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STUDENTS' ACTIVENESS MEASURE IN MOODLE LEARNING MANAGEMENT SYSTEM USING MACHINE LEARNING

Chandrakumar Thangave[1], Valliammai S. E[2], Amritha P. P[3], Karthik Chandran[4], Subrata Chowdhury[5], Nguyen Thi Thu[6], Bo Quoc Bao[7], Duc-Tan Tran[8*], Duc-Nghia Tran[9], Do Quang Trang[10]
Department of Applied Mathematics and Computational Science, Thiagarajar College of Engineering, 625 015 India[123]
Department of Robotics and Automation, Jyothi Engineering College, Thrissur, Kerala, 625015 India[4]
Sri Venkateswara College of Engineering &Technology (A), Chittoor, Andhra Pradesh, 625015 India[5]
Faculty of Electronic Engineering, Hanoi University of Industry, Hanoi, 10000 Vietnam[67]
Faculty of Electrical and Electronic Engineering, Phenikaa University, Hanoi, 10000 Vietnam[8]
Institute of Information Technology, Vietnam Academy of Science and Technology, Hanoi, 10000 Vietnam[9]
Vietnam National Post and Telecommunication Group, Ho Chi Minh, 10000 Vietnam[10]
tan.tranduc@phenikaa-uni.edu.vn[8]

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**Corresponding Author*

ABSTRACT
Due to COVID-19, the need for online education has increased worldwide, prompting students to shift from traditional learning methods to online platforms as guided by higher education departments. Higher learning institutes are focused on developing constructive online learning platforms. This research aims to measure students' academic performance on an online learning platform – Moodle Learning Management System (LMS) – using machine learning techniques. Moodle LMS, a popular free and open-source system, has seen significant growth since the COVID-19 lockdown. Many researchers have analyzed student performance in online learning, yet there remains a need to predict academic outcomes effectively. In this study, data were collected from a higher learning institute in Tamil Nadu, and linear regression was applied to predict students' final course outcomes. The analysis, based on students' activity in Moodle LMS across both theory and laboratory courses, helps faculty identify students at risk of failing and adjust instructional methods and assignments accordingly. This approach aims to reduce failure rates by providing timely warnings and encouraging students to improve their engagement with LMS resources.
Keywords: *COVID-19, Moodle, Online Learning, Management System, Machine Learning*.

1. Introduction

As the world moves towards digital, the education also moves towards digital environment. This transformation was accelerated by the Global Pandemic that is COVID – 19 (Alizadeh et al., 2023; Adedoyin & Soykan, 2023; Al Lily et al., 2020). When education was shifted to an online based platform there was rapid decrease in student's performance (Alizadeh & Sharifi, 2021; Aloi et al., 2020). The reason behind this plunge was analyzed by using various data available in Online Learning Platforms. The main focus lies in the relationship between the student's performance and student's attention. Different analysis was carried out using student's activity in online platforms and student's results (Azorín, 2020; Bonal & González, 2020; Cavus et al., 2021). The hypothesis is that the student's activeness is directly correlated to the student's performance (Chaturvedi et al., 2021; DeCoito & Estaiteyeh, 2022). Thus, the problem statement is to know whether there is any correlation between the student's activeness in Moodle platform and their corresponding results.

1.1 Global Pandemic

The world today is facing the global pandemic, the COVID – 19. And every domain has switched from traditional methods to virtual platforms. One of the main fields that use conventional learning methods has changed to this new online method. Thus the need for E-learning has developed in large (Dhawan, 2020; Drane et al., 2021) Schools and Colleges around the world are establishing E-learning platforms vigorously. The need for an online platform has become necessary as it avoids crowd gathering and supports Social distancing. Thus, supporting COVID-19 protocols and still helping students keep track of their academic course (Aiken et al., 2020). "Online learning during COVID-19: Key challenges and suggestions to enhance effectiveness", deals with how the pandemic has impacted society. Faced with this pandemic, we had an opportunity to try digital learning (Pokhrel & Chhetri, 2021). And people are moving from face-to-face platforms to online platforms. This sudden transition imposed several challenges upon the students. They have mentioned key challenges that students face and the suggestion to adopt online and blended learning (Aleksandrova, 2019). “Student's perspective on distance learning during COVID-19 pandemic: A case study of Western Michigan University, United States”, have provided keynotes to improve online learning. During the period last two years, there was an increase in the number of articles that were released related to the research of online learning.

