Activity and Dropout Tracking in Moodle using UBUMonitor application

Yi Peng Ji, Raúl Marticorena-Sánchez, Carlos Pardo-Aguilar, Carlos López-Nozal, Mario Juez-Gil

Abstract— **Teaching with online learning platforms should simplify the monitoring of students' activity, particularly when evaluating student dropout. Popular learning environments such as Moodle should implement visual analytic tools that facilitate such tasks, nevertheless, institutions are usually reluctant to incorporate them. This paper presents UBUMonitor, a desktop application that allows the visualization of student's activity data, extended as a proof of concept with a module for dropout tracking. Therefore, by using UBUMonitor, teachers will be able to easily visualize their students' engagement with their subject, which can facilitate early action to prevent students from dropping out more effectively.**

Index Terms—**dropout, logs, monitoring, Moodle, teaching-learning, visual analytics**

I. Introduction

LEARNING Management Systems (LMS) are at the top of the list of computer-based educational systems [1]. In particular, Moodle (Modular Object-Oriented Dynamic Learning Environment) is one of the most widely used LMS in use nowadays. Like other LMS tools, Moodle is gathering a large amount of data, including all grades and interactions of the participants. These data allow the applicability of a full set of Learning Analytics (LA) techniques. Managing courses with thousands of records makes the need for specialised LA tools evident.

Thus, the relevance of LA is a fact. It is impossible to ignore these techniques as something fundamental embedded in the learning process and in higher education, to manage learning improvement actions [2]. The number of works focusing on their applications has increased as reported in [3] and in previous works [1], [4]. In particular, Computer-Supported Visualisation Analytics (CSVA), as an integral part of LA, has a relevant role, which is not always properly considered. According to [3], the percentage of work in this CSVA field is not as large as in the other areas of LA (9.5%) and there is a need for tools that enable more efficient visualisation to improve the teaching-learning process [4]–[6].

From a thorough study of LA dashboards [7], it can be observed that they are generally more learner-oriented, and to a lesser extent teacher- and administrator-oriented, because the main focus is on students' self-regulated learning. In general, the use of bar charts is predominant in terms of the visualisations being used.

As a particular case study, it should be noted that Moodle does not include visual learning analytics functionality in its core modules. There are functional extensions to Moodle-based plugins that support the visual exploration of student activity and performance. But the decision to make a new extension available to teachers depends on multiple factors in the academic institution: size, organisation structure, economics, etc., which are beyond the scope of the teacher's decision-making. This is more noticeable from the particular point of view of monitoring dropout in Moodle, the main objective of the present work, as it offers few visualisation solutions at present.

The problem of dropout in university education is widespread worldwide. Consulting sources such as [8], it can be seen that the costs associated with dropout are enormous (i.e., 3.8 billion US dollars per year). Specifically, the dropout rates in the Spanish-speaking population reflected in this publication are 21% in two-year studies and 40% in four-year studies.

The interest in dropout studies, particularly in Latin America, can be endorsed in systematic reviews such as [9], where an increase in studies on this particular topic is noted in recent years. This highlights the problem of the high dropout rate and the economic effect this brings.

This problem has also been pointed out by the Spanish Ministry of Science and Universities [10]. Dropout rates stand at 21.5%, a figure that rises to 60% if the data are broken down into face-to-face and online teaching, and the focus is on the latter.

Universities have tried or are trying to tackle this problem. They usually take a general view of the institution as a whole, with the use of dashboards that provide an overall view of the current dropout rate in the degree programmes.

However, as pointed out in [11], dropout can be defined from different scopes: dropout of a subject, of the semester, of the course, and even of the degree. Or it can focus on a particular case, such as dropping out in the first year, which is usually the most critical.

In this particular line in Moodle, from version 3.4, the

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learning analytics module was incorporated into its core development (called Analytics[1]). Through the use of machine learning techniques, a dropout prediction can be given, based on the knowledge already acquired in previous courses. However, the responsibility for installing modules such as Analytics, which provide additional functionality to the LMS, falls on the educational institution [12]. Normally, such changes can present bureaucratic, technical and economic problems in terms of installation and version upgrades. As a result, institutions may be reticent to change [13] and will not always allow functionality to be added to the core of their LMS to facilitate teacher tasks such as visual and descriptive tracking of student dropout.

This work is an extension of our previous work [14], where the first proof of concept of the UBUMonitor application was proposed, regarding the visualisation in relation to grades and records to monitor student activity and performance. In this new work, a version of the software is presented that extends the visualisation of logs on new aspects (from 2 to 11 visualisations). The interest in using logs as an indicator of student engagement has been highlighted in other work [15] from the point of view of the advantages of being minimally disruptive, scalable and allowing analysis at activity or resource level. In addition, the main contribution of this work, with respect to the previously published one, is the inclusion of a new module with 5 new charts, for tracking potential dropout from a temporal perspective. This provides an improved visual learning analysis application on Moodle, which also allows the monitoring of the activity and the visualisation of the evolution of the possible dropout that occurs in the subjects. Knowing the risk of dropout will be of great interest to the teacher, who is responsible for carrying out a teaching-learning process that maximises the student's opportunities for success. Tools such as UBUMonitor make it possible to know this dropout risk at any time during the course, interpret it and compare it with other student information in order to be able to take corrective action, such as sending motivational messages, offering tutorials, or adapting the student's work experience team, among others. Each teacher, in each subject and group of students, will be able to take the corrective actions he/she feels appropriate. UBUMonitor is available to all teachers regardless of other decisions of academic institutions responsible for the administration of Moodle.

