Online-Journals.org

iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 19 No. 11 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v19i11.39471

PAPER

Newly Proposed Student Performance Indicators Based on Learning Analytics for Continuous Monitoring in Learning Management Systems

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ABSTRACT

E-learning platforms have become increasingly popular across various industries, with higher education institutions being among the primary adopters. Learning management systems (LMSs) have emerged as valuable tools that facilitate the management of learning and training processes while providing support for learning administration. However, LMS platforms often offer limited functionality for monitoring students' instructional progress, which is essential for understanding how learners interact with courses and materials. As a result, identifying at-risk students, tracking their progress, and intervening when necessary can be challenging. The substantial amount of data generated by LMS platforms can be transformed into meaningful indicators that allow for monitoring learners' progress and enhancing their self-regulation. Our research project focuses on developing a set of pedagogical indicators using learning analytics to monitor students' progress. We present a case study where we tracked and monitored the progress of students in the Web Technologies course on the e-campus platform at Cadi Ayyad University (Morocco), using a set of student performance indicators (SPIs). The findings of this study suggest that employing SPIs can help faculty members identify underperforming students, project their progress, and anticipate those at risk, ultimately enabling them to provide timely interventions to support learners' progress.

KEYWORDS

learning analytics, technology-enhanced learning, data driven, ABC Learning Design, academic performance

1 INTRODUCTION

The COVID-19 pandemic has led to significant changes in various global systems, including education. With the abrupt closure of institutions, many affected countries and communities were forced to seek rapid solutions based on innovative technologies,

Qazdar, A., Hasidi, O., Qassimi, S., Abdelwahed, E.H. (2023). Newly Proposed Student Performance Indicators Based on Learning Analytics for Continuous Monitoring in Learning Management Systems. *International Journal of Online and Biomedical Engineering (iJOE)*, 19(11), pp. 19–30. https://doi.org/10.3991/ijoe.v19i11.39471

Article submitted 2023-03-09. Resubmitted 2023-05-23. Final acceptance 2023-05-29. Final version published as submitted by the authors.

such as online learning platforms (learning management systems [LMSs] and MOOCs) to cope with the crisis. As a result, institutions have transitioned from face-to-face teaching to fully online or hybrid courses with fewer students [1], [2].

LMSs have particularly gained popularity. They are integrated systems that support the teaching and learning process and its administration [3]. LMSs, such as Moodle, Blackboard, and Sakai, offer a suite of services and features capable of enhancing e-learning. They assist faculty in developing courses and virtual classrooms where students can enroll and study. Additionally, they allow the inclusion of external learning materials and the reuse of previously developed ones. An LMS can support the creation and administering of tests, grading assignments, and publishing course material. They also enable synchronous and/or asynchronous communication and interaction between all users (faculty, students, tutors, or administrators) through chat rooms, discussion forums, blog posts, and so on. However, LMSs provide limited functionality for monitoring the instructional progress of students.

In the field of education and training, the use of LMSs generates a vast amount of raw data. This data is vital for educational institutions, particularly higher education institutions. If analyzed and transformed into effective knowledge, it can be a crucial factor in decision support and advice for all stakeholders, including faculty, tutors, students, administrators, and parents/guardians. Moreover, such data can enhance the quality of teaching and learning and improve overall student performance and academic success [4].

A data-driven approach in education is relatively associated with educational data mining (EDM) and learning analytics (LA). EDM and LA are not two new fields of study. In fact, it is the emergence of using "disruptive" technologies in education and the massive amount of data stored that has turned LA and EDM into two promising fields of research that enhance educational experiences and decision-making based on data [5].

