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Moodle interactions and academic performance: educational data mining in a Philippine university

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ABSTRACT

Poor academic performance remains among the most concerning educational issues, especially in higher education and online learning. To address the concern, institutions like the University of Southeastern Philippines (USeP) leverage educational data mining (EDM) techniques to generate relevant information from learning management systems (LMS) like Moodle, supporting the overall student learning experience. Moodle, considered the most widely used LMS platform, allows researchers and educators to access course logs to generate valuable insights. This EDM study at USeP explored the relationship between Moodle interactions and academic performance using data wrangling and correlation analysis. By examining various interactions from 16 courses collected with a sample size of 682, the study revealed weak correlations between students' Assignment, Create, and Forum actions and academic performance. While Assignment and Create actions show a weak positive association, Forum actions exhibit a weak negative correlation. The majority of Moodle interactions demonstrate a negligible relationship with academic performance. These findings aim to inform educators and administrators about optimizing the use of Moodle to foster a supportive digital learning environment at USeP. This study recommends further explorations, analyses, and other approaches to deepen understanding of the relationship between Moodle interactions and academic performance.

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1. INTRODUCTION

Poor academic performance is one of the major concerns in educational institutions worldwide. Poor academic performance leads to students failing to achieve the minimum requirements of enrolled courses, resulting in dropouts [1]. The dropout concern is prevalent in higher education, offering online or blended courses [2]. The dropout rate for online courses worldwide is 25% to 90%, significantly higher than traditional face-to-face courses [3]. In the Philippines, the Universal Access to Quality Tertiary Education Act, an act providing free tuition and other school fees to State Universities and Colleges (SUCs), Local Universities and Colleges (LUCs), and State-Run Technical-Vocational Institutions (STVIs), has resulted to increased student enrollments. However, this increase has also led to an alarming overall dropout rate of 83.7% at some point in the country, regardless of learning modality [4].

In recent years, institutions have leveraged technological advancements to support students' overall learning experience. Institutions leverage the power of educational data mining (EDM) to cope with educational challenges. Using data mining techniques, EDM extracts valuable insights from educational data [5]. EDM has increased research interest over the years [6] due to its practical and advanced approach to analyzing data. The popularity of online learning through the use of learning management systems (LMS) has dramatically enhanced EDM opportunities due to the vast amounts of data that can be generated [7], [8].

Academic institutions use LMS, one of the most popular online learning platforms, to deliver online, flexible, and blended learning modalities. LMS is progressing in higher educational institutions in developed and developing countries [9] due to its many advantages, such as distance learning, automated grading, and data storage. With LMS comes a considerable amount of data users produce, and a research trend continues to grow involving analysis of student interaction and learning analytics within the LMS [10]. LMS includes various platforms such as Blackboard, Google Classroom, Canvas, and Moodle.

Moodle, an open-source LMS, is the most popular among these LMS platforms, with over 160,000 registered sites worldwide, according to the 2023 Moodle site registration statistics. Moodle has gained research interest over the years, becoming the most researched LMS based on the number of SSCI-index articles published in the Web of Science database [11]. In Moodle, information about how students interact with the LMS can be collected through EDM techniques. Moodle collects information from students, such as the frequency of course access and submission of requirements [12]. This information can be accessed through the Moodle database or the Moodle logs.

Over the years, LMS use has been proven beneficial to students' multiple times [13]. While other factors contribute to the success of students, such as social, human, and reinforcement factors [9], several studies [14]–[18] suggest correlations between LMS interactions and academic performance. In contrast, some studies, such as [19], found significant and non-significant relationships. Some studies also found LMS interactions to be predictors of student success. However, these studies do not generalize findings since LMS course designs and the variables used in the analysis differ from course to course [19]. Therefore, there is a need to institutionalize the research involving LMS to generate meaningful results for an institution.

