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An Adaptive Methodology for the Improvement of Knowledge Acquisition by a Multimedia Web Tool*

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Adaptive learning is a method that personalizes the teaching-learning strategies in accordance with the needs and preferences of each student. This article describes the design, the implementation and the tests of a web application developed with adaptive learning in order to improve student knowledge acquisition and to simplify the teacher's work. The tool uses EventSource technologies combined with heuristic functions to produce a predictive algorithm, which is capable of being adapted to the students in a customized way by presenting the content adjusted according to their cognitive needs. The design is based on the hypothesis that the acquisition of knowledge can be improved by using a computing application which presents a syllabus to be learned in various forms. In this way, the application determines students' progress within the content of the material, which is classified by branches of knowledge. The tool was applied to one group of students and the data that we obtained was compared with the results of the rest, subject to the usual knowledge transmission system. The results obtained not only improve the academic results, but also enhance the heuristic decision-making about the content to be taught.

Keywords: adaptive teaching; predictive algorithm; evaluation; improved learning

1. Introduction

In regard to teaching-learning processes, recent decades have witnessed a growing concern to ensure that learning is meaningful; that is, that students should acquire in-depth knowledge, and by the same token that teachers should be increasingly involved in this process.

Regardless of the learning theories employed, what Jong et al. set out in their article, "Physical and virtual laboratories in science and engineering" [1], is that the challenge for educators consists in helping students to follow the pathway from prior learning to deep learning in the Zone of Proximal Development (ZDP), a concept put forward by Jerome Bruner and Lev Vigotsky in the 20th century [2–4].

Information and communication technologies enable in-person and on-line learning environments to be combined (blended learning) [5], thereby providing teachers with powerful tools for digital inquiry, representation, reflection and the communication of knowledge [6].

The prior knowledge acquired by students will determine the results of their learning [7]. The greater the prior knowledge, the greater the benefits derived from the guidance given by teachers. This relation between students' prior knowledge and the guidance provided by teachers (scaffolding) has a decisive influence on learning outcomes [8, 9].

Rapid changes are taking place in university education and in other spheres of higher education, in which technological factors figure largely, such as new developments on the Internet and the accelerated evolution of hardware in devices. These changes, together with the growing trend in the use of social networks and web access for obtaining information, have given rise to important challenges for improving knowledge transmission techniques in order to make them more effective. This is highlighted by Sidhpura et al. [10], who point out the need to bridge the gap that exists between education and professional practice by employing methods that can be adapted for a better way of teaching, such as the use of agents of Artificial Intelligence (hereafter AI).

As stated by Torres et al. in their article, *"Personal Learning Environment Based on Web 2.0 services"* [11], technological changes have had a great impact on the way that learning processes are approached. This raises the possibility of creating new web-based teaching methods capable of improving the results of learning in universities.

Agreda et al. [12] review the use of technologies emerging in education: collaborative learning, adaptive learning, learning analytics and e-learning.

Learning analytics, in particular, have been focused on improving students' learning processes through the use of technology ramification that takes into account students' actions according to their responses, and by providing them with a learning pathway adapted to their prior knowledge.

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For its part, UNESCO in [13] proposes learning analytics as a viable option for a greater understanding of students' learning processes, as well as the possibility of adapting and improving these processes.

This would also involve the use of data-mining as a tool for adapting content to students by employing the prediction of student performance, as described in the article by Bindhia et al. [14], as well as the use of EDM (Educational Data Mining) set out by authors such as Sokkey, Ching-Yuan, Siemens o Berland, among others, [12, 15–19], in order to detect low learning achievement in schools.

To that end, we propose a methodology that constitutes a natural evolution in education, adapted to the new university student environment and creating a web-based system that would make it possible to provide content tailored to student performance as well as dynamically adapted to the way they learn. Below we describe not only how different types of exercises can be put into practice, but also how the most appropriate content for each student can be predicted; that is, according to which subject matter shows a certain deficit.