This study introduces a new set of student performance indicators (SPIs) that enable continuous monitoring and tracking of student progress within an LMS based on the generated data. The primary objective is to monitor the progress of students enrolled in a web technologies course at the UCA digital campus of Cadi Ayyad University (Morocco) and anticipate any difficulties in their learning to prevent them from failing. The proposed system utilizes a dataset collected through log files from the UCA digital campus to generate predictive SPIs. These SPIs are used and visualized to engage students in continuous monitoring and self-regulation and to identify those who are not progressing adequately, are low performing, or are in need of reinforcement and tutoring. The outline of this paper is as follows: Section 2 presents a literature review of learning analytics and relevant research. Section 3 describes the context. The proposed methodology is discussed in Section 4. The analysis results are presented in Section 5. Section 6 provides a discussion of the outcomes of the research. Finally, the conclusion and the planned future work are presented in the last section.

2 LITERATURE REVIEW

In this section, an overview of LA is provided alongside a spotlight on select research studies conducted in this field.

2.1 Learning analytics

LA is a rapidly expanding field within technology-enhanced learning (TEL) research, which has garnered substantial attention from researchers over the past decade. Since 2008, educational analysis has centered on understanding, enhancing, and optimizing the teaching and learning process.

In 2010, the concept of LA diverged from the broader area of analytics, establishing itself as an independent field [6]. LA is an interdisciplinary area that integrates big data, data mining, artificial intelligence, machine learning, learning technology, pedagogy, business intelligence, and statistics [6], [7]. During this period, LA was defined as "The use of intelligent data, learner-centered data generation and analysis models to explore information and social interactions, predict learning, and provide recommendations for learning" [8].

In 2011, the First International Conference on Learning Analytics and Knowledge (LAK) was inaugurated in Banff, Alberta (Canada). The first LAK conference organizing committee defined learning analytics as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [8].

Initially, LA was focused on studying student retention and dropout rates, but it later evolved to encompass the prediction and forecasting of student performance and the improvement of learning strategies [9]. Implementing LA can assist higher education institutions in gaining a deeper understanding of their students and the challenges they face in their learning journey, ultimately promoting academic success and the retention of a larger and more diverse student body. This is significant for operational facilities, fundraising, and admissions [10].

2.2 Previous work

Numerous research studies have been conducted to understand students' learning behaviors and enhance the learning process using LA. Most LA models and indicators have been developed to aid faculty and educational institutions in identifying students' attitudes and detecting those who are underperforming or at risk. Student performance indicators (SPIs) depend on the learning activities and resources utilized in the LMS. According to [11], these indicators can be classified as Productive, Assimilative, Evaluation, Interactive, and Communicative.

A systematic review conducted in [12] revealed that the most commonly used indicators are Evaluation and Productive activities. Evaluation activities are employed to ascertain the results of activities and evaluations (both formative and summative). Productive indicators can determine the productive actions of students, such as creating, completing, and engaging in various tasks. The Interactive category also demonstrated considerable representativeness. However, Assimilative and Communicative indicators are the least used. The analysis suggested that a combination of multiple indicators best represents the evaluation of student engagement and participation [12].

Dublin City University provides an example of how LA is utilized in higher education institutions to enhance test performance, identify study groups, assess the performance peer effect, and detect underperforming or at-risk students in programming modules [13]. LA can also be used in a computational environment to analyze and visualize student discussion groups working collaboratively to complete a task [14]. Purdue University employs course signals to allow professors to provide real-time feedback to students. The system generates various measures, such as grades, demographic data, interaction, and students' effort, by adopting the traffic light metaphor. In the same context, personalized emails are also delivered to students to inform them of their status. This system aids in retention of information and evaluation of performance outcomes [15]. LA dashboards (LADs) support previous findings that visualizing learning behavior aids students in reflecting on their learning. The LA framework LAViEW provides an overview of students' engagement indicators, allowing faculty to directly send personalized feedback to selected cohorts of students grouped by their engagement indicator scores [16].

3 STUDY CONTEXT

The case study at hand was conducted at the Department of Computer Science within the Faculty of Sciences Semlalia at Cadi Ayyad University in Marrakech, Morocco. The dataset used in the study consisted of 154 instances of students enrolled in the third semester of the Mathematical and Computer Sciences Bachelor program. The data was collected in the autumn of 2020 from the Web Technologies course hosted on the e-campus platform.