The rest of the paper is structured as follows. Sec. II describes the related work. Sec. III gives an overview of the presented software application, including its architecture and functionality. Sec. IV then describes proofs of concept applying basic-visual analysis on real pedagogical cases. Section V describes the new extension with the dropout module and its implementation. Subsequently, the evaluation data of the software application are shown in Sec. VI. Finally, in Sec. VII, we conclude and detail some lines of future work.

II. Related works

Some papers such as [16] have reviewed and enumerated LA tools with Moodle, giving an exhaustive list based on previous work [17], [18]. In the last 10 years in Spanish national conferences, there is a trend of using third party plugins, developing proprietary extensions and modules or developing plugins that interact with other servers/services. In the end, the focus is on the use of LA in [19], [20].

For data extraction and visualisation in Moodle, one of the most common references is GISMO [21]. It is a plugin that offers a graphical visualisation focused on students' activities in online courses. This work was extended in [22] in the MOCLog tool. This is a tool "*for the analysis and presentation of log data on a Moodle server*" [22]. In the case of GISMO, the latest available updated version is from 2014 for Moodle 2.x version. In the case of MOCLog, the latest version is from 2012. Other tools in the design of Moodle blocks, restricted to teachers, such as AAT (Academic Analytics Tool) [23], analyse student behaviour in an attempt to detect complex or confusing material.

In the dashboard category, there are plugins such as SmartKlass[2] and very complete commercial solutions (even multi-LMS) such as Intelliboard[3].

Similar work can be found with the Loop web application [24]. It coincides with some of the approaches of our work, to the best of our knowledge it offers a smaller set of visualisations, in particular in terms of dropout, and completely different architecture, with deployment requirements in the institution that is not always feasible. Its strength is that it includes integration not only with Moodle but also with Blackboard.

Very targeted commercial products focused only on dropout for multiple LMSs, such as Dropout DetectiveTM [25]. It requires server deployment and the granting of access and data hosting permissions to the provider for processing, which may raise certain legal and institutional data privacy issues.

After reviewing current work, we believe that UBUMonitor makes sense for those educational institutions that cannot invest in commercial solutions such as Intelliboard or Detective DropoutTM and that do not have development teams on their technical staff to maintain specialised plugins in their LMS. Our software is primarily designed for use by teachers in institutions where the ultimate responsibility for learning falls on them. In addition, these teachers have a high level of engagement with teaching within the LMS and would like to have learning analytics software that helps them to detect dropout problems and improve their pedagogical actions in teaching.

III. Solution approach

In Moodle, it is now possible to monitor student progress and activity using interaction logs and activity completion checks. Latest course access time data is also collected, and it is possible to cross-reference this time data with the latest access to Moodle. However, the plain text display of such data is not, in our opinion, the most appropriate way within the platform itself.

To advance in a solution, in this work we present

[1] https://docs.moodle.org/34/en/Analytics
[2] https://moodle.org/plugins/local_smart_klass
[3] https://intelliboard.net/

UBUMonitor. This is a desktop application for teachers, which once connected to their Moodle server, downloads and visualises the access data for their subjects. Although the most common solutions for adding functionalities to Moodle are plugins or blocks, as indicated above, their setup and maintenance depend on the institution and not on the teacher. To avoid any problems caused by this factor, which is common in institutionally managed LMSs [12], [13], our solution involves a desktop application that the teacher can install on his or her computer.

Using the classification criteria of [26], UBUMonitor belongs to the following context:

Target user: teacher or lecturer.

Learning scenario: formal learning.

Educational level: university.

Pedagogical approach: blended and online.

Granularity: learning objects in a course.

The taxonomy defined in [26] also allows categorising the proposed solution as a visualisation tool (learning dashboard). From this point of view, UBUMonitor has the following characteristics:

Purpose: third-party monitoring.

Data source types: action records (logs).

Platform (LMS): Moodle.

Types of indicators: actions (aggregated and de-aggregated); last access dates.

Indicator targets: individuals, groups and course.

Types of visualisations: bars, lines, kiviat, heat maps, stacked, boxplot, violin, bubbles, tables, and scatter.

Technology: Java, JavaFX, web services, web scraping, and JavaScript.

A. Architecture

The scheme of the software architecture is shown in Fig. 1. The teacher validates against the server, selects to download one of his or her courses, and a data extraction process is carried out with the web services available in Moodle or with web scraping. All communication with the Moodle server is encrypted by SSL/TLS and all local files are stored encrypted with the teacher's key, using the Blowfish algorithm. For a detailed description of its installation and use, it is recommended to consult the online user manual[4].

This software is open-source and free to use under the MIT license. With the latest version available for download from the GitHub[5] repository.

Most third-party tools focus on the progress and evolution of the subject as a whole. Although this global vision is very important, our solution is oriented towards a more particularised monitoring of the student or group of students, on the learning objects that are part of the design of a course in Moodle.

Therefore, UBUMonitor facilitates the teacher's work from the point of view of data treatment and processing, adding a suitable and simple, but at the same time useful and practical, visualisation for the students' learning analysis.