1.2 E-Learning

As E-learning increases, students' perception of this online platform needs high concentration. This change has created an impact on students. And there is a high chance that students may be suffering because of this change (Bangdiwala, 2018). “The Effects of Student Engagement, Student Satisfaction, and Perceived Learning in Online Learning Environments”, is an article that shows how course organization and structure, student engagement, learner interaction, and instructor have an impact on student satisfaction and perceived learning in online platform, thus creating a relationship between student engagement and course result (Bognár & Fauszt, 2021). “Improving online learning: Student perceptions of useful and challenging characteristics”, deals with the problems faced by the students from the perception of the student. Handles difficulties like Technical issues, time imperatives, and the trouble in understanding the destinations and provides suggestions for the struggles faced by the students.

People changed from traditional methods to new-formed methods of the virtual platform. This switch triggered many issues that we did not face before, and also it gave data-miners a great advantage. Online platforms record every data file and use those files to analyze patterns, thus predicting future results. Applying this into the E-learning domain was one of the chief research that dominated this era. The focus was to identify low-grade students by analyzing the log files and giving warnings beforehand. Thus, creating an effective and efficient E-learning model.

1.3 Outcomes

After entering the E-learning platform, it is necessary to know these two things. How do the students react to such new learning methods? And how do the students adapt to those things? And thus emerged a large number of people researching the outcomes of the students on such platforms (Cabral & Figueira, 2019). “Online Learning, Offline Outcomes: Online Course Taking and High School Student Performance”, suggest that virtual classes are better for students who are trying to recover their grade rather than first-timers. There is another article dealing with the outcome of the student (Estacio & Raga, 2017). “Online Learning and Student Outcomes in California’s Community Colleges”, which states that students are less inclined to finish an internet-based course than a conventional course, and it is important to note that students are less likely to complete a web-based course with a passing grade.

As we move to online mode, there is a gap in teaching in lab courses than theory courses. It is hard for students to understand lab classes without practical knowledge and experience. So, this research also focuses on lab class and checks the correlation between activeness and the practical score. And this research also checks the correlation between the activeness in Moodle and mark scored in the terminal and internals to identify the comfort zone of the students. Thus, helping them to achieve more focus in their academics during this pandemic period.

2. Literature Review

Moodle LMS has every detail stored in log files. These data files are heavily used by researchers and data miners (Horvat et al., 2015; Zhang et al., 2020). Since a large amount of data is readily available, researchers can analyze these log files to address key challenges faced in online learning platforms. For instance, "Using Machine Learning to Predict the Low-Grade Risk for Students Based on Log Files in Moodle Learning Management System" assesses the risk level of students during the completion of their courses. Moodle log files contain details about course interactions, such as login activities and submissions, which are used to predict students at risk of failing and to provide early warnings (Jacob & Hill, 2020).

Similarly, "Predicting Students' Performance in Moodle Platforms Using Machine Learning Algorithms" utilized Moodle LMS log data to examine whether there is a correlation between log data and student performance on the platform. The study confirms that a significant correlation exists between these two factors (Hussain et al., 2018).

In "Mining Moodle Data to Detect the Inactive and Low-Performance Students During the Moodle Course," researchers applied various machine learning classification and clustering techniques to analyze student data patterns. This approach enabled the early detection of low-performing students, sending alert signals to inactive or low-performing students and creating a more effective educational environment (Johnson & Cuellar, 2014).

Another study, "On the Development of a Model to Prevent Failures, Built from Interactions with Moodle," used data mining and a self-feedback machine learning algorithm with Moodle LMS. The system analyzes the interaction patterns of students and predicts their grade levels based solely on their interaction structure. This model automatically alerts students who deviate from the virtual learning path, providing timely guidance (Mazza et al., 2012).

The study "Analyzing Students' Online Learning Behavior in Blended Courses Using Moodle" conducted an investigation in an actual information technology course, yielding fascinating findings. It was found that female students were generally more active and successful than male students, and there was a significant relationship between login frequency and academic outcomes (Nguyen, 2021).

