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Academic engagement and management of personalised active learning in higher education digital ecosystems

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Abstract
The flexible, changing, and uncertain nature of present-day society requires its citizens have new personal, professional, and social competences which exceed the traditional knowledge-based, academic skills imparted in higher education. This study aims to identify those factors associated with active methodologies that predict university students' learning achievements in a digital ecosystem and thus, optimize the learning-teaching process. The teaching management tool Learning Analytics in Higher Education (LAHE) has been applied to a 200-student non-probabilistic incidental sample spread over 5 different university courses, enabling a personalized learning-teaching process tailored to the needs of each group and /or student. Based on a pre-experimental design without a control group, an analysis through decision trees based on educational data mining has been undertaken on the predictive potential of the active methodologies employed, and their effects on students' learning achievements. The criterion variable of the study was the final exam grade, and the explanatory variables included student characteristics, indicators of the teaching–learning process and non-cognitive factors. Results show that factors associated with active methodologies correctly predict a significant portion of the learning achieved by students. More specifically, the factors that have the greatest impact on learning are those related to academic engagement and to a student continuous learning process.

Keywords Active learning · University education · Digital society · Educational innovation · Academic engagement · Educational data mining

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1 Introduction

Different actors -civil society, companies, the European Union- are calling for an integrated vision of people in society, pivoting on psycho-socio-political capabilities as an element of possibility for a sustainable future at all levels (Amaya et al., 2021; Brandenburg et al., 2020).

The university must play a decisive role in this new scenario by providing global educational responses to citizens and professionals who will face global challenges (Massaro, 2022; Moscardini et al., 2022), consequently, university education is fully immersed in a process of transformation in which many elements converge: pedagogy, professional training, and knowledge transfer, among others.

University education must foster learning to be more effective, efficient, and attractive (Singh & Miah, 2020) assuming that technology is a driver of university transformation (Goh et al., 2020). Otherwise, the institutional challenges that the university faces are far-reaching; jobs that require new professional competencies, mobility (geographic and between specialties) and the unwieldy mindset of universities in adapting to new professional profiles (Benito Mundet et al., 2021) are the most important. In addition, professionals must think critically and have the necessary skills to gather data and interpret them according to the changing contingencies of the environment and the new needs of the firm -mostly still undefined- to make decisions that maximize value generation in their personal, professional, and social environments. Finally, the pandemic has accelerated the university transformation process, highlighting, in general, that online teaching is not at the same level as face-to-face, and that many universities are not strategically prepared to offer quality education under such contingencies (Gavesic, 2020).

Currently, the learning process has several critical success factors, as such as, new interdisciplinary concepts or new technological realities (Alé-Ruiz & Earle, 2020; Bonami et al., 2020). Hwang and Choi (2016) and Massaro (2022) go further, and state that the University must enable today's students to take on global leadership roles in the future.

Thus, it is essential to consider what are the multiple personal and professional competencies demanded by the labour market, and that are also essential for the adequate performance of people in society as digital citizens capable of exercising civic leadership (Tenuto, 2021) and to do so in accordance with lines of research suggested in the literature on virtual learning environments (Flavin & Bhandari, 2021) to include them in the teaching–learning process of university students.

The main objective of this study is to identify the factors associated with active methodologies, implemented in a digital teaching–learning ecosystem, that predict the level of learning achieved by university students. For this purpose, the Learning Analytics in Higher Education (LAHE) teaching management tool is used, a tool specifically designed for its application in digital educational ecosystems.

There are two fundamental axes of this work, which expressed as research questions are:

Q1: Is it possible to create a predictive model, based on the decision tree technique, with a good fit?
Q2: What are the main factors, associated with active methodologies, that predict the level of learning of students in a digital teaching–learning ecosystem?

1.1 State of the art

In the current teaching–learning process there are new elements and approaches. There are also new actors: companies, professionals, and society. In addition, university education must equip students with skills that will enable them to generate personal, professional, and social value throughout their lives, skills whose benchmark must lie in employability and the full exercise of the status of digital citizen. Consequently, any educational model, pedagogical framework or university syllabus must include aspects related to knowledge, and also to the production and access to distributed knowledge, meta-learning approaches, use of open educational resources, problem-based learning, gamification, active learning, digital portfolios, student and teacher mobility, flexible learning and skills and values (Benito Mundet et al., 2021; Brandenburg et al., 2020; Fadel & Groff, 2019; Guàrdia et al., 2021; Hamzah et al., 2022; Hwang & Chien, 2022; Vânia et al., 2023). Therefore, any teaching management tool should be able to operationally envisage them.