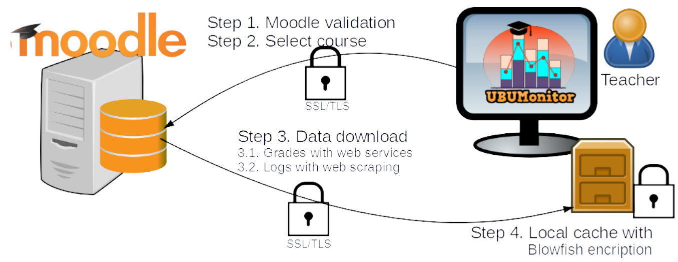


Fig. 1: Deployment architecture and interaction with UBUMonitor.

B. Functional description

UBUMonitor enables the extraction, loading and cleaning of Moodle access log data, linking this data with the structure of the modules that are part of the course, and with the currently enrolled users (students and teaching staff).

Fig. 2 shows the main window of the software, once the actual data of a subject has been loaded. On the left, the enrolled students are shown on the upper part and on the lower part are the panels with filters for logs, grades or activity completion. In the middle panel, the dynamic chart resulting from the selections is shown. In the example, a heat map illustrates the number of accesses to the subject, grouped by weeks. The time dimension (which can be discretionally changed) is represented on the X-axis and the selected students on the Y-axis. The intersection shows the number of matching logs (component accesses over time) using the criterion of assigning the highest value a deeper green colour and the lowest values a soft yellow colour. Proportionally to the numerical value, more or less intense colours are assigned in the palette. The colour red is used to show an absence of access. Students with many red cells reflect a total absence of accesses and show a certain risk of dropping out. The software allows to configure the colour palette and to adjust the maximum value.

The logs panel (see Fig. 3) allows the teacher to select four different filters: by type of component, type of event, section or module of the course. In log charts, advanced filtering is also applied which allows grouping the data temporally (e.g., days, weeks, months, etc.) and filtering only between certain dates. The charts calculate the maximum for scaling, but this value can be set later.

Depending on the previous selection, and on the set of students chosen, the following types of charts can be displayed:

Total: shows in a bar chart the total number of accesses to the selected course components of the user group.

Stacked bars: shows a stacked bar for each student, with the number of log entries according to the previous selection. If multiple course components have been chosen, according to the filter applied in the log panel, the bar is expanded by stacking the log entries for each course component. If several learners are chosen, they are displayed in the timeline paired together. An example is shown in Fig. 4.

Heatmap: shows the "heatmap" of accesses in a palette of colours from red (no logs) to deep green (maximum values) with yellow as an intermediate colour (see Fig. 2). It enables the comparison at a glance of the difference in access between students to the selected course components and in the time frame chosen.

[4] https://ubumonitordocs.readthedocs.io/es/latest/

[5] https://github.com/yjx0003/UBUMonitorLauncher/releases

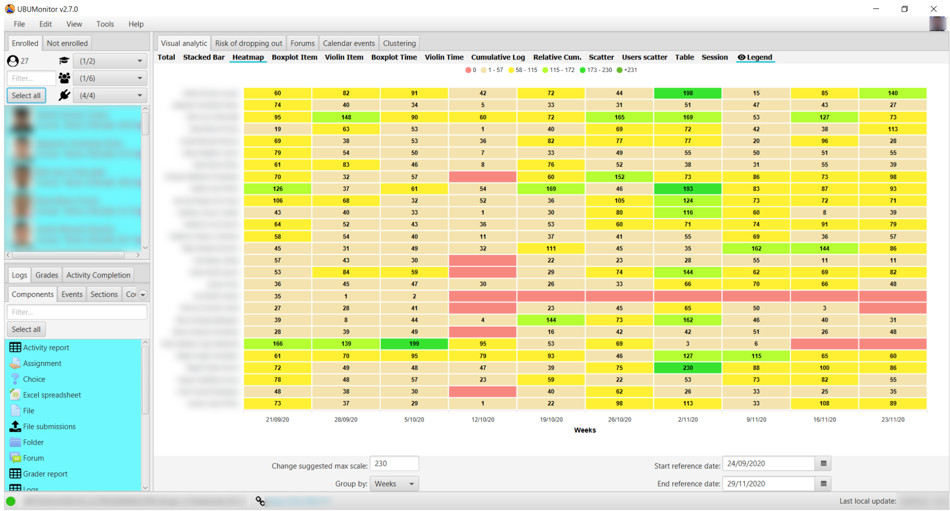


Fig. 2: UBUMonitor main view.

Boxplot Component/ Violin Component: show boxplot and violin plots with the accesses per selected course component. Fig. 5 shows an example of a violin plot generated with the number of logs on the quiz and task components.

Boxplot Time / Violin Time: show boxplot and violin plots with the accesses grouped by time unit of the group of users on the set of course components.

Scattering: shows a scatter plot over time, with the access of each user to the different course components chosen. As an example, Fig. 6 shows the time sequence of dispersion of student accesses to the quizzes of a subject.

User scattering: shows a scatter plot over time for each selected course item for the selected group of students.

Table: displays logs in a table, for filtering, sorting and searching.

Session: shows an estimate of the session time spent by each learner on the platform for the chosen components. Fig. 7 shows a stacked bar chart with this time estimate, for three different learners' accesses.

Cumulative: shows a cumulative line chart with the number of accesses for each student for comparison over time.

Relative cumulates: shows a line chart of cumulates relative to the mean of values as the X-axis. Fig. 8 shows the graph taking the mean as the baseline.

As can be seen, the wide range of views offered by the tool enables very different strategies to be applied when monitoring the activity of the students or group. In Sec. IV, some proofs of concept regarding its practical teaching use will be described.