Higher learning institutions in the Philippines use LMS to deliver online or blended courses. The University of the Philippines (UP), De La Salle University, and the University of Sto. Thomas integrated LMS into their instructional offerings. However, there is still a concern about LMS acceptance, especially among students who are not ready to embrace technological advancements [20]. Nevertheless, this concern did not hinder Philippine institutions from using LMS, especially during the COVID-19 pandemic. For instance, Isabela State University developed a Moodle-based LMS as a customized LMS to fit their needs [21]. Their Moodle-based LMS has proven more effective in their flexible learning implementation than other LMS platforms.

The University of Southeastern Philippines (USeP), an SUC in Davao Region, Philippines, established through Republic Act 12, 1979, used Moodle in its LMS implementation as mandated by the Commission on Higher Education (CHED) during the COVID-19 pandemic through commission memorandum order (CMO) No. 04 series of 2020–Guidelines on the Implementation of Flexible Learning. With continued LMS operations, there is a noticeable gap in research studies conducted within USeP that are relevant to its LMS implementation. The lack of institutional research leaves the USeP community unaware of the potential drawbacks of its LMS implementation.

While studying a specific institution's LMS implementation can be a broad area for research, this study plans explicitly to investigate the relationship between USeP students' LMS interactions and academic performance using EDM through data wrangling and correlation analysis to determine the types of interactions significantly correlated to student grades. By analyzing these correlations, the university can identify trends and insights that may help educators understand students' learning patterns and how these relate to their grades. Doing so can assess the USeP community's LMS implementation. This information can be valuable for designing targeted interventions and improving instructional strategies to enhance students' overall learning experience and performance. The correlation between Moodle interactions and academic performance provides a data-driven approach to understanding the factors influencing student success in the digital learning environment.

2. METHOD

The research used correlation analysis as the central aspect of the EDM study. Using an EDM approach to collect data from the LMS logs, correlation analysis is performed on feature-engineered variables (independent) and students' grades (dependent variable). The feature-engineered variables represent students' Moodle interactions within a course, while students' grades represent academic performance. All methodological aspects of the study were performed using the R programming language with its relevant packages.

2.1. Data collection

Course logs and students' grades were collected from the University's College of Information and Computing (CIC) Moodle courses and class records through convenience sampling. Sixteen (16) courses from the Bachelor of Science in Information Technology (BSIT) and Bachelor of Science in Computer Science (BSCS) programs in the academic years 2021-2022 and 2022-2023 were used as sampled courses. These courses used Moodle through blended modality and flexible learning approaches.

The entire data collection process using EDM techniques followed the framework shown in Figure 1. Because raw Moodle course logs are unstructured, each course log must undergo a data-wrangling process to create a data structure suitable for analysis. The transformed course log data is combined with the course grade data to create complete course data. The process is done for all 16 courses and merged into a final data set ready for feature engineering and correlation analysis.