1.1.1 Competences-Technology: Educational innovation and intelligent education

Competences-Technology is a core binomial in the current teaching–learning process. This binomial presents challenges and opportunities that arise from the combination of the digital era and education. We understand competence as the student's ability (which implies possessing the cognitive structure that supports it) to perform tasks and participate in various situations of political, social, and cultural life in an effective and conscious way, adapting to a given context, so it is necessary to mobilize attitudes, skills, and knowledge, orchestrating and interrelating them. As for technology, we consider it as a vehicle for competencies in the teaching–learning process (Hwang, 2014).

Combining the above aspects and focusing them, we assert that educational innovation entails making changes in the teaching–learning process to improve student learning outcomes. We think, in line with Baumann et al. (2016), that, in order to achieve these improvements, any educational innovation must be adopted in a holistic and inclusive manner. Ramirez and Valenzuela (2020) propose a general framework for the development of educational innovation under the above prism, defining four categories of innovation: psycho-pedagogical studies, use and development of technology in education, educational management, and socio-cultural environment: elements confirmed in subsequent works (Johnson et al., 2020).

Smart education is identified in the literature (Yoo et al., 2015) as the compendium of learner-centred, personalized, adaptive, interactive, collaborative, context-dependent, and ubiquitous learning. These aspects are affirmed by Li and Wong (2021a) in their comprehensive review on the use of smart learning in the decade

2010–2018. Technology and smart education mediated by competencies (Guàrdia et al., 2021), are not only at the epicentre of development and change in higher education but are the key players in many of the challenges, associated pedagogical practices and trends in university education today, which must crystallize in a digital educational ecosystem for their successful practical application, as described by Gros (2016).

1.1.2 Learner-focused learning—Personalised learning

There is extensive literature on the need to place the learner at the core of the teaching–learning process and the impacts it entails. The role -active and leading- of the learner in this process is redefined. The multiple facets of this Copernican turn are brought together under the generic meaning of active learning, an umbrella concept, which generates advantages from exposing students to complex realities and real problems that activate their knowledge, skills, energy, dedication, and commitment. These advantages are seen as positive by students and teachers (Crisol-Moya et al., 2020), confirming that active learning is more about cooperation than competition.

There is also consensus that digital learning environments offer possibilities for immediate feedback, time-based student progress reports and the application of short- and long-term reward mechanisms that motivate student progress and self-regulation in their learning (Hernández Rivero et al., 2021; Lucieer et al., 2016; Theobald et al., 2020). Equally important is the role of the generation and use of learning analytics and associated tools for their practical application in the management of the teaching–learning process, helping, for example, the early identification of students at risk of failure, the satisfaction of students' personal needs in relation to their learning, and the adaptation of teaching activities to changing realities (Tsai et al., 2021).

Personalized learning is another vector of change in university education (Li & Wong, 2021b), beyond the many definitions of the term and its pros and cons (Groff, 2017). Customization focuses primarily on the use of technology as a vehicle for teaching and learning. Its impact on learner performance, increased motivation, academic engagement and satisfaction are its main benefits. The theoretical concepts and latest trends in personalised learning are described by Walkington and Bernacki (2020) and best practices, relevant case studies and key elements of success are reported in Cheung et al. (2021).

This pairing leads to several important impacts. The increased use of automatic response systems (Li & Wong, 2020) is the first. These authors also highlight the symbiotic relationship of these systems with learning analytics and the measurement of learner cognition.

Learner cognition is the second impact of this pairing. Cognition is particularly enhanced by using gamification methodological strategies. Gamification, necessarily learner-centred, has a favourable perception on learners if it is properly designed (Pegalajar, 2021). Otherwise, authors such as Dascalu et al. (2016) refer to the positive effect of gamification on the development of skills that favour the employability and later working life of students, such as creativity, problem solving, teamwork, discovery learning and decision making. Positive contributions of gamification on academic engagement (Sánchez-Martín et al., 2017) and on the increased meaningfulness of learning (Fernández Gavira et al., 2018) are also reported in the literature.