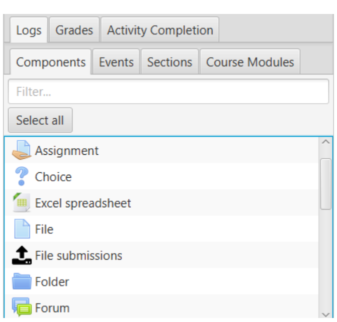


Fig. 3: Logs panel.

IV. Proofs of Concept in Teaching

This section presents two proofs of concept on visual learning analytics using UBUMonitor. Only log data are used to solve questions related to monitoring activity in group works, as well as checking the correct sequencing of learning. The student log data shown in this paper are from an actual university academic year in an undergraduate course.

A. Group works comparison

When comparing group works, it can be seen, based on the access logs, which students have a higher degree of involvement with the work.

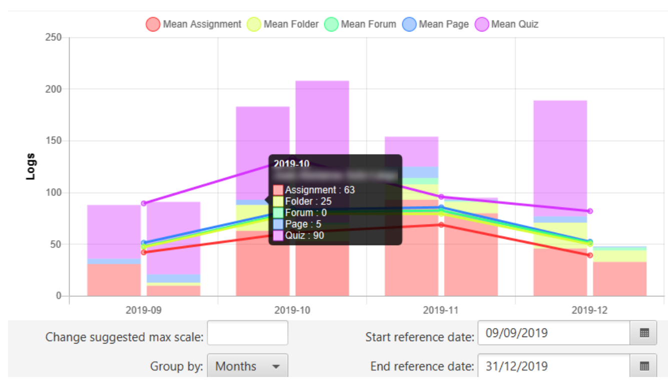


Fig. 4: Stacked bar chart of accesses by elements and students.

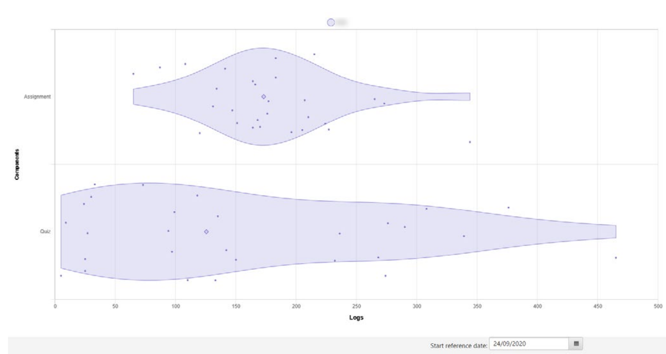


Fig. 5: Violin chart of accesses by elements.

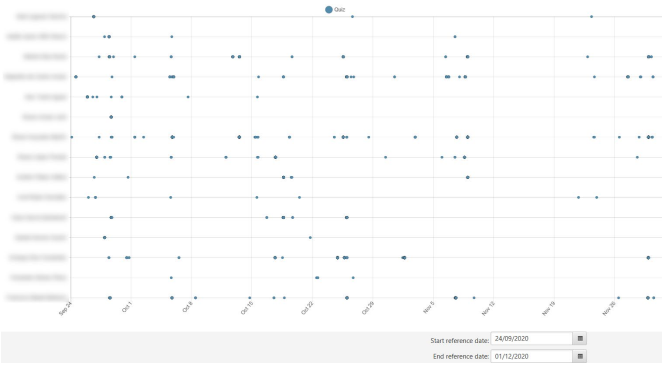


Fig. 6: Scatter plot.

Fig. 8: Cumulative accesses relative to the average.

Fig. 9 shows a comparison of the number of accesses of the two members of a working pair. In this first case, there is a similarity in the number of accesses, even with a similar access pattern over time. This shows balanced teamwork between the team members.

Nevertheless, in Fig. 10 it can be seen that the two team members have very different values for the access logs (i.e., one of them is clearly below the average), indicating that one of the members is probably doing most of the group work. This can also be checked with the heat map as well as with the session time data of both students.

B. *Learning sequencing*

The sequence of accesses along the time on the topics can be observed. In Fig. 11, the accesses of a student (with high performance in the subject) to the 7 topics that compose it are shown. Each colour corresponds to a topic, and it can be seen that the access is consistent with the planning intended by the teacher. However, it can be seen that topics 1 and 3 take longer than expected, suggesting a revision and reordering of activities and resources in the subject.

V. Dropout Tracking

The proposal of this work, integrated into the UBUMonitor application, provides visual feedback on student dropout in the course. Like other existing proposals, UBUMonitor shares the idea of anticipating dropout with a descriptive approach to facilitate early detection. The main difference between UBUMonitor, and other solutions, is that UBUMonitor provides a lightweight solution focused on the teacher and the subject, as opposed to global solutions that involve a great deal of administrative and regulatory effort in the institutional virtual environment.

A. *Available data about dropout in Moodle*

As we have already pointed out, Moodle is a platform oriented to the teaching-learning process, rather than being directly oriented towards monitoring student activity and dropout. Although the teacher can check the dates of the latest access to the subject by checking the list of participants or the student's profile, the user experience concerning the dropout control is not very adequate.

However, the following data are available:

- Date of the latest access to the course.
- Date of the latest access to Moodle.
- Course access logs.

The following is a description of the graphic indicators of dropout that can be generated through UBUMonitor and by correctly extracting, cleaning and processing the available data.

