Using Learning Analytics for Analyzing Students' Behavior in Online Learning

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Abstract: Online education is one of the fastest emerging markets globally. There is a variety of tools, technologies and platforms, which augment learning in the online environments. Moodle and Sakai are probably the most popular open-source learning management systems (LMS) around the world, although there are alternative professional solutions such as TalentLMS or other platforms. Student interaction is one of the success factors of effective online teaching and learning. It is important to understand how students behave in an online environment. This provides good feedback to the syllabus developers and instructors, in order to examine what should be improved. The learning management systems provide a good way for analyzing learners' behavior through log reports. The LMS records all kinds of interactions by all users. These data are processed using learning analytics, in order to obtain a good picture of the progress achieved by the students during the lectures and the laboratories and of the manner in which the professors manage the students' learning curves. This paper explains the use of learning analytics in examining learners' engagement, interaction and behavior in an online environment. The results revealed interesting findings on how the assessment should be organized, in order to find maximum learning attainment.

Keywords: Assessment, Evaluation, e-Learning, Learning analytics, MOODLE, Learning management system, Feedback.

1. Introduction

E-Learning and the web-based applications have been very popular, allowing users to access information via the Internet directly from their personal computer and devices. Developments and innovations in the digital technologies and products have transformed how the educational knowledge transfer is carried out. An efficient communication is a very important key for a successful teaching and learning process. The effectiveness is obtained by using synchronous and asynchronous tools. Real-time communications tools have been found to be very effective in cooperative and collaborative learning (Sharma, 2005). These tools can easily be integrated with a learning management system. LMS implementation in classroom facilitates learning and enhances students' commitment and involvement along with realization of the learning outcomes. They recommend the effective engagement of learners in the classroom, by developing online pedagogy and training materials. Cigdem & Ozturk (2016) recommended an increased use of interactivity and multimedia options to enhance the engagement of students (Santi et. al., 2022). In order to efficiently familiarize the students to use the technology, special attention should be paid to three key-factors: learner characteristics, instructional structure and interactions in the course curriculum (Liaw, 2004). There are certain universal instructional design (UID) principles which make learning goals achievable. This is possible through flexible curricular abilities (Burgstahler, 2007). Some of the ways for customizing the courses for each student are: modeling the user profile, acquiring user information, and generating personalized services.

Broadly, the educational system is made up of five important resources:

- R1 - people who are learning, represented by students, or any other person who wants to improve in a certain field;
- R2 - teachers or trainers represented by people who make the educational and

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material resources available to R1, after which R1 must acquire new knowledge;

- R3 - the educational materials represented by the materials made available by R2 for R1;
- R4 - the answers that the R1 resource gives for the evaluation of the R2 resource;
- R5 - the results represented by the grades obtained by R1 when evaluating the R4 answers, obtained after consulting the R3 resources made available to the R1 resource by the R2 resource.

The wave of latest technologies that started at the late XX century, particularly when the Internet presence had a significant impact on the society. Information and Communication Technologies (ICT) induced major changes in most life aspects, within the way people work, communicate, develop, or have fun. Additional, ICT triggered a large digital transformation which made North American to return to and redefine the daily life roles, especially in the education field (Sharma, Yildirim & Kurubacak, 2020).

Education is the domain which has quickly improved over the past years due to the use of ICT. By using various types of software programs and services, the teaching, learning as well as collaborative work are supported. All the persons implicated in the learning process, namely teachers, students and even parents, understand the potential of digital content and agree that the quality of learning can be improved by the proper use of ICT applications (Shaikh & Khoja, 2011; Stroe, 2021).

It can be said that E-Learning can be viewed both as the cause and the result of the major changes within the core definitions of academic ideas. Thus, E-Learning has been involved in changes within the understanding of the manner in which educational processes should be planned and managed.

Infrastructural provisions made for online programme delivery can also result in widening the gap between learners living in large cities and those living in small cities because online educational resources, mechanisms and internet facilities may not be available in small cities (Sharma, 2001).

Shaikh & Khoja (2013) researched the major causes of deprived standards in education establishments. The result of their research proved to be the poor or the uneven distribution of ICT infrastructure or of the available resources. Also, the ICT policy can be viewed as poor or with a weak efficiency, if shaping the role of ICT as a remedy for structure transformation, creating a responsive ICT for the structure vision and mission, and developing a non-systemic technique of implementing ICT policy are not taken into consideration.

On the other hand, Shaikh & Khoja (2013) suggested that university personnel ought to use ICT tools/applications in their job-related tasks, since the best ICT tools and associated applications have alleviated the ways of distributing learning materials from educators to learners, from learners to educators and between learners. New technologies have improved the potency, data and skills of the educational process and, therefore, the scholar performance overall.

The best ICT tool is actually the Internet itself, and by using this with associated applications, the result is an innovative way of distributing learning materials from teachers and students, but also between learners. Because the technology field has been improved over time, the skills, the knowledge and the overall scholar performance have also been improved (Sharma, Yildirim & Kurubacak, 2020). As a consequence, most of the universities are currently encouraging their students to use online tools such as audio/video lectures, online textbooks, interactive simulations and assessments, online courses etc.

