation of models that include algorithms for analysing the data extracted from all these variables [38]. In this context, supervised machine learning techniques such as feature selection will allow the prior analysis of which of these variables is most important. This will allow explanations of learning outcomes, for example, or students' motivation towards each type of specially designed serious game activity. The ultimate goal is to achieve individualised learning and to detect specific patterns [39]. In other words, the aim is to optimise the resources for each learner profile by seeking the greatest possible personalisation [40].

Recent research has focused on the use of linear support vector classifiers (SVM) [41]. Castilla et al. [42] found that three algorithms (the Long Short-Term Memory recurrent neural network—LSTM, Random Forest, and Multilayer Perceptron Neural Network—MLP) were more effective in classifying user records.

In summary, within the framework of behavioural analysis, a large volume of data are obtained, and analysing it requires computational techniques such as data fusion, machine learning [supervised (prediction and classification) or unsupervised (clustering)] [43], and the application of Transformer models [44,45]—which are particularly useful in the analysis of time series data and apply generative artificial intelligence algorithms. This is the great challenge and opportunity for the study of human behaviour in different contexts, such as education.

In line with the theoretical basis outlined above, the objectives of this study were to (1) identify the most significant characteristics; (2) determine the most relevant predictors of learning outcomes; (3) identify groupings with respect to the different serious game activities; and (4) to determine students' perceptions of the usefulness of the simple and complex serious game activities. These objectives determined the following research questions.

RQ1: What are the most significant characteristics in terms of data mining with respect to the variables studied?

RQ2: Which variables are the best predictors of the different learning outcomes for the participating students?

RQ3: Which groupings—without prior labelling—are the most significant with respect to the different serious game activities?

RQ4: How useful do health sciences and biomedical engineering students find the simple and complex serious game activities in the study?

2. Materials and Methods

2.1. Participants

This study used convenience sampling. As the sample included health science and biomedical engineering students who agreed to participate and excluded those who did not, we worked with a total sample of 130 students, 111 from health sciences (45 in the third year of an occupational therapy degree: 42 women and 3 men; and 66 doing a nursing degree: 57 women and 9 men), and 19 engineering students doing a degree in biomedical engineering (11 women and 8 men). The students were split into three groups: Group 1 (occupational therapy students who participated voluntarily in complex and simple serious game activities; n = 18, 40% of the total and non-participation n = 27, 64%); Group 2 (health engineering students, who participated in complex and simple serious game activities; n = 17, 89.5% of the total and non-participation n = 2, 10.53%); and Group 3 (nursing students; n = 58 participated in simple serious game activities while n = 8 did not participate). All of the participants were students at the University of Burgos, and received no financial rewards for participating in the serious game activities. In addition, all the participating students signed their written informed consent.

2.2. Instruments

The instruments used in the study are described below:

(a) UBUVirtual Platform based on Moodle. UBUVirtual is a learning management system based on the Modular Object-oriented Dynamic Learning Environment (Moodle). Currently, Moodle is the most widely used LMS tool worldwide. It has over 90,000 registered sites in more than 200 countries. In Spain, Moodle is the most commonly used platform by universities. Its most widely noted characteristics include its flexibility and ease of personalisation. It is also free to use and is based on open code, meaning that anyone can modify Moodle. From a user's point of view, Moodle's creators have worked to improve its accessibility and usability in recent years with the aim of making it an intuitive, easy-to-use platform. It also has a huge number of well-documented, well-organised resources available. This study used Moodle version 4.1.4.

(b) Complex serious game activities performed using an H5P-type branching scenario. These are scenarios that make it easier for students to make decisions. Branching scenarios offer students different routes through the learning content, so each learning story will be different depending on learners' decisions. Branching scenarios also improve learning the practical application of conceptual content. These scenarios are recommended for simulation activities in degrees that need students to acquire skills that facilitate future professional practical activity.
In short, branching scenarios increase learner engagement, improve their retention of information, and provide a safe space for the practical application of theoretical content. They also make it easier for learners to learn from their mistakes, and they respect each learner's pace of learning.

(c) Serious game activities using simple H5P (crossword puzzles, memory games, true–false questions, and word searches).
(d) UBUMonitor [46,47]. UBUMonitor is a monitoring tool for visualising student activity data on Moodle-type LMS platforms. It is a desktop application that facilitates the extraction and visualisation of subject access data. In this study, specifically, we worked with UBUVirtual (Moodle-type LMS of the University of Burgos (Spain)). The application is open source and free of charge (more information can be found at https://www3.ubu.es/ubucevblog/seguimiento-interaccion-alumnos-ubumonitor/ (accessed on 10 December 2024)).
(e) Questionnaire assessing perceived satisfaction with simple and complex serious game activities. This instrument was created specifically for this study. It had 4 closed questions measured on a Likert-type scale from 1 to 5, where 1 is not at all or never and 5 is completely or always. It also had 4 open-ended questions (see Table A1). Reliability indicators were calculated for the instrument. Cronbach's Alpha (α) for the overall instrument was α = 0.93, while for each item it was as follows: item 1 α = 0.92, item 2 α = 0.91, item 3 α = 0.88, and item 4 α = 0.91, while McDonald's omega (ω) for each item was as follows: item 1 ω = 0.93; item 2 ω = 0.94; item 3 ω = 0.88; and item 4 ω = 0.92. The acceptable values for reliability indices are 0.70- $\geq$ 0.90.
(f) Questionnaire of perceived satisfaction with simple serious game activities. This instrument was created specifically for the study. It had 1 closed question measured on a Likert-type scale from 1 to 5, where 1 is not at all or never and 5 is all or always. It also included 3 open-ended questions (see Table A2).
(g) Learning outcomes in the following assessment tests. The structure was similar in the three groups, and the content was adapted to the characteristics of each of the subjects: (1) a multiple-choice test with 30 questions, each with 4 possible answers, only one of which was correct. Each student completed this test individually; (2) an assessment related to completing a project about solving a problem within a project-based learning methodological structure. This assessment was carried out as a group; (3) project presentation test (in groups). The groups in the group evaluation tests were made up of 3–5 members.

2.3. Procedure

This study was first approved by the Bioethics Commission of the University of Burgos for the SmartLearnUni project No. IO 03/2022. Then, simple serious game activities (crossword puzzles, memory games, true–false questions, and word searches) and complex serious game activities (such as branching scenarios, which included interactive videos and comprehension questions) were developed. An example of the applied branching scenario design is shown in Figure 1.

All the serious game activities used H5P and were included in the UBUVirtual LMS. Afterwards, informed consent was obtained from the students who were eligible to participate. We worked with three groups. Because of the nature of their subjects (which had theoretical and practical components related to clinical intervention), Group 1 and Group 2 were given both simple and complex serious game activities, Group 3 were given only simple serious game activities, as their subject was primarily theoretical and did not include clinical practice. The students completed the different serious game activities throughout the semester. All of the simple serious games were about theoretical subject content, while the complex serious games addressed the practical course content. At the end of the semester, the participating students completed the satisfaction questionnaires about the serious game activities with H5P depending on the type of serious games they had participated in. In addition, the students' interactions throughout the semester on the UBUVirtual platform were monitored using the UBUMonitor tool. Figure A1 show the structure of the serious games given to Group 1 in a branching scenario. The structure given to Group 2 is shown in Figure A2.

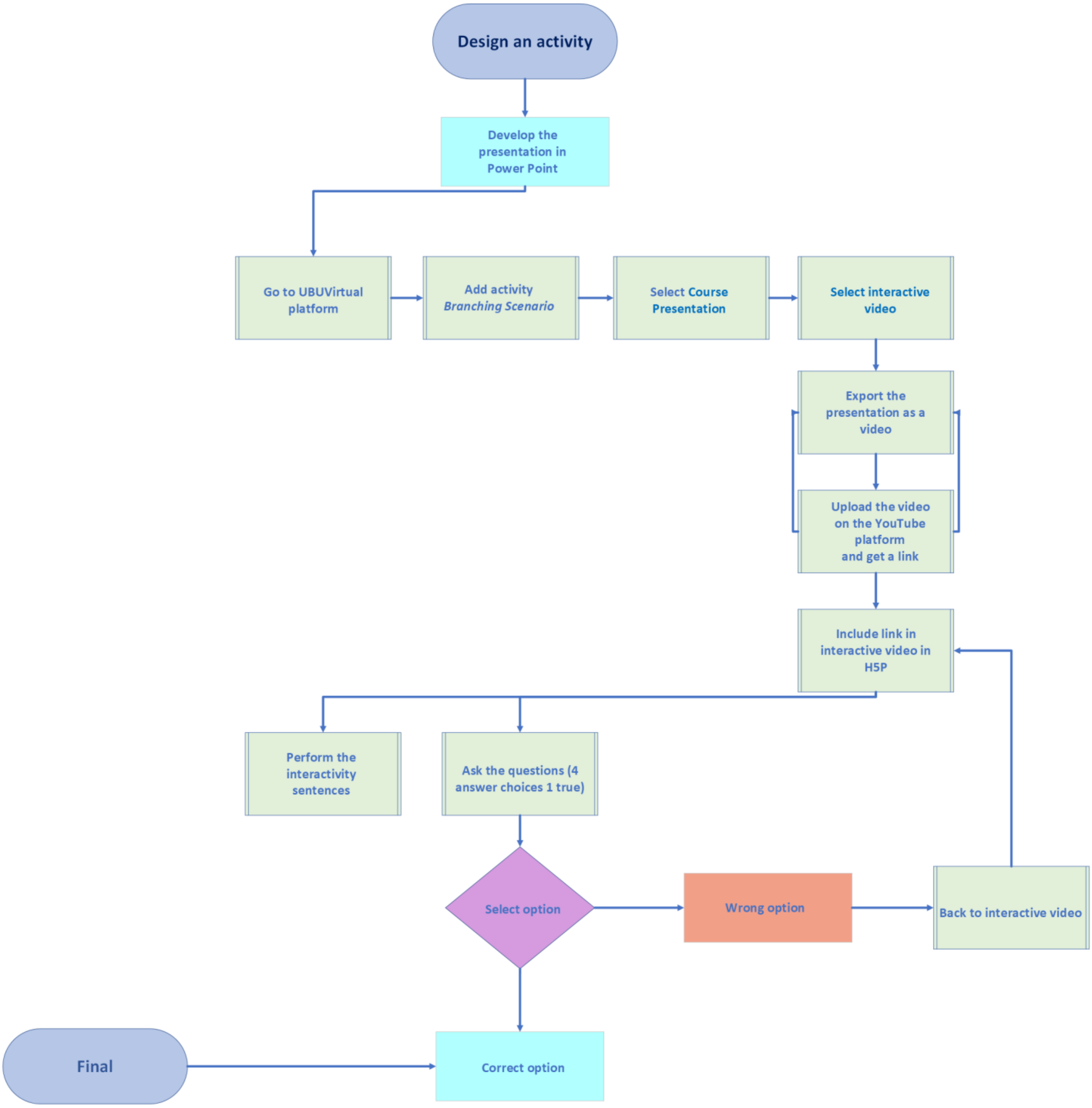


Figure 1. Decision-making model applied in the branching scenario.