Finally, "MOCLog – Monitoring Online Courses with Log Data" aimed to develop a tool for analyzing and visualizing log data from Moodle servers. This tool combines instructional theory with user data and is based on didactical principles and user requirements gathered from interviews. The MOCLog framework is now available for deployment in academic institutions, offering educators valuable insights into student behavior and engagement (Pongpaichet, S et al., 2014).

3. Methods

This study is done by referring to the log data of MOODLE, an online platform for learning, which contains detailed data of students' activities in MOODLE (Karagiannis & Atratzemi, 2018), (Karagiannis & Atratzemi, 2017). To study and analyze the relationship between students' activeness in online platform-MOODLE Vs. their marks scored, a python programming language is used to reproduce data and to find the relation and predict the correlation and model fit, Linear Regression algorithm and Multiple Linear Regression algorithm is used.

3.1 Online Learning

Online Learning Platform

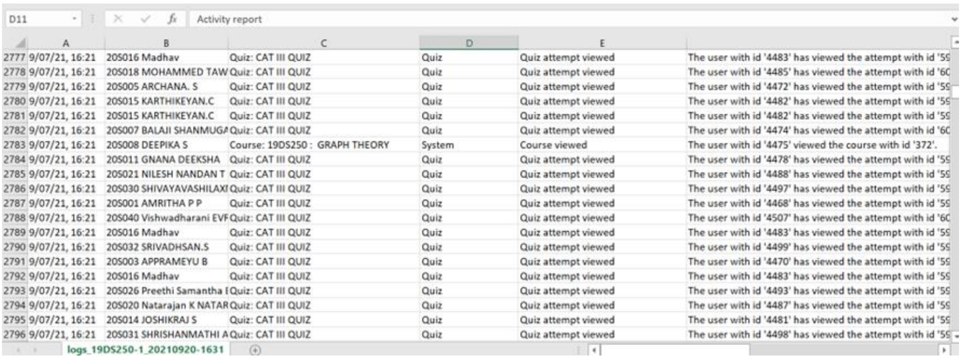
The online learning platform is a virtual platform that offers students educational content and resources with everything bound in one place. It helps students chat and interact with one another in a virtual webspace. It also allows the teacher to monitor the activity of the students regularly. These activities are recorded and stored as log files. These systems have a great scope since it connects students across the world. This method helps the students to learn new things from others. In 2019, As COVID-19 started to spread, copious schools and colleges moved to the online mode of learning. Teachers first started to use social media platforms like WhatsApp to distribute material and conducted meetings on platforms like Google meeting, zoom, and etcetera. And now colleges have begun to use platforms like Moodle canvas that integrate everything.

Moodle Learning Platform

Moodle LMS is a popular free, open-source learning management system written in PHP. It has customizable management feature and is used to create private website for educators and instructors. Moodle has made a boost ever since the lockdown due to COVID -19 and many universities are using this platform to host their courses.

Moodle LMS is an open-source learning management system. It helps instructors conceptualize the courses, course designs, and curriculum by working with students. It is an innovative model that has brought numerous utilities to help students and teachers. It permits instructors to assign classes, post assignments and assessments, calculate grades, etc. Students can access these classes, submit these assignments and look at the grades on this Moodle platform. This system provides instructors to create online courses effortlessly (an example in Figure 1). Moodle LMS also offers rich data saved in the system's database. That enables the data-miners to use these data files to create an online learning environment that is powerful and efficient. This data collected is known as the log files, stores every activity that has taken place on the Moodle platform, records admin activity, lecturers’ activity, and students who have interacted with the course activity, also stores the grades evaluated by the instructor for each course. Each course contains login time, user name, event name, submissions, component, and IP address (Figure 2).

Fig.1. Moodle LMS, https://coursesoddsem.tce.edu/ online.