There are some trends that support the idea of renouncing completely to the physical classroom, but in most cases, this is not possible nor desirable. Also, it is clear that the educational process needs to fit the field of the studied discipline – e.g., the practical activities for the students in the ICT field should involve time for teaching, searching, writing and debugging on their own, while for the students in the medicine field, it is important to be assisted by a specialist, a doctor, a professor, a medical robot etc., when operating a patient. The E-Learning technologies are still developing towards assisting these situations, resulting in cases such as a flipped classroom where students learn theory during their own time and the classroom is used only for applying the theoretical areas by working on projects along with the teachers and other colleagues (Bishop & Verleger, 2013).

In recent years, numerous E-Learning-specific systems have been created, put into practice, and utilised. E-Learning systems are being utilized to teach entirely online courses and, even more extensively, fully online study programs, in addition to supporting face-to-face instruction (Downing & Dyment, 2013). E-Learning platforms like Moodle, Sakai, Edmodo, Canvas, Schoology, Blackboard Learn, and others are used by educational systems all over the world, particularly in higher education. This paper analyses the logs from the LMS and tries to cluster them, by improving the way of calculating the students' confidence degree in their responses on the LMS platforms.

The paper is structured in five sections followed by conclusion. Section 2 presents the existing research works related to this domain. This is relevant for understanding the placement and the purpose of the present research. Section 3 presents the methods and methodologies used in the present analysis. All the analyses obtained based on the collected data as well as the obtained results are presented in Section 4. Section 5 presents a new platform that can be used to evaluate the students and to automatically calculate they confidence degree. The paper ends with conclusion and directions for a future work.

2. Background

At present, there are several web applications dedicated to tutoring on the market, among which: Tutoringgo, Wyzant, Tutorsbox, Scoodle, Whiztutorapp, Tutorme, etc. In major universities around the world, this type of application is used to enhance the classical learning process, but also to facilitate distance learning (Philipsen et al., 2019).

One of the most important aspects of E-Learning is student motivation, yet this is a challenging problem to solve (Sharma, Kawachi & Bozkurt, 2019). This problem can be directly handled by the teacher (resource R2) in a classroom, but on E-Learning platforms, different approaches to motivation are required. The learning environments may offer a variety of features and enhance user interactions, but without the student's participation, these advantages cannot be fully realized. Students may seem disinterested for a variety of reasons. For example, one student may act bored because the work is too easy, while another student may be capable of completing the work but, at the same time, may lack confidence in himself/herself and feel too anxious about solving the task, which could be the cause of his/her inability to focus. Moreover, another student may lack the necessary skills, but be hesitant to seek out assistance in the learning environment, because he/she has not learned to count on helpful assistance from peers, parents, or even teachers (Beal et. al. 2006).

Gamification is one of the techniques that can increase motivation and encourage the involvement of beneficiaries, especially in the field of education where teaching activities need to be more interesting and fun. Gamification is a tool that provides the framework needed for increasing the quality of learning. Among the benefits of gamification in education is the increased level of involvement and concentration during classes, which helps students to memorize the information taught in the course on long term, because the beneficiaries associate that information with something fun. The elements of gamification can arouse the beneficiaries' curiosity and competition to be better at school and to learn with pleasure in an environment that rewards their efforts. Thus, they receive feedback directly related to their involvement. Also, a gamified environment creates the context needed for the students to interact with each other, through competitions, to solve the tasks in team work and to visualize their progress and final results.

In Octalysis project, Chou (2019) presents the impact of holistic gamification on the educational or training environment for employees of companies. When it comes to education, it is important to understand what motivates the human behavior in such a way that people are determined to learn and then look for learning techniques which rely on these specific human conditions. Moreover, the reason for choosing to include certain gamified elements in order to accelerate and improve the learning process starts from the selection of those neural functions that activate the desire for knowledge.

Moodle Platform was used to conduct the present analysis, but any other MOOC - Massive Open Online Courses, can also be used (Khalil, 2018). A social constructionist pedagogy informs the creation of Moodle, an open-source learning management system that offers teachers and students a single strong, secure, and integrated system to create personalized learning environments. All layers of Moodle are very extensible (Ramesh et al., 2015). Its implementation is based on the LAMP (Linux, Apache, MySQL, PHP) stack; the front-end and back-end are written in PHP, MySQL serves as the database system, and Apache is used as the web server. More than 100 languages are supported by the platform (Umek et al., 2015). Despite the concerns regarding the performance and scalability, from a technical standpoint, Moodle is widely used by individuals and organizations mostly due to its integrated suite of capabilities that were initially developed from a socially constructive perspective.

3. Methodology and Datasets

However, smart learning environments should offer individualized support to help a learner use, manage, and interact with the learning system, in order to enhance the current E-Learning applications. Numerous studies have looked into the usage of intelligent and virtual tutoring methods such as personalized learning interfaces and adaptive examinations (Oneț-Marian et al., 2021).