The Web Technologies course was designed using the ABC Learning Design framework [17]. Since its introduction in 2015, the ABC Learning Design framework has seen extensive adoption across universities in Europe and beyond. The framework was developed by a team from University College London (UCL) and focuses on the types of learning that will occur and what students need to do to comprehend concepts, rather than the technology itself. ABC LD is constructed on the concept of six learning types proposed in [18]: Acquisition, Inquiry, Collaboration, Discussion, Practice, and Production [19]. An effective learning design incorporates a mixture of these types of learning. Figure 1 provides an illustration of a portion of the Web Technologies course, emphasizing the different learning types used.

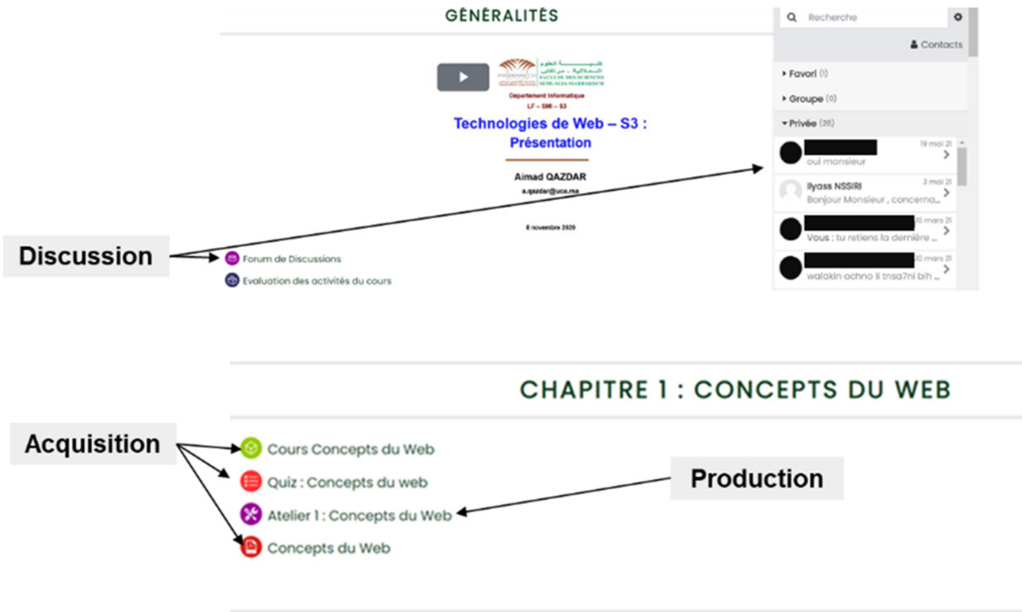


Fig. 1. Web Technologie course design

4 PROPOSED METHODOLOGY

Figure 2 outlines the various steps of the proposed methodology. The methodology commences with data collection from the LMS to generate a dataset, followed by data analysis and aggregation to define SPIs.