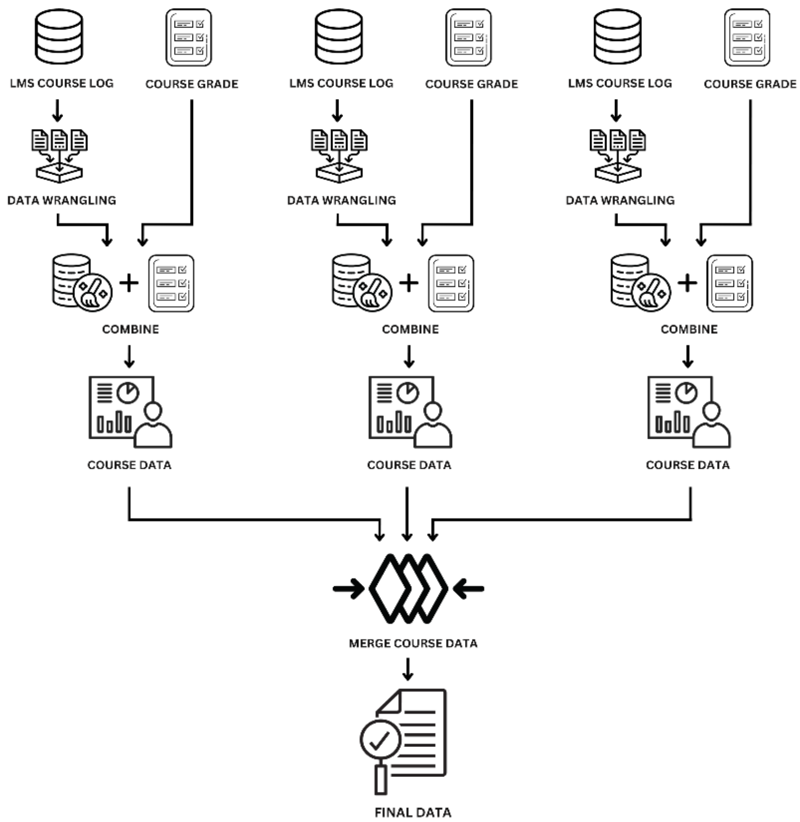

Figure 1. Data collection EDM framework used in the study

The Moodle course logs' student names and event names (type of student action) are transformed into column headers, where each student's actions are recorded as frequencies based on a particular event name. The time column from the course logs was also transformed as a new column header. The time-based column was added to each course data representing the number of days logged in. This column was generated by data wrangling that involved identifying distinct date entries per student; the first feature engineering performed on a per-course basis.

Table 1 shows the 16 courses collected, indicating the academic year and the number of rows and columns after transforming the course log. The student’s name column was deleted for data integrity. The number of rows represents the number of students (observations) enrolled in the course, and the columns are the number of event names, including the number of days logged in column recorded by students in each course. The data wrangling aspect of this phase is performed using the dplyr and tidyr packages of the R programming language. These two (2) packages are part of the tidy verse meta package in R, providing a straightforward data analysis approach [22].

Table 1. The 16 courses' data before merging with course grade data

Academic Year	Course	Number of Rows (Observations)	Number of Columns (Variables)
2021-2022	Advanced algebra (BSCS)	34	43
	applied data science (BSCS)	22	44
	computer networks concepts and theories (BSCS)	45	39
	Data analytics (BSCS)	32	35
	Social network analysis (BSCS)	34	40
2022-2023	Business analytics (BSIT)	20	33
	Computer networks concepts and theories (BSCS)	30	38
	Data analytics (BSCS)	26	32
	Data structures (BSCS)	35	21
	Data structures (BSIT)	72	21
	Digital image processing (BSCS)	42	20
	Digital image processing (BSIT)	48	18
	Probability and statistics for computing (BSCS, BSIT)	107	50
	Programming paradigm 2 (BSCS)	31	21
	Programming paradigm 2 (BSIT)	77	23
	Social network analysis (BSCS)	33	35

Due to the variations in the courses' number of columns, data wrangling is performed by removing course-unique columns while imputing values with 0 for the common columns not logged in some courses. Doing this ensures that each course will have an equal number of columns before combining with the course grade data. Following the framework in Figure 1, each course data was combined with the course grade data, and consequently, all complete course data were merged into a single final data set. Removing outliers makes this data set suitable for analysis.

The final data set contains six hundred eighty-two (682) rows or observations with thirty-eight (38) columns or variables (including grades), no missing values, and all numeric data types. Table 2 shows the 38 variables of the final data set. Excluding number of days logged in and academic performance, these variables are the Moodle event names from the raw Moodle course log. Each event name is logged by students in at least 8 of the 16 courses.