Almost all educational institutions obtain data from their students through the admission process. These data are processed for improving teaching, analyzing the student's behavior and predicting success arising from the courses (Joseph-Richard & Uhomoibhi, 2021). Collecting student data has often been discussed in terms of breaching the ethics and privacy as it depends upon the processes involved in harvesting students' sensitive data. Such data are obtained for details regarding the students' demographics, interaction with their instructors and course content, assignment submissions, participations in discussion forums and various kinds of performing different activities. With the advancements in the field of data analytics, researchers and scholars are paying greater attention in analyzing the students' behavior regarding the manner in which they interact with the courses and how it impacts their learning attainment.

According to Long & Siemens (2011) learning analytics is "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". Learning analytics has great implications not only for the faculty, but for learners as well. It helps in generating useful insights at the course level, such as discourse analysis, conceptual development and social networks, and at the departmental level, such as predictive modeling and identification of success or failure patterns. By incorporating learning analytics into the curriculum transactions, faculty and administrators can achieve a better understanding of the effect that the curriculum usage has on teachers and students (Hayag, 2018). Hayag (2018) further recommends applying learning analytics for applicable pedagogies, as well as supporting the data obtained in face-to-face settings about student inquiry, practical activities and class discussions. By creating a proper profile of the student, teachers can develop suitable pedagogies, create authentic learning experiences and address the at-risk students (Zeirhun, 2018).

Another significant aspect related to learning analytics is providing a real-time perception of the learning behavior. The way the data are processed from the stage of simple pieces of information to the stage of optimization, Gartner (2012) proposed an Analytics Ascendancy Model. The research identified four types of analytics: descriptive (what happened), diagnostic (why did it happen), predictive (what will happen), and prescriptive (how can we make it happen). Rajabalee et al. (2020) examined the potential, constraints and impacts of learning analytics as applied to an online course and recommended activity-based learning experiences for learners.

Online examinations have the primary advantage that the feedback can be automatic and quick, giving students the chance to obtain immediate feedback on their understanding as well as the opportunity to do better. Studies on the results of feedback from quizzes demonstrate that quick feedback creates new channels of contact between instructors and students (Rinaldi et al., 2017)

A quiz with 22 different answer choices and a 15-minute time limit was developed within the MOODLE platform. This quiz was supported by 15 students (resource R1 of the educational system). The results obtained by the students from the small set are presented in (Zamfiroiu et al., 2019). Then, these results are clustered and the behavior of students is interpreted by each cluster.

The timing of the quiz or exam, the type of the questions (file upload, essays, multiple choice, etc.), the unpredictability of the questions within the tests, and the associated points and/or penalties are all very crucial.

This 15-minute test resulted in the production of 947 logs. These logs must be manually analyzed, which takes a lot of time and resources.

Nevertheless, this study offers important details regarding the student's test-taking strategy. In order to maintain their privacy, instead of the students' name, the formula [Student1: Student15] was used.

Events such as "Quiz attempt started," "Quiz attempt submitted," "Quiz attempt summary seen," and "Quiz attempt watched" are recorded in the logs. Based on these logs the students' behaviors are analyzed on the platform and clustered by the time spent on the test, by the confidence degree or by the obtained degree (Khalil & Ebner, 2017).

This paper presents the results of the analysis of a set of 15 students. The set was chosen to be small, in order to simplify their presentation and clustering. More sets from more quizzes, with more students have also been analyzed to validate the obtained results. Tests with a longer duration of time in which students answered various questions have been also analyzed. In this way the distributions of clusters on small intervals of time and on large intervals of time were compared.

The sets of students involved in these analyses are from different environments, from different universities. In this way the influence of the environment is excluded from the present analysis.

4. Findings and Analysis

During this period, each student had the chance to go over any question whose answer he/she was not sure about. The page loaded with a question is visible in "Quiz attempt viewed" event.

The formula for calculating the degree of confidence (CD - Confidence Degree) is presented in (Zamfiroiu et al., 2019) and is as follows:

$$CD = \frac{noQ}{noL} * 100 \quad (1)$$

where:

noQ – represents the number of questions;

noL – represents the number of page loadings.

Once the level of confidence for each student has been determined, this grade of confidence is examined along with the score attained on the test and the amount of time spent on it. Table 1 illustrates this comparison.

The values acquired for time in minutes are normalized using the von Neumann Morgenstern 3 normalization method by the following formula so that the time may be compared with the note and degree of confidence obtained:

$$TimeN_i = \frac{Time_i}{MaxTime} \quad (2)$$

where:

$TimeN_i$ – the normalized value for the time spent in the quiz by student i;

$Time_i$ – the time spent by the i student in the quiz;

$MaxTime$ – the maximum time for this quiz = 15 minutes.