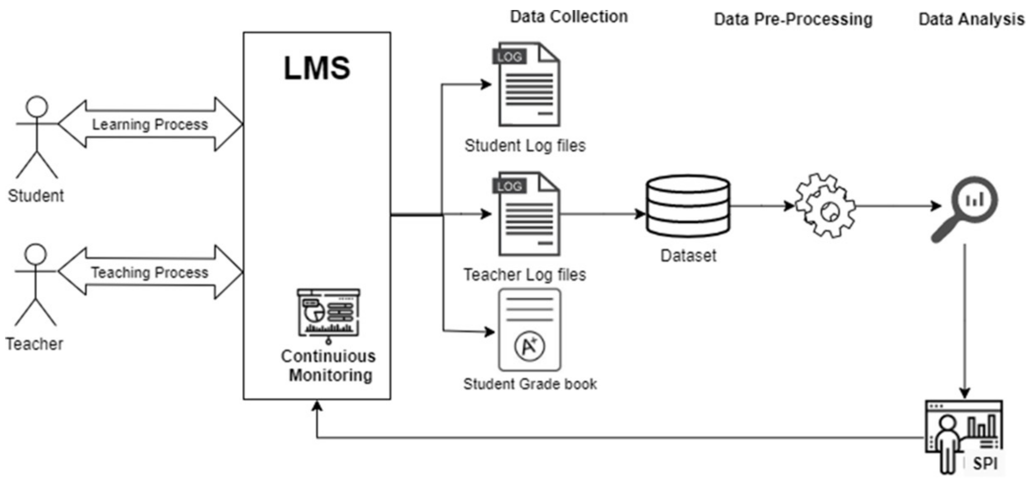


Fig. 2. The methodology conducted

After generating the SPIs, we visualize students' progress via SPIs within the LMS. This is designed to engage students in continuous monitoring and self-regulation of their learning process, as well as to support teacher decision-making within their teaching process. In the following sections, we discuss the first steps of the proposed methodology: data collection, data pre-processing, and data analysis. The visualization in the LMS and decision-making steps will be discussed in subsequent papers.

4.1 Data collection

The dataset used in this study was composed of teacher log files, student log files, and student grade books. The course log files provide the faculty member with a view of accessed resources or activities and their corresponding timestamps. These files detail essential information such as the student's name, the date and time of the action, completed actions (such as view, add, update, or delete), activities performed in various modules (such as the course, forum, or quiz), the internet protocol (IP) address used to access the resource, and additional information regarding the action [20]. Figure 3 displays a portion of these log files.

	A
1	Heure,"Nom complet","Utilisateur touché","Contexte de l'événement",Composant,"Nom de l'événement",Description,Origine,"Adresse IP"
2	23 mars 21, 14:27,"[redacted]",-,"Cours: S3 -Téchnologie du Web ",Système,"Cours consulté","The user with id '4636' viewed the course with id '388'.",web,172.20.178.31
3	22 mars 21, 10:27,"[redacted]",-,"Fichier: JavaScript",Fichier,"Module de cours consulté","The user with id '4636' viewed the 'resource' activity with course module id '11804'.",web,172.20.178.31
4	22 mars 21, 10:26,"[redacted]",-,"Cours: S3 -Téchnologie du Web ",Système,"Cours consulté","The user with id '4636' viewed the course with id '388'.",web,172.20.178.31
5	22 mars 21, 08:20,"[redacted]",-,"Fichier: JavaScript",Fichier,"Module de cours consulté","The user with id '4636' viewed the 'resource' activity with course module id '11804'.",web,172.20.178.31
6	22 mars 21, 07:55,"[redacted]",-,"Fichier: HTML 5 - Avancée",Fichier,"Module de cours consulté","The user with id '4636' viewed the 'resource' activity with course module id '11802'.",web,172.20.1
7	22 mars 21, 07:50,"[redacted]",-,"Fichier: Conception de site web",Fichier,"Module de cours consulté","The user with id '4636' viewed the 'resource' activity with course module id '11799'.",web,172
8	22 mars 21, 06:55,"[redacted]",-,"Fichier: Concepts du Web",Fichier,"Module de cours consulté","The user with id '4636' viewed the 'resource' activity with course module id '11798'.",web,172.20.1
9	22 mars 21, 06:55,"[redacted]",-,"Cours: S3 -Téchnologie du Web ",Système,"Cours consulté","The user with id '4636' viewed the course with id '388'.",web,172.20.178.31
10	21 mars 21, 22:36,"[redacted]",-,"Fichier: CSS3",Fichier,"Module de cours consulté","The user with id '4636' viewed the 'resource' activity with course module id '11803'.",web,172.20.178.31
11	21 mars 21, 22:19,"[redacted]",-,"Fichier: CSS3",Fichier,"Module de cours consulté","The user with id '4636' viewed the 'resource' activity with course module id '11803'.",web,172.20.178.31
12	21 mars 21, 22:18,"[redacted]",-,"Cours: S3 -Téchnologie du Web ",Système,"Cours consulté","The user with id '4636' viewed the course with id '388'.",web,172.20.178.31
13	21 mars 21, 21:30,"[redacted]",-,"Fichier: CSS3",Fichier,"Module de cours consulté","The user with id '4636' viewed the 'resource' activity with course module id '11803'.",web,172.20.178.31
14	21 mars 21, 21:30,"[redacted]",-,"Cours: S3 -Téchnologie du Web ",Système,"Cours consulté","The user with id '4636' viewed the course with id '388'.",web,172.20.178.31