The health crisis occasioned by the COVID-19 pandemic during the years 2020, 2021 and 2022 has obliged us to address other non-traditional blended approaches to learning based on Cloud Computing environments and collaborative environments, such as those described by Jamalpur et al. in their article [20], which not only include multimedia tools but also combine them with videoconferencing tools. These are aimed at students born in the digital age, as described by Pinc'jer and Bosman [21, 22] in their articles, and which provide us with two ways of approaching education in these conditions.

This has also made it perfectly clear to us that it is necessary to create new tools for teaching at a university level for the purpose of improving the transmission of knowledge.

Furthermore, we know that one of the challenges facing the teaching-learning process at present consists in adapting content to the different ways in which students learn.

As an improvement to learning, this article proposes the modification of the systems for the generation of review contents, adapting them to the personal characteristics of each student. The procedure of adaptation to each student involves the following variables:

- The syllabus to be learned.
- The student's performance in each level of the system.
- The performance of other students with similar results.
- The socio-economic environment based on the geographical area where the academic activity takes place.

The question we therefore ask ourselves is as follows: Does the generation of review contents adapted to each student based on the syllabus, his or her own performance compared to other students, plus their socioeconomic environment, improve their acquisition of knowledge?

A brief description of the method developed, the tools used and the baseline formulas employed for evaluating the activities undertaken by each student can be found in Chapter 2 of this article. After that, in Chapter 3 the experiment is described; in Chapter 4 the results obtained thereby are given, and lastly in Chapter 5 the conclusions arrived at are presented.

2. Adaptive Method Proposal

The purpose of the method proposed for improving the acquisition of knowledge by using a multimedia tool is to adapt the content in each iteration of the student, which is achieved by means of the relation of the elements of the programme shown in Fig. 1, as described in the following section.

The method is basically founded on the student completing daily activities corresponding to the content he or she is required to review. The complexity of this content varies in real time according to the iteration of the student with the system, and once the activity has been completed it is assessed by means of a system of evaluation capable of using the results of other students in order to predict the activities the student will undertake as a consequence of the results he or she has obtained.

In order to validate this method, an experiment has been designed in which content was created for a common core subject belonging to the course of a Degree in Industrial Engineering at the Diagonal-Besòs Campus of the *Universitat Politècnica de Catalunya*, namely Graphic Expression in Engineering.

Graphic Expression in Engineering is a subject that is suitable for the use of this system because to a large extent it involves theory, and also enables the results to be measured thanks to specific tests, which can be expressed as revision exercises in the method described herein.

2.1 Description of the Tools Used in the Method

The components used by this tool for implementing this adaptive method are as follows:

Subject content. This is a syllabus consisting of one or more subjects to be reinforced, which are arranged in branches of knowledge that make up the content in an evolving manner and divided