Table 1 also shows the distribution of the groups of students, the type of serious games applied and the cognitive and metacognitive strategies that these games set in motion.

A diagram of the study process is given below (see Figure 2). The game activities had no set time limit; each student could take as long as they needed to do each task. This helps respect each student's pace of learning, which is one of the benefits of using serious game methodology.

Table 1. Group of students, type of serious game applied and cognitive and metacognitive strategies used.

Group	Serious Game Activity	Serious Game Type	Cognitive Strategies and Metacognitive
Group 1 Group 2 Group 3	Crossword (see Figure S1)	simple	Relationship between the question and the possible answer. This involves cognitive strategies of memory and conceptual association.
Group 1 Group 2 Group 3	Memory game (see Figure S2)	simple	Image association search. This involves cognitive strategies of memory and conceptual association.
Group 1 Group 2 Group 3	True–false question (see Figure S3)	simple	Discriminating whether a sentence is true or false. This involve cognitive strategies of memory and conceptual association.
Group 1 Group 2 Group 3	Alphabet soup (see Figure S4)	simple	Finding the right word for a question. This involves cognitive strategies of memory and conceptual association.
Group 1 and Group 2	Branching scenario (see Figures S5 and S6)	complex (includes an interactive video with comprehension questions and choices of response routes)	It involves the use of metacognitive strategies for orientation, planning, evaluation, and information processing.

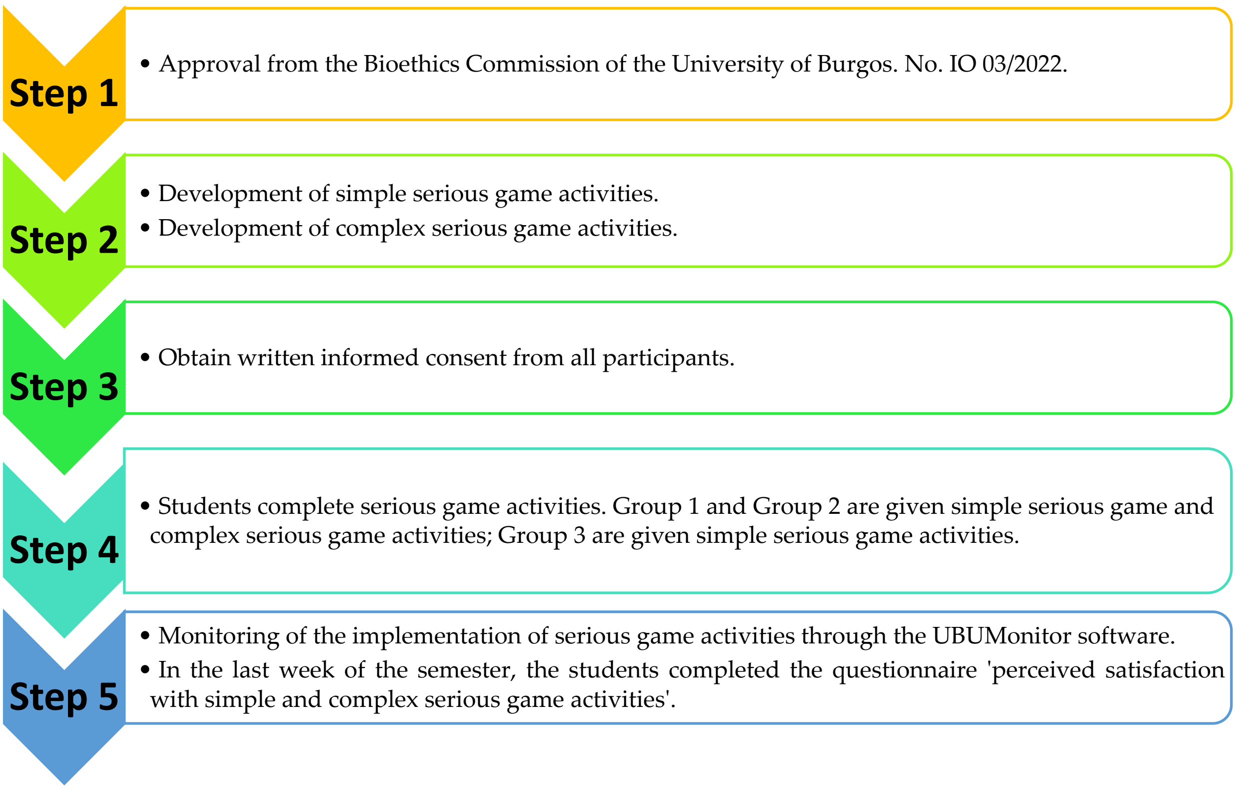


Figure 2. Steps followed in the study.

2.4. Data Analysis

In order to test RQ1, a feature selection was performed [48]. This was carried out using WEKA v.3.8.6 [49,50], a machine learning and data mining software platform written in Java and developed at the University of Waikato. The statistical analysis software SPSS v.28 [51] was used to test RQ2. To test RQ3, a cluster analysis was performed using Python libraries and Orange data mining software v.3.37.0 [50]. To test RQ4 in relation to the quantitative data, a descriptive analysis was performed using SPSS [51]. The qualitative data were analysed through the categorisation of the responses and a code-document analysis using Atlas.ti v.24 [52]. The results are presented in the form of a Sankey diagram. In addition, the UBUMonitor v2.10.6 monitoring software [46,47] was used to monitor the students' learning behaviours.

3. Results

The results are presented for each of the research questions.

3.1. Selection of Features with Regard to the Serious Game Activities

To test RQ1 ("What are the most significant characteristics in terms of data mining with respect to the variables studied?"). The different learning outcomes, the type of group, the serious game type, and the learner were considered as characteristics (variables). The WEKA algorithm "CorrelationAttributeEval" was applied to find the most significant features. This algorithm evaluates the value of an attribute by measuring the Pearson's correlation between the attribute and the class. The ranking of attributes in hierarchical order was as follows: learning outcomes in the project performance assessment r = 0.92, learning outcomes in the project presentation assessment r = 0.88, learning outcomes in the multiple-choice test r = 0.42, the group that the participants belonged to (in this case the type of degree that they were studying) r = 0.41, the serious game type r = 0.17, and finally the participant (each student) r = 0.12. This result indicates the importance of the type of student whom the serious games are aimed at, the type of group (degree, course, etc.), and the type of serious game design applied. These are important variables that researchers should consider when it comes to serious games.

3.2. Predictors of Academic Performance with Respect to the Serious Game Activities

To test RQ2 ("Which variables are the best predictors of the different learning outcomes of the participating students?"), a multiple regression analysis was performed on the effect of the variables "doing a specific degree" and "serious game type" on the learning outcomes. For the learning outcomes in the multiple-choice tests, the variables predicted 34.3% (R^2 = 0.343) of the variance. In this case, the significant variable was participation in complex serious game activities (t = 6.75 $p \leq 0.001$). The tolerance indicators did not approach 0, so the independent variables were not considered redundant, and none had to be eliminated. In addition, the values for VIFs (Variance Inflation Values) were less than 10, which means that they were within the fit values (1–10) (see Table A3).

For the learning outcomes in the project performance assessment, these variables predicted 11.2% (R^2 = 0.112) of the variance. The group type variable was significant in this case (t =3.82 $p < 0.001$) (see Table A3). For the learning outcomes in the project presentation assessment, these variables predicted 25% of the variance (R^2 = 0.256). In this case, the group type variable was significant (t = 6.54 $p < 0.001$). The tolerance indicators did not approach 0, so the independent variables were not considered redundant, and none had to be eliminated with respect to the dependent variable (the learning outcomes in the project presentation assessment). In addition, the values for the VIFs were less than 10, which means that they were within the fit values (1–10) (see Table A5).

In summary, the participation in serious game activities seems to have had a different weight in the prediction of student learning outcomes in the different learning assessment tests: multiple-choice (34.3%), project performance assessment (11.2%), and project presentation assessment (25.6%). It should be borne in mind that the first of the three involved individual assessment, while the others were group activities. Subsequent studies might focus on analysing how the use of serious games influences group learning vs. individual learning in higher education.

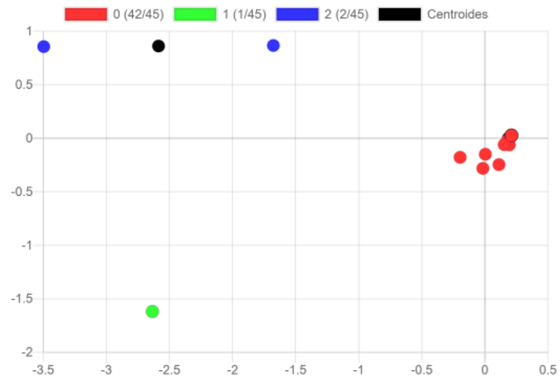
3.3. Groupings with Regard to the Serious Game Activities

To test RQ3 (“Which groupings—without prior labelling—are the most significant with respect to the different serious game activities?”).