Fig. 3. Logs files

The dataset was supplemented with the course grade book, which documented all the grades for each student enrolled in the course. The grade book, also referred to as the "assessor's report," consolidated the evaluated items from the different

Moodle components that were assessed. It provided teachers with the flexibility to view and edit them, sort them into categories, and calculate totals in various ways. Initially, the grades were displayed as the raw scores from the assessments themselves and could be presented as either a raw score or a percentage, contingent on the teacher's setup [21]. Figure 4 illustrates an example of a student's grade book.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	First name	Last name	Identification number	Institution	Departement	email	Paquetage SCORM: Cours Concepts du Web (Brut)	Paquetage SCORM: Cours Concepts du Web (Pourcentage)	Test: Quiz : Concepts du web (Brut)	Test: Quiz : Concepts du web (Pourcentage)	Atelier: Atelier 1 : Concepts du Web (travail remis) (Brut)	Atelier: Atelier 1 : Concepts du Web (travail remis) (Pourcentage)	Atelier: Atelier 1 : Concepts du Web (Rattrapage) (travail remis) (Brut)	Atelier: Atelier 1 : Concepts du Web (Rattrapage) (travail remis) (Pourcentage)	Atelier: Atelier 1 : Concepts du Web (,valuation) (Brut)
2	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]@edu.uca.ma	26	100.00 %	13,4	67.00 %	53,06	66.32 %	-	-	19,42
3	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]@edu.uca.ma	22	84.62 %	12,2	61.00 %	69,72	87.15 %	-	-	-
4	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]@edu.uca.ma	21	80.77 %	16,73	83.67 %	65,28	81.60 %	-	-	-
5	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]@edu.uca.ma	12	46.15 %	14,6	73.00 %	55,28	69.10 %	-	-	-
6	[redacted]	[redacted]	[redacted]	FSSM	Math,matiques	[redacted]@edu.uca.ma	-	-	-	-	-	-	-	-	-
7	[redacted]	[redacted]	[redacted]			[redacted]@edu.uca.ma	25	96.15 %	12	60.00 %	-	-	80	100.00 %	-
8	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]@edu.uca.ma	26	100.00 %	13,73	68.67 %	63,89	79.86 %	-	-	19,96
9	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]@edu.uca.ma	26	100.00 %	14	70.00 %	-	-	-	-	-
10	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]@edu.uca.ma	12	46.15 %	16,2	81.00 %	61,94	77.43 %	-	-	20
11	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]@edu.uca.ma	14	53.85 %	13,53	67.67 %			69,58	86.98 %	
12	[redacted]	[redacted]	[redacted]	FSSM	Chimie	[redacted]roum@edu.uc									
13	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]@edu.uca.ma	1	3.85 %	10,6	53.00 %	20	25.00 %			
14	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]t@gmail.com	1	3.85 %							
15	[redacted]	[redacted]	[redacted]	FSSM	Informatique	[redacted]@edu.uca.ma	-	-	12	60.00 %	-	-	69.07	86.34 %	-

Fig. 4. Student's grade-book file

4.2 Data pre-processing

Data pre-processing is the procedure for transforming raw data into a comprehensible and useful format [22]. It also aids in verifying and validating the quality of the data prior to applying any analysis algorithms. Two primary techniques were employed for data pre-processing: data cleansing and data formatting. In data cleansing, we discarded empty rows, rows with anonymous users, and rows corresponding to students who were absent during the final exam. Given the significance of the date and time of student activities within the LMS for this study, the majority of data formatting was centered around these parameters. The date and time in the log files required separation, formatting (conversion from text to numerical values), and transformation into weeks.

