

Real-Time Monitoring of Progress on a Smart Learning Platform

Alberto Real-Fernández , Patricia Compañ-Rosique , Juan Luis López-Javaloyes , Rafael Molina-Carmona , Faraón Llorens-Largo  *

Smart Learning Research Group, University of Alicante (Spain)

* Corresponding author: alberto.real@ua.es (A. Real-Fernández), patricia.company@ua.es (P. Compañ-Rosique), juanluis.lopez@ua.es (J. L. López-Javaloyes), rmolina@ua.es (R. Molina-Carmona), faraon.llorens@ua.es (F. Llorens-Largo).

Received 16 April 2025 | Accepted 22 July 2025 | Published 28 August 2026



ABSTRACT

In the context of Smart Education, real-time monitoring of learning is consolidating as a key tool for both teachers and students. This approach allows teachers to early detect both high-achieving students and those facing difficulties, favoring timely pedagogical interventions that address these situations. On the other hand, the possibility for learners to visualize their progress encourages autonomous learning, as having a clear representation of their progress helps them to set personal goals and take a more active role in their formation. This article discusses how AI-supported systems, such as the Khipulearn platform, address these needs through a dashboard designed to provide accurate, real-time information on academic performance, participation and skill development. Visual representations, such as intuitive graphs and charts, not only optimize teaching by facilitating agile analysis of group and individual progress, but also empower students, transforming the learning process into a more personalized and engaging experience.

KEYWORDS

Artificial Intelligence,
Learning Analytics,
Smart Learning.

DOI: 10.9781/ijimai.2026.6564
eLocator: e6564

I. INTRODUCTION

In recent years, the evolution of intelligent technologies, concretely Artificial Intelligence (AI) in education has transformed traditional learning environments into dynamic systems, that aim to adapt to the needs of each student [1], [2]. This evolution has led to the emergence of smart learning platforms that support personalized, data-driven instruction, offering students greater autonomy while providing teachers with comprehensive oversight tools [3]. However, the efficacy of these platforms depends not only on the quality of the learning content, but also on the capacity of educators to interpret and act upon the substantial volumes of data they generate.

As educational systems evolve toward student-centered models, the role of the teacher is shifting from content delivery to strategic facilitation. In this context, real-time monitoring tools have become essential, analyzing learners' engagement, performance, and progression. They provide not merely data collection, but actionable insights that support instruction and early intervention.

As an additional factor in this transformation, Learning Analytics (LA) emerged to help in the visualization of patterns, the identification of strengths and weaknesses and the optimization of both the learning experience and the course design [4].

However, there is still a lack of learning platforms that combine real-time learner monitoring with interpretable feedback for teachers, with instructional decision-making support. To this end, in this article we analyze how the AI-supported learning platform Khipulearn¹ addresses these needs, through a dashboard designed to provide real-time information on learners' performance, engagement and skill development.

Thus, we firstly expose the background of the research in Section II, that explains the current needs of education, focused on the teaching tools used in the learning process, and describes the main concepts of Khipulearn platform and the teaching tools it provides. Then, in Section III we explain a learning experiment carried out with two subjects, describing them and exposing their results with the teaching tools of Khipulearn. After describing this experiment, in Section IV, we carry out a study to determine the relationship between the work of the learners on Khipulearn and their results in the final exam. In Section V we expose a discussion of the results obtained in the previous two sections. Finally, Section VI analyses the conclusions drawn from the research.

¹ <https://khipulearn.com/>

II. BACKGROUND

A. Teaching Tools in the Learning Process

Recent technological advances have enabled the development of systems based on smart learning methodologies, aiming to enhance the learning experience of the students [5]-[7]. But at this point, it is crucial to implement solutions that help teachers to efficiently monitor student progress and performance throughout the learning process, while reducing their workload. These solutions should facilitate the effective processing of system-generated data, the so-called learning analytics [4], [8], while concurrently provides meaningful and clear visual representations. The implementation of such functionalities would facilitate real-time analysis, thereby helping teachers in decision-making and in identifying patterns and make possible adjustments to enhance student performance.

One of the main focus relies on the academic performance of students, usually conditioned by the score obtained in the activities done in a course. This data offers information about the progress of the learners, as well as their comprehension of the knowledge, but it also can reveal the effectiveness of an activity. If some atypical values are observed, it may indicate the necessity for adjustments to be made to the activity.

Another value of interest is the learners' engagement, that can be determined by how frequently they access and complete activities. Such information serves as an indicator of their level of engagement and motivation, and it could also help to detect low participation by some learners who might need personalized support measures.

On the other hand, it is necessary to monitor students' achievement of partial objectives in order to guide teachers in optimizing the learning experience [9]. Measurable and observable achievements that allow for performance assessment are essential for this purpose, as such assessment enables early detection of problem areas for students or areas that may need improvement.

Furthermore, the analysis of trends and patterns in learning facilitates the recognition of recurrent behaviors and changes over time, aiming to improve student learning and satisfaction. Besides, provided by metrics that monitor individual progress and engagement, the early identification of students with a low performance or engagement enables the implementation of targeted interventions [10]. Additionally, the recognition of students with exceptional aptitude or outstanding performance enables the adaptation of learning strategies to further support their motivation and keep their engagement.

B. Teaching Tools of Khipulearn

Khipulearn is a smart learning platform built upon the model CALM (Customized Adaptive Learning Model), with the objective to create a personalized and adaptive experience for learners [11], [12]. Besides, the platform also aims to provide the teacher with a tool to monitor learner progress in real-time.

In Khipulearn the learning content relies on the so-called competence map, a directed graph in which nodes represent competences and edges define their dependence relationships. Each competence is associated with a numeric strength value that reflects the learner's performance and level of understanding. Learners progress by choosing from unlocked competences, completing associated activities, and increasing their strength in each. Once the minimum threshold is reached, the competence is marked as passed, and in the case of the maximum threshold, the competence is completed. That means the learner has achieved the necessary knowledge to acquired a competence, or the maximum possible strength, respectively. At the same time, new ones may be unlocked if the connection threshold is reached. This structure allows learners a dynamic and autonomous

progression while offers teachers a continuous view of each learner's status and potential difficulties.

To further support adaptivity, Khipulearn includes an artificial intelligence engine capable of selecting the most appropriate learning activity for each student in real-time [13]. The engine considers various factors, such as performance metrics and time spent on tasks, to recommend content that aligns with the learner's selected strategy. These same indicators serve a dual role by informing the teacher about possible gaps in comprehension, enabling more informed instructional decisions.

In this way, Khipulearn promotes both learner autonomy and instructional oversight, by offering a personalized and adaptive experience to the learners and a fully customization in the design of the learning process. Besides, it includes a complete teaching dashboard with tools to evaluate the global progress of the course, identify learning issues and analyze individual learners' progress [14].

Aiming to assist teachers in monitoring the global progress and engagement in their courses, Khipulearn offers a tool with several views based on the competence map structure. These views are designed not only to reflect students' achievements, but also to offer a continuous review of how learners interact with the content and structure of the course.

Concretely, it provides three different views of the map:

- Unlocking of competences by learners: it displays, for each competence, the percentage of learners that have unlocked them. That means their dependency or dependencies have been unlocked, reaching the required threshold in the preceding competence.
- Passing of competences by learners: it displays, for each competence, the percentage of learners that have passed them. That means learners have reached the minimum threshold, so the required knowledge is acquired.
- Completion of competences by learners: it displays, for each competence, the percentage of learners that have completed them. That means the maximum threshold has been reached, so the maximum score is acquired.