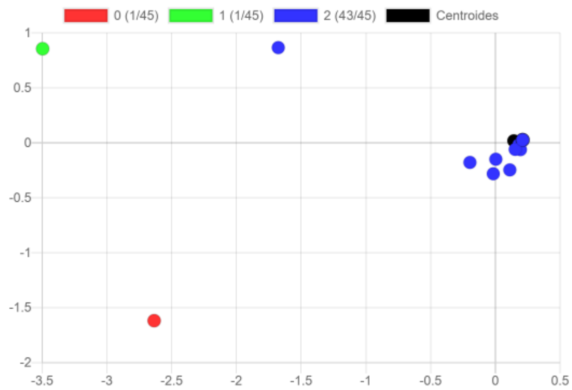
It is important to note that cluster analysis is an unsupervised machine learning test, meaning that no labels are applied beforehand to the instances or variables.

Clusters were found for each group of students and serious game type, which involved predicting the number of clusters first in each case. This was performed using the elbow method, which consists of plotting the sum of the squared distances between each data point and its assigned centroid for different values of k. The aim is to find the value of k where the decrease in the sum of the squared distances slows down and forms an elbow-like curve.

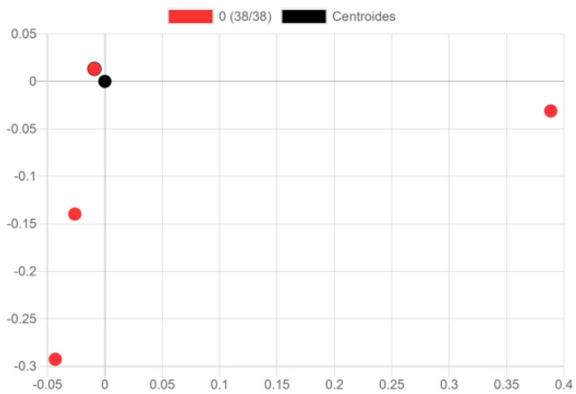
In Group 1 (students studying a bachelor’s degree in occupational therapy), after the simple serious game activities, three possible clusters were predicted (see Figure A3). The following algorithms were then applied: *k*-Means++, Fuzzy-*k*-Means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and Multi-*k*-Means++. An explanation of each of the clusters can be found in [50]. The representation of the clusters in each of the algorithms is shown in Figure 3.



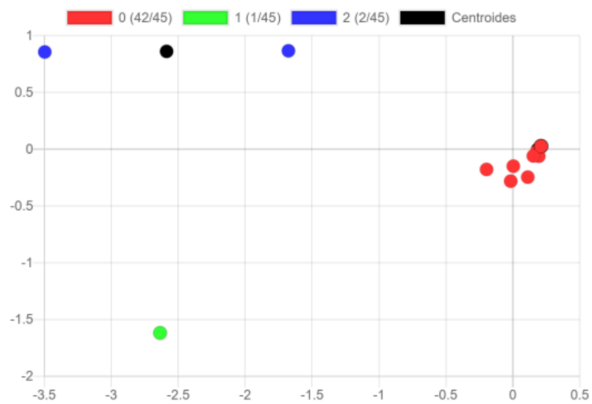
k-Means++ Group 1 simple serious game



Fuzzy-*k*-Means Group 1 simple serious game



DBSCAN Group 1 simple serious game



Multi-*k*-Means++ Group 1 simple serious game

Figure 3. Representation of clusters with different algorithms in Group 1 in simple serious games. Note. centroides = centroids; the different coloured points represent the different groupings found with the different algorithms.

Next, the Adjusted Rand Index (ARI) was applied to check the degree of fit of the algorithms. The ARI can have a value between −1 and 1, −1 being the worst fit and 1 the best fit. The score closest to 1 indicates the best fit. The formula applied was:

$$ARI = \frac{\sum_{ij}\binom{n_{ij}}{2} - \left[\sum_i \binom{a_i}{2} \sum_j \binom{b_j}{2}\right] \Big/ \binom{n}{2}}{\frac{1}{2}\left[\sum_i \binom{a_i}{2} \sum_j \binom{b_j}{2}\right] \Big/ \binom{n}{2}}$$

The algorithms that provided the best fit in this case were *k*-Means++ and Multi-*k*-Means++ (ARI = 1) (see Table 2).

Table 2. Adjusted Rand index (ARI) for Group 1 clustering related to simple serious games.

	***k*-Means++**	**Fuzzy-*k*-Means**	**DBSCAN**	**Multi-*k*-Means++**
k-Means++	1	−0.1	0	1
Fuzzy-*k*-Means	−0.1	1	0	−0.1
DBSCAN	0	0	1	0
Multi-*k*-Means++	1	0	0	1

Note. A higher intensity of blue indicates a better fit and a lower intensity a worse fit.

Moving on to the possible groupings for Group 1 (occupational therapy) students in terms of their complex serious game activity on the UBUVirtual learning platform, three potential clusters were predicted (see Figure A4). The clusters were found by applying four algorithms *k*-Means++, Fuzzy-*k*-Means, DBSCAN, and Multi-*k*-Means++ (see Figure 4). In this case, ARI was equal to 1 in all the possible combinations (see Table 3).

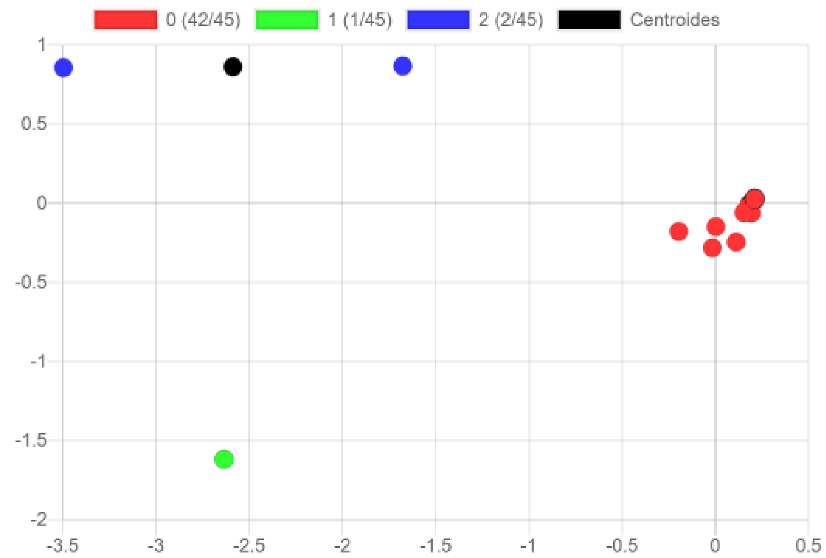


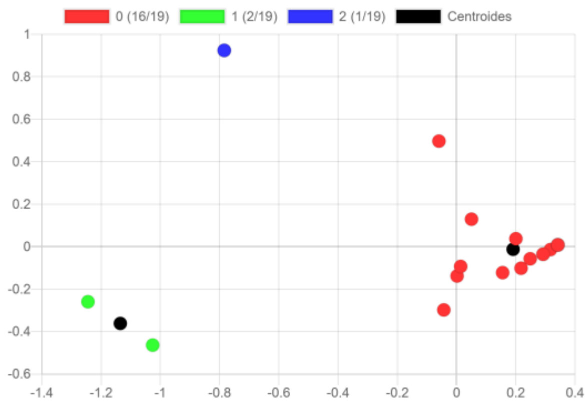
Figure 4. Representation of clusters in *k*-Means++, Fuzzy-*k*-Means, DBSCAN, and Multi-k-Means++ algorithms for Group 1 in complex serious game activity. Note. centroides = centroids.

Table 3. Adjusted Rand index (ARI) for Group 1 clustering related to complex serious games.

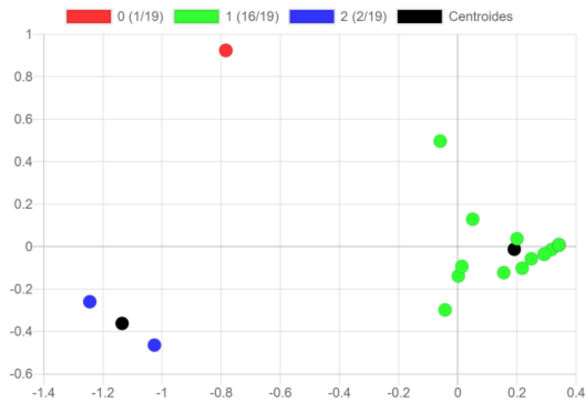
	***k*-Means++**	**Fuzzy-*k*-Means**	**DBSCAN**	**Multi-*k*-Means++**
k-Means++	1	1	1	1
Fuzzy-*k*-Means	1	1	1	1
DBSCAN	1	1	1	1
Multi-*k*-Means++	1	1	1	1

Note. A higher intensity of blue indicates a better fit and a lower intensity a worse fit.

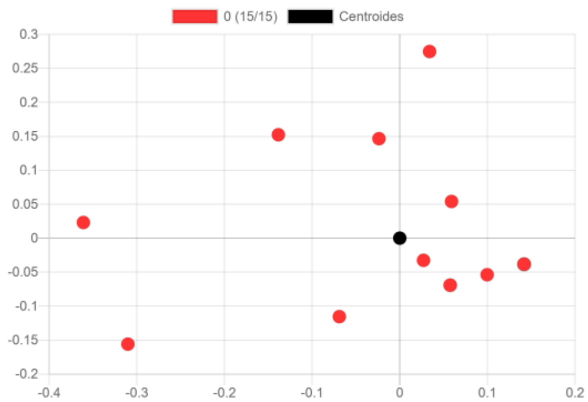
Moving on to Group 2 (students studying a degree in biomedical engineering), three possible clusters were predicted for the groupings related to the simple serious game activities (see Figure A5). The following algorithms were applied: *k*-Means++, Fuzzy-*k*-Means, DBSCAN, and Multi-*k*-Means++. The representation of the clusters in each of the algorithms is shown in Figure 5. In this case, the algorithms providing the best fit were *k*-Means++ and Multi-*k*-Means++ (ARI = 1); see Table 4.