4.3 Data analysis

Following data collection, preprocessing, and cleaning, a crucial question arose: What data and indicators should be displayed on the LA report to provide insights into student performance for teachers and students? Key success indicators (KSIs) or key performance indicators (KPIs) are quantifiable metrics that reflect essential success factors across different levels [23], [24]. Faculty members and educational institutions commonly use KPIs to identify students' attitudes and pinpoint those who are underperforming or at risk.

SPIs are deeply influenced by the learning design activities utilized, as well as the data available in the LMS [25]. To reliably and effectively enhance learning outcomes, it's important for SPIs to be thoughtfully designed to measure and track authentic indicators or proxies of learning.

In this study, we identified five distinct SPIs: connectivity, acquisition, productivity, interactivity, and reactivity. The proposed SPIs align well with activities delivered through the ABC Learning Design framework, offering a comprehensive view of student activities within the LMS.

Connectivity indicator assesses the level and degree of student engagement with the course. It is measured using three factors: course frequency consultation (FC), average of session duration (SD), and the number of visited units (NVU).

$$\text{Connectivity} = \alpha_1 \times \text{FC} + \alpha_2 \times \text{SD} + \alpha_3 \times \text{NVU} \tag{1}$$

Acquisition indicator monitors the student's progress in concept acquisition, based on the number of achieved units (NAU) and the average of quiz scores (QS).

$$\text{Acquisition} = \alpha_1 \times \text{QS} + \alpha_2 \times \text{NAU} \tag{2}$$

Productivity indicator evaluates the degree of the learner's productivity in the course. This indicator is obtained based on the workshop grade (WG), workshop peer-evaluation grade (WP), and assignment grade (AG).

$$\text{Productivity} = \alpha_1 \times \text{WG} + \alpha_2 \times \text{WSP} + \alpha_3 \times \text{AG} \tag{3}$$

Interactivity indicator reflects the degree of interaction and communication in the platform. It is determined that using the number of student posts (NP) and the number of forum consultations (NFC).

$$\text{Interactivity} = \alpha_1 \times \text{NP} + \alpha_2 \times \text{NFC} \tag{4}$$

Reactivity indicator measures the learner's responsiveness to the course. This indicator is measured using the time of resource publication (TFC) and the time of the first learner's consultation (TRP).

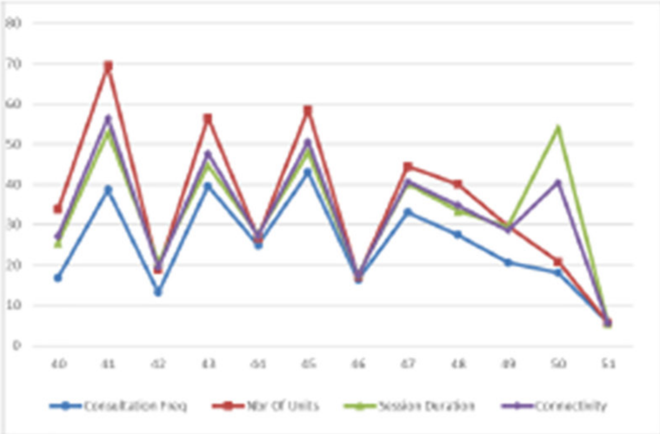
$$\text{Reactivity} = \text{TFC} - \text{TRP} \tag{5}$$

It is important to note that the α_n coefficient in the calculation formulas must be specified according to the weight of each sub-indicator, which may vary depending on the teaching approach, the objectives, and the expected skills.