The value obtained for $TimeN_i$ ranges within [0, 1]. For being included in the interval [0, 100] it is multiplied by 100. Thus, the formula for determining the time is:

$$TimeN_i = \frac{Time_i}{MaxTime} * 100 \quad (3)$$

Table 1. Comparison between confidence degree and obtained grade (Zamfiroiu et al., 2019)

Username	Confidence degree	The obtained grade (R5)	Time spent in test (minutes)	Time with normalized values
STUDENT1	55.00	70	15	100.00
STUDENT2	66.67	72.5	15	100.00
STUDENT3	33.85	72.5	11	73.33
STUDENT4	32.84	85	13	86.67
STUDENT5	38.60	85	15	100.00
STUDENT6	48.89	95	12	80.00
STUDENT7	48.89	95	15	100.00
STUDENT8	45.83	75	13	86.67
STUDENT9	41.51	92.5	15	100.00
STUDENT10	43.14	97.5	12	80.00
STUDENT11	48.89	85	13	86.67
STUDENT12	56.41	87.5	13	86.67
STUDENT13	50.00	95	13	86.67
STUDENT14	34.38	82.5	11	73.33
STUDENT15	36.67	90	15	100.00

The normalized values for the time spent in the test are illustrated in the last column of Table 1.

Despite investing a lot of time in the test, Student 2 had the best approximation between the grade received and the level of confidence displayed during it. This demonstrates that the pupil has attentively read each question. For Student 10, this scenario is also crucial. Despite having a low level of confidence, this student still received the highest score: 97.5. This demonstrates that the student may not be particularly secure in understanding the information and likely picked up new information just before the test. It is possible to perform a thorough study of all the Moodle platform logs to see the behavior of this student.

After analyzing the information pertaining to each student's grade and confidence level, the clustered groups were identified, as illustrated in Figure 1.

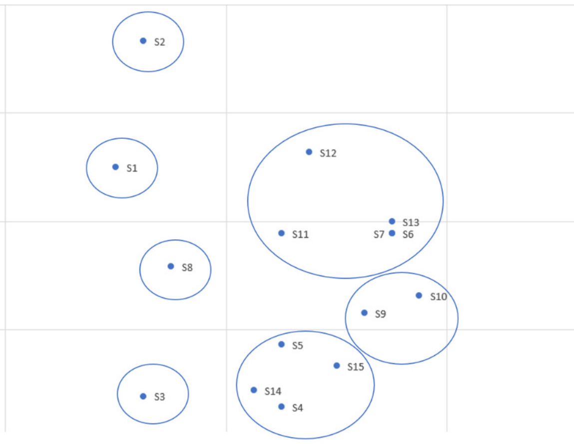

Figure 1. Clustered groups according to grade and confidence degree

The clusters are established by using the Euclidean distance between the points and the nearest area to these respective points, thus being considered part of the same cluster.

In this way, three clusters composed by more than one student and four clusters composed of only one student were obtained. Because the time spent on the quiz by each student should also be taken into consideration, another analysis was made, regarding the time and the grade obtained on the quiz by each student. In this way, other clusters were obtained, as seen in Figure 2.

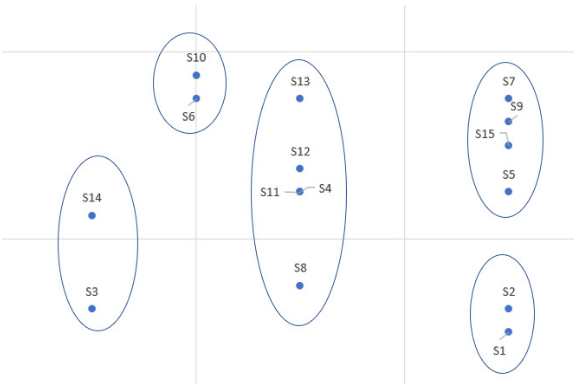

Figure 2. Clustered groups according to grade and time spent on the quiz

This resulted in creation of five groups. Each group contains at least two students. It is important to analyze the correspondence between these clusters. This investigation has to take into consideration which students from the second cluster are grouped in the first one. Therefore, a double clustering according to grade, confidence degree and time was obtained, as shown in Figure 3.

From this figure, it can be observed that only one group is clustered in terms of time spent on the quiz. This cluster is composed by the group of students that spent 13 minutes on the quiz. From here, it can be concluded that the students who are spending average time on the quiz are highly divided regarding the obtained grade and their confidence degree.

The obtained degree has been investigated in correlation with the time spent on the quiz by each student, but the clusters are similar with the ones from Figure 2.

Also, a larger than first set of students was analyzed. This other set is composed by 96 students, and the graphic of the obtained degree and time spent on test is presented in Figure 4.

These clusters are created to help the instructors and the teachers – resource R2 – to understand the types of the students or learners – resource R1.

It can be observed that even if the number of clusters is greater, their positioning is similar.