1.1.3 Academic engagement

Purely regarding the academic context, Christenson et al. (2012) identify academic engagement with the involvement and active participation of the learner in the learning process. Dynamicity, dynamism as a prominent characteristic of academic engagement, was later introduced (Picton et al., 2018). Academic engagement is thus something that is being done and includes teaching practices, student behaviours and elements that relate to student achievement and satisfaction, both during their time at university and in their lifelong learning. Academic engagement is also closely related to cognitive, affective, and motivational elements that teachers must assess—in terms of effectiveness and efficiency—in their teaching (Schnitzler et al., 2020).

Academic engagement is a multidimensional construct (Kahu, 2013; Rodríguez-Izquierdo, 2020) that changes according to the stages of the learner's life, their biopsychosocial development and the experience lived in the institution where they learn (Lam et al., 2016).

The literature also shows a pair of interesting aspects: firstly, academic engagement has a huge impact on the academic results achieved by students (Chipchase, et al., 2017); secondly, academic engagement is lower in non-face-to-face classes compared to face-to-face classes (Farrell & Brunton, 2020).

2 Material and methods

2.1 Design, participants and data collection

Based on a quantitative paradigm, a pre-experimental design (Campbell & Stanley, 1963) without a control group was applied. From a population of undergraduate Social Sciences students during the 2020–21 academic year, a non-probabilistic accessibility sample of 200 students from the Universidad Francisco de Vitoria (Madrid) was obtained in the following subjects:

- Introduction to Business ($n = 30$)
- Business Organisation and Administration I ($n = 69$)
- Business Organisation and Administration II ($n = 101$, three groups of different degrees).

The teaching–learning process in the five groups was developed in face-to-face teaching mode.

The information was collected using a computer tool for managing the teaching–learning process: the LAHE tool. All individual and group events and performances of the students were recorded in this tool. This information was extracted and a database with a total of 36 variables was generated:

- Final exam grade (criterion variable).
- General student and subject data: student assessment regime, type of student assessment, etc.
- Awards: total number of awards obtained, commitment award, regularity award, success award, personal growth award.
- Quizzes: number of quizzes completed by the student and grade for each quiz.
- Short tasks: score on each of the six short tasks in the course.
- Extensive assignment: score on the extensive course assignment and 360º peer feedback score
- Attendance: percentage of attendance and absences, both approved and unapproved
- Supplementary assignments: number of assignments handed in and grades obtained
- Expected grade: minimum and maximum grade expected by the student.
- Discretionary mark: extraordinary award achieved for outstanding performance
- Grade obtained in the mid-term examination

A non-random distribution of missing values was considered, and it was decided to include them as a separate category in each variable. Thus, all quantitative variables were categorised into four groups, using the distribution's thirds:

- Non-response
- Low score (bottom third)
- Medium score (second third)
- High score (highest third)

Certain activities (awards, quizzes, etc.) were present only in some subjects. In these cases, a new category was included in the corresponding variable to differentiate non-response (subjects not delivering the activity) from non-availability of the activity (subject matter in subjects where the activity was not included).

2.2 Learning Analytics in Higher Education (LAHE), a digital tool for teaching–learning management

The digital teaching management tool LAHE (V. 6.0) has been designed and implemented for application in the university teaching–learning process with active learning methodologies in digital ecosystems (Alé-Ruiz & Earle, 2020). It collects data from various sources with sufficient flexibility to meet any teaching needs. Its design is modular and scalable to meet future educational needs and functionalities.

Some of the elements it allows to define and use are:

- Independently configurable assessment regimes (continuous, extraordinary, personalised, etc.).

- Student type categories (delegate, academic waiver, etc.).
- Class modalities (seminar, gaming, guest lecturer, etc.).
- Exam modalities (ordinary, extraordinary, etc.).
- Challenges: independently configurable (problems, case studies, research proposals, etc.).
- Quizzes (individual, team, etc.). The tool interacts automatically with Socrative platform.
- Short and long tasks: the tool randomly defines the desired number of teams, assigning a leader per team.
- 360° peer assessment configurable for any activity carried out by the learners.
- Rewards ("prizes"): independently configurable motivational elements, designed following the remuneration pattern used in companies. Those applied in this work are:

  (1) Commitment award: no more than X unapproved absences during the course.
  (2) Regularity award: average grade in questionnaires > = X with a minimum % of questionnaires completed and a grade per questionnaire > = Y.
  (3) Success award: Z top students in a summative assessment at different moments in time of the course.
  (4) Personal growth award: summative assessment mark > = X at different moments in time of the course, with Y% growth between moments (with minimum mark > = Z at the first moment in time).