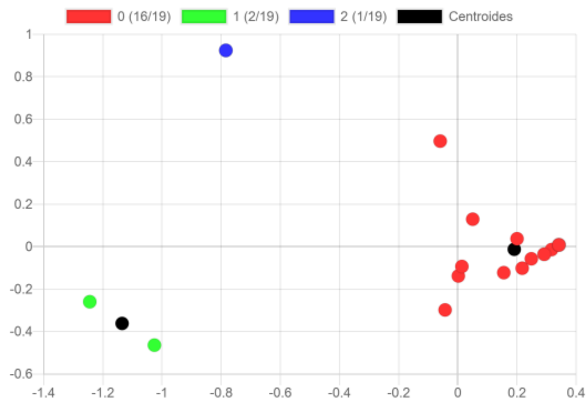
k-Means++ Group 2 simple serious game



Fuzzy-*k*-Means Group 2 simple serious game



DBSCAN Group 2 simple serious game



Multi-*k*-Means++ Group 2 simple serious game

Figure 5. Representation of clusters with different algorithms in Group 2 for simple serious games. Note. centroides = centroids.

For the cluster analysis for Group 2′s complex serious game activities, the elbow method suggested applying three clusters (see Figure A6). The following algorithms were applied: *k*-Means++, Fuzzy-*k*-Means, DBSCAN, and Multi-*k*-Means++. The representation of the clusters in each of the algorithms is shown in Figure 6. In this case, the algorithms providing the best fit were *k*-Means++ and Multi-*k*-Means++ (ARI = 1); see Table 5.

Table 4. Adjusted Rand index (ARI) clustering for Group 2 related to simple serious games.

	***k*-Means++**	**Fuzzy-*k*-Means**	**DBSCAN**	**Multi-*k*-Means++**
k-Means++	1	0.5	0	1
Fuzzy-*k*-Means	0.5	1	0	0.5
DBSCAN	0	0	1	0
Multi-*k*-Means++	1	0	0	1

Note. A higher intensity of blue indicates a better fit and a lower intensity a worse fit.

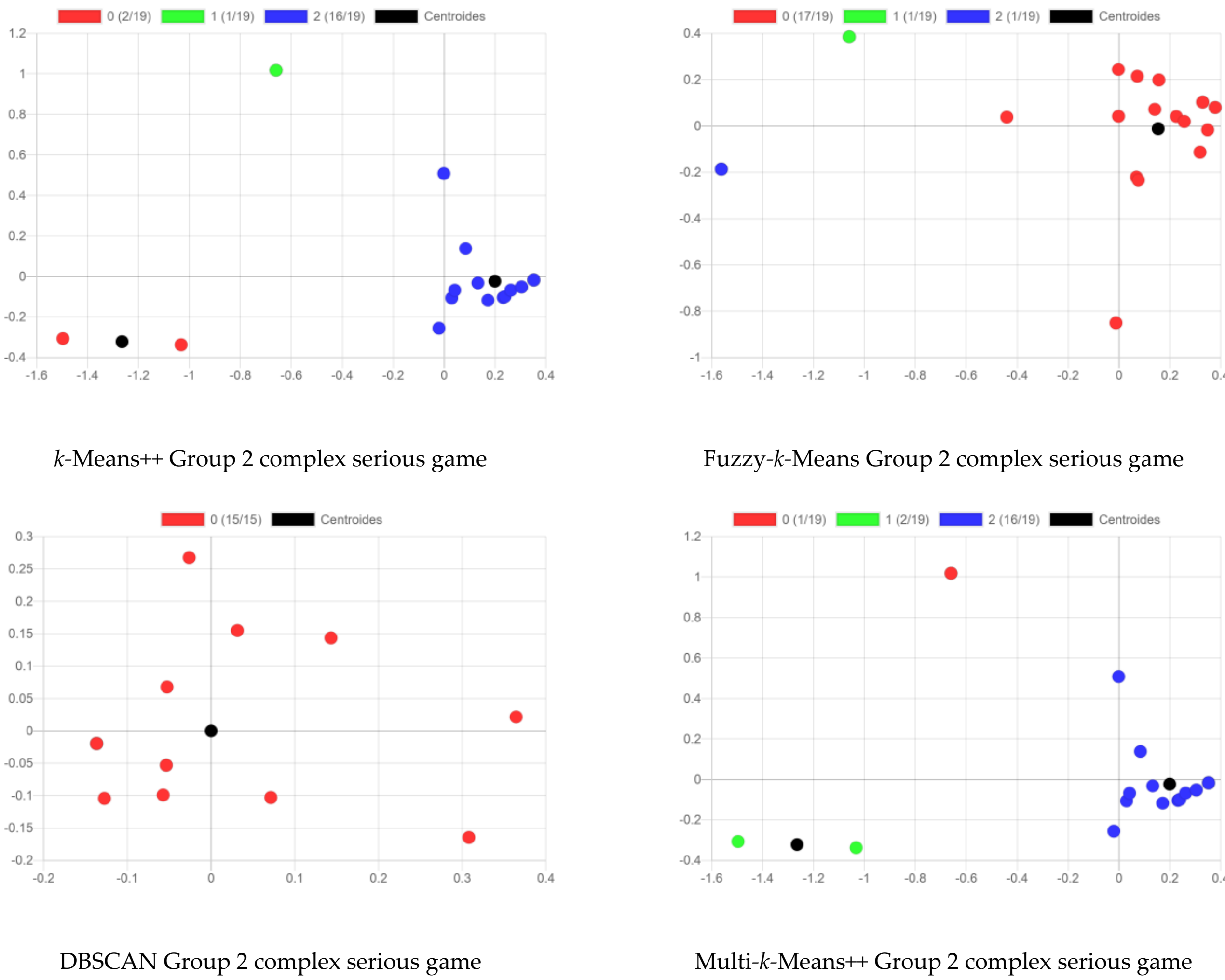


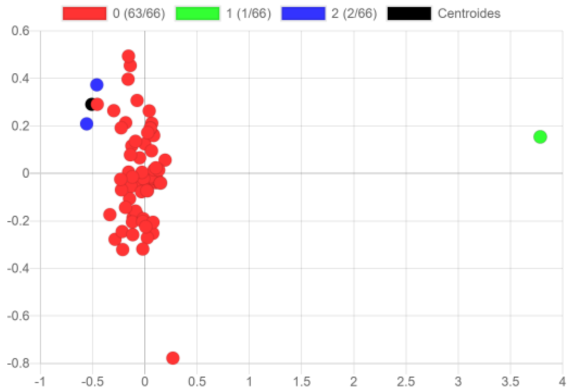
Figure 6. Representation of clusters with different algorithms for Group 2 in complex serious games. Note. centroides = centroids.

Table 5. Adjusted Rand index (ARI) clustering for Group 2 related to complex serious games.

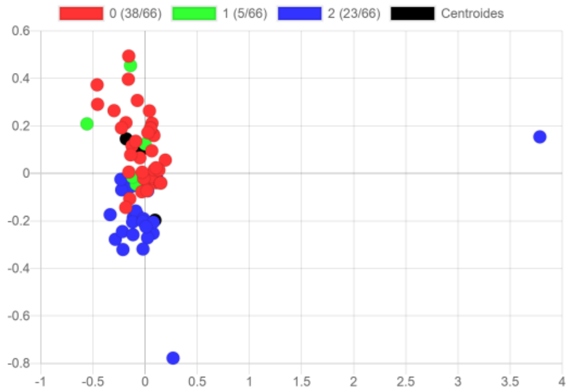
	***k*-Means++**	**Fuzzy-*k*-Means**	**DBSCAN**	**Multi-*k*-Means++**
k-Means++	1	0.5	0	1
Fuzzy-*k*-Means	0.5	1	0	0.5
DBSCAN	0	0	1	0
Multi-*k*-Means++	1	0	0	1

Note. A higher intensity of blue indicates a better fit and a lower intensity a worse fit.

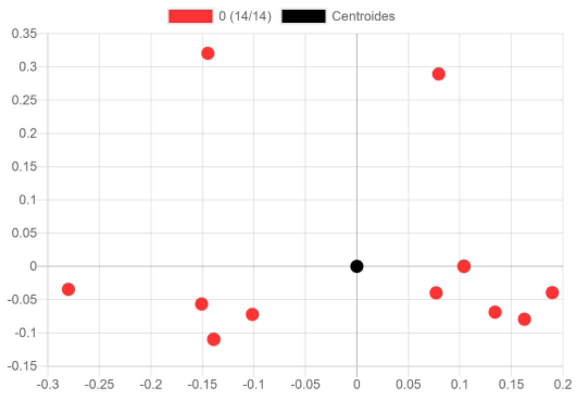
For Group 3 (nursing degree students), who only participated in the simple serious game activities, the elbow method suggested applying three clusters (see Figure A7). The following algorithms were applied: *k*-Means++, Fuzzy-*k*-Means, DBSCAN, and Multi-*k*-Means++ (see Figure 7). In this case, the algorithms providing the best fit were *k*-Means++ and Fuzzy-*k*-Means (ARI = 0.92); see Table 6.



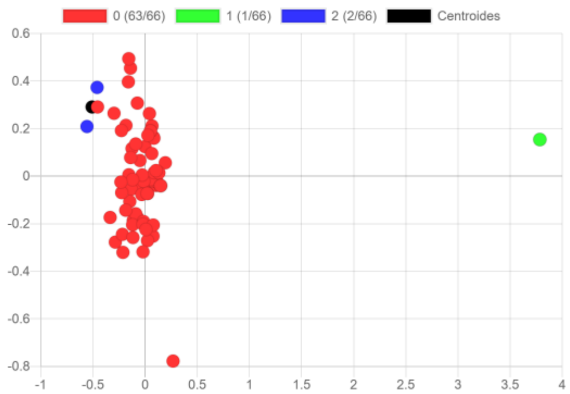
k-Means++ Group 3 simple serious game



Fuzzy-*k*-Means Group 2 simple serious game



DBSCAN Group 2 simple serious game



Multi-*k*-Means++ Group 2 simple serious game

Figure 7. Representation of clusters with different algorithms for Group 3 in simple serious games. Note. centroides = centroids.