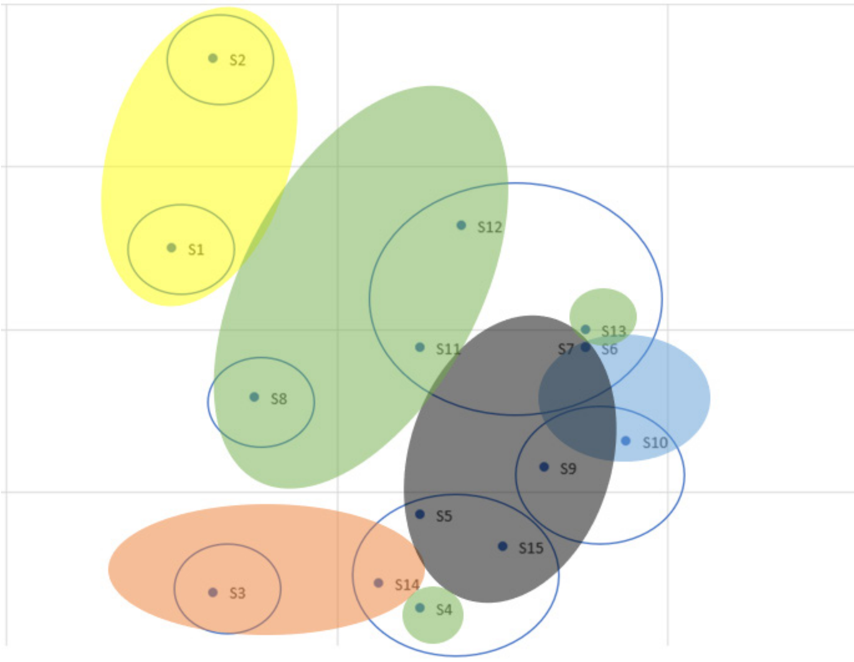

Figure 3. Double clustering according to grade, confidence degree and time spent on the quiz

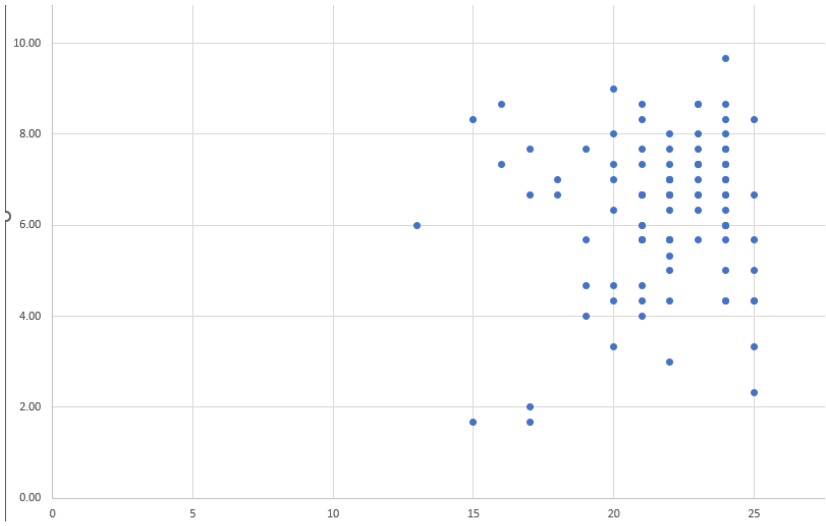

Figure 4. Large dataset analyzes

Because the confidence degree is calculated by the number of refreshes of the pages with questions, a new modality to calculate this degree and save new logs for each change of the answers in the quiz was proposed. This proposal is presented in the next section.

5. LMS Logs for Analyzing Students' Interactions

In order to demonstrate the importance of logs in the interaction between students and educational platforms a learning management system that combines the main components of the learning process has been developed. In this system, knowledge is accumulated by completing the courses (R3) and the information learned from the courses is tested in exams (R4 – R5). The main functionality of this platform is to identify students based on how they type any kind of text during the working session with the objective of distinguishing the users, ensuring the authenticity and preventing data compromise.

Logs play a key-role in determining and analyzing the user's (R1) behavior in multiple-choice questions. This platform monitors and saves the information about the student's behavior in logs during both the course and the exam. When a user views a course, the teacher will have information such as: course accessed / not accessed, course downloaded / not downloaded, number of views / per course, the number of students who took preparation tests within the course. The information displayed in logs regarding the multiple-choice questions in the exams presents the choices made by a student in real time as well as the number of hesitations he/she had in choosing the final answer / answers. This monitoring analysis of all the answers checked by the student shows the level of confidence in his/her degree of knowledge, and in the long term it can help to increase his/her knowledge, since the student cannot "cheat" the system by taking someone else's exams.

The platform has been tested by 15 users. They viewed the courses and took different exams in order to be able to analyze their behavior later, by means of logs.

As it can be seen in Figure 5, an answer to a question can be: wrong and unchecked, correct and checked, correct and unchecked, incorrect and checked. Next to each answer is the number of choices for that answer (how many times the answer was checked). This number represents the most important indicator in the analysis because it shows the students' confidence in their own knowledge.

In Figure 5 for question number 5, the user had to choose the correct answer from four existing options. As shown in Figure 5, the first answer is wrong and was not chosen. The number in the round brackets indicates how many times the student has chosen that answer (for example, for 3 choices of a response, the following actions were performed: checked - unchecked - checked). The final user response options are those that have an odd number of choices. In this case, the user chose the final answer as variants 2, 3, 4, which makes the answer wrong because the question had only one correct answer, the third one. Although it is a low difficulty question, the high number of oscillations between the final answer variants (sum of changing each answer = 7) determined the student to answer the question incorrectly.

Based on these indicators, the teacher can identify both the students' deficiencies and the notions they confuse and can make the entire process of information transmission more efficient.