- Discretionary mark: awarded by the teacher for outstanding performance during the course.
- Attendance (attendance, approved absences, unapproved absences).

The elements described above make up most digital university teaching ecosystems applied in active learning.

2.3 Data processing and analysis

An initial univariate exploration of the original (non-categorised) variables was carried out using the free software JASP (V.0.14.1.1) and Microsoft Excel.

After categorisation of the relevant variables, the decision tree was computed. For this purpose, the free specialised data mining software Weka (V.3.8.5) was selected. Given that it is an appropriate algorithm for categorical variables that promotes the obtaining of simple and easily construed predictive models (Martínez-Abad et al., 2020), the J48 algorithm (Quinlan, 1992; Witten et al., 2017) was used. To reduce the size of the tree and to obtain a parsimonious and easily interpretable model, a minimum of 10 elements per final leaf was established.

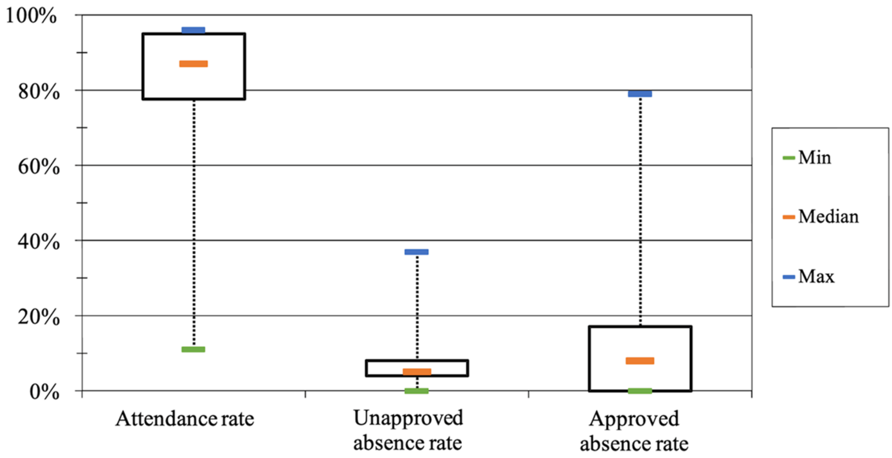

Fig. 1 Distribution of rates of attendance and non-attendance

3 Results

3.1 Descriptive exploration

The attendance rate is high (Fig. 1), which is indicative of the commitment shown by the students. It is important to note that the rate of student achievement is high: commitment (70.7%), regularity (81.2%), success (73.5%) and growth (73.5%). Despite this, a large proportion of absences are unapproved (Average = 18.2%, P75 = 17%).

In addition, 15% of students receive an additional discretionary mark for particularly positive participation or attitude. These rewards can amount to 0.1 points (1.5% of students), 0.2 points (1.5%), 0.3 points (3.5%), 0.4 points (2%) or 0.5 points (6.5%) on the final mark, depending on the achievement.

Table 1 shows how the overall response rate to the questionnaires is above 80%. In fact, there is little fluctuation in the response rate between questionnaires, all of them being above 70%. Students therefore achieve a high level of regularity. In terms of marks, most students (more than 75%) obtain a mark of 50 points or higher in almost all questionnaires, although the general standard deviation is high. Moreover, the completion rate of the mid-term and final exams is at high levels (above 80%), with lower average marks and higher variances.

Table 1 Questionnaires carried out. Descriptive statistics

	Median	S_x	P_{25}	P_{50}	P_{75}	% Resp.
Mid-term review	6.55	2.48	6.00	8.00	8.00	81.9%
Final examination	4.47	2.39	2.78	4.00	6.00	84.0%
Nr. of questionnaires completed	3.14	2.18	1.50	2.70	4.50	84.5%