B. *List of categorized students*

The software allows to display the list of currently enrolled students and to colour them according to their last access to the subject as shown in Fig. 12. This, combined with other graphs already displayed (e.g., heat maps, stacked bar charts, cumulative accesses, etc.) on a particular student or group of students, allows detecting those suspected of being at risk of dropping out.

For the choice of colours, the current date and the number of days elapsed since the latest access to the course are taken as reference. Threshold values are defined according to the data calculated between [0, 3) days, [3, 7) days, [7, 14) days or [14, ∞) days, with their corresponding colours (i.e., green, blue, yellow and red). A period of two weeks is taken as a critical

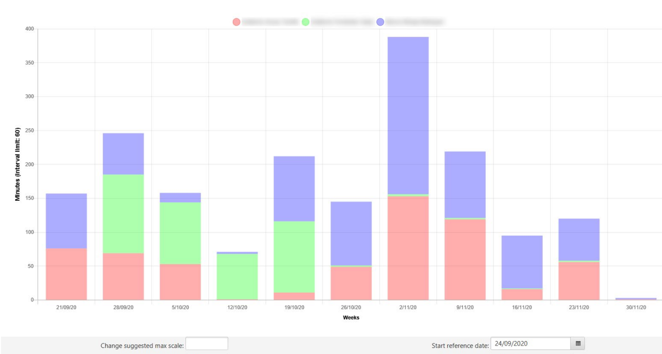


Fig. 7: Session time chart.

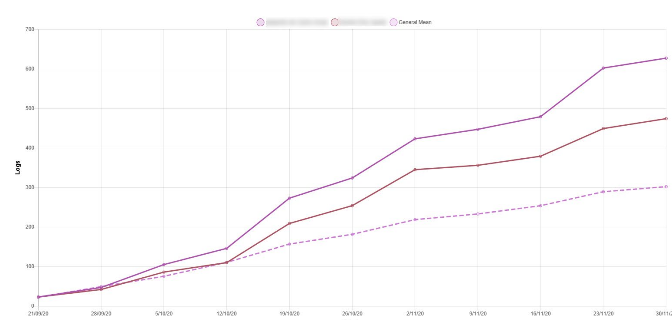


Fig. 9: Equivalent cumulative accesses in a working group.

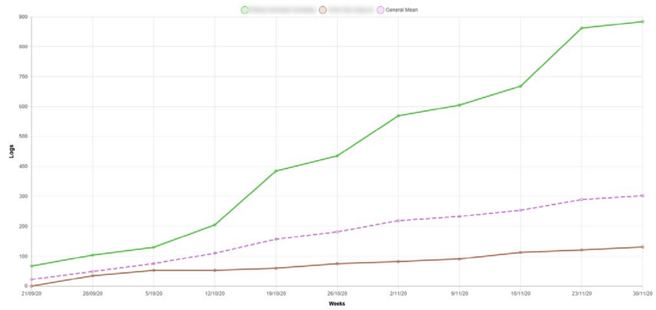


Fig. 10: Differentiated cumulative accesses in a working group.

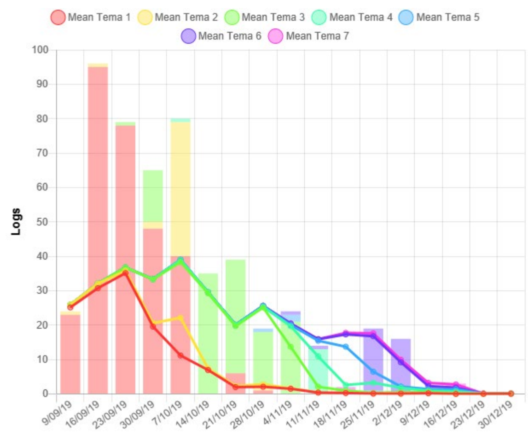


Fig. 11: Cumulative accesses relative to the average.

value, following the recommendations of the Moodle Analytics module. Additionally, the number of days elapsed since the latest access to Moodle is also shown for information purposes.

C. *Course risk*

The date and time of the latest access are recorded for each user of the platform. The teacher can check the list of participants in Moodle, and sort them in ascending or descending order by such date. Although this provides a partial view of the current situation, it has been thought convenient to add a global or summary view, in the form of a bar chart, using the previous categorisation based on the thresholds of the time elapsed since their latest access to the current date of the course.

In this way, the total number of students is broken down into their respective categories, with their corresponding colours. For each category or interval of days elapsed, a bar proportional in height to the number of students in the category is shown, and the number and percentage of students about the total are detailed, as shown in the example in Fig. 13. Additionally, by placing the cursor over a bar, a tooltip with the list of students in the category is displayed.

The ideal situation is to keep a high percentage of students in the [0,3) or [3,7) day intervals (i.e., green and blue). The interval [7,14), in yellow, starts to show a dropout trend in students, while students in the group [14, ∞), in red, should be targeted for intervention, either by the teaching staff or by the corresponding institutional unit.

D. *Comparative risk*

While in Subsec. V.C. the risk of dropout has been represented from the particular view of the subject, it should be noted that the subject is not an isolated entity, but that students are normally enrolled in a set of subjects that are taken concurrently.

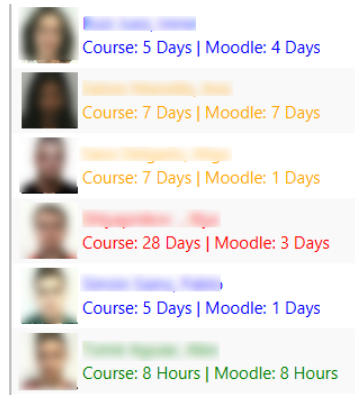


Fig. 12: List of users categorised by date of latest connection.