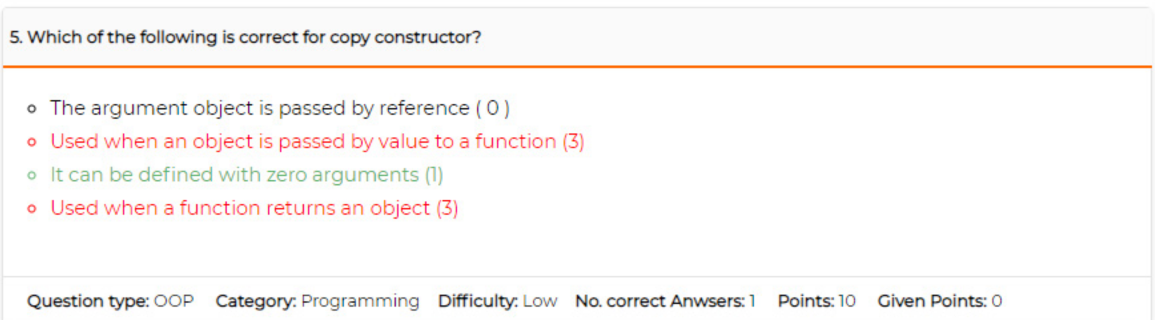

Figure 5. One question of the exam

Table 2 illustrates the students' confidence in their own knowledge based on the total number of changes in the answers to each question during an exam. For each question, correct answer is marked with green, while the wrong one is marked with red.

The lack of changing in answers to questions Q1, Q2, Q9, Q10 indicates that those are questions with free answers. Thus, these questions will not be considered in the analysis. For the multiple-choice questions (from Q3 to Q8) it is observed that most of the times a small number of oscillations between the options of the answer has finally led to the choice of the correct answer. This suggests that the confidence of a student in his/her own knowledge is: inversely proportional to the number of oscillations between answers and directly proportional to the choice of the correct option. Each student's confidence for a question (CDQ – Confidence Degree per Question) can be calculated using the formula:

$$CDQ = \frac{noCA * AT}{noC} * 100 \tag{4}$$

where:

AT – represents the type of the answer (correct or incorrect) and uses these default values {0.5 – for incorrect answer, 1 – for correct answer};

noC – represents the number of changes;

noCA – represents the number of correct answers of the question.

In order to highlight what has been mentioned above, the students' confidence in their answers will be determined, as seen in Table 3.

Table 2. Number of changes in the answers

Student	Q3	Q4	Q5	Q6	Q7	Q8
Student1	1	1	5	6	7	1
Student2	6	5	3	9	3	3
Student3	7	5	3	7	1	5
Student4	5	3	1	4	3	8
Student5	4	4	7	7	3	6
Student6	1	8	3	6	1	3
Student7	9	7	1	4	2	3
Student8	7	1	3	4	1	1
Student9	8	5	8	4	3	9
Student10	4	1	3	2	8	2
Student11	3	1	3	2	7	5
Student12	1	4	4	1	5	9
Student13	3	5	3	1	1	3
Student14	1	2	1	3	3	7
Student15	1	3	3	3	1	1

Table 3. Comparison between average confidence degree and obtained grade

Student	CDQ3	CDQ4	CDQ5	CDQ6	CDQ7	CDQ8	Average confidence degree (%)	Obtained grade (%)
Student1	100.00	100.00	20.00	8.33	7.14	100.00	55.91	60
Student2	8.33	20.00	33.33	5.55	33.33	33.33	22.31	70
Student3	7.14	20.00	33.33	7.14	100.00	10.00	29.60	60
Student4	20.00	33.33	100.00	12.50	33.33	6.25	34.23	60
Student5	12.50	12.50	7.14	7.14	33.33	16.66	14.87	50
Student6	100.00	6.25	33.33	8.33	100.00	33.33	46.87	70
Student7	5.55	7.14	100.00	12.50	25.00	33.33	30.58	50
Student8	7.14	100.00	33.33	12.50	100.00	100.00	58.82	70
Student9	6.25	9.35	6.25	12.50	16.66	5.55	9.42	0
Student10	12.50	100.00	33.33	25.00	6.25	25.00	33.68	50
Student11	33.33	100.00	33.33	25.00	7.14	10.00	34.8	50
Student12	100.00	12.50	12.50	100.00	20.00	5.55	41.75	60
Student13	33.33	20.00	33.33	100.00	100.00	33.33	53.33	70
Student14	100.00	25.00	100.00	33.33	33.33	14.28	50.99	50
Student15	100.00	33.33	33.33	33.33	100.00	100.00	66.66	100

Based on information given in Table 3, it can be observed that a better prepared student (Student15) tends to be more confident in his knowledge and to answer the question correctly.

Another interesting situation is the one of Student9. The student did not answer any questions correctly and also obtained the lowest confidence degree (9.43%). This aspect indicates that students who do not trust their knowledge tend to score lower on the exam.