An example of this tool is shown below in section 3, for example in Fig. 3, that shows the view of unlocked competences by the learners, with the case of one of the subjects exposed.

In addition, the platform provides a course overview that represents the status of the learners, displayed as a pie chart. It is divided into sectors that represent the amount of learners in the possible course status: not initiated, started, passed or completed. It is important to mention the difference between passed and completed. A course is considered as passed when there is a path between an initial and a final competence in which all the competences are passed. And it is completed when this path has all the competences completed. In this way, this chart offers a clear snapshot of overall progression and helps the teacher to detect if any intervention is needed. There is also a chart used to visualize the global performance of learners, concretely regarding activities. It displays the average score of all course activities done by the learners, whose value ranges from 0 to 100. This data is displayed as a circular progress bar that represents, in a general way, the degree of understanding of the contents by the learners. An example of both charts is shown in Fig. 5.

Finally, the teacher dashboard of Khipulearn shows the list of learners in a table with multiple variables. In this tool teachers can select different values to filter, order and analyze data according to their instructional needs. It allows them to detect patterns, monitor and compare the progress of the learners, in order to adapt some aspects if necessary. Below, Fig. 6 shows an example of this tool, with some indicators selected, used in a real subject.

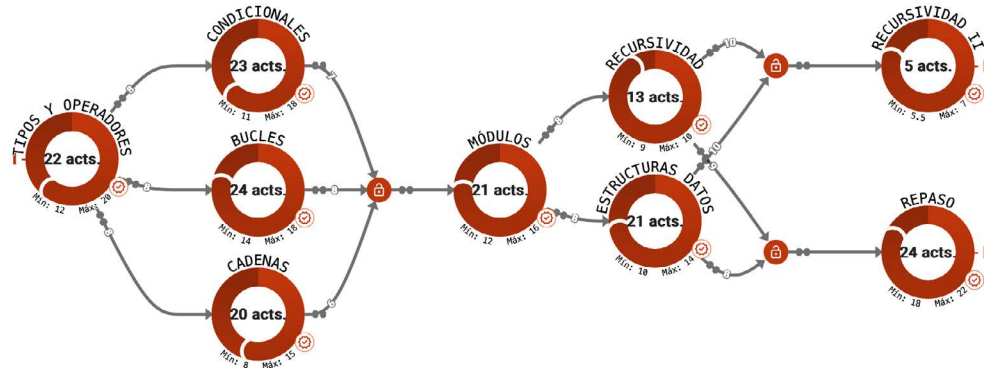


Fig. 1. Competence map corresponding to the subject Programming I.

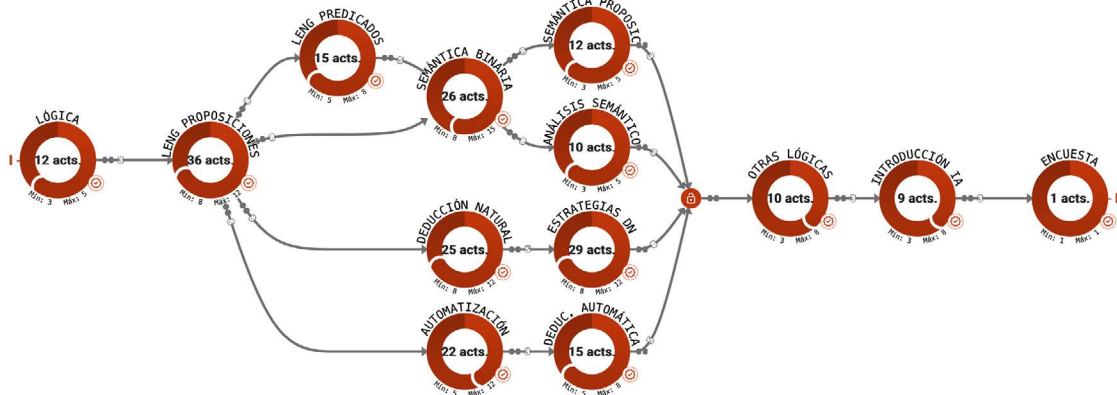


Fig. 2. Competence map corresponding to the subject Logic for Artificial Intelligence.

III. LEARNING PROCESS TRACKING AND RESULTS

As we mentioned above, Khipulearn contains a complete dashboard, in which teachers can monitor both the global state of the course, in terms of progress, scores and activity of the learners; and the individual detailed state for each learner. Making use of this tools, this section exposes the results obtained in Khipulearn applied in two university subjects.

A. Learning Experiment

Khipulearn platform is being used in several subjects of different university degrees, as well as to teach special courses. Two application cases are presented in this section: Programming I and Logic for Artificial Intelligence, both belonging to the first year of the Undergraduate Degree in Artificial Intelligence Engineering.

Programming I is the student's first contact with computer programming, its objective is to design algorithms to solve problems that can be addressed by a computer, implement them using structured programming techniques, and develop proficiency in a high-level language, specifically Python. Additionally, learn to program both individually and as part of a team. The subject has 76 students enrolled. Computer programming is a subject that traditionally generates many difficulties for students, so providing interactive and active tools to encourage learning is very important. The evaluation of the subject is based on the marks obtained in:

- Final exam: Test consisting of performing a computer program. This exam takes place at the end of the subject.
- Partial exam: Test consisting of performing a computer program. This exam takes place during the teaching of the subject.
- Project: Group realization of a programming project.
- Monitoring: Various tests will be carried out as continuous evaluation (participation in forums, controls in theory and/or

practice sessions, class participation, attendance, score obtained on Khipulearn platform, etc.)

The main objective of the course Logic for Artificial Intelligence is to provide students with a solid foundation in formal and symbolic logic, along with its practical application in the development of intelligent systems. This knowledge serves as a critical basis for more advanced topics in the field of artificial intelligence, such as machine learning, probabilistic reasoning, and decision-making. In the 2024-2025 academic year, the course enrolled 66 students. Given its interdisciplinary nature - combining theoretical and practical, philosophical and mathematical dimensions-, a multidimensional assessment approach has been designed, comprising the following components:

- Final exam: focused on solving problems and constructing formal logical proofs.
- Practicals: development of three practical exercises using the logic programming language Prolog (a knowledge base, a logic puzzle and a free-choice project).
- Reflective and critical work: solving logic puzzles and delivering an oral presentation of the relationship between logic and AI (logical fallacies, cognitive biases ...).
- Learning activities: conducted through the Khipulearn platform to reinforce core content and promote autonomous learning.

Both subjects have been taught in Khipulearn during the current academic year 2024-2025, concretely in the first semester. To do so, two different courses have been designed:

- Programming I: 9 competences created and 163 activities associated, designed as shown in the competence map in Fig. 1.
- Logic For Artificial Intelligence: 13 competences created and 222 activities associated, designed as shown in the competence map in Fig. 2.