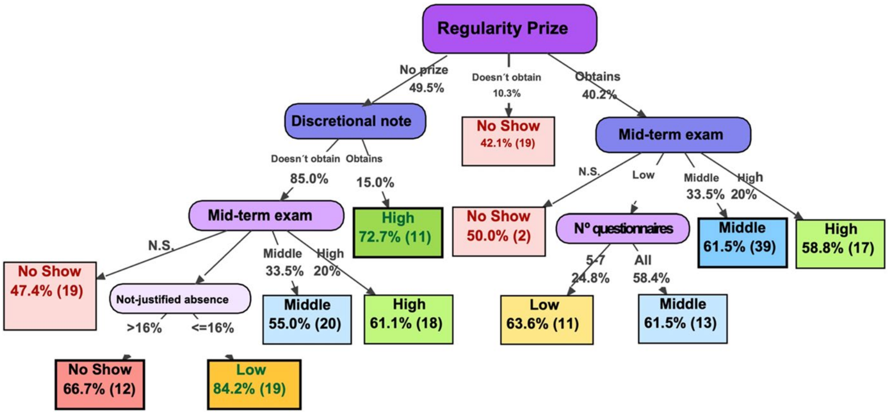

Fig. 2 Final decision tree

3.2 Predictive model: Decision tree

A model with 17 branches and 12 leaves is obtained. Furthermore, in relation to the base model (accuracy = 31%), the level of accuracy of the model obtained is 60.5%. Given that the base accuracy level is doubled from a reduced size model, we can affirm that the model is parsimonious and with an acceptable global fit.

Figure 2 shows the decision tree obtained. The ellipses represent the predictor variables that divide the sample, and the rectangles represent the final leaves. Each leaf indicates the predicted category (No performance; Low performance; Medium performance; High performance) in the criterion variable (performance in the final exam) for the included students; the % accuracy of this prediction and the number of students included in that branch. The leaves of each of the four categories with the highest accuracy levels are also highlighted.

The factor with the greatest impact on the final exam score is the regularity of the student. It should be recalled that this factor, listed as a "prize", was awarded to students with a minimum average mark, both overall and on each questionnaire, and who had completed a minimum number of questionnaires in the course.

While the prediction for the approximately 10% of students who did not receive a regularity award (20% of the total number of students whose subjects included this award) is that they will not sit the final exam (a prediction with low accuracy), most students who get this award predict average or high scores (69 of the 82 who go down this route). In this group, performance in the mid-term exam is the most relevant predictor: students with low scores in the mid-term exam predict low or medium scores in the final exam, based on whether they have completed all the questionnaires or not; and students with medium or high scores in the mid-term exam predict the same level on the criterion variable. The accuracy levels of these predictions remain at acceptable values of around 60%.

In the case of subjects without a regularity award, the most discriminating variable is the discretionary mark. Those students who obtain this reward predict high performance (with an accuracy of over 70%). Therefore, it seems that the

Table 2 Confusion matrix decision tree

		Prediction				Total
		No show	Low s	Medium s	High s	
Final Review Score	No show	25	4	1	1	31
	Low score	10	35	8	4	57
	Medium s	11	7	32	12	62
	High s	4	6	11	29	50
Total		50	52	52	46	200

detailed student monitoring enabled by the LAHE tool provides the teacher with reliable information on student performance, which is clearly related to the level of knowledge and competences that the student is achieving. For students who do not receive a discretionary mark, the mid-term exam is again the best predictor of their final performance, with a similar distribution to the group obtaining the regularity award. In this case, the biggest difference in those students who obtain low marks is in the mid-term exam: while those with a percentage of unapproved absences below 16% predict low performance, those with more unapproved absences are likely to miss the final exam. Both predictions have high levels of accuracy. The high prediction accuracy of the 19 students with lower levels of unapproved absences, almost 85%, stands out. Therefore, students who during the course show the above indicators most likely obtain a low level of performance.

The confusion matrix (Table 2) shows how the prediction is mainly located on or near the main diagonal, with fewer cases observed at the extremes of the secondary diagonal. This indicates that, while correct predictions are achieved in a good proportion of the cases (61.8% of the total), incorrect predictions are placed close to the scores of the criterion variable. For example, although incorrect prediction of high scores occurs in 17 of the 46 cases, 12 of these incorrect assignments predict average performance, with the model predicting only five students with low scores or no-show students.

In the case of the prediction of no-show students, although the accuracy is at low levels (50%), we can observe that the model is able to detect almost all the no-show students (25 out of 31), predicting low scores for four of the six incorrect detections.

Table 3 presents the levels of adjustment of the model. The relative error is reduced by almost 30% with respect to the base model and the area under the

Table 3 Decision tree adjustment indexes. Base model and final model

		TP	Precision	ROC	Kappa	EAR
Base model. ZeroR (Average fit)		0.310	0.310	0.484	0	100.00%
Final model	No-show	0.806	0.500	0.892	–	–
	Low score	0.614	0.673	0.821	–	–
	Medium score	0.516	0.615	0.783	–	–
	High score	0.580	0.630	0.826	–	–
	Average fit	0.605	0.618	0.822	0.265	72.1%

ROC curve reaches considerable levels (more than 80% overall), although the Kappa statistic obtains limited levels. While the accuracy levels are significantly lower for the prediction of students who do not sit the exam, the highest accuracy is found when predicting students who achieve lower marks in the exam.