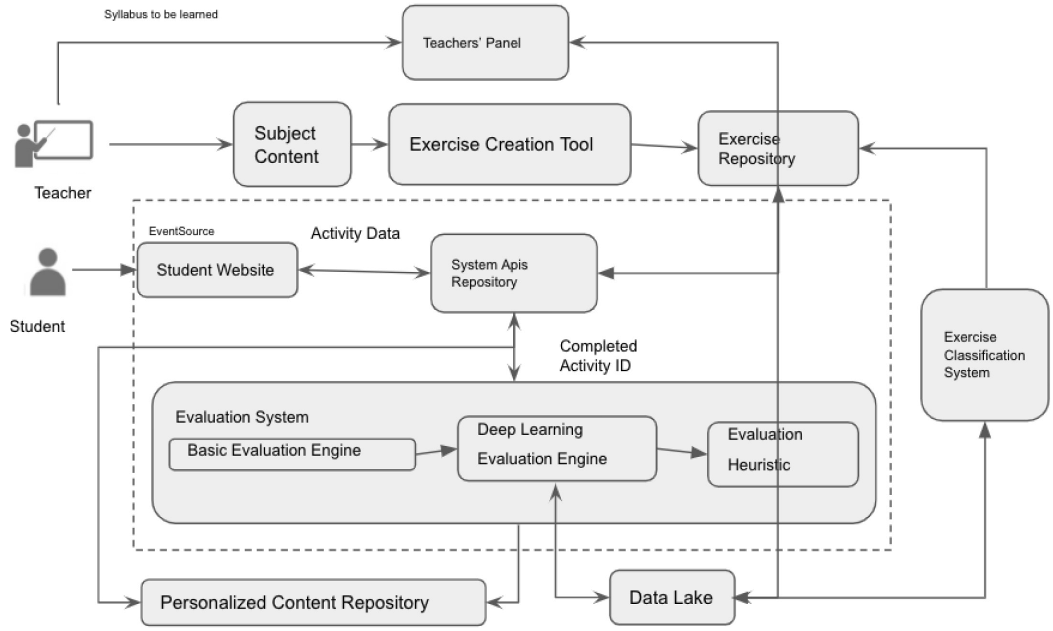

Fig. 1. Diagram of the backup tool for implementing the method.

hierarchically, ranging from subjects to subtopics and competencies, and finally to activities that include exercises.

In this article, these consist of the Graphic Expression in Engineering syllabus (EGE DAO), which contains the normative subtopics, geometrics, surfaces, sketching, 3D and warm-up exercises. These subtopics can be arranged in competencies, which also contain activities, as may be observed in Fig. 2.

Tools for creating exercises. An application with which teachers can create a set of exercises; that is, activities of the subject content using the following typologies: Drag & Drop Groups, Puzzle, Grid Calculator, Memory, Matching, Reading Comprehension and Recognition of Terminology: Button Panel with audio and/or text and/or image, Button Panel with maximum response time, Drag and Drop Text, Drag and Drop, Reading, Alphabet Soup, Word Count, Reading and Questions, Read-

Itinerary			Learning itinerary content									
Normalización	1									Dimensional tolerances	Geometric tolerances	Adjustments
	2	Normalization	Normalized formats				Cuts, sections and breaks		Surface states			
	3		Normative scales					Threaded elements				
	4				Representation of parts, Normalized views	Normalized lines						
	5					Dimensioning						
	6						Conicity					
	7						Normalized elements					
Geometry of space, Analysis and Synthesis												
	6		Geometry of space	particular positions and relative to points, lines and planes	Notions of Polyhedra							
	7			Metrics								
	8		Introduction to descriptive geometry	Representation in the direct dihedral system	Dihedral operations							
Surfaces	9					Surfaces						
Sketching practice												
	10		Sketches									
WarmUp												
	12		WarmUp									

Fig. 2. Categorization of EGEDAO into subtopics, competencies and independent content itineraries to be presented.

Table 1. Distribution of exercises according to type of presentation

Number of Exercises	Type of Representation
430	Button panel
80	Button panel with text
84	Matching
86	Drag and Drop
82	Alphabet Soup
84	Puzzle
76	Word Count
78	Drag & Drop Groups
1	Close Text

ing speed, Drag and Drop Phrases and Close Text; all of which enable activities that are not monotonous.

Exercise repository. This component contains all the exercises that one or more teachers have created using the tool mentioned above.

In this case 1001 exercises have been generated, corresponding to the subject to which the experiment has been applied, and the exercises are shown in Table 1.

Exercise classification system. The function of this component is to categorize each exercise as "easy", "normal" or "difficult" according to the statistics of success or failure in each case. This categorization is renewed automatically, depending on the results obtained.

Student website. Five daily activities are presented to the student, of which the first is always a warm-up activity, the aim of which is to prepare the student.

APIs system repositories. The purpose of this component is to interrelate all the components of the tool, and carries out actions ranging from requesting the contents to be undertaken by the student to pasting the evaluations or updating the data in the Data Lake, among others.

Data Lake. This is the non-hierarchical information centre of the repository in which all the information about the tool can be found, including the data bases, the socio-economic and cultural statistics of the GPS regions where the activities have been carried out, as well as the clicks on the interface, images and sound.

Customized content repository. This component consists of all the contents that should be addressed by the student, and the personalized order for each individual case.

Teachers' panel. A website that enables the day-to-day progress of students to be monitored, and where all the information regarding student performance at each interaction with the system can be seen, which is referred to as the "session".

Evaluation system. The purpose of this component is to evaluate the activity conducted by the student and to decide what the next content to be presented will be. This system may cause the student to go back in the content, remain at the same point or move on to the following content, depending on the results obtained.