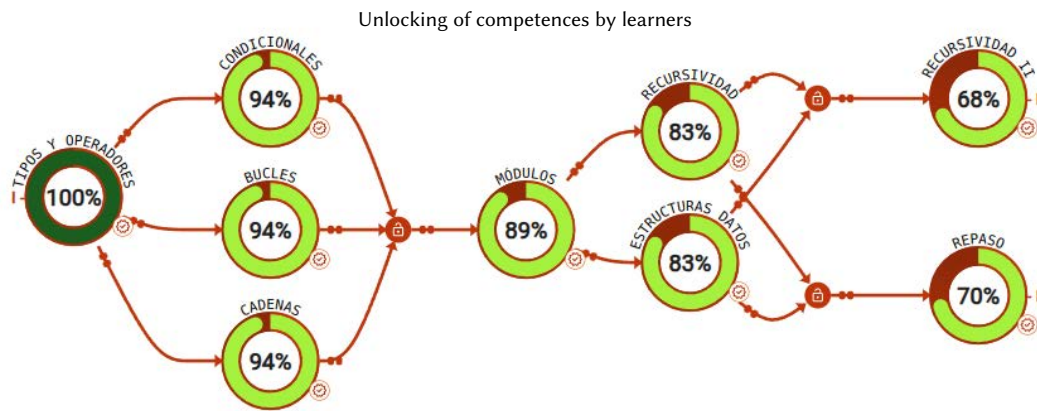


Fig. 3. Percentage of learners who have unlocked each competence of the subject Programming I.

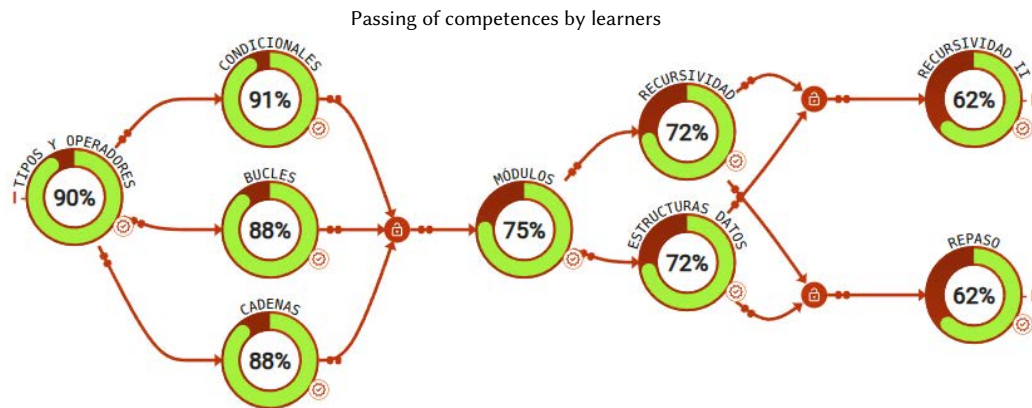


Fig. 4. Percentage of learners who have passed each competence of the subject Programming I.

At this point, in the next section we expose the learning results obtained in both subjects, using the teaching revision tools that Khipulearn provides, including global and individual approaches, as explained in Section II.

B. Case 1: Programming I

Firstly, we analyze the case of Programming I, composed by 76 students as previously mentioned.

On one hand, regarding the global results obtained, the first tool used from the dashboard is the completion map. As explained in section 2, this tool displays the corresponding competence map but showing the percentage of students that have unlocked, passed and completed each competence. In this case we expose this tool with the results at the end of the subject, but it provides this information in real-time. So that it allows the teacher to monitor the whole group performance in the course.

Concretely, for this analysis we have selected the unlocked and passed results, shown in Fig. 3 and Fig. 4 respectively, since we consider them to be the most descriptive ones.

The first map reflects that between 68% and 70% of students have unlocked the two final competences, being 83% and higher for the rest of competences. This is a positive result, meaning a high amount of students that have arrived until the end of the map. And it is further supported by the results obtained in the second map. This case shows that 62% of students have passed the two final competences, which means those who have passed the course.

This data implies a difference of less than 10% between the students that have reached the final competences and those that have passed them. Therefore, the result of these maps show a great level of completion of the course.

Furthermore, the dashboard contains two graphs that represent the global progress of learners: one with the status of the course and other with the information about the activities, both of them displayed in Fig. 5.

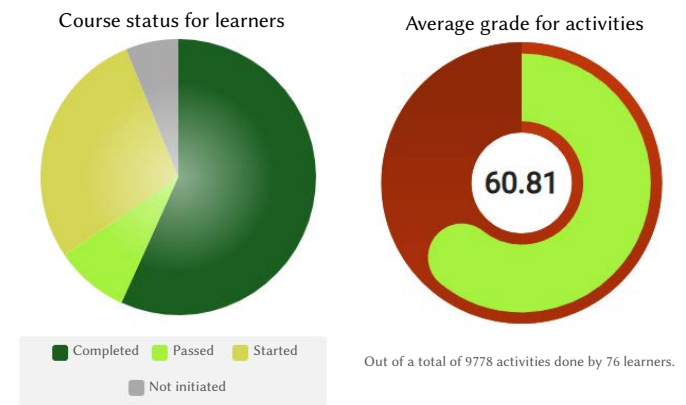


Fig. 5. Pie charts with the course status for learners (left) and the average score obtained in activities (right).

The first one shows the general status of the course, that is as mentioned before: not initiated, started, passed or completed. In this pie chart we can observe that most of the learners have passed or completed the course, as reflected in the previous competence maps. Concretely, from the 76 students enrolled in the course, the status is as follows:

- 5 not initiated.
- 23 started, but neither passed nor completed.
- 7 passed, but not completed,
- 46 completed.

Learners

Customise table

Avatar	Course status	Act. done in the course ↓	Average act. scores in the course	Average time spent on act. in the course	
	COMPLETED	164	59.59	2 m, 47 s	
	COMPLETED	164	53.55	4 m, 7 s	
	COMPLETED	163	52.49	1 m, 6 s	
	COMPLETED	163	53.73	1 m, 59 s	
	COMPLETED	162	48.23	3 m, 5 s	
	COMPLETED	162	50.49	2 m, 37 s	
	COMPLETED	161	64.63	3 m, 28 s	
	COMPLETED	161	62.32	3 m, 36 s	
	COMPLETED	160	54.55	2 m, 24 s	
	COMPLETED	159	48.59	55 s	

Items per page 10 1 – 10 of 81 |< < > >|

Fig. 6. Table with the individual status of the learners showing different selected metrics.

The most interesting aspect of this chart is the information about started and completed status. It reflects that from the 53 students (almost 70%) that have finished the course, 46 have completed it. These results indicate that most of the students have reached the maximum scores of all the competences.

Regarding the second chart, it shows the information about activities. In this case, we can observe that learners have done a total of 9778 activities, which means an average of 128 per person, with an average score of 60.81.

On the other hand, the individual data of the learners is given in the final section of the teacher dashboard. As explained before, it consists on a table with multiple data for each student in the course. We expose an example for this concrete case, shown in Fig. 6, in which the list is ordered by activities done in the course. This table displays selected metrics such as course status, completed activities, average scores, and time spent, supporting comparisons of performance and engagement.

We have selected these four variables in order to compare the performance between students, based on the activities and the information related to them. It is important to recall that activities can be done more than once. It is an option that Khipulearn offers to the teacher, aiming learners to repeat activities, either to refresh those who have completed successfully or to reinforce those who have failed. In the case of Programming I this option is enabled, and it has a total of 163 activities created, as mentioned before. The button on the right of each row display a view of the status of each learner, with their current competence map and their history of activities.