As it can be seen from Figure 6, the average confidence degree is close to the obtained grade for most students, which indicates that the confidence in their knowledge reflects the grade they obtain in an exam. However, there may be exceptions when a high score has been obtained based on a large number of changes in responses (Student2 and Student5). This difference between the indicators may suggest that the students did not read the questions carefully or they learned for the test in the last moment.

6. Conclusion and Future Work

These days, active learning is preferred over a learning process based on listening and memorizing, and it's important to involve the students (R1) in the learning resources (R3), encourage active participation in class, and foster collaboration between the students (R1) and the teacher (R3). In order to illustrate a process or analyze an argument, the students should be inspired to use simulation, critical thinking or application of their knowledge in real-world scenarios. Therefore, the material organization of the E-Learning platform must be thought out very well.

The findings of this present paper are significant for personalized learning, because now it is widely acknowledged that the traditional scholar approach "one size fits all" is inadequate for the modern knowledge society.

In order to improve in areas where they are underperforming, students must identify their own learning requirements and expand their knowledge and experience in those areas. To take the appropriate steps in personalized learning in order to enhance and increase each student's potential, it is necessary to identify these areas first. The teacher can choose which course of action to take into account based on the learner's profile, including suggesting books, tasks, and activities, or a new learning path, and offering advices to raise the level of confidence and the grades (R3 – R5).

The LMS gives teachers unbiased feedback on the lessons they are teaching by examining the behavior and performance of their students. Teachers should monitor how students learn, identify the most likely errors, and, most importantly, determine which students need a certain type of assistance.

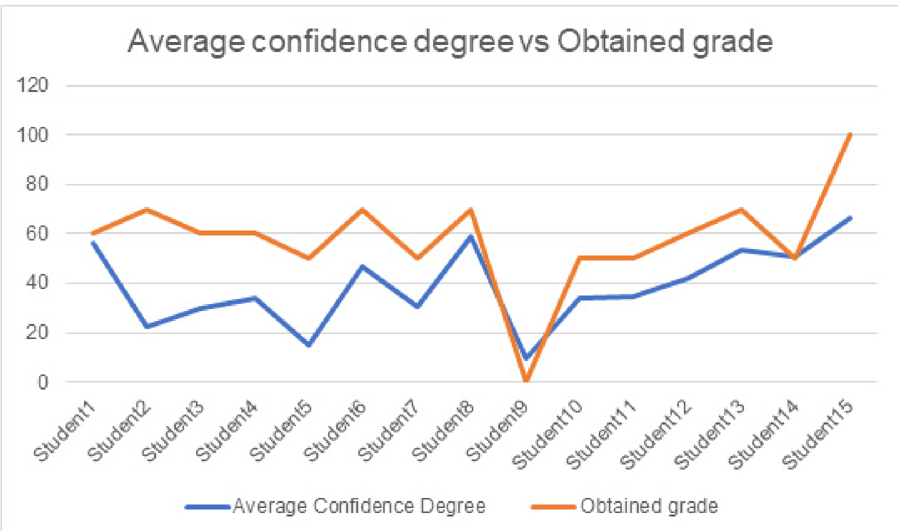

Figure 6. Average confidence degree vs. obtained grade

In a future work, a complex analysis of all platform logs should be considered to identify the students' learning clusters and their best time for learning. To enable everyone who uses the Moodle platform to use these analyses for themselves, it would be excellent to create a plugin for Moodle.

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REFERENCES

Beal, C. R., Qu, L. & Lee, H. (2006). Classifying learner engagement through integration of multiple data sources. In *Proceedings of the 21st National Conference on Artificial Intelligence*, *21*(1), (pp. 151-156).

Bishop, J. & Verleger, M. (2013, October). Testing the flipped classroom with model-eliciting activities and video lectures in a mid-level undergraduate engineering course. *In 2013 IEEE Frontiers in Education Conference (FIE)*, (pp. 161-163). IEEE.

Burgstahler, S. (2007). *Universal design of instruction: Definition, principles, and examples*. University of Washington. Available at: <http://www.washington.edu/doit/Brochures/Academics/instruction.html>, last accessed: August 2022.

Chou, Y. K. (2019). *Actionable Gamification: Beyond Points, Badges, and Leaderboards*. Packt Publishing Ltd.

Cigdem, H. & Ozturk, M. (2016). Factors Affecting Students' Behavioral Intention to Use LMS at a Turkish Post-Secondary Vocational School, *The International Review of Research in Open and Distributed Learning, 17*(3), 276-295.

Downing, J. J. & Dyment, J. E. (2013). Teacher educators' readiness, preparation, and perceptions of preparing preservice teachers in a fully online environment: An exploratory study, *The Teacher Educator, 48*(2), 96-109.

Gartner Research (2012). *Best Practices in Analytics: Integrating Analytical Capabilities and Process Flows*. Available at <https://www.gartner.com/en/documents/1964015>, last accessed: August 2022.