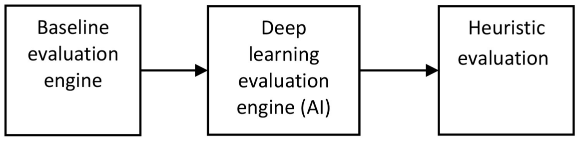

Fig. 3. Steps in the Evaluation System.

It is composed of three sub-components that form the engine of baseline evaluation, of deep learning evaluation and the heuristic evaluation.

This component keeps a record of all the data arising from all the exercises of the activity in a database. Furthermore, it places in a queue all these data, pending the process that will evaluate the activity according to the availability of the system, as well as registering the final result in the customized content repository.

The *Evaluation System* works sequentially, as may be seen in Fig. 3. The efficacy of the activity is calculated on the basis of the mean of all the users who have completed it, then passes to the deep learning evaluation, which subsequently seeks to correct or reinforce this evaluation, and finally a set of rules described in the heuristic evaluation is applied. By means of this evaluation, the other subjects are analyzed with the aim of identifying a pattern in order to detect whether a user requires further assistance due to his or her overall low performance.

Baseline evaluation engine. This component runs an algorithm that evaluates the activity in accordance with the following considerations:

The success is added and the failures deducted, the latter being reduced by a factor Kr.

To this end, the exercise mean (MId) is employed, which is defined as the mean of exercises completed at a certain level throughout an academic year. Likewise, the cycles are defined as the ceiling of the exercises completed by students between the exercise mean of that activity, the formula of which is as follows:

$$cycles = cell\left(\frac{exercises\ completed}{MId}\right) \tag{1}$$

On this basis, we have two cases in which the effectiveness is defined as:

- Case 1. Cycles from 0 to 1, as shown in Formula 2.

$$effectivity = \frac{\sum successes - Kr * \sum failures}{Mid} \tag{2}$$

- Case 2. Cycles greater than 1 show the calculation of the effectiveness, as indicated in Formulas 3 and 4.

These equations are only applied when the student has completed a minimum number of exercises within the activity, which is defined for each level, and which has been initially established at 10%. These exercises will subsequently be adjusted according to the statistics gathered from this activity.

- Number of consecutive exercises correctly completed in order to denote 100% effectiveness and an advance in level.
- Marked in an activity as 'retro1', 'retro2', 'retro3', in the case of performance lower than 60%.

Should an activity be marked as 'retro1', the student is regarded as having encountered an incidental difficulty unrelated with him or her, and is thus required to repeat that level.

When an activity is marked as 'retro2', the student is regarded as having encountered a difficulty with the content, and is thus required to repeat the level, but only those exercises that are categorized as "easy".

If an activity is marked as 'retro3', the student is regarded as lacking the basic knowledge required for completing the activity correctly, and is required by the system to go back to previous activities in accordance with his or her performance.

$$Baseline = \left(\sum_{i=0}^{cell(MId)} success_i - \left(Kr * \sum_{i=0}^{cell(MId)} failure_i\right)\right)$$
$$+ \left(\sum_{j=cell(MId)+1}^{2*cell(MId)} 0.9 * success_j - \left(0.4 * \sum_{j=cell(MId)+1}^{2*cell(MId)} failure_j\right)\right) \quad (3)$$
$$+ \left(\sum_{k=2*cell(MId)+1}^{Completed\ exercises} 0.8 * success_k - \left(0.6 * \sum_{k=2*cell(MId)+1}^{Completed\ exercises} failure_k\right)\right)$$

$$effectivity = \frac{Baseline}{Completed\ exercises} \quad (4)$$

Deep Learning evaluation engine. This component employs an algorithm for neighbourhood analysis in order to determine if, for these users and their completed exercises, there exists a set of other users with similar characteristics. If this is so, on the basis of what these users have done, a move back or move forward in the content is prescribed.

It is important to point out that, for this component, the GPS of this user, the socio-economic data associated with this position, and the school attended by the user come under consideration and are employed as vectors, the aim of which is to find a group with the closest similarities to those of the student in question.