Considering this, in the table we can observe that the students with the highest number of completed activities are two, with 164, followed by two with 163, two with 162, another two with 161 and one with 160. So these numbers are near and higher than the total of activities in the course, even though repeated activities are included. It reflects a great level of student engagement and an active learning process.

Moreover, with this table we can compare the performance with the score obtained and the time spent in the activities. For instance, if we focus on the first learner, with 164 activities done, the average score obtained is 59.59 and the average time spent 2 minutes 47 seconds. However, the sixth learner has a score of 50.49, which means almost 10 points less, with only two activities less and even 10 seconds faster. It is an interesting point to consider, that reflects the essence of personalized and adaptive learning, in which students can complete the learning process in different ways and paces.

Therefore, this tool provides the teacher with a whole view of the progress of each learner individually, with multiple variables to analyze. The examples are shown with the results at the end of the course, but the information is computed along the whole process.

Being real-time, teachers can monitor the course and make some decisions at any time, so that it becomes a useful and powerful teaching tool.

C. Case 2: Logic for Artificial Intelligence

Secondly, we analyze the case of Logic For Artificial Intelligence, composed by 66 students as previously mentioned, following the structure used in the case of Programming I, using the tools of the dashboard.

On one hand, let us check the global results obtained, starting with the completion map, selecting the unlocked (shown in Fig. 7) and passed (shown in Fig. 8 as the most descriptive ones. As in the case of Programming I, the shown information belongs to the end of the subject, but it is provided in real-time.

The first map reflects that 93% of students have unlocked the final competence, being between 93% and 97% for the rest of competences. This is a positive result, even more than the case of Programming I, meaning almost all of the students that have arrived until the end of the map. This result is reinforced when comparing it with the second map,

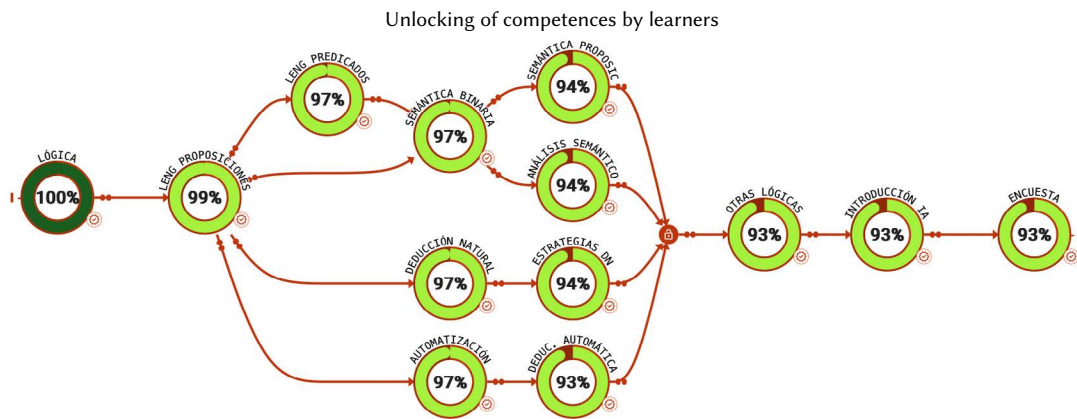


Fig. 7. Percentage of learners who have unlocked each competence of the subject Logic for Artificial Intelligence.

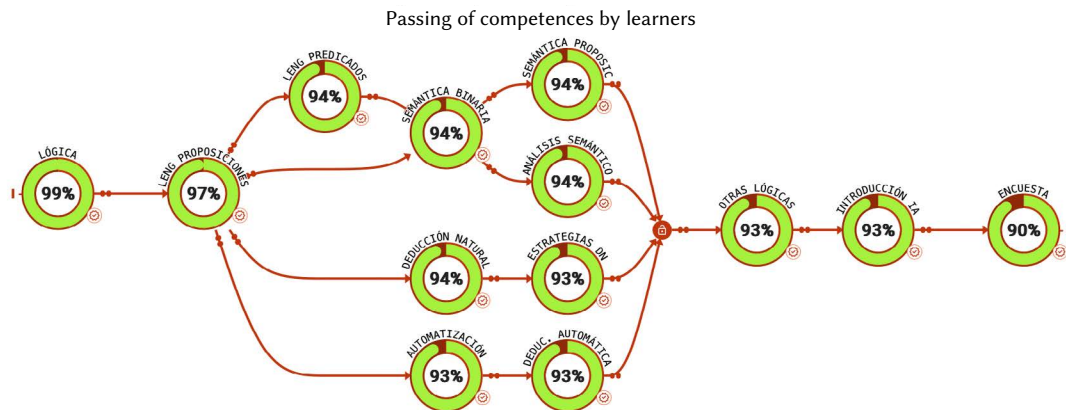


Fig. 8. Percentage of learners who have passed each competence of the subject Logic for Artificial Intelligence.

with the percentage of students that have passed each competence. It displays also 93% of students have passed the final competence.

It means the same who have arrived to the final competence have passed the course. Therefore, the result of these maps show a great level of completion of the course.

Furthermore, let us observe the graphs with the course status and the information about activities, displayed in Fig. 9.

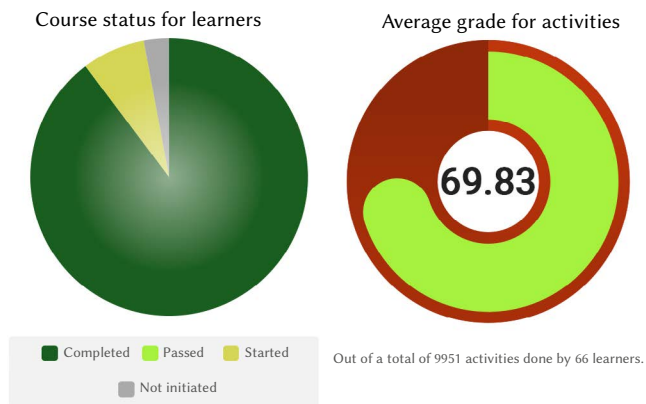


Fig. 9. Pie charts with the course status for learners (left) and the average score obtained in activities (right).

In the first pie chart we can observe that most of the learners have passed or completed the course, as the former map graphs reflected. Concretely, from the 66 students enrolled in the course, the status is as follows:

- 1 not initiated.

- 4 started, but neither passed nor completed.
- 61 completed.

The most interesting aspect of this chart, as in the case of Programming I, is the information about started and completed status. It reflects that 61 students (92%) have completed it, and the 5 students left are between started or not initiated. Such results indicate that all the students that have finished the course (in this case most of them) have reached the maximum scores of all the competences.

Regarding the second chart that shows the information about activities, we can observe that learners have done a total of 9951 activities, which means an average of 148 per person, with an average score of 69.83.

On the other hand, the individual data of the learners is given in the final section of the teacher dashboard, as explained before. We expose an example for this concrete case, shown in Fig. 10, in which the list is also ordered by activities done in the course. This table displays the same selected metrics than the previous case, such as course status, completed activities, average scores, and time spent.

In the case of Logic for Artificial Intelligence the option of repeating activities is also enabled, and it has a total of 222 activities created, as previously mentioned.

Considering this, in the table we can observe that the student with the highest number of completed activities is one with 201, followed by one with 196, one with 189, another one with 188 and one with 187. These numbers are close to the total number of activities in the course, even though repeated activities are included. It reflects a great level of student engagement and an active learning process.