D11 | Activity report

	A	B	C	D	E	
2777	9/07/21, 16:21	20S016 Madhav	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4483' has viewed the attempt with id '5
2778	9/07/21, 16:21	20S018 MOHAMMED TAW	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4485' has viewed the attempt with id '6
2779	9/07/21, 16:21	20S005 ARCHANA. S	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4472' has viewed the attempt with id '5
2780	9/07/21, 16:21	20S015 KARTHIKEYAN.C	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4482' has viewed the attempt with id '5
2781	9/07/21, 16:21	20S015 KARTHIKEYAN.C	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4482' has viewed the attempt with id '5
2782	9/07/21, 16:21	20S007 BALAJI SHANMUGA	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4474' has viewed the attempt with id '6
2783	9/07/21, 16:21	20S008 DEEPIKA S	Course: 19DS250 : GRAPH THEORY	System	Course viewed	The user with id '4475' viewed the course with id '372'.
2784	9/07/21, 16:21	20S011 GNANA DEEKSHA	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4478' has viewed the attempt with id '5
2785	9/07/21, 16:21	20S021 NILESH NANDAN T	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4488' has viewed the attempt with id '5
2786	9/07/21, 16:21	20S030 SHIVAYAVASHILAXI	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4497' has viewed the attempt with id '5
2787	9/07/21, 16:21	20S001 AMRITHA P P	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4468' has viewed the attempt with id '5
2788	9/07/21, 16:21	20S040 Vishwadharani EVF	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4507' has viewed the attempt with id '6
2789	9/07/21, 16:21	20S016 Madhav	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4483' has viewed the attempt with id '5
2790	9/07/21, 16:21	20S032 SRIVADHSAN.S	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4499' has viewed the attempt with id '5
2791	9/07/21, 16:21	20S003 APPRAMEYU B	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4470' has viewed the attempt with id '5
2792	9/07/21, 16:21	20S016 Madhav	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4483' has viewed the attempt with id '5
2793	9/07/21, 16:21	20S026 Preethi Samantha I	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4493' has viewed the attempt with id '5
2794	9/07/21, 16:21	20S020 Natarajan K NATAR	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4487' has viewed the attempt with id '5
2795	9/07/21, 16:21	20S014 JOSHIKRAJ S	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4481' has viewed the attempt with id '5
2796	9/07/21, 16:21	20S031 SHRISHANMATHI A	Quiz: CAT III QUIZ	Quiz	Quiz attempt viewed	The user with id '4498' has viewed the attempt with id '5

logs_19DS250-1_20210920-1631

Fig. 2. Moodle Data data for theory course.

Log Activity

Log activity is the activity of the student in the Moodle platform. Every activity is recorded in this platform, that includes Login, file downloads, file submissions, assessments and extra. All activity is noted and one point is provided for each activity. Summation of these activities will provide the activeness in that CAT (Continuous assessment test) and total activeness will give the activeness of the student in that semester.

3.2 Machine Learning Techniques used in this study

Linear Regression

Regression is a statistical term that shows the relationship between variables. Linear Regression deals with the connection between one dependent variable and one or more independent variables. Simple linear regression has only one independent (Bangdiwala, 2018) as equation (1).

$$y = w_0 + w_1x \qquad (1)$$

where
w_1 is slope of the equation
w_0 is y-intercept
y is dependent variable
x is independent variable.
x is the independent variable and y is the predicted variable with the corresponding value of x, and find the variables m and c using the least square formula to get the most suitable straight line:

$$w_1 = \frac{\sum_{i=1}^{|D|}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{|D|}(x_i - \bar{x})^2} \qquad (2)$$

$$w_0 = \bar{y} - w_1\bar{x} \qquad (3)$$

Multiple Linear Regression

Multiple linear regression studies the relationship between a single dependent variable and a collection of independent variables (Aiken *et al*., 2020).

$$y = w_0x_0 + w_1x_1 + w_2x_2 + \ldots\ldots + w_ix_i \qquad (4)$$

where
w_1 is slope of the equation
w_0 is y-intercept
y is dependent variable
x_i is independent variable.

Pearson correlation coefficient

Pearson orrelation coefficient is a statistical test that measures the relationship between two cont

$$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}} \qquad (5)$$

where
r is correlation coefficient.
w_0 is y-intercept
x_i are values of x in a sample
$\bar{x}$ is mean of x variables.
y_i is values of y variable in a sample.
$\bar{y}$ is mean of y variables.