Specifically, this system was developed on the basis of the K-Nearest Neighbors (KNN) algorithm, described in detail by Zhang [23]. This solution was chosen because the algorithm requires little data to start learning and identifying similarities between users. It is necessary for this model to take into account, at the time of recommending the next level to a learner (Ui), the behavior of other users who in the last four levels have shown a series of similar patterns.

KNN has also been used to increase the rate of graduating students using data from other students who did not graduate, as shown by Nugruho et al in their paper [24].

To implement this evaluation engine, vectors of variables are defined with the following data:

- The times used to perform the level.
- The number of correct exercises.
- The number of wrong exercises.
- The efficiency achieved in the level.
- Branch-course-level structure
- Difficulty of the exercises performed in the level.
- Difficulty of the exercises performed in the next level by other users with similar patterns.
- GPS coordinates where the activity is conducted.

The implemented algorithm works as follows:

1. If Ui has failed the performed level (Na), it selects all other vectors relative to failed levels. While if Ui has passed Na, it selects the other vectors relative to passed levels.
2. Compute the distance between the other vectors, using the cosine metric.
3. Sort the other vectors by increasing distance values.
4. Selects the n closest vectors.
5. Among these n neighbors, selects the m vectors associated with the highest scores ($m \leq n$).
6. Calculate the average of the variables associated with these m vectors.

This value, rounded up or down to the nearest integer, is the recommended level jump to the user U.

Heuristic Evaluation. This component uses the results of the student in the other branches of the other subtopics in order to determine if the user is experiencing greater difficulties.

Were the EGE DAO subtopic to consist of more than three academic years, this process would seek to determine whether the software user is well-placed in the current academic year or whether he or she should be relocated in the previous academic year. To that end, a series of rules would be applied based on how many different itineraries had obtained a negative result.

Each activity includes a set of exercises that will be asynchronously evaluated using an events administrator, thereby preventing the system from collapsing due to overload by placing in a queue each process that will be executed when the system is able to do so.

EventSource. By using the EventSource technique to optimize the flow of data of the application, and by unlinking each evaluation or presentation process from the system, it is prevented from collapsing at times when the tool is subject to high demand. Each request is pasted in a process manager and the results are returned when they become available, without the need for users to wait in the browser.

2.2 Tests Conducted

Tests common to all the Industrial Engineering Degree courses at the EEBE-UPC were conducted in the first-year course of the Graphic Expression subject

The tests were carried out in the first quarter of the 2012–2022 academic year, during which 708 students were enrolled in this subject and organized into 24 class groups. The groups contained a maximum of 32 students and were distributed throughout all the days of the week, both in the morning and in the afternoon.

Four of the morning groups were chosen for participation in the web tool trial, referred to herein as the "experimental groups". These groups were selected because their teachers already participated in the audit of this trial. However, these researchers were not involved in the assignation of the groups to teachers, and thus the selection process was subject to a certain degree of randomness.

It is well-known that students are assigned to lecture halls by order of preference and according to their university entry exam results, so it is difficult to make comparisons between groups. In order to overcome this problem, a further 4 control groups were selected, whose classes coincided with the experimental groups in both day and hour, and thus their members had similar entry exam results. None of the teachers of the experimental groups gave classes to the control groups.

The subject was evaluated by means of seven independent tests:

- Tests on CAD skills and practical work on Normative knowledge. design of parts, assemblies and planes. (25% of the overall grade).
- 1 test on CAD skills and work on knowledge of Geometry and Surfaces (15% of the overall grade).
- 1 practical test on freehand sketching. (10% of the overall grade).
- 1 theory test on Normative technical drawing. (15% of the overall grade).
- 1 theory test on Geometry. (10% of the overall grade).
- 1 project undertaken by a group consisting of 3 students. (15% of the overall grade).

Since students tend to achieve the poorest results in the theory tests, the trial consisted in duplicating these two theory tests with the evaluation being conducted directly by means of the web tool.