Moreover, with this table we can compare the performance with the score obtained and the time spent in the activities. For instance, if we

Learners

Customise table

Avatar	Course status	Act. done in the course ↓	Average act. scores in the course	Average time spent on act. in the course	
	COMPLETED	201	98.67	1 m, 35 s	
	COMPLETED	196	61.53	56 s	
	COMPLETED	189	81.73	47 s	
	COMPLETED	188	89.15	47 s	
	COMPLETED	187	59.67	50 s	
	COMPLETED	185	60.57	44 s	
	COMPLETED	185	57.91	33 s	
	COMPLETED	185	61.24	41 s	
	COMPLETED	183	71.58	1 m, 31 s	
	COMPLETED	183	62.51	1 m, 51 s	

Items per page 10 1 - 10 of 66 < > >>

Fig. 10. Table with the individual status of the learners showing different selected metrics.

focus on the first learner, with 201 activities done, the average score obtained is 98.67 (really high) and the average time spent 1 minute 35 seconds. However, the second one, with only five activities less, has a score of 61.53, which means more than 30 points less, and however is 40 seconds faster than the first one. Indeed, if we compare it to the third one, with 189 activities, the average score is 81.73, 20 points more, and a few seconds faster.

These results reflect, like the previous case, the essence of personalized and adaptive learning, in which students can complete the learning process in different ways and paces.

IV. KHIPULEARN USE VERSUS ACADEMIC PERFORMANCE

In the previous section we exposed the learning results obtained in Khipulearn platform in two proposed subjects. Now, in this section, we carried out a study to determine whether there is any relationship between the work done by the students on the platform and the success obtained in the final exam.

To this end, we obtained a series of data on use and performance on the platform and we made an attempt to determine whether there is a relationship between any of the variables of use of the platform and the final exam.

A. Case 1: Programming I

In this case, the following variables have been considered:

- *Ex*: Exam mark
- *NAP*: Number of activities carried out on the platform
- *APS*: Average performance scores on the platform
- *ASTO*: average scores in types and operators
- *ASC*: average scores in conditionals
- *ASL*: average scores in loops
- *ASR*: average scores in recursion
- *ASDS*: average scores in data structures
- *ASS*: average scores in strings
- *ASMP*: average scores in module programming

- *ASR2*: average scores in recursion 2
- *ASREV*: average scores in review

The first thing that has been done is to determine whether the data are normally distributed or not. For this purpose, the Shapiro-Wilk test [15] has been used. Table I shows the results of the test on the study variables. The normality hypothesis is rejected for all variables where $p \leq 0.05$, therefore the only variables that are normally distributed are *APS*, *ASC* and *ASL*.

TABLE I. SHAPIRO-WILK TEST FOR THE VARIABLES: PROGRAMMING I

Var	W	p	Var	W	p
<i>Ex</i>	.95	.005	<i>ASR</i>	.89	.000
<i>NAP</i>	.84	.000	<i>ASDS</i>	.86	.000
<i>APS</i>	.98	.170	<i>ASS</i>	.96	.019
<i>ASTO</i>	.96	.015	<i>ASMP</i>	.93	.000
<i>ASC</i>	.98	.381	<i>ASR2</i>	.86	.000
<i>ASL</i>	.99	.624	<i>ASREV</i>	.80	.000

Once it has been determined that most of the variables are not normally distributed, Spearman's correlation [16], which does not assume normality in the data, will be used to study correlations between the grade obtained in the exam and the variables corresponding to the use of the platform. In order to analyse the possible relationships between variables, only the data of the students who took the final exam were considered, 75 students out of the 76 students enrolled in the subject.

The first is to determine whether there is a relationship between a student's participation in the platform and the final exam. It is expected that more participation on the platform will lead to a better result in the final exam. For this analysis, the scatter diagram shown in Fig. 11 ($x = NAP$, $y = Ex$) has been constructed. The figure also depicts the regression confidence interval indicating the uncertainty of the trend line estimate (95% confidence interval). Spearman's correlation, $r_s = .25$, $p = .028$, has also been calculated. This result indicates a weak positive correlation. Although the strength of the relationship is not high (0.25), there is a consistent trend between the two variables, and it is unlikely that the relationship is a product of chance.

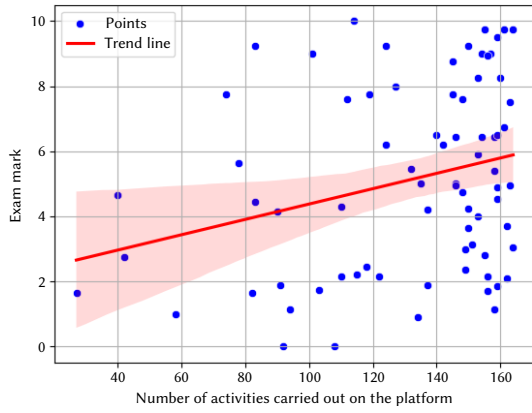


Fig. 11. Scatter diagram: Number of activities carried out on the platform-final examination: Programming I.

The next test is to analyse the relationship between the student's score in the different activities in which he/she participates and the final exam. It would be expected that students who obtain better scores in the platform activities will do better in the final exam. The *APS* variable corresponds to the average score obtained by the student in the different activities in which he/she participates.

Fig. 12 ($x = APS$, $y = Ex$) shows the scatter plot to analyse this relationship. Spearman's correlation coefficient has also been calculated $r_s = .35$, $p = .002$, which indicates an average correlation between the scores obtained by the students in the platform activities and the final exam grade. The statistical evidence ($p = 0.002$) supports that the relationship exists, and the correlation of 0.35 suggests a clear, though not extremely strong, monotonic association.

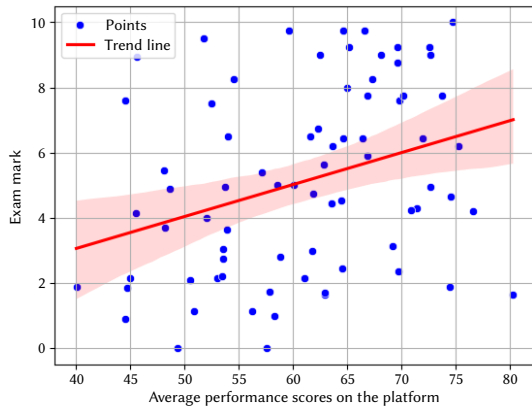


Fig. 12. Scatter diagram: Average performance scores on the platform-final examination: Programming I.

The activities on the platform are structured into different programming competences. It is interesting to see if there is a more prominent relationship between any competences and the final exam score. Table II shows the Spearman coefficients between the mean scores of each competence and the final exam grade, it also shows the p-value. Values with $p < 0.05$ are indicated with "*" to highlight their statistical significance. It is particularly interesting that just these variables are the ones with the highest correlation with the final exam. In general, correlations are low and in some cases medium. The competence with which there is the highest correlation is recursion 2 (*ASR2*). This makes a lot of sense since the activities corresponding to this competence are among the most difficult ones, so it is expected that students who have scored well in this competence will also have done well in the exam and vice versa. In addition, for this competence to be unlocked, students must have achieved certain values in the recursion (*ASR*) and data structures (*ASDS*) scores (Fig. 1).