Hayag Jr., M. R. (2018). Learning Analytics: Application on Curriculum Design and Assessment. In Kumar Singh, M., Zerihun, Z. & Singh, N. (Eds.), *Impact of Learning Analytics on Curriculum Design and Student Performance*, 113-124. IGI Global. DOI: 10.4018/978-1-5225-5369-4.ch008

Joseph-Richard, P. & Uhomoibhi, J. O. (2021). Ethics in Predictive Learning Analytics: An Empirical Case Study on Students Perceptions in a Northern Irish University. In Azevedo, A., Azevedo, J., Onohuome Uhomoibhi, J. & Ossiannilsson, E. (Eds.), *Advancing the Power of Learning Analytics and Big Data in Education*, 86-107. IGI Global. DOI: 10.4018/978-1-7998-7103-3.ch004

Khalil, M. (2018). *Learning Analytics in Massive Open Online Courses*. Doctoral Thesis, University of Technology. Available at: <arXiv preprint arXiv:1802.09344>, last accessed: August 2022

Khalil, M. & Ebner, M. (2017). Clustering patterns of engagement in Massive Open Online Courses (MOOCs): the use of learning analytics to reveal student categories, *Journal of Computing in Higher Education, 29*(1), 114-132.

Liaw, S.-S. (2004). Considerations for developing constructivist Web-based learning, *International Journal of Instructional Media, 31*(3), 309-321. Available at: <http://blog.ncue.edu.tw/sys/lib/read_attach.php?id=3093>, last accessed: August 2022.

Long, P. & Siemens, G. (2011). Penetrating the Fog: Analytics in Learning and Education, *EDUCAUSE Review*, *September/October 2011*, pp.34.

Oneț-Marian, Z., Czibula, G. & Maier, M. (2021). Using Self-Organizing Maps for Comparing Students' Academic Performance in Online and Traditional Learning Environments, *Studies in Informatics and Control, 30*(4), 31-42. DOI: 10.24846/v30i4y202103

Philipsen, B., Tondeur, J., Roblin, N. P., Vanslambrouck, S. & Zhu, C. (2019). Improving teacher professional development for online and blended learning: A systematic meta-aggregative review, *Educational Technology Research and Development, 67*(5), 1145-1174.

Rajabalee, Y. B., Santally, M. I. & Rennie, F. (2020). Modeling Students' Performances in Activity-Based E-Learning from a Learning Analytics Perspective: Implications and Relevance for Learning Design, *International Journal of Distance Education Technologies (IJDET), 18*(4), 71-93. DOI: 10.4018/IJDET.2020100105

Ramesh, V. M., Rao, N. J. & Ramanathan, C. (2015). Implementation of an intelligent tutoring system using Moodle. In *2015 IEEE Frontiers in Education Conference (FIE)*, (pp. 1-9).

Rinaldi, V. D., Lorr, N. A. & Williams, K. (2017). Evaluating a technology supported interactive response system during the laboratory section of a histology course, *Anatomical Sciences Education, 10*(4), 328-338.

Santi, E. A., Gorghiu, G. & Pribeanu, C. (2022). Students' Engagement and Active Participation During the Pandemic*, Informatica Economica, 26*(1), 5-15.

Shaikh, Z. A. & Khoja, S. A. (2011). Role of ICT in Shaping the Future of Pakistani Higher Education System, *Turkish Online Journal of Educational Technology-TOJET, 10*(1), 149-161.

Shaikh, Z. A. & Khoja, S. A. (2013). Higher education in Pakistan: An ICT integration viewpoint, *International Journal of Computer Theory and Engineering, 5*(3), 410-413.

Sharma, R. (2001). Online Delivery of Programmes: A case study of IGNOU*, The International Review of Research in Open and Distributed Learning, 1*(2), 1-15. DOI: 10.19173/irrodl.v1i2.18

Sharma, R. C. (2005). E-Learning in India. In Howard, C., Boettcher, J. V., Justice, L., Schenk, K., Rogers, P. L. & Berg, G. (Eds.), *Encyclopedia of Distance Learning*, 772 -778. Hershey, PA: Idea Pub.

Sharma, R. C., Kawachi, P. & Bozkurt, A. (2019). Exploring Changing Perspectives in Distance Education, *Asian Journal of Distance Education, 14*(1), 1-6.

Sharma, R. C., Yildirim, H. & Kurubacak, G. (2020). *Blockchain Technology Applications in Education*. IGI Global. DOI: 10.4018/978-1-5225-9478-9

Stroe, A. C. (2021). Teachers' Perspective on Integration of Mobile Solutions in Romanian Undergraduate Education System, *Informatica Economica, 25*(2), 75-87.

Umek, L., Keržic, D., Tomaževic, N. & Aristovnik, A. (2015). *Moodle E-Learning System and Students' Performance in Higher Education: The Case of Public Administration Programmes*. International Association for Development of the Information Society.

Zamfiroiu, A., Petre, I. & Boncea R. (2019) Quiz logs analyse on Moodle E-Learning platform. In *International Open and Distance Learning Conference Proceedings Book* (p. 51).

Zeirhun, Z. (2018). Learning Analytics: A Critical Review of the Role and Implementation in Educational Institutions. In Kumar Singh, M., Zerihun, Z. &. Singh, N. (Eds.), *Impact of Learning Analytics on Curriculum Design and Student Performance*, 41-55. IGI Global. DOI: 10.4018/978-1-5225-5369-4.ch004