In other words, the experimental groups were able to monitor the course by using the web tool, and were required to take the same theory tests as the other groups engaged in the subject (internal control test). In order to circumvent to Pygmalion effect, the students belonging to the experimental groups were able to choose whether or not they wished to monitor the course with the web tool or whether to depart from it at any given moment. These students were aware that they would eventually receive the better of the two grades obtained (web tool or internal control test), so that whether or not they decided to monitor the course, the highest grade would also be applied in the theory tests.

The decision to monitor the course with the web tool would for the experimental groups connote indicate a greater level of dedication. The web tool restricts the time they devote daily and weekly the course, so students should sustain their commitment in order not to fall behind, which may mean that they fail to complete all the exercises and therefore fall short of the best possible grade.

The control groups had only the test days at their disposal, so it was up to them to prepare themselves either little by little or only on the days prior to the test.

Neither the students nor the teachers belonging to the control groups (or the rest of the subject) were aware of the trial being conducted.

3. Results

For the presentation of the results, we used a method of grade comparison described by Alpiste et al in [25], who propose a way to equalize the grades of students awarded by teachers with different criteria, in order to compare them.

First of all, the mean grades obtained both by the experimental groups and the control groups are shown below.

Experimental group mean grades:

Thus, an 8% improvement in the grades obtained in the Nominative theory test and 6% in the Geometry theory test was achieved in comparison with the control groups.

A bilateral Pearson correlation with the IBM SPSS Statistics 28.0.1.0 software package was performed on the experimental group grades in the Normative and Geometry tests, on those obtained using the web tool, and on the web tool operational data.

Only those correlations yielding statistically significant linear associations on fulfilment of the bilateral $p < 0.01$ Level of Significance are shown (i.e., the null hypothesis is rejected, and thus the correlation is reliable). All these correlations are positive, and the Pearson correlation coefficient values are found within the range of "considerable" ($0.5 < r_P < 0.75$) or "strong" ($0.75 < r_P < 0.9$).

Table 3 shows the Pearson correlation coefficients (r_P) between the web tool operational data using the variables F-1, TE and Ej:

- F-1: Number of times the web tool requires the student to repeat the exercises.
- TE: Total amount of time spent by the student on the web tool.

Ej: Total number of exercises completed by the student with the web tool.

Table 2. List of test results of the groups using the web application and the control groups

Variable	Value	Meaning
S1	5.8	Grade of the Normative content using the web tool
S2	6.7	Grade of the Geometry content using the web tool
T1	5.2	Grade in the Normative theory test
T2	5.7	Grade in the Geometry theory test
T1c	4.6	Grade of the Normative theory test (Control group)
T2c	5.2	Grade of the Geometry theory test (Control group)

Table 3. Pearson correlation coefficients (r_P) between the web tool operational variables, p<0.001 and N=122

r_P	TE	Ej
F-1	0.51	0.61

Table 4. Pearson correlation coefficients (r_P) between web tool operational variables and student grades, $p < 0.001$ y $N = 122$

r_P	T1	T2	S1	S2
Ej	0.61	0.51	0.78	0.67

Table 5. Pearson correlation coefficients (r_P) between the web tool grades and those obtained in the theory control test of the experimental group, $p < 0.001$ and $N = 122$

r_P	T1	T2
S1	0.81	
S2		0.77

Table 4 shows the Pearson correlation coefficients (r_P) between the web tool operational variables, Ej and the student grades T1, T2, S1 and S3.

- T1: Normative test grades
- T2: Geometry test grades
- S1: Web tool grades in Normative
- S2: web tool grades in Geometry

The correlations between the F-1 variable (number of times that the web tool requires the student to repeat the exercises) are not shown, and neither are the grades found in the "very weak" range ($-0,1 < r_P < 0,1$), that is, the grades obtained by the student are not correlated with the number of times the web has required repetition of the exercises. This latter is important for the evaluation of the efficacy of the web tool.

In Table 5 one may see the correlation between the web tool grades and the grades obtained in the theory control test of the experimental group T1, T2, S1 and S2.

Also of interest is the correlation between the theory test grades compared with the overall result for the subject. Table 6 shows the correlations conducted on the experimental groups and those between the groups over the whole subject, defining the variables NFC and NF.