TABLE II. SPEARMAN CORRELATION BETWEEN THE MEAN SCORES OF EACH COMPETENCE AND THE FINAL EXAM GRADE: PROGRAMMING I

Var	r_s	p	Var	r_s	p
<i>ASTO</i>	.28	.013	<i>ASS</i>	.19	.108
<i>ASC</i>	.28	.016	<i>ASMP</i>	.03	.825
<i>ASL</i>	.33*	.004	<i>ASR2</i>	.39*	.000
<i>ASR</i>	.10	.379	<i>ASREV</i>	.24	.036
<i>ASDS</i>	.36*	.001			

B. Case 2: Logic for Artificial Intelligence

The following variables have been considered:

- *ExL*: Exam mark
- *NAPL*: Number of activities carried out on the platform
- *APSL*: Average performance scores on the platform
- *ASL*: average scores in logic
- *ASPL*: average scores in propositional language
- *ASPL*: average scores in predicate language
- *ASBS*: average scores in binary semantics
- *ASPS*: average scores in propositional semantics
- *ASSA*: average scores in semantic analysis
- *ASND*: average scores in natural deduction
- *ASDN*: average scores in DN strategies
- *ASA*: average scores in automation
- *ASAD*: average scores in automatic deduction
- *ASOL*: average scores in other logics
- *ASIIA*: average scores in introduction IA

As in the case of Programming I, the Shapiro-Wilk test has been passed to determine whether the variables are normally distributed. Table III shows the results of the test on the study variables. The normality hypothesis is rejected for all variables where $p \leq 0.05$, therefore the only variables that are normally distributed are *APSL* and *ASL*.

TABLE III. SHAPIRO-WILK TEST FOR THE VARIABLES: LOGIC FOR ARTIFICIAL INTELLIGENCE

Var	W	p	Var	W	p
<i>ExL</i>	.95	.008	<i>ASSA</i>	.92	.000
<i>NAPL</i>	.89	.000	<i>ASND</i>	.84	.000
<i>APSL</i>	.99	.851	<i>ASDN</i>	.90	.000
<i>ASL</i>	.97	.069	<i>ASA</i>	.81	.000
<i>ASPL</i>	.94	.004	<i>ASAD</i>	.87	.000
<i>ASPL</i>	.93	.001	<i>ASOL</i>	.73	.000
<i>ASBS</i>	.87	.000	<i>ASIIA</i>	.88	.000
<i>ASPS</i>	.87	.000			

Since most of the variables are not normally distributed, the Spearman's correlation will be used to study the relationship between the exam score and the platform usage variables. In the case of this subject, 65 out of the 66 students enrolled took the exam.

The Spearman's correlation between the final exam grade and the student's participation in the platform (number of activities completed) has been calculated, $r_s = .04$, $p = .725$. Fig. 13 shows the scatter plot between a student's participation in the platform and the final exam ($x = NAPL$, $y = ExL$). The high p-value obtained (0.725) indicates that there is no statistical evidence to reject the null hypothesis (that there is no correlation).

Fig. 14 ($x = APSL$, $y = Ex$) shows the scatter plot to analyse the relationship between the final exam and the average score obtained by the student in the different activities in which he/she participates.

Spearman's correlation coefficient has also been calculated $r_s = .42$, $p < .001$. This value indicates an average correlation between the scores obtained by the students in the platform activities and the final exam grade. The p-value obtained (0) means that the probability that this correlation is due to chance is practically zero, it is statistically significant. It can be stated with high confidence that there is a relationship between the variables.

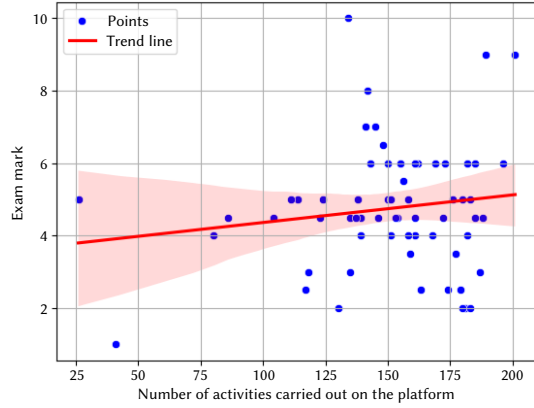


Fig. 13. Scatter diagram: Number of activities carried out on the platform-final examination: Logic for Artificial Intelligence.

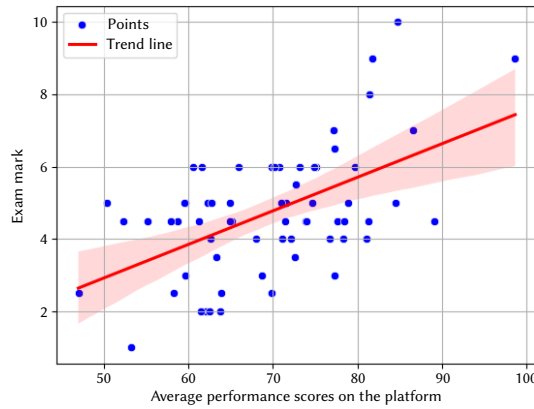


Fig. 14. Scatter diagram: Average performance scores on the platform-final examination: Logic for Artificial Intelligence.

Finally, the Table IV displays the Spearman correlation coefficients between the average scores for each competence and the final exam grade, along with their corresponding p-values. As in the Programming I case, statistically significant coefficients ($p < 0.05$) are marked with an asterisk (*). Overall, the correlations range from low to moderate, with the highest values observed in the competencies related to predicate language (*ASPL*), reasoning automation (*ASA*), other logics (*ASOL*), and introduction to artificial intelligence (*ASIIA*). This stronger correlation is expected, as these areas represent the highest conceptual complexity for first-year students. Consequently, those who perform well in these competencies are also more likely to achieve higher scores on the final exam.

TABLE IV. SPEARMAN CORRELATION BETWEEN THE MEAN SCORES OF EACH COMPETENCE AND THE FINAL EXAM GRADE: LOGIC FOR ARTIFICIAL INTELLIGENCE

Var	r_s	p	Var	r_s	p
ASL	.17	.181	ASND	.34	.005
ASPRL	.21	.009	ASDN	.33	.007
ASPL	.38*	.002	ASA	.38*	.002
ASBS	.28	.022	ASAD	.05	.678
ASPS	.32	.010	ASOL	.38*	.002

ASSA	.32	.010	ASIIA	.38*	.002
------	-----	------	-------	------	------

V. DISCUSSION

A. Learning Process Tracking

The analysis of the data collected in both courses using Khipulearn tools reveals relevant patterns that allow a better understanding of the learning processes and the degree of student engagement.

In both cases, the completion maps show a high and consistent progression. Although the Programming I map has two possible completion nodes, which could indicate that students choose one or the other destination, the level of attainment of the two is the same (62%), and close to that of the previous mandatory nodes (72%), indicating that students have not opted for the minimum path and have chosen to perform activities from all competencies. In Logic for Artificial Intelligence, this percentage rises to 93%, indicating an even higher performance. This significant difference may be related to the inherent difficulty of the subjects and the design of the activities. Future research will be conducted to advance this issue. Nevertheless, the figures in both cases reflect that the competence-based structure facilitates significant progression and maintains student interest.