Table 6. Adjusted Rand index (ARI) clustering for Group 3 in relation to simple serious games.

	***k*-Means++**	**Fuzzy-*k*-Means**	**DBSCAN**	**Multi-*k*-Means++**
k-Means++	1	0.92	−0.02	0.01
Fuzzy-*k*-Means	0.92	1	−0.01	0.02
DBSCAN	−0.02	−0.01	1	0.73
Multi-*k*-Means++	0.01	0.02	0.73	1

Note. A higher intensity of blue indicates a better fit and a lower intensity a worse fit.

In summary, using unsupervised machine learning clustering tests helps identify participant groupings without prior labelling of the variables that the study is examining. Applying tests of fit helps determine which types of clustering algorithm are more accurate in each case, which is particularly important when preparing the materials (in this case, serious games) tailored to each cluster.

3.4. Students' Perceived Usefulness of the Simple and Complex Serious Game Activities

To test RQ 4 ("How useful do health sciences and biomedical engineering students find the simple and complex serious game activities in the study?"). First, descriptive statistics were calculated for the questionnaire of perceived satisfaction with simple and complex serious game activities (see Instrument 2). Moderate to high levels of mean satisfaction, with low dispersion values, were found for both the simple and complex serious game activities. However, the mean satisfaction values were higher, and the dispersion values were lower for the complex serious game activities (see Table 7). Skewness and kurtosis values were also calculated for the perceived usability of the serious game activities. No extreme values were found for skewness (values of ∣2.00∣ or higher would indicate extreme skewness) or kurtosis (extreme values are considered to be between ∣8∣ and∣20∣) [53]. This indicates that the sample in these groups had a distribution that was compatible with normality.

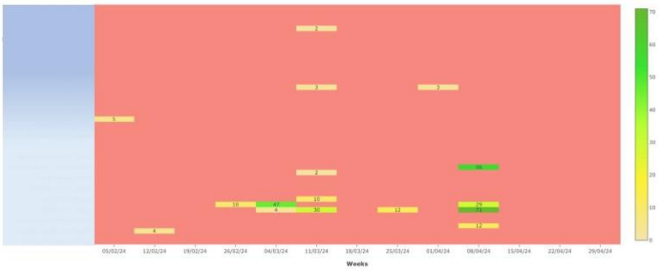
Table 7. Descriptive statistics and indicators of skewness and kurtosis for students' perceived satisfaction with serious game activities in Group 1 and Group 2.

Descriptive Statistics	Mean	SD	Asymmetry		Kurtosis	
			E	SE	E	SE
1. The branching scenario serious game activities made it easier for me to understand the theoretical concepts.	4.3	0.7	−0.4	0.5	−0.7	0.9
2. The branching scenario serious game activities made it easier for me to understand the practical concepts.	4.0	0.8	−0.7	0.5	1.02	0.9
3. The simple serious game activities (word search, crosswords, comprehension questions, etc.) made it easier for me to understand the theoretical concepts.	3.6	1.2	−1.1	0.5	0.8	0.9
4. The simple serious game activities (word search, crosswords, comprehension questions, etc.) made it easier for me to understand the practical concepts.	3.3	1.3	−0.6	0.5	-0.4	0.9

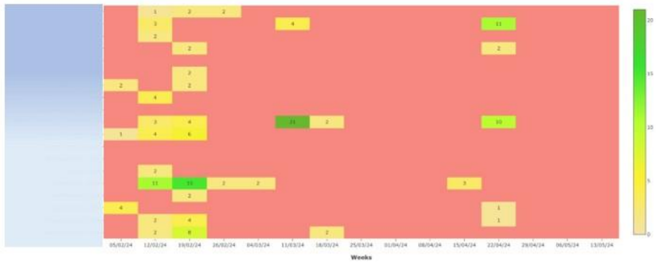
More specifically, the students rated the branching scenarios very highly for acquiring both theoretical and practical concepts. The simple serious game activities were also rated as useful, although with lower scores. To check whether there were significant differences in the perceived usefulness of the branching scenario activities vs. simple serious game activities between Group 1 and Group 2, the non-parametric Wilcoxon Ranks test was applied. There were significant differences in the perceived usefulness for the acquisition of theoretical concepts ($Z = -2.9$, $p = 0.003$) and practical concepts ($Z = -2.3$, $p = 0.02$), with Group 2 giving higher scores.

We also analysed the responses to the open-ended questions. Figure A8 shows a Sankey diagram representing the categorisation of answers to questions about which serious game materials were the most useful, which of the materials should be expanded, and which of the materials should be eliminated for Group 1, Group 2, and Group 3. The results show that in Groups 1 and 2—where simple and complex serious game materials were offered—the students preferred the complex activities, and in particular the branching scenario with interactive videos and comprehension questions. Similarly, in Group 3—where only simple serious games were offered—students preferred crosswords and true–false questions. Groups 1 and 2 both indicated that they would like more branching scenarios, more interactive videos, and more comprehension questions. All of the groups indicated that they would not eliminate any of the materials.

Next, the frequency of simple and complex serious game activities in both groups was analysed. This was performed using heat maps from the UBUMonitor application (see Figure 8), where brighter, greener colours indicate more instances of access, and red indicates no instances of access.

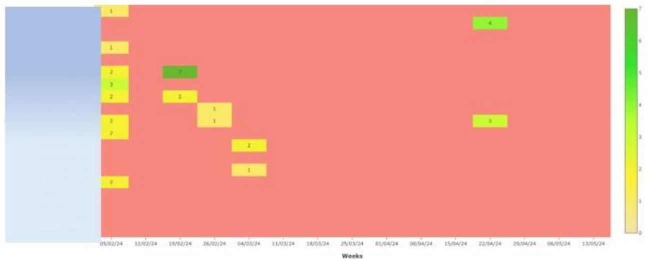


Group 1. Frequency of simple serious game activities during the six-month period



Group 1. Frequency of carrying out complex serious game activities during the semester.

Group 2. Frequency of simple serious game activities during the six-month period



Group 2. Frequency of carrying out complex serious game activities throughout the semester.

Figure 8. Heat map for Groups 1 and 2 simple and complex serious game activities.

Group 3, which only participated in simple serious game activities, also had a high level of satisfaction (M = 4.2 out of 5) and a low level of dispersion (SE = 0.8) (see Table 8). Furthermore, no extreme skewness or kurtosis values were found, indicating that this sample also followed a normal distribution. A heat map of frequency of use is shown in Figure 9.

Table 8. Descriptive statistics and indicators of skewness and kurtosis for students' satisfaction with the serious game activities in Group 3.

Descriptive Statistics	Mean	SD	Asymmetry		Kurtosis	
			E	SE	E	SE
1. The serious game activities have made it easier for me to understand the theoretical concepts.	4.2	0.8	−0.6	0.2	−0.3	0.4

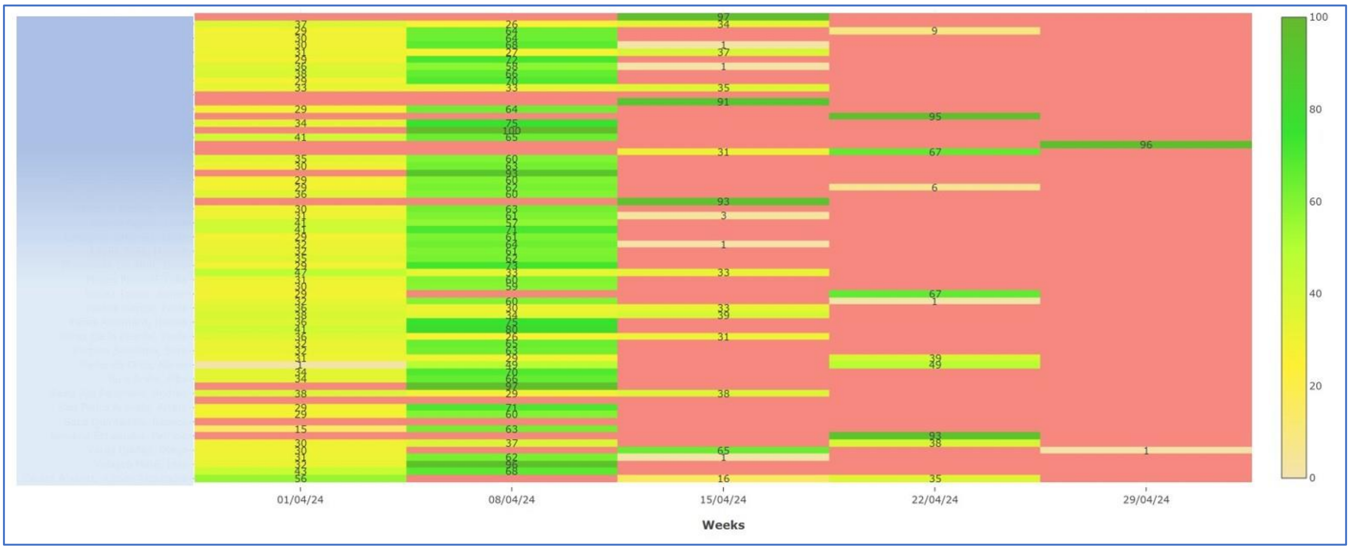


Figure 9. Heat map for Group 3 simple serious game activities.

As Figures 8 and 9 show, access to serious game activities mainly took place in the first few weeks of the semester. In Group 1 and Group 2, the activity was split between simple and complex serious game activities, with the latter being participated in more often.

In summary, monitoring the students' learning behaviours on virtual platforms through applications such as UBUMonitor helped us to follow them over the course of a semester, which allows the detection of students who are at risk of dropping out, and application of measures for student retention during the learning process.