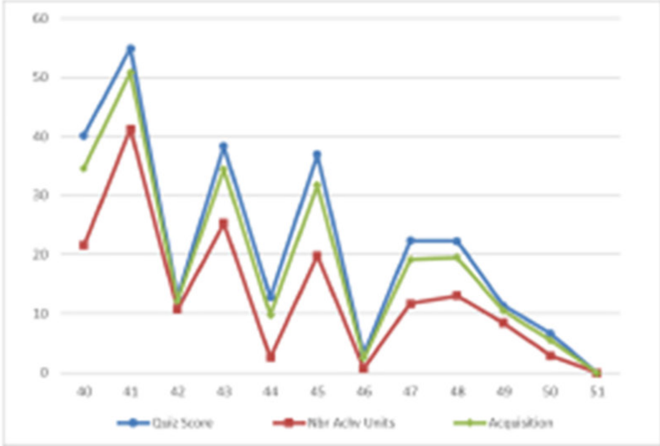
5 ANALYSIS RESULTS

The connectivity graph depicted in Figure 5a reveals that student connectivity, session duration, and number of visited units decreased as the course progressed between weeks 40 and 45. However, the frequency of course consultations during this period increased. From week 46 to week 51, all the parameters continued to decrease except for week 50, when the duration of the student session reached 50 minutes.

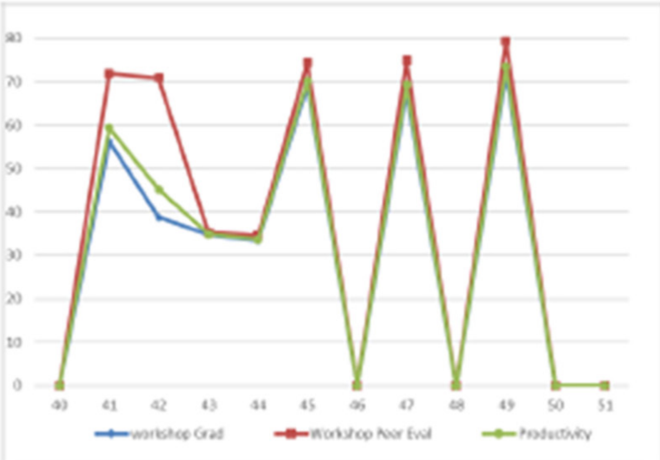
Analysis of Figure 5b demonstrates a consistent decline in student acquisition from week 41, which aligns with a corresponding decrease in the number of accomplished course units. The highest number of completed units (41) was recorded in week 41, but quiz scores significantly dropped during this period, with the average score being 51/100 in week 41.



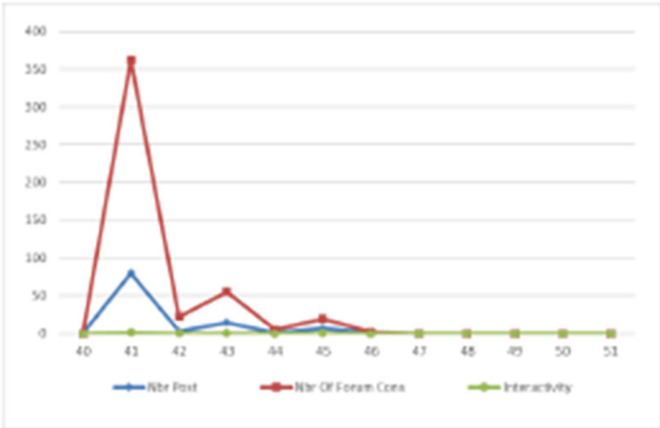
(a) *Connectivity*



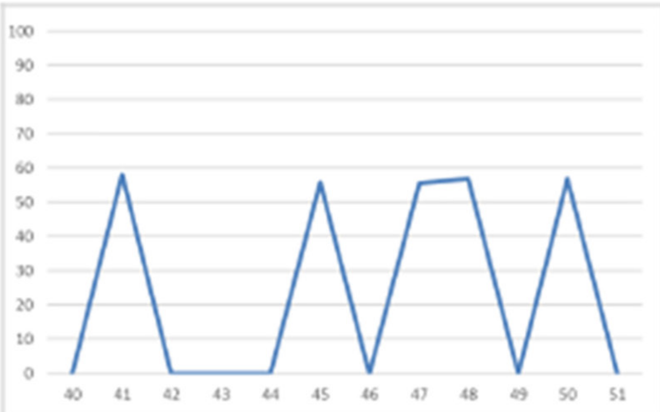
(b) *Acquisition*



(c) *Productivity*



(d) *Interactivity*



(e) *Reactivity*

Fig. 5. Results of the analysis of student performance in LMS

Productivity was used to assess student ability to produce in course-related work. As demonstrated in Figure 5c, productivity saw a decline between weeks 41 and 44, with values ranging between 33% and 59%. The period between weeks 45 and 49 represented an improvement in student productivity, with scores exceeding 70%. The workshop peer evaluation rate was higher than the workshop grades during the initial weeks, but the values were almost the same from week 45 onwards.