3.3 Data Collection and Processing

Collect data. This research uses the log data of 2 theory courses and 2 practical courses taught through Moodle platform in the second semester of 2020-2021 in the online platform of Thiagarajar College of Engineering (https://courses.tce.edu/). Thus the research analysis is made from real-world data.

Preprocess data. The log data contains various log details, most of which are needed and few are not needed. Thus data cleaning is done. The data is abstracted according to our needs. Thus data cleaning is done. The data is abstracted based on our needs. The activeness of students is analyzed from the log data in different intervals and a new excel file is created with students' activeness in different intervals and their marks in those intervals (CAT-Continuous assessment test) and also the total percentage of activeness in Moodle platform. It also contains the total activeness in the semester and consolidated CAT marks. Hence, the activeness file is integrated with the marks file of students. This is converted to a (.csv) file which contains the details in Fig. 3 and analyzed.

	A	B	C	D	E	F	G	H	I	J	K
1	Reg number	Activeness CAT1	Percent CAT1	Activeness CAT2	Percent CAT2	Activeness CAT3	Percent CAT3	Total Activeness	Cat Marks	CAT	Sem Marks
2	20S001	105	2.339051014	50	3.422313484	112	2.909846713	89	48	96	97
3	20S002	68	1.51481399	22	1.505817933	52	1.35100026	47.33333333	46	92	92
4	20S003	109	2.428157719	28	1.916495551	123	3.19563523	86.66666667	47	94	96
5	20S004	86	1.915794164	46	3.148528405	100	2.598077423	77.33333333	48	96	95
6	20S005	114	2.5395411	26	1.779603012	81	2.104442712	73.66666667	45	90	85
7	20S006	128	2.851414569	32	2.19028063	100	2.598077423	86.66666667	48	96	97
8	20S007	95	2.11628425	35	2.395619439	70	1.818654196	66.66666667	48	96	97
9	20S008	99	2.205390956	33	2.258726899	54	1.402961808	62	47	94	91
10	20S009	152	3.386054801	54	3.696098563	114	2.961808262	106.6666667	49	98	98
11	20S010	102	2.272220985	22	1.505817933	105	2.727981294	76.33333333	46	92	90
12	20S011	83	1.848964135	40	2.737850787	70	1.818654196	64.33333333	47	94	92
13	20S012	93	2.071730898	34	2.327173169	103	2.676019745	76.66666667	48	96	97
14	20S013	85	1.893517487	33	2.258726899	75	1.948558067	64.33333333	47	94	93
15	20S014	120	2.673201158	41	2.806297057	93	2.416212003	84.66666667	47	94	96
16	20S015	83	1.848964135	31	2.12183436	83	2.156404261	65.66666667	47	94	95
17	20S016	75	1.670750724	24	1.642710472	104	2.70200052	67.66666667	46	92	95
18	20S017	136	3.02962798	33	2.258726899	131	3.403481424	100	47	94	93
19	20S018	125	2.78458454	35	2.395619439	60	1.558846454	73.33333333	48	96	92
20	20S019	85	1.893517487	35	2.395619439	71	1.84463497	63.66666667	48	96	95
21	20S020	109	2.428157719	39	2.669404517	57	1.480904131	68.33333333	47	94	96
22	20S021	85	1.893517487	29	1.984941821	68	1.766692647	60.66666667	47	94	91
23	20S022	162	3.608821564	49	3.353867214	100	2.598077423	103.6666667	47	94	90
24	20S023	103	2.294497661	37	2.532511978	102	2.650038971	80.66666667	46	92	95
25	20S024	102	2.272220985	52	3.559206023	120	3.117692907	91.33333333	48	96	95
26	20S025	84	1.871240811	41	2.806297057	66	1.714731099	63.66666667	47	94	94
27	20S026	499	11.11606148	66	4.517453799	450	11.6913484	338.3333333	48	96	97

Fig. 3. Students CAT mark

3.4 Data Analysis

This study used python programming language to analyze and generate graphs to find the relation between the activeness of students in a Moodle-online platform for learning and their relative marks scored. A conclusion is drawn from the results of the above-simulated graphs, further conclusions are made by applying linear regression and Multiple Linear Regression to arrive with yet more conclusions.