4. Discussion

In this study, first of all, a selection of characteristics was made in relation to variables specific to each student and also to the reference group. It turned out that the variables or characteristics with the most weight were those related to both collaborative and individual learning outcomes as well as the type of degree and the type of serious game applied, in that order. These data are significant in the analysis of pattern detection and optimisation of learning patterns [39]. The type of degree being studied and the type of serious game activities predicted 34.3% of the learning results obtained in the multiple-choice test (completed individually). They predicted 11.2% of the results in the project performance assessment and 25.6% in the project presentation assessment (both of which were collaborative group activities). It seems that the type of serious game applied [33] and other variables specific to each student, the type of degree, and the type of collaboration have an effect on the learning results [22].

Likewise, the cluster analysis carried out in each of the degree groups participating in this study showed that there were clusters in each one. These clusters—without prior assignment variables—were differentiated in the activities participated in on the learning platform (UBUVirtual) and in all cases had $k = 3$ clusters. The algorithms best suited for the analysis were k-Means++, Fuzzy-k-Means, and Multi-k-Means++.

With regard to the students' perceptions of usefulness, there was a high degree of perceived usefulness in all the cases, for both the simple and complex serious game activities. However, the students who participated in both types of activities found the complex serious game activities to be more useful. They preferred the branching scenario activities that included interactive videos with questions to test the knowledge that they had acquired. This confirms the findings from the previous studies in this field [2,10,11,13–17,29,30]. We also found different patterns of behaviour on the UBUVirtual platform depending on the type of serious game. There was a higher frequency of activities in the group of students who only had the option of simple serious games than those who had the option of both types. In the latter groups, the students divided their time between the two types, with a higher frequency of complex serious game activities. This can be explained in two ways. Firstly, given the choice, students prefer complex serious game activities to simple activities. Secondly, simple serious game activities need less time than the complex serious game activities, which demand time for watching and thinking about the content [11,33,39,40].

Table 9 summarises the relationship between the studies noted in the background section of the introduction and the results that we found in the present study.

Table 9. Summary of the relationship between prior research used as the basis for this study and the results of the current study.

Studies Referenced in the Background Section in the Introduction	Results of the Current Study
The use of simulation-based learning practices in virtual laboratories has been shown to be an important support for teaching in health sciences degrees [2]	This study supports the findings from [2].
Virtual simulation scenarios contribute to increased deductive reasoning, cognitive and metacognitive knowledge, self-efficacy, and student engagement [6].	This study found that participating in serious game activities in virtual learning scenarios (UBUVirtual platform) explained 34.3% of the students' results in the multiple-choice knowledge test, 11.2% of the results in the project performance assessment, and 25.6% of the results in the project presentation assessment.

Table 9. *Cont.*

Studies Referenced in the Background Section in the Introduction	Results of the Current Study
Although the design of these simulation spaces is initially costly, it later significantly reduces the teacher's work time without reducing the quality of teaching [4].	This aspect was tested with RQ4, the long-term monitoring of students' learning behaviours with serious game activities confirmed students' engagement with them.
In summary, H5P is a versatile and powerful tool that can help to reinforce effective learning in b-Learning or e-Learning environments. Specifically, students can increase their critical thinking skills, problem solving, and understanding of content [22].	The versatility of the H5P environment on the Moodle platform was confirmed by the results related to RQ2, RQ3, and RQ4.
In recent years, interactive activities based on H5P have been incorporated into e-learning environments, and the research results indicate that they are more effective than other types of activities in regard to the learning outcomes and increasing student motivation [21–24].	The study was able to confirm that the type of serious game used predicted 34.3% of the students' results in the results in the multiple-choice knowledge test, 11.2% of the results in the project performance assessment, and 25.6% of the results in the project presentation assessment.
The appropriateness of H5P interactive activities allows the learner to develop their learning process at their own pace which induces a greater commitment to more autonomous and self-directed learning [25]. Specifically, within the possible resources that can be developed on the H5P platform, the use of interactive videos seems to be very useful as it increases understanding of content and increases student engagement [20,26]. Also, the use of 360° videos plays an important role in creating realistic virtual tour experiences [10,27]. Similarly, the use of H5P resources such as branching scenarios involving interactive 360° videos and comprehension questions [28] seems to increase students' hypothetical deductive reasoning and scientific explanation skills [29].	Considering the results related to RQ4, the students who participated in them rated the usefulness of the virtual scenarios very highly for acquiring both theoretical and practical concepts. The students thought that the simple serious games were also useful, although their scores were lower than for the complex games. There were differences in the perceived usefulness in acquiring theoretical and practical concepts between the different groups of students. The students who were offered both types tended to prefer the complex games, particularly the branching scenarios with interactive videos and comprehension questions. The students who were only offered simple serious games preferred the crosswords and true/false questions.

To summarise, selecting characteristics related to the variables of type of student, type of course, academic year, etc. seems to be a key factor for the design and creation of serious games. The participation in serious game activities had different weights in the prediction of the students' results in the different learning assessment tests. It had a greater effect in the individual assessments than in the group assessments. Furthermore, the use of clustering tests helped to identify the groupings of participants without prior labelling of the variables that the study examined. In addition, the application of tests of fit helped determine what types of grouping algorithm were more accurate in each case. This is particularly important when it comes to tailoring the design of serious game tasks and materials. Lastly, the students' levels of satisfaction with using the serious games were moderate to high, with low levels of dispersion for both the simple and complex serious games. The complex serious games had higher satisfaction scores and greater dispersion. These complex games, which included branching scenarios and 360° videos, required more effort, but the students who participated in both types of games gave them higher satisfaction scores.

5. Conclusions

In summary, with respect to the research questions proposed in this study, it can be concluded that in relation to RQ1, the use of the automatic learning tool for feature selection prior to data analysis is a very effective instrument for finding out the most relevant variables in each case study. In this study, these were the type of group (degree, course, etc.) and the type of serious game design applied. Regarding RQ2 in this study, the use of serious games explained 34.4% of the learning outcomes in the individual assessment tests and obtained smaller percentages (11.2% and 25.6%) in the group assessment tests. This result opens up a new line of research related to the analysis of serious games in collaborative work environments. Regarding RQ3, the results indicate that the use of unsupervised machine learning techniques (clustering) facilitates the knowledge of groupings without prior labelling by the researcher. This fact sheds light on contingencies that previously would not have been considered. The application of fit tests helps to determine which type of clustering algorithm is most accurate in each case, which is especially important for adjusting the individualised educational response. Finally, regarding RQ4, it has been found that the use of serious games does not have the same effect on different groups of learners. It seems that each group, depending on the type of qualification, behaves differently with regard to the use of this pedagogical resource. However, in order to check this use of serious games in virtual learning environments, we have used a tool such as UBUMonitor to collect and analyse the interaction logs. These facilitate the individualised monitoring of each student and the early detection of students at risk. Therefore, we can conclude that the hypotheses put forward in this study have been contrasted.

In view of the above, it is important to emphasise the need for research into effectiveness and perceived usefulness for simple and complex serious game activities within LMSs applied to learning in university teaching environments [32,35]. Only through the analysis of the results from such research will it be possible to advance our knowledge of the effectiveness of these types of activities in order to offer optimised, tailored learning experiences [39,40]. Indeed, such results may shed light on the type of student characteristics in both individual and group behaviour related to the type of serious game activities aimed at acquiring conceptual and procedural knowledge which may be used in order to achieve the most effective learning outcomes possible.

In summary, the initial problem that this study examined was about the importance, especially in higher education, of using virtual-lab type technological resources—in this case for practicals in health sciences and biomedical engineering degrees. One of the resources that has been shown to be versatile and cost-effective is the H5P tool, which is included in various LMSs such as Moodle, Canvas, Brightspace, and Blackboard. It does, however, present challenges when using it, such as pre-processing, analysis, and interpretation of the large volume of data that these platforms record. One way to address this is by using supervised and unsupervised educational data mining techniques. The present study has demonstrated practical examples of using these techniques to process and analyse data. In this regard, the study provides conclusions aimed at facilitating the personalisation of learning. Another of the current issues in this area relates to the use of virtual labs and how they facilitate the development of hypothetico-deductive reasoning and the use of metacognitive strategies. More specifically, the challenge in the present study was in the design of these virtual learning spaces. It provided design examples, from the simplest (crosswords, true–false questions, etc.) to more elaborate options (the inclusion of 360° video environments and branching scenarios) within an H5P environment. Finally, although the data from this study should be considered with caution in terms of generalising the results, the findings highlight various aspects that university authorities may find illuminating related to the provision of material resources (better automation of LMSs to incorporate serious games) in order to increase teachers', use of these resources in their routine teaching. University authorities also need to provide ongoing training for teachers, aimed at different levels (beginner, intermediate, and advanced), so that they can design their own serious games autonomously. Similarly, it is important to ensure that university LMS platforms can incorporate all of the functionality of H5P tools (e.g., virtual reality and augmented reality). LMSs should also include EDM techniques that will make automatic, real-time data analysis easier for teachers. The use of generative artificial intelligence techniques should also be addressed to help teachers tailor material based on analysing the usage data. This is the great challenge that 21st-century higher education must face.

Summing up, it is important to define tasks, and to define their goals and plans for how to tackle them. In addition, monitoring the learning process and observing the strategies that each student uses will help facilitate teachers' cognitive and metacognitive evaluations. Similarly, once task execution has been analysed from the records in LMSs, the results will allow the tasks to be tailored to each student. In this regard, using machine learning techniques will make it easier to diagnose execution and detect problems by examining device records. This means that teachers must have the control, the technology, and the machine learning techniques supporting that and providing information. However, as already noted, this will need the automation of the analytical processes to facilitate the data interpretation process for teachers. It is possible that using this hybrid methodology between teachers and technology, along with machine learning techniques, will strengthen students' activation of prior knowledge, acquisition of learning goals, and the provision of individualised teaching and practice of content. In addition, data protection rules must be respected throughout this process so that both student and teacher have confidence in the teaching–learning process occurring in virtual environments with the application of machine learning techniques.