4 Discussion and conclusions

The results found in this study show that the objective has been achieved. Regarding the first research question (Is it possible to create a predictive model, based on the decision tree technique, with a good fit?), it is in fact as we shown, possible to use the decision tree technique to predict, with good fit, the academic success of students.

Regarding the second of our research questions (What are the main factors, associated with active methodologies, that predict the level of learning of students in a digital teaching–learning ecosystem?), the digital educational ecosystem –made up of elements characteristic of active learning, adapted to a highly changing and volatile environment– focused on the learner has proven to be effective in achieving university student performance objectives, as well as in the development of skills. The practical implementation of this digital ecosystem has been carried out assuming: the catalytic role of technology (Goh et al., 2020), the sheer magnitude of the challenges facing the university (Collie et al., 2017) and an efficiency-enhancing orientation of the teaching–learning process that also makes it attractive to the learner (Singh & Miah, 2020). The aim was not only to optimise student results, but also to develop professional skills (Benito Mundet et al., 2021) based on the redefinition of the roles of the learner and the teacher (Bonami et al., 2020). This digital ecosystem has made it possible to incorporate the new elements, approaches and actors present in university education into the educational process (Fadel & Groff, 2019; Tharwat & Schenck, 2023) with positive results. In this sense, and answering the second research question, the analysis of the data collected with the LAHE teaching management tool shows that there is a clear direct relationship between the academic results obtained by the student and the development of other essential professional and personal skills, but with a more transversal nature, for example the assumption of a personal commitment and regular effort throughout the teaching–learning process.

Educational innovation (Guàrdia et al., 2021) and "smart education" (Hwang, 2014) –understood as the conjunction of a digital ecosystem and an active learning methodology– provide a robust conceptual framework for its practical implementation, in line with a holistic and inclusive vision of education (Baumann et al., 2016). Such educational innovation must it be done applying an academic framework that includes: the characteristics of smart learning (Yoo et al., 2015), comprehensive review of its elements (Li & Wong, 2021a), personalisation (Li & Wong, 2021b; Walkington & Bernacki, 2020), interactivity (Hernández Rivero et al., 2021; Zamora-Polo & Sánchez-Martín, 2019) and gamification strategy (Pegalajar, 2021). The analysis of the data shows that the adaptation to the socio-economic context of the teaching–learning process, the collaboration and the ubiquity that a digital ecosystem allows, make a positive contribution to both the outcome and the significance of university student learning (Crisol-Moya et al., 2020; Fernández Gavira et al., 2018). This positive contribution is quantitatively confirmed by the results obtained in the decision tree, highlighting the factors of the teaching–learning process that can predict student learning with acceptable levels of accuracy.

Immediate feedback (Li & Wong, 2020), time-spaced learning progress reports and "prizes" –reward and motivational mechanisms– (Hernández Rivero et al., 2021) favour achievement, both in results and in the development of student skills, having contributed value to student learning. In this regard, it is important to highlight that academic engagement (Christenson et al., 2012) is also favoured by the use of multiple academic activities with different timeframes, placing value on the dynamicity (Kahu & Nelson, 2018; Picton et al., 2018) and multidimensionality of this educational concept (Gil-Fernández et al., 2023; Rodríguez-Izquierdo, 2020). The results obtained in this work abound in this issue, stressing the importance of monitoring and managing the teaching–learning process, in order to be able to make an early detection of strengths and weaknesses in it, both at an individual and group level.

Real-time analysis of student learning data enables early identification of potential failures for individual and group corrective action (Tsai et al., 2021). It also allows for positive motivation of students' performance towards excellence. In this sense, the LAHE tool, as a complement to the learning management systems commonly used in higher education (e.g., Moodle), allows for a more detailed, personal and comprehensive control of student learning (Alé-Ruiz & Earle, 2020).

Data availability The datasets generated and/or analysed during the current study are not publicly available due to privateness but are available from the corresponding author on reasonable request.

Declarations

Disclosure statement The authors report there are no competing interests to declare.

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