Although teachers are primarily concerned with their subject, the information from the latest access activity to the other courses in which a student is enrolled can and should also be taken as a reference. This provides a global view of Moodle and the rest of the subjects, highlighting a possible dropout from the whole degree and not only in the subject, particularly within the university context.

Fig. 14 shows how, by means of a comparative bar chart, the risk of dropping out of the course versus the risk of dropping out of the Moodle access, and thus of the degree, is again represented. Two bars are used for each interval, using a softer colour for the course data and a stronger colour for Moodle access.

The example shows how, comparatively speaking, the dropout rate for the subject is much higher than for the rest of the subjects taken on the platform in the same time interval. This indicates that students "move away" from our subject while they remain connected to at least one subject on the platform. In this specific case, the example shows a dropout problem in our subject, that should be reviewed by the teacher.

E. *Engagement (linear)*

Taking the above reasoning regarding comparative risk (course vs. platform) as a reference point, a graph called "engagement" has been designed. Taking into account both dropout indicators, the number of days elapsed since the latest access to the course and the Moodle platform, we have chosen to represent the risk of dropout in a bubble chart.

The X-axis shows the number of days since the latest access to the course, while the Y-axis shows the number of days since

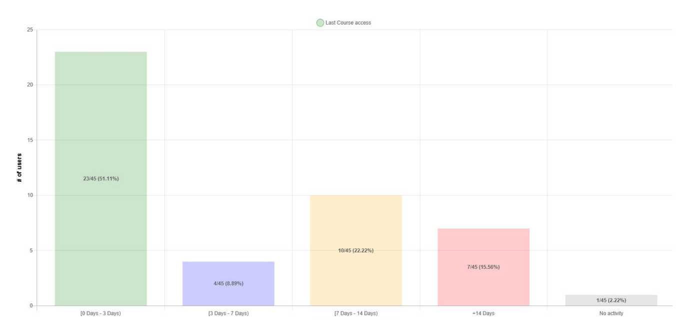


Fig. 13: Risk of dropout in a course.

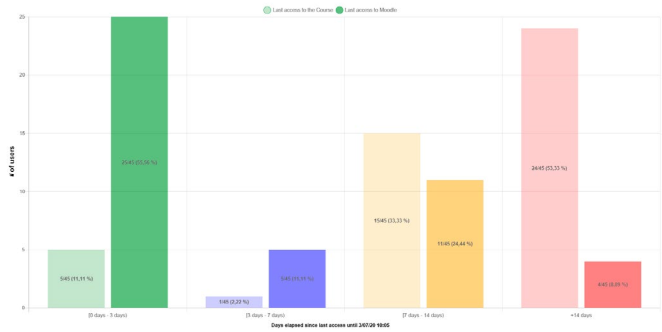


Fig. 14: Dropout risk in a course compared to dropout risk in Moodle platform.

the latest access to Moodle. A linear scale is used on both axes. Each bubble has a radius proportional to the number of students at the intersection of the values. Green, yellow, beige and red colours are used to indicate the level of remoteness and risk of dropping out, from lowest to highest. In this graph there will never be bubbles above the main diagonal, since the time of latest access to the course will always be greater than or equal to the time of latest access to Moodle (i.e., it is impossible to access a course without having previously accessed Moodle). If both timestamps coincide, the bubble will always be on the main diagonal.

An example of visualisation is shown in Fig. 15(a). The green bubbles closest to the point (0,0) show the set of students most engaged with the subject, and thus, with the lowest risk of dropping out. The larger the bubble size, the higher the number of students in this situation. Bubbles moving away from this point (0,0) to the right on the X-axis represent a dropout from the subject. The bubbles moving away vertically on the Y-axis from the point (0,0) show an overall dropout from Moodle. The worst-case scenario is the bubble in the upper right corner, which shows a total dropout both from the course and Moodle.

F. *Engagement (logarithmic)*

The logarithmic engagement graph is equivalent to the one described in Subsec. VI.E but changing the scale format. Whereas in Fig. 15(a), the data are shown grouped by days on a linear scale in the range [0,14] (case 14 is actually ≥ 14), in this graph the data in each grouping are twice as long as the previous one (logarithmic scale), and the range goes from the latest 6 hours to more than 32 days. This allows the more numerous cases to be split into smaller bubbles, while some of the more time-distant ones, which are less numerous, are clustered together, as shown in Fig. 15(b).

G. *Risk evolution*

The previous charts have used the latest access data, giving a snapshot at a specific point in time or period. But the teacher may be interested in showing the evolution of dropout along the entire timeline. For this purpose, the evolution diagram has been generated. This diagram shows the distribution of students in each of these four predefined intervals, using a grouping by time (e.g., days, weeks, months, etc.). This makes it possible to check at each instant of time, the ratio of students who are engaged or disengaged to the subject and how this ratio has evolved over time.