The graphs of final course status and activities completed reinforce this interpretation. In Programming I, 70% of the students completed the course; in Logic for Artificial Intelligence, 90%. This consistency between maps and graphs confirms that Khipulearn's modular design encourages participation and improves results.

As for student activity, the average number of activities per student is high in both courses (128 in Programming I and 148 in Logic). The higher average score in Logic (69.83 vs. 60.81) could be due to a better appropriateness of the activities, lower difficulty or more effective feedback. The possibility of repeating activities also seems to positively influence learning, as observed in highly engaged students who exceed even the total number of activities planned. This supports the value of adaptive repetition and active learning.

The individual performance charts also allow us to identify different rates of learning. Some students, with fewer activities performed, achieve better scores, evidencing diverse approaches and reinforcing the usefulness of tools that enable personalized learning. Khipulearn, in this sense, favors both student autonomy and informed decision-making by the teacher.

In view of these results, it is proposed to perform more frequent analysis in future courses - in real-time or at least monthly - to detect and support students who may be lagging behind in advance.

B. Khipulearn Use Versus Academic Performance

The analysis of both case studies—Programming I and Logic for Artificial Intelligence—reveals relevant patterns regarding the relationship between students' activity on the Khipulearn platform and their academic performance in the final exam. Although they are very different subjects, certain similarities have been found.

In both subjects, a positive correlation was observed between students' average performance on the platform activities and their final exam grades. This correlation was moderate in both courses ($r_s = .35$ for Programming I, $r_s = .42$ for Logic), suggesting that consistent and effective engagement with the learning platform can be a reliable indicator of academic success. Interestingly, the sheer number of activities completed (NAP and NAPL) showed a weaker or even negligible correlation with exam performance ($r_s = .25$ in Programming I; $r_s = .04$ in Logic), indicating that quantity of participation alone is not a sufficient predictor of learning outcomes. Instead, the quality of engagement—as measured by average scores—proves to be more significant.

A deeper analysis of specific competencies reveals further insights. In both courses, those competencies that demand higher-order cognitive skills or involve more complex content—such as recursion in Programming I and predicate language or reasoning automation in Logic—display the highest correlations with final exam scores. This finding supports the notion that mastery of conceptually demanding content reflects and reinforces overall academic performance. Moreover, in Programming I, the highest correlation appeared in a late-stage competence (Recursion 2), which students can only access after demonstrating proficiency in earlier modules. This progression requirement likely strengthens the link between success in that competence and final exam performance.

These patterns underline the pedagogical value of adaptive learning environments like Khipulearn. By encouraging meaningful engagement and scaffolding complex competencies, such platforms do more than track student activity—they actively support and structure the learning process. The results also highlight the importance of focusing not only on participation but also on the quality of student performance within each learning module.

It is well known that there is widespread use of AI assistants among students. The assistants have been thoroughly trained with programming activities. This fact may give a possible clue as to why the correlations obtained in the Logic subject are higher than in the Programming subject. It is easy for any assistant to solve the activities on the platform, especially considering that they are of low difficulty since it is an introductory subject to programming. The assistant probably does not work as well with the logic activities and if it fails to do the activities, the student has to work hard to try to find the solution. This process results in more learning on the part of the student.

In sum, the correlations observed point to a significant association between students' platform performance and their academic outcomes. These insights can inform future improvements in both course design and instructional strategies, emphasizing adaptive progression, targeted feedback, and differentiated support for students who may struggle with higher-level competencies.

VI. CONCLUSIONS

This research aimed to analyze the integration of AI-supported platforms into educational environment, through the use of Khipulearn. Its objective is to enhance both learners and teachers experience, by offering an adaptive and personalized learning, and providing real-time monitoring tools.

On one hand, we have analyzed the teacher dashboard that Khipulearn presents, aiming to fulfill the needs of evaluating and monitoring a course throughout its lifecycle. The exposed results reflect that this dashboard allows teachers to analyze both global and individual progress, becoming a useful tool to support pedagogical decisions. The different global graphs presented, such as the competence map for displaying the completion percentage of learners and the pie charts for checking the status of the course and activities done, have proven to be intuitive and meaningful tools to monitor the group progress of the course. Also, the individual performance table, with the status and progress of the learners, has also become a useful means to check for individual status and needs of the learners. With this tool, teachers are able to identify different patterns of learning, evidencing its usefulness for personalized learning and future improvements, both in the design of the course and instructional strategies. Moreover, the results are shown of two already finished subjects, but the tools are displayed real-time, which provides the teacher with a complete monitoring tool for a better understanding

of the whole learning process and the degree of student engagement.

Besides, the learning results for both subjects have been positive, reflecting that the competence-based structure of Khipulearn facilitates significant progression and maintains student interest, reinforced with the results on the course status of the learners and activities they completed.

On the other hand, the comparative analyses carried out have shown a connection between the use Khipulearn and the academic performance. Despite the two subjects are so different, in both of them there is a correlation between the results of the learners in the platform and their results in the final exam.

These results highlight Khipulearn's effectiveness in both encouraging students' engagement and improving their learning outcomes. Also, they reinforce the relevance of visual analytics and data-driven systems in the learning process, as well as real-time tools to support educational decisions and monitoring. It is crucial to detect learning individual needs and make decisions for different learning situations that require attention.

We think these factors are appropriate and positive in different educational levels. This study has been made in university degrees, but the platform could also be useful in secondary school or primary school, in which we believe adaptive and personalized learning are also crucial. However, there are different aspects to be considered, such as the interface design and the available activities. It could be an important future research to carry out.

Furthermore, we would like to continue with the development of some features of the platform, mainly regarding the teacher dashboard, specifically timeline-based analytics, and explainable AI. To that end, we propose a roadmap to define this future work:

- Include a visualization of the progress of each learner over the time. We think it could be useful that the individual visualization of the map can be changed using a timeline. With this feature, the teacher could go back in time to a concrete state of the learner, and checking their progress in another interesting way.
- Research about different progression profiles of the learners, such as those who progress in the map from the beginning, those who wait until the middle of the course, or those who wait until the days before the final exam. This could give information about the different profiles of learners, and if these different patterns affects the academic results.
- Look into the integration of the explainability of the AI model's decisions. Currently the platform informs the teacher of the activities assigned by the selection engine, but want to integrate this information in the teacher dashboard. Therefore, the teacher could analyze how the activity selection and the strategy impact in the learning process, in order to detect some needs or making decisions.
- Include control or baseline groups to compare the results. With this data, the study of Khipulearn's effectiveness could be strengthened.

CREDiT AUTHORSHIP CONTRIBUTION STATEMENT

Alberto Real-Fernández: conceptualization, software, supervision, validation, investigation, methodology, writing – original draft, writing – review, editing.

Patricia Compañ-Rosique: validation, investigation, writing – original draft, writing – review, editing.

Juan Luis López-Javaloyes: software, methodology, writing – original draft, editing.

Rafael Molina-Carmona: conceptualization, supervision, validation, investigation, methodology, writing – review.

Faraón Llorens-Largo: conceptualization, supervision, validation, investigation, methodology, writing – review, editing.

DATA STATEMENT

Data used in this research is not publicly available, due to Data Protection aspects, since it is personal data related to students and its academic results.

DECLARATION OF CONFLICTS OF INTEREST

We have no conflict of interest to declare.