- NFC: Overall results of the 4 experimental groups
- NF: Overall results of the 24 groups belonging to the subject

Apart from the results regarding the student grades, the tests have also enabled the web tool to change part of the heuristic, thereby reclassifying the complexity of the exercises. The system began with a neutral classification of the exercises; that is, all the exercises were regarded as normal. At the end of the quarter, the system had classified the exercises as shown in Table 7.

Table 6. Pearson correlation coefficients (r_P) between the theory test grades, the overall grades of the subject for the 4 experimental groups and for the 24 groups belonging to the subject, $p < 0.001$

r_P	T1	T2
NFC N = 122	0.70	0.57
NF N = 708	0.68	0.64

Table 7. Number of exercises according to complexity on completion of the experiment

Complexity	Nº of exercises
Easy	519
Normal	173
Difficult	34

4. Discussion

It has been possible to establish that there has been an improvement in the mean theory grades of the experimental groups of 8% (Normative) and 6% (Geometry) in the results of the control groups.

Furthermore, in Table 4 it can be observed that in the experimental groups the correlations between the web tool grades and the theory test grades (which in an experimental group are control tests) are "strong" ($r_P = 0.81$ y $r_P = 0.77$). In other words, one may assume that an improvement in the web tool grades undoubtedly leads to an improvement in the results of the theory test. Thus, we may state that the improvement compared with the control groups is definitely due to the use of the web tool.

This affirmation is backed up by the data shown in Table 3, where the more intensive use of the web tool (variable Ej Exercises completed) gives rise to better grades ("strong", with $r_P = 0.78$, and "considerable", with $r_P = 0.67$), and logically to improved grades in the theory tests ("considerable", with $r_P = 0.61$ and $r_P = 0.51$), a foreseeable outcome given that they were already correlated in Table 4.

From Table 2 it may be observed that a considerable correlation ($r_P = 0.61$) exists between the penalizations of the tool (F-1) and the number of exercises completed (Ej). However, the correlation between the penalizations and the grades actually obtained, both in the theory tests and with the tool, is either "very weak" or "null" ($-0.1 < r_P < 0.1$). That is to say, in this case the null hypothesis is correct and a correlation between the penalizations and the grades obtained cannot be said to exist. Thus, we may state that the design of the penalization heuristic is not prejudicial to the student.

Similarly, in Table 5 one may observe the existence of significant correlations ($0.57 <= r_P <= 0.70$) between the theory test grades and the overall grade for the course, and this correlation only ensures that by improving the theory grades do the overall grades improve, as occurs to a greater or lesser extent with any other grade of the remaining 5 control tests. However, this does not invalidate the decision to use the theory content for the trial.

The results are satisfactory and sufficiently beneficial for the students to justify an increase in the number of participants in the subsequent web tool tests.

Should different levels of difficulty be included in the exercises, those proposed in the adaptive web tool would be improved. Indeed, in light of the results of the heuristic decisions regarding the complexity of the exercises (Table 6), it would be advisable to increase the number of normal and difficult exercises for the subsequent web tool test.

Likewise, the algorithmic and heuristic methodology employed with this web tool in the subject of Graphic Expression in Engineering would be equally applicable in other university course subjects with theoretical content, as well as many others with practical content, thanks to the multiple forms of presentation, particularly in the teaching of Computer Science.

The most significant limitations of this work are as follows:

- The data collected come from one subject and during a single course. Increasing these values would give greater weight to the results obtained.
- In the course, it was possible to structure the content into 16 levels. However, for the effects of the algorithms on the students to be more significant, it would be advisable to have many more levels, approximately 50, for example.

Since the academic contents of Primary, Secondary and Baccalaureate are widely structured, they could also provide a suitable environment for this tool.

5. Conclusions

The tool described in this article has been tested in a single university subject with a limited structuring of contents, according to subjects, sub-subjects, competencies and levels.

It is expected that a higher level of structuring would lead to a better performance of the system, despite which an improvement in grades of between 8% and 6% has been obtained.

These results suggest that continued use of the tool, combined with greater structuring of subjects, could help improve student performance.

It is also proposed to conduct tests in Primary, Secondary and Baccalaureate subjects.

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