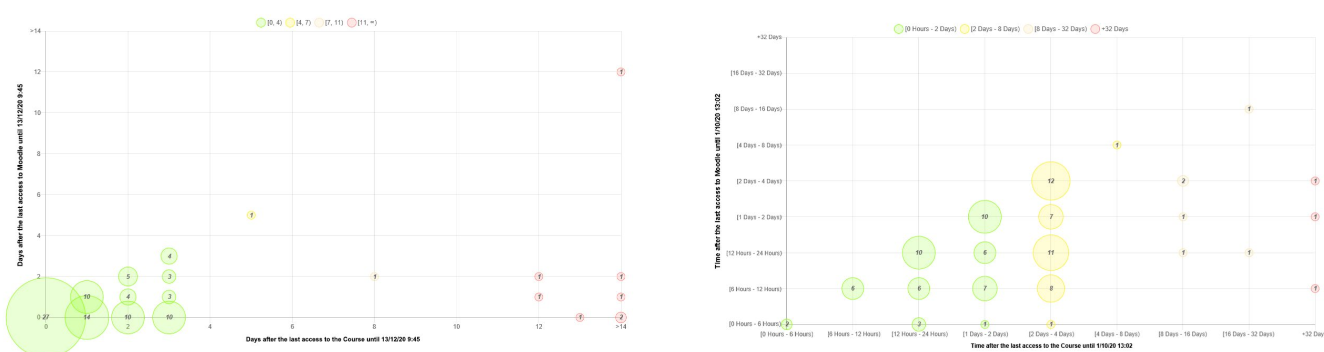
Fig. 16 shows an evolution per day in one subject. On each day, the number of students in each category is represented, using the colour legend described above. The sum of values always coincides with the total number of students chosen. The green and blue areas represent active students, while the yellow area indicates the dropout risk and the red area the current dropout. In this graph, one can observe the downward peaks in the green and blue region, usually associated with weekends, holidays or after some summative training test, which always leads to a certain decrease in the following days. In this particular example, it is calculated on a total of 79 enrolled students.

VI. EVALUATION

The software has been evaluated over the last year and a half, using our university's institutional Moodle server (versions 3.5, 3.7 and 3.9). In addition, it has also been tested with other Moodle instances such as Mount Orange School[6] and local Moodle instances.

A. *Participants*

In the first phase, it has been validated by 4 teachers (3 from the area of Computer Engineering and 1 in Health Sciences)



(a) Linear scale

(b) Logarithmic scale

Fig. 15: Engagement in linear scale vs. logarithmic scale.

[6] https://school.moodledemo.net

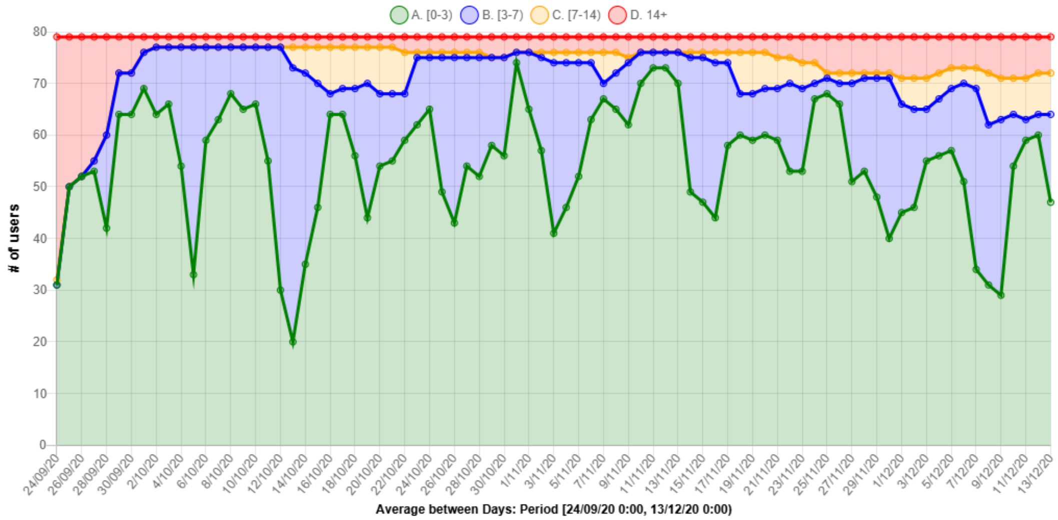


Fig. 16: Dropout risk evolution.

checking the software with their courses and reporting errors or improvements. These teachers have tested about twenty courses, with an actual load of data. Subsequently, another teacher has joined this phase, testing the software with non-regulated teaching courses at our institution. TABLE I shows data on dropout in two of the courses where the use of UBUMonitor was tested to detect dropout early and carry out corrective actions. The data show the 2019-2020 academic year where the tool was not used, versus the 2020-2021 academic year where it was tested. These are official data provided by the Information System of the University of Burgos (SIUBU[7]).

In the second phase, where a stable version of the tool was already available, an internal workshop for teachers in our institution was proposed. The workshop is now part of the training programme in e-learning, managed by the Institute for Teacher Training at the University. The initial enrolment was for 16 attendants, but in the end, the workshop was attended by 13. The audience includes a very varied profile with teachers from different areas.

B. Resources

The following resources were used for the evaluation and survey of participants:

- Moodle Institutional Server v.3.7
- UBUMonitor software 2.6.4
- Usability survey based on the Spanish model [27], the original is described in [28].

TABLE I
DROPOUT DATA FOR TWO SUBJECTS IN TWO DIFFERENT COURSES. THE COURSE WHERE UBUMONITOR WAS USED IS HIGHLIGHTED IN BOLD.