5.1. Limitations of the Study

The limitations of this study are mainly related to the sample selection. This was performed through convenience sampling, in specific groups of students (health sciences students and biomedical engineering students). This may affect how generalisable the results are. That said, all the studies in this area involve very detailed work with students, and significant work creating serious game materials, which makes it very difficult to have large, random samples. Nonetheless, future studies will expand the samples and the degree courses that they are selected from. In this regard, it is important to emphasise that performing these studies is not easy; it requires the design and development of serious game materials, they have to be incorporated into virtual learning platforms (LMS), participants' use of them needs monitoring, the data need to be analysed using EDM, and machine learning techniques and the results must be interpreted. More detail is provided below about the limitations of the study and future lines of research in this area. The study also had limitations related to gender balance, as there are far more women than men currently studying health sciences. In addition, the study only examined the health sciences area, it only looked at a single geographical setting, and it only applied certain types of serious games. However, it is worth emphasising that this type of study requires the detailed monitoring of students' work, which makes it challenging to work with larger samples, in different geographical settings, and with the full range of possible serious games.

5.2. Future Lines of Research

Future studies will also seek to include more participant variables (the analysis of the way they learn, the type of information processing, the perceived cognitive load, etc.) and more variables related to the serious game materials (serious game type, duration of the serious game activity, etc.), as well as examining how those variables are related to the learning outcomes. This will lead to models whose data can be processed using (preferably generative) artificial intelligence resources [42,43]. However, there is still a long way to go in the educational context. Research along the lines indicated above will surely be able to provide data on the most important variables and characteristics and their relative impact on the learning outcomes, which is why the present study examined some of these variables in terms of the possible prediction or grouping of different learning outcomes. In addition, future studies will address how the use of serious games influences group learning compared to individual learning in higher education.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/info15120804/s1, Figure S1: Example simple games Crosswords; Figure S2. Example memory game using pictures; Figure S3. True–false question; Figure S4. Alphabet soup; Figure S5. Branching scenario Group 1; Figure S6. Branching scenario Group 2.

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Institutional Review Board Statement: This study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Ethics Committee of the University of Burgos (protocol code IO 03/2022 and date of approval 7 April 2022 for the SmartLearnUni project.

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

Data Availability Statement: Data will be made available upon the request of the researchers and signature of responsible use and privacy due to ethical reasons.

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

Appendix A

Table A1. Questionnaire of perceived satisfaction with simple and complex serious game activities.

Questions	Rating Scale				
	1	2	3	4	5
1. The branching scenario activities have made it easier for me to understand the theoretical concepts.					
2. The branching scenario activities have made it easier for me to understand the practical concepts.					
3. The simple serious game activities (word searches, crosswords, comprehension questions, etc.) made it easier for me to understand the theoretical concepts.					
4. The simple serious game activities (word searches, crosswords, comprehension questions, etc.) made it easier for me to understand the practical concepts.					
5. Which of the serious game materials did you find the most useful for understanding the theoretical concepts, the branching scenario or the simple ones?					
6. Which of the serious game materials did you find the most useful for understanding the practical concepts, the branching scenario or the simple ones?					
7. What elements would you add or increase in the serious game materials?					
8. Which of the serious game elements would you eliminate and why?					

Table A2. Questionnaire of perceived satisfaction with simple serious game activities.

Questions	Rating Scale				
	1	2	3	4	5
1. The serious game activities have made it easier for me to understand the concepts.					
2. Which of the serious game materials did you find the most useful for understanding the concepts?					
3. What elements would you include or increase in the serious game materials?					
4. Which of the serious game elements would you eliminate and why?					

Table A3. Prediction coefficients of the learning outcomes in the test-type assessment test with respect to the variables group type and type of participation in serious game activities.

	Unstandardised Coefficients		Standardised Coefficients	*t*	*p*	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
	B	SE	Beta			Lower Bound	Upper Bound	Zero-Order	Partial	Part	Tolerance	VIF
(Constant)	2.30	0.78		3.12	<0.002 *	0.84	3.76					
Group Type	0.20	0.23	0.07	0.89	0.38	−0.25	0.64	0.33	0.08	0.06	0.79	1.27
Serious game Type	3.1	0.46	0.55	6.75	<0.001 *	2.19	4.002	0.58	0.52	0.49	0.79	1.27

Note. R^2 adjusted = 0.33; * $p < 0.05$.

Table A4. Prediction coefficients of the learning outcomes in the project development assessment test for the variables type of group and type of participation in serious game activities.

	Unstandardised Coefficients		Standardised Coefficients	*t*	*p*	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
	B	SE	Beta			Lower Bound	Upper Bound	Zero-Order	Partial	Part	Tolerance	VIF
(Constant)	7.86	0.51		15.44	<0.001 *	6.85	8.87					
Group serious game Type	0.60	0.16	0.36	3.83	<0.001 *	0.27	0.90	0.33	0.32	0.32	0.79	1.27
	−0.25	0.32	−0.7	−0.78	0.38	−0.87	0.38	0.09	−0.07	−0.07	0.79	1.27

Note. R^2 adjusted = 0.10; * $p < 0.05$.

Table A5. Prediction coefficients of the learning outcomes in the project defence assessment test with respect to the variables type of group and type of participation in serious game activities.

	Unstandardised Coefficients		Standardised Coefficients	*t*	*p*	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
	B	SE	Beta			Lower Bound	Upper Bound	Zero-Order	Partial	Part	Tolerance	VIF
(Constant)	7.57	0.51		14.87	<0.001 *	6.56	8.56					
Group serious game Type	1.01	0.16	0.57	6.54	<0.001 *	0.71	1.32	0.48	0.50	0.50	0.79	1.27
	−0.72	0.32	−0.20	−2.27	0.03	−1.35	−0.09	0.06	−0.20	−0.17	0.79	1.27

Note. R^2 adjusted = 0.24; * $p < 0.05$.

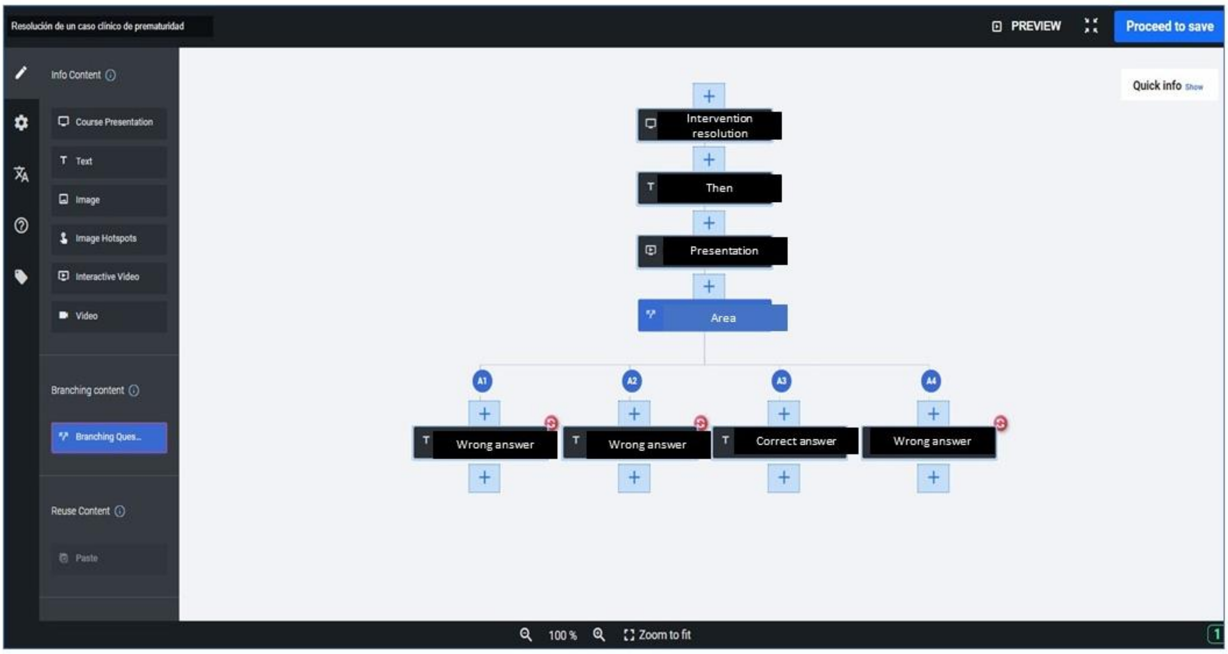

Figure A1. Flow chart of branching scenario applied in Group 1.

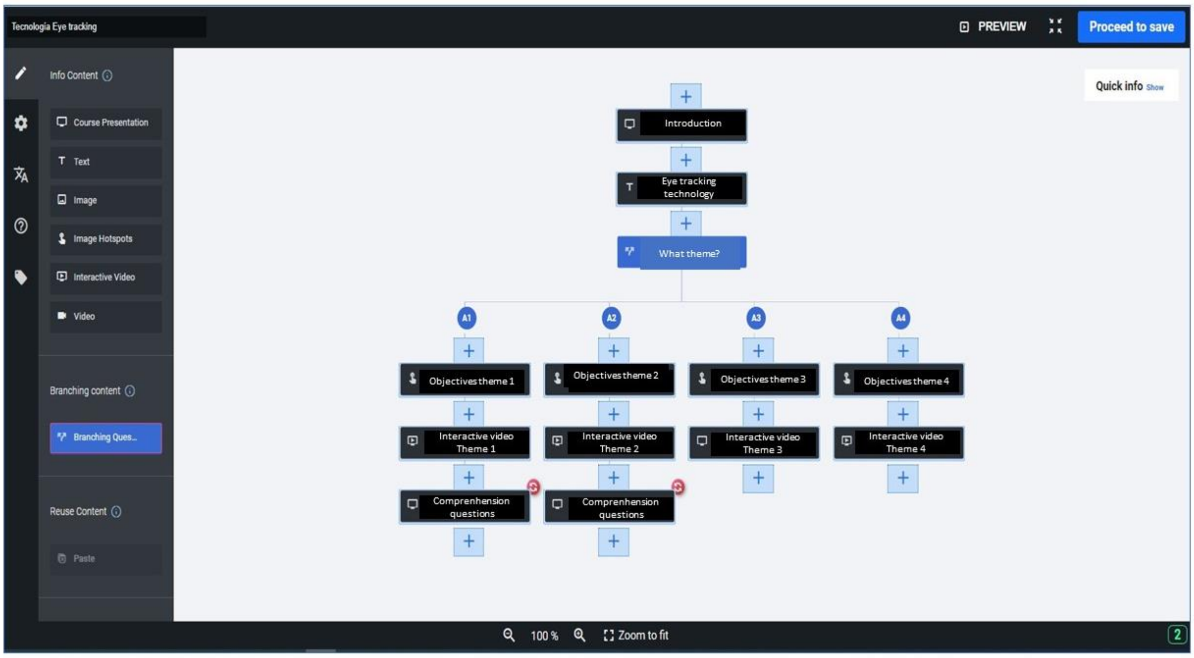

Figure A2. Flow chart of branching scenario applied in Group 2.