ACKNOWLEDGMENT

Khipulearn is a platform partially funded by the project ‘ADAPTLEARN - Adaptive Learning: Adaptive Learning Platform based on competences and activities’, Recovery, Transformation and Resilience Plan (UniDigital), Ministry of Universities of the Government of Spain, funded by the European Union - NextGenerationE.

REFERENCES

- [1] T. K.F. Chiu, Qi Xia, X. Zhou, C. Sing Chai, M. Cheng, “Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education,” *Computers and Education: Artificial Intelligence*, vol. 4, p. 100118, 2023, doi: <https://doi.org/10.1016/j.caeai.2022.100118>
- [2] F. J. García Peñalvo, F. Llorens-Largo, J. Vidal, “The new reality of education in the face of advances in generative artificial intelligence,” *RIED. Revista Iberoamericana de Educación a Distancia*, vol. 27, no. 1, pp. 9–39, 2024, doi: <https://doi.org/10.5944/ried.27.1.37716>
- [3] A. Goodwill, S. Chen, “Embracing a Culture of Lifelong Learning: the science of lifelong learning,” *UNESCO Institute for Lifelong Learning*, 2021.
- [4] C. Lang, A. Wise, A. Merceron, D. Gasevic, G. Siemens, “What is learning analytics,” 2022, doi: <https://doi.org/10.18608/hla22.001>
- [5] M. Area-Moreira, J. Adell-Segura, “Tecnologías digitales y cambio educativo. Una aproximación crítica,” in *REICE. Revista Iberoamericana sobre Calidad, Eficacia y Cambio en Educación*, 2021, pp. 83–96.
- [6] S. Bedenlier, M. Bond, K. Buntins, O. Zawacki-Richter, M. Kerres, “Facilitating student engagement through educational technology in higher education: A systematic review in the field of arts and humanities,” *Australasian Journal of Educational Technology*, vol. 36, no. 4, pp. 126–150, 2020, doi: <https://doi.org/10.14742/ajet.5477>
- [7] F. García-Peñalvo, A. Vázquez-Ingelmo, “What Do We Mean by GenAI? A Systematic Mapping of The Evolution, Trends, and Techniques Involved in Generative AI,” *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 8, no. 4, pp. 7–16, 2023, doi: <https://doi.org/10.9781/ijimai.2023.07.006>
- [8] F. García-Peñalvo, “Learning Analytics as a Breakthrough in Educational Improvement,” 2020, doi: https://doi.org/10.1007/978-981-15-4526-9_1
- [9] J.-L. López-Javaloyes, A. Real-Fernández, J. García-Sigüenza, F. Llorens-Largo, R. Molina-Carmona, “Tools to Support the Design of Network-Structured Courses Assisted by AI,” in *Learning and Collaboration Technologies*, Cham, 2024, pp. 53–64, Springer Nature Switzerland.
- [10] A. Wolff, Z. Zdrahal, A. Nikolov, M. Pantucek, “Improving retention: predicting at-risk students by analysing clicking behaviour in a virtual learning environment,” in *Proceedings of the Third International Conference on Learning Analytics and Knowledge*, New York, NY, USA, 2013, pp. 145–149, Association for Computing Machinery.
- [11] A. Real-Fernández, F. Llorens, R. Molina-Carmona, “Smart Learning Model Based on Competences and Activities,” in *Innovative Trends in Flipped Teaching and Adaptive Learning*, IGI-Global, 2019, pp. 228–251, doi: <https://doi.org/10.4018/978-1-5225-8142-0.ch011>
- [12] A. Real-Fernández, “CALM: un modelo de aprendizaje personalizado y adaptativo,” 2022.
- [13] J. García-Sigüenza, A. Real-Fernández, R. Molina-Carmona, F. Llorens-Largo, “Two-Phases AI Model for a Smart Learning System,” in *Learning and Collaboration Technologies*, Cham, 2023, pp. 42–53, Springer Nature Switzerland.
- [14] J. L. López-Javaloyes, L. López-Mira, C. R. Constán-Nava, A. Real-Fernández, “Monitoring tools for the Khipulearn smart learning platform,” 2024.
- [15] S. S. Shapiro, M. B. Wilk, “An Analysis of Variance Test for Normality (Complete Samples),” *Biometrika*, vol. 52, no. 3/4, pp. 591–611, 1965.
- [16] R. Martínez Ortega, L. Tuya Pendas, M. Martínez Ortega, A. Pérez Abreu, A. M. Cánovas, “El coeficiente de correlación de los rangos de Spearman, caracterización,” *Revista Habanera de Ciencias Médicas*, vol. 8, no. 2, 2009.



Alberto Real-Fernández

Lecturer at the University of Alicante, in the Department of Computer Science and Artificial Intelligence. PhD in Computer Science (University of Alicante, 2022). He is the technical director of AdaptLearn project, within the UniDigital plan, whose objective was to develop a smart learning platform based on AI (Khipulearn), as a collaborative and open tool between different universities. Is one of the

authors of CALM, the learning model this platform is based on. His main researches and publications are focused on smart learning systems, learning models, students and activities characterization and AI applied to education.



Patricia Compañ-Rosique

She has a PhD in Computer Science (University of Alicante, 2004). Since 1994 she has been working as a lecturer in the Department of Computer Science and Artificial Intelligence at the University of Alicante, where she is a full professor since 2008. She has held positions of leadership and management since she joined the University of Alicante: Deputy Head of Computer Engineering of the

Polytechnic School (2009–2012) and deputy director of the Polytechnic School (2012–2013). She has taught various subjects throughout her teaching career, especially computer programming and artificial intelligence. Her research lines are within the application of AI techniques: evolutionary algorithms for solving mathematical problems and neural networks applied to coastal engineering problems. Furthermore, she works in game development and the application of digital technologies to education.



Juan Luis López-Javaloyes

Graduated in Technical Engineering Telecommunication of Sound and Picture (University of Alicante, 2012), in Multimedia Engineering (University of Alicante, 2017), and with a Master's degree in Software Development for Mobile Devices (University of Alicante, 2021). He has participated in several research and development projects related to adaptive learning technologies and digital

platforms. In the AdaptLearn project, within the UniDigital plan, whose objective is to develop a smart learning platform based on AI, as a collaborative and open tool between different universities, he worked on the conceptual and technical development and maintenance of the Khipulearn platform, focusing on database design, feature implementation, and system integration. He also contributed to the *Guerra e Historia Pública* project, designing and implementing a digital collaborative platform. His main interests include adaptive learning systems, software development for web and mobile environments, and educational technologies.



Rafael Molina-Carmona

Professor of Computer Science and Artificial Intelligence of the University of Alicante. PhD in Computer Science. Former Director of department of Computer Science and Artificial Intelligence (2008–2012). Current Vice Rector for Digital Transformation at University of Alicante. Coordinator of the Smart Learning Research Group. Research interests on the applications of Artificial Intelligence to different fields:

computer aided design and manufacture, computer graphics, learning, creativity, information representation and IT governance.



Faraón Llorens-Largo

Professor of Computer Science and Artificial Intelligence of the University of Alicante. PhD in Computer Science. Director of the Polytechnic School (2000-2005) and Vice-rector of Technology and Educational Innovation (2005-2012), both at the UA and Executive Secretary of the ICT Sector Commission of the CRUE (2010-2012). His work is in the fields of artificial intelligence, adaptive learning, gamification and video games, IT governance and digital transformation of educational institutions.