The interactivity indicator was used to give the faculty an idea about the degree of interaction and the communication of students in the course, specifically through the forum. As presented in Figure 5d, it was observed that students were not highly interactive on the platform, with most of them only consulting the forum rather than participating in discussions. Week 41 recorded the highest frequency of forum consultations (360 consultations) and shared posts (80 posts).

Finally, the reactivity indicator was used to assess student responsiveness to course resources and activities. From Figure 5e, it appeared that students were not very reactive.

6 DISCUSSION

This study was conducted with the objective of exploring the utility of SPIs for monitoring and assessing student progress throughout an online course, and for identifying students who are underperforming or at risk. Five SPIs were defined based on the ABC Learning Design framework: connectivity, acquisition, productivity, interactivity, and reactivity. These indicators were validated through a quantitative analysis.

The study uncovered that the usage of PDF files as course content impacted the precision of the connectivity indicator. This was because students often accessed the platform solely to download these PDF files and then proceeded to read them offline. This offline reading made it challenging to track the number of units visited or completed, as well as the actual duration of sessions. Furthermore, the utilization of external resources might have had a negative influence on the acquisition indicator and quiz scores.

The productivity indicator showed that students were productive in the course, but there was a drop in productivity during the period between week 41 and week 44. This drop was due to the non-achievement of some workshops, which according to survey analysis, may have been due to internet access problems and time management. The interactivity indicator was difficult to assess, as students preferred to use other communication tools and channels, such as the student WhatsApp group and face-to-face communication. While students consulted the course page regularly, their first access to resources was often delayed, indicating that students may be trying to manage their time between the publication of the resource and the deadlines.

Rather than simply describing the decline in indicators, the study delved deeper to understand the reasons for these declines. For example, the decrease in student connectivity was linked to a decrease in the number of units visited and the length of sessions, which resulted from the use of PDF files. Similarly, the drop in productivity was linked to the non-performance of certain workshop activities, a consequence of problems with internet access and time management.

The knowledge obtained through LA in this study could be useful for faculty to help students improve their learning. By tracking and monitoring students' progress using different performance indicators, the faculty could identify students who are struggling and provide them with targeted support to improve their learning outcomes. Overall, the knowledge obtained through LA can be a valuable tool for faculty to support students in their learning and improve their learning outcomes.

In summary, the study's findings underscore the efficacy of the proposed SPIs for tracking and monitoring student progress within an LMS. The proposed indicators—connectivity, acquisition, productivity, interactivity, and reactivity—can offer valuable insights into various aspects of students' learning progress.

7 CONCLUSIONS AND PERSPECTIVES

In this study, we investigated the effectiveness of utilizing SPIs to track and monitor learners' progression and performance on a learning platform. The proposed SPIs, consisting of connectivity, acquisition, productivity, interactivity, and reactivity, were developed based on the ABC Learning design framework. A dataset consisting of 154 instances of students registered in the third semester of the Mathematical and Computer Sciences Bachelor program was generated using the students' logs file, grade book file, and teacher logs file. The data were processed and analyzed to determine the different indicators in each week for all students or a specific one.

At this stage of the study, the proposed SPIs are effective in continuously monitoring students' progress throughout their online courses. However, these indicators do not determine students' academic performance at the end of the semester. Therefore, we have identified three objectives for future work: (1) utilize these SPIs to predict students' academic performance at the end of the semester; (2) define optimal values for each SPI; and (3) investigate the potential of utilizing machine-learning algorithms to automatically identify students at risk for low performance and provide timely recommendations to improve their learning outcomes. Finally, there is a need to integrate all these functionalities in the form of an extension module in the LMS.

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