Subject	Course	Enrolled	Not presented	% Not presented
#1	2019/2020	101	27	26,7%
	2020/2021	**135**	**36**	**26,7%**
#2	2019/2020	57	18	31,6%
	2020/2021	**75**	**14**	**18,7%**

C. Methodology

A 2-hour workshop was given, guided by the designers of the software, leaving a couple of weeks for testing after the course.

At the end of this period, the results of the online survey were collected on the Moodle platform itself. For the analysis of the data collected, the spreadsheet provided on the web[8] by the authors [28] was used. This spreadsheet performs statistical analyses on the data entered.

D. Results

In the comparison between courses without using UBUMonitor vs. using it (TABLE I), although the sample is small and may limit the drawing of robust conclusions, it can be observed that the percentage of students not presented is maintained for the first subject and is reduced for the second. In addition, the course where UBUMonitor was used to guide the implementation of corrective actions had a higher number of students enrolled. Therefore, it is estimated that the use of the tool helped teachers to implement effective corrective actions to prevent dropouts.

Concerning the survey of workshop participants, it was completed by 11 participants (68% of those enrolled and 84% of those attending). We then analysed the results using the spreadsheet provided on the website[9], obtaining the results in TABLE II below.

TABLE II
USER EXPERIENCE ACCORDING TO THE UEQ SCALE (MEAN AND VARIANCE).

Property	Mean	Variance
Attraction	1,722	0,28
Perspicuity	2,028	0,69
Efficiency	1,472	0,73
Dependability	1,500	0,75
Stimulation	1,417	1,55
Novelty	1,500	0,58

[7] https://www.ubu.es/unidad-tecnica-de-calidad/gestion-de-encuestas-y-estudios-estadisticos/sistema-de-informacion-de-la-ubu-siubu

[8] https://www.ueq-online.org

[9] https://www.ueq-online.org

The results in the six main aspects measured by the survey are very satisfactory (on a scale ranging from -3 to +3), with values of 1.5 and above being considered quite good, although obviously, some aspects need to be revised. As further editions of this training course will be held, it is expected that more evaluation data will be collected in the future.

Another proof of the good reception is that the development and evolution of the software are currently being carried out under the umbrella of the University's Virtual Teaching Training Centre since October 2019, with one-year recruitment of one person, allowing to improve many features of the software, so future versions will be released.

E. Limitations

However, we must also point out some limitations detected in our experience, particularly with regard to the adoption of the application. Although it was well-received at the workshop, technical problems have been observed in its setup and deployment. Despite opting for very simple (portable) solutions, not all teachers have the expected technical skills and competencies. What could initially be taken for granted, despite more than 10 years of experience with Moodle and the use of desktop applications, was not the case. The philosophy of open-source software and having a free application also generates some mistrust, despite being endorsed by the institution itself. This problem of adopting innovations in the short/medium term has already been mentioned in [29], [30], where the authors point to the additional problem of generating interest in LA among the teaching staff. A dissemination and training effort is always required and must be supported by the institution itself.

VII. Conclusions and Future lines

This paper has presented UBUMonitor, a learning analytics software that facilitates the personalised visualisation of activity and dropout risk in Moodle. Its customizability based on the simple combination of student selection and access data, with multiple filters, groupings and graph types, has resulted in an up-to-date application with multiple teaching uses.

While many solutions exist, both commercial and open source, these tools and applications focus on a more global view, whereas our application allows the teacher to investigate student activity and development in the subject, down to specific module and access levels. This can aid decision making in a subject, analysing specific student behaviour on activities, resources and their risk of dropping out, with a level of detail that other applications do not cover.

UBUMonitor is applicable in blended or online learning environments, where student interaction with learning objects, and particularly in Moodle with resources and activities, is almost continuous. In learning with little interactivity with the LMS, the usefulness of logs as an indicator of activity is threatened. On the other hand, there is also the added problem of students who are retaking the subject, and from whom a different pattern of access can obviously be expected. This together with the teacher's own activity and the outsourcing of activities outside the LMS (e.g., LTI, xAPI, etc.) can be considered as additional risks. These factors should be taken into account in the future.

From the point of view of implementation in more educational centres, an architectural and open-source solution within the reach of most teachers is proposed. Even some technological challenges to be addressed, such as integration in those institutions that implement their own Single Sign On (SSO) validation systems, as opposed to login/password validation in Moodle, have already been integrated into recent versions.

On the other hand, we are aware that there is still Moodle information to be included and other aspects to be improved, in particular regarding usability and user experience. In terms of dropout rates, the present work provides a merely descriptive solution, but the data export and comparative studies between different cohorts may help in the generation of predictive dropout models. It would also be interesting for the application to allow the configuration and variability of the established time intervals, to fit other centres with different restrictions in the length of the course and frequency of access demanded in its instructional design.

Reporting and data export is another aspect to work on according to the surveys conducted, as it can be integrated with other third-party tools, such as spreadsheets, statistical packages, libraries, machine learning tools, etc. Given that the main focus of the software is visualisation and analytics, integration with third-party software will be a major improvement in the future.

UBUMonitor, in its current version, only makes use of student access logs, both to the platform and to the different resources of a course. Although such logs already allow for a detailed analysis of the risk of student dropout, some LMSs such as Moodle also log other types of student interactions with content. These alternative logs could be useful to track the students and measure their risk of dropping out in a more effective way. Therefore, an interesting future line of work will be to provide UBUMonitor with new functionalities that allow to visualise the rest of the interaction logs offered by Moodle, and to study if they effectively contribute to improve dropout prediction.

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