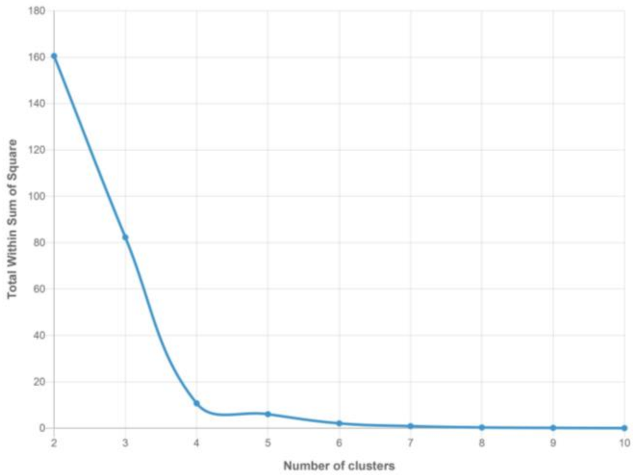

Figure A3. Elbow method Group 1 in simple serious games.

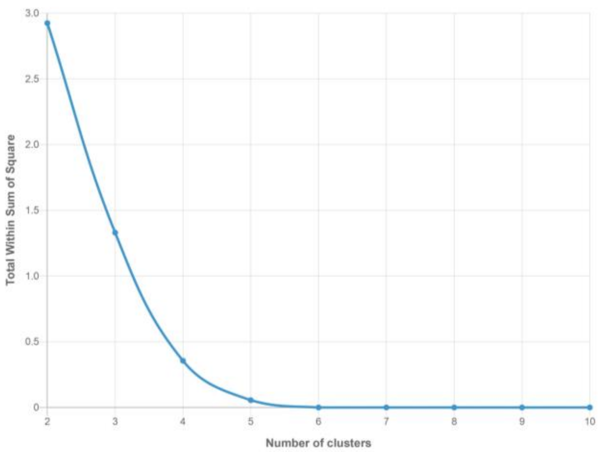

Figure A4. Elbow method Group 1 in complex serious games.

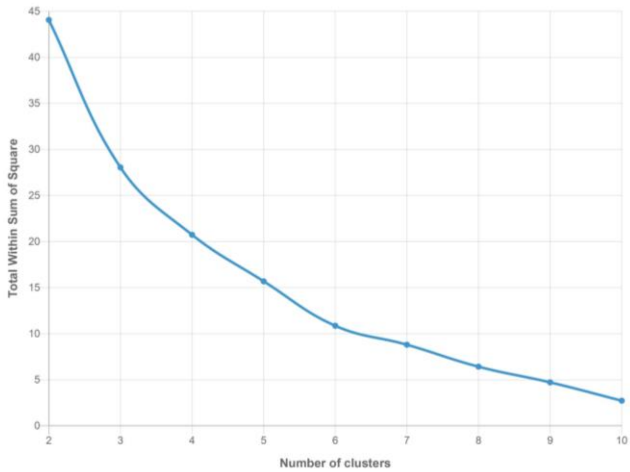

Figure A5. Elbow method Group 2 in simple serious games.

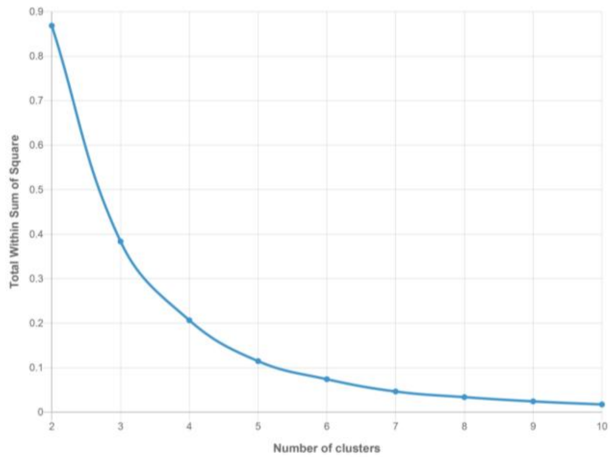

Figure A6. Elbow method Group 2 in complex serious games.

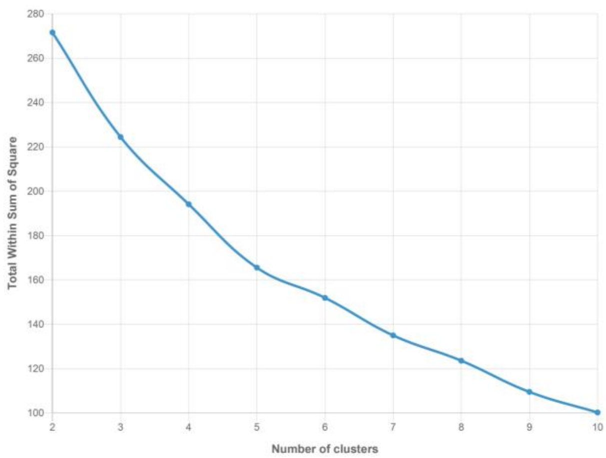

Figure A7. Elbow method Group 3 in simple serious games.

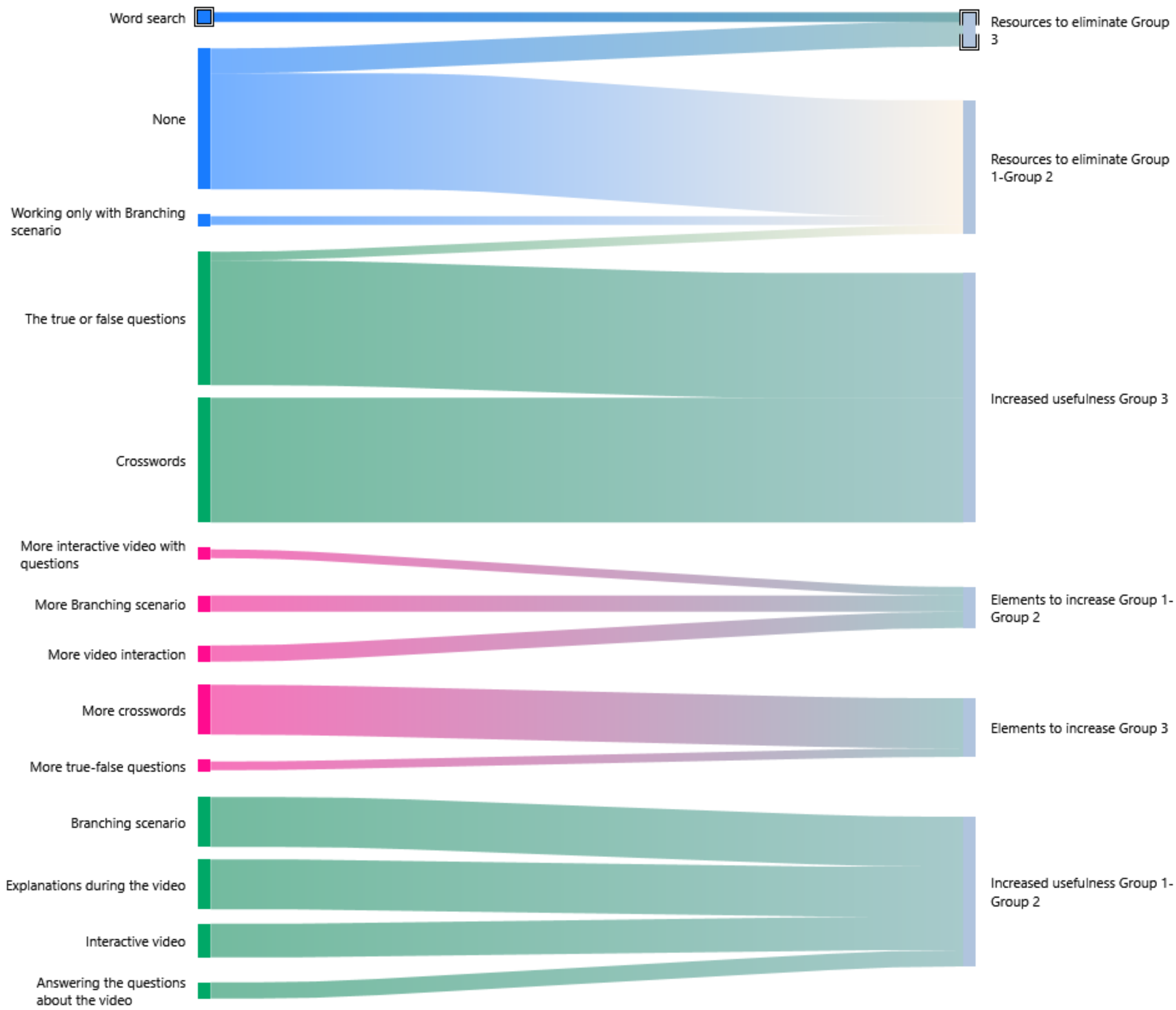

Figure A8. Sankey diagram categorisation of open-ended responses.

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