4. Results and Discussions

4.1 Results

The analysis done is picturized and summarized. In Fig. 4, the linear regression fit is not perfect. This indicated the internal marks are less dependent on their activeness on Moodle website.

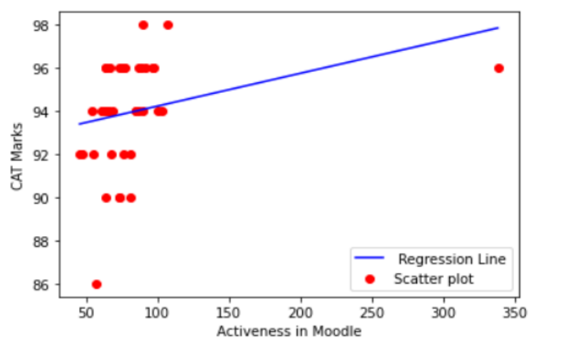


Fig. 4. A linear relationship between internal marks and students' activeness

In Fig.5, the linear regression fit is not perfect. This indicated the terminal semester marks are also less dependent on their activeness on Moodle website.

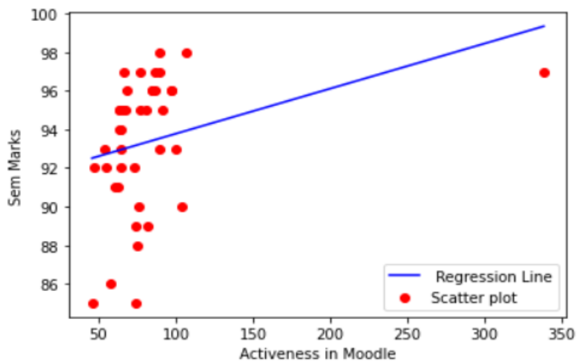


Fig. 5. A linear relationship between semester marks and students' activeness

In Fig. 6, there is a better relationship between a student's internal exams marks and end-semester marks. Thus a student who scored good marks in internal is most probable to score better marks in a semester.

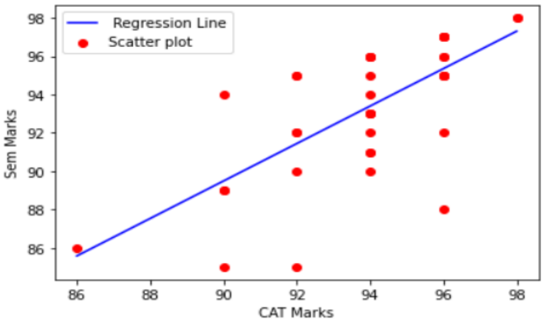


Fig. 6. A linear relationship between semester marks and CAT marks

Fig. 7 depicts the error rate of the correlation between the total activeness of the student in Moodle and their semester marks.

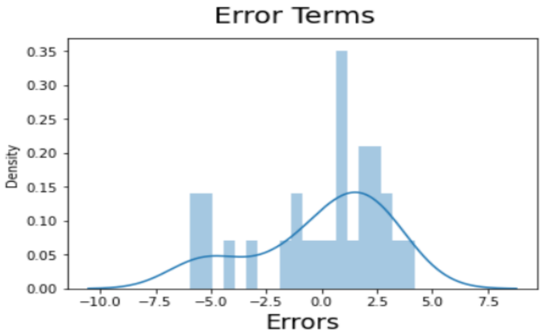


Fig. 7. Total Activeness vs. Semester marks

Fig. 8 depicts the error rate of the correlation between the total activeness of the student in Moodle and their consolidated internal marks.

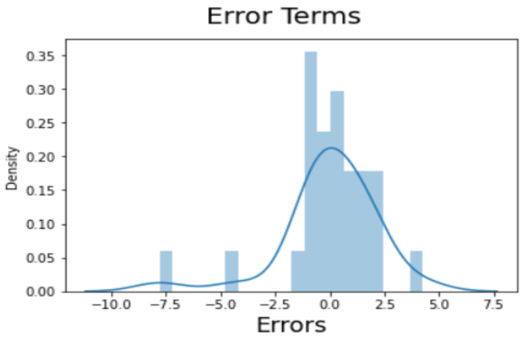


Fig. 8. Total Activeness vs. CAT

4.2 Discussion

The helpful assessments for online learners are an important part of online learning (Dhawan, 2020). The analysis of the data collected from the Moodle platform indicates that student activity in online learning environments is not a strong predictor of their academic performance. Specifically, the linear regression analysis reveals weak correlations between students' activeness on the Moodle platform and their internal and semester marks. Figures 4 and 5 demonstrate that both internal and terminal marks show minimal dependence on a student's online engagement.

However, the relationship between internal exam marks and end-semester results, shown in Figure 6, suggests that students who perform well in their internal assessments tend to achieve higher grades in the final semester exams. This finding indicates that internal performance is a more reliable indicator of overall academic success than simple online activeness.

Figures 7 and 8 further highlight the lack of a strong correlation between overall Moodle activeness and academic outcomes. The error rates depicted in these figures suggest that activeness on the platform, while useful for tracking participation, is not a sufficient metric for predicting student success. This could be due to the variety of learning methods students employ, many of which are not captured by Moodle's log data. Activities such as offline study, note-taking, and independent problem-solving contribute significantly to student performance but remain outside the scope of the Moodle log analysis.

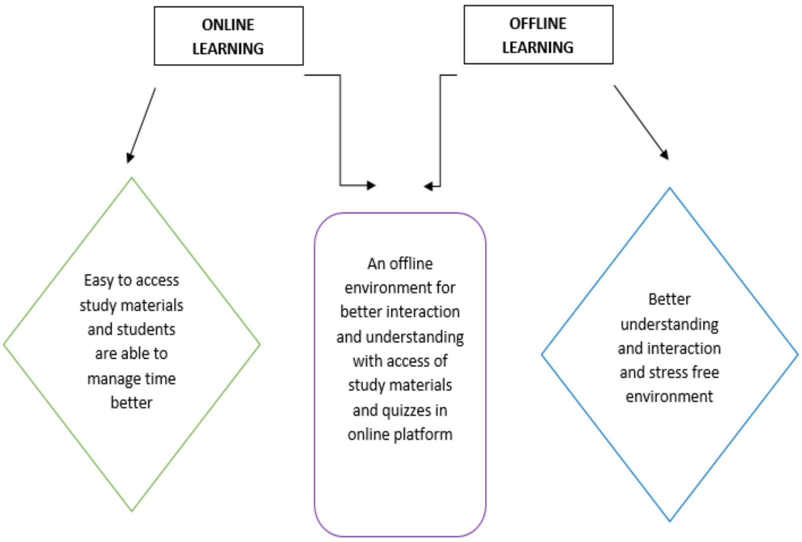


Fig. 9. An Outcome framework

E-learning tools helped schools and universities facilitate student online learning (Subedi et al., 2020). Moodle is a valuable tool for facilitating online learning and monitoring student participation, the data it provides may not fully reflect the comprehensive learning process. Students also face difficulties in learning/understanding during online learning due to the lack of consultation with teachers (Sintema, 2020). The findings underscore the need for a more holistic approach to assessing student performance that considers both online activity and offline efforts. An outcome framework has been framed as shown in Figure 9. Note that for online/offline learning, different subjects require different approaches (Basilaia & Kvavadze, 2020). Thus, governments should invest more funds to support the education sector (Jacob et al., 2020; David, 2009; Babbar & Gupta, 2022).

5. Conclusion

This study provides a novel perspective on the relationship between student engagement in Moodle and academic performance. While previous research has often focused on direct correlations between online activity and outcomes, our findings reveal that simple activeness in the Moodle platform is not a strong predictor of academic success. Instead, internal assessments, such as CAT marks, serve as more reliable indicators of a student’s final semester performance. By integrating both internal and external assessment data, this study introduces a more comprehensive framework for predicting at-risk students. This new approach acknowledges the multifaceted nature of learning, where offline activities such as note-taking, independent study, and problem-solving play critical roles that cannot be captured solely through Moodle activity logs. Our research contributes to the development of more adaptive online learning systems that go beyond tracking participation, offering a more holistic method for early intervention and support of students. This framework can serve as the foundation for creating more personalized and effective learning environments in higher education.

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