Table 2. The 38 variables of the final data set

Column Names (Variables)		
Course viewed	Submission removed	Quiz attempt abandoned
Course module viewed	Submission viewed	Quiz attempt auto-saved
Grade user report viewed	Some content has been posted	Quiz attempt time limit exceeded
Grade overview report viewed	Course searched	Quiz attempt question restarted
Comment created	Discussion created	Quiz attempt reviewed
Comment deleted	Discussion subscription created	Quiz attempt started
A file has been uploaded	Discussion subscription deleted	Quiz attempt submitted
An online text has been uploaded	Discussion viewed	Quiz attempt summary viewed
Submission created	Post created	Quiz attempt updated
Submission updated	Post updated	Quiz attempt viewed
A submission has been submitted	Subscription created	Number of days logged in
Feedback viewed	Subscription deleted	Academic performance
The user duplicated their submission	User report viewed	

2.2. Feature engineering

The final data set was analyzed to create new variables or features based on student actions. Thirty-six (36) of the 38 variables of the final data set were categorized into seven (7) Moodle interactions through feature engineering. Through the tidy verse package, feature engineering involved appropriately adding these variables' frequencies as logged per student. In addition to the previously feature-engineered number of days logged in variable, the data set now has 8 variables as the Moodle interactions. These variables are assignment actions, quiz actions, forum actions, create actions, read actions, update actions, delete actions, and number of days logged in.

As part of the EDM process, feature engineering aims to generalize results to other courses within the university. The university's most widely used Moodle activities and resources are the assignment, quiz, and forum modules. The create, read, update, delete (CRUD) actions represent standard database query types. They are categorized records of Moodle event names within a course log, representing the four (4) basic operations involving data [23]. The number of days logged in represents a time-based feature based on daily student visits in a course. The feature engineering aspect of the study is necessary due to the complexity of the dimensions of the Moodle logs [24].

Table 3 shows the 8 Moodle interactions generated from the feature engineering performed on the Moodle course log's event names and the time column. These are the independent variables of the study. The columns include all independent variables (feature-engineered) and the dependent variable, academic performance, which refers to students' actual grades from the course grade data in percentages at the end of the course. The data set now contains 682 observations with only nine (9) variables, no missing values, and all numeric data types.

Table 3. Moodle interactions generated from log records using feature engineering

Moodle interaction	Log record/event name
Assignment actions	A file has been uploaded
	An online text has been uploaded
	A submission has been submitted
	The user duplicated their submission
	Submission removed
	Submission viewed
Quiz actions	Quiz attempt abandoned
	Quiz attempt time limit exceeded
	Quiz attempt question restarted
	Quiz attempt reviewed
	Quiz attempt started
	Quiz attempt submitted
	Quiz attempt summary viewed
	Quiz attempt updated
	Quiz attempt viewed
Forum actions	Discussion created
	Discussion viewed
	Discussion subscription created
	Discussion subscription deleted
	Some content has been posted
	Post created
	Post updated
	Subscription created
	Subscription deleted
Create actions	Comment created
	A file has been uploaded
	An online text has been uploaded
	Submission created
	The user duplicated their submission
	Some content has been posted
	Discussion created
	Discussion subscription created
	Post created
	Subscription created
	Quiz attempt started
Read actions	Course viewed
	Course module viewed
	Grade user report viewed
	Grade overview report viewed
	Feedback viewed
	Course searched
	Discussion viewed
	User report viewed
	Quiz attempt reviewed
	Quiz attempt summary viewed
	Quiz attempt viewed
Update actions	Submission updated
	A submission has been submitted
	Post updated
	Quiz attempt abandoned
	Quiz attempt time limit exceeded
	Quiz attempt question restarted
	Quiz attempt submitted
	Quiz attempt updated
Delete actions	Comment deleted
	Submission removed
	Discussion subscription deleted
	Subscription deleted
Number of days logged in	Time and date variables in the course log (count of distinct days)

2.3. Correlation analysis

Correlation analysis includes normality, correlation, and significance tests. A test for normality is performed on each Moodle interaction and students' grades using the Shapiro-Wilk test with a significance level alpha of 0.05. A test of normality is necessary to determine if the correlation test to be performed is parametric or non-parametric [25]. For non-normally distributed data, an exploration is conducted to determine if multiple rank ties within the observation exist. Based on the correlation analysis, the Kendall rank test (non-parametric) is used because of the non-normal distribution of all variables, and multiple rank ties exist [26]. To ensure the reliability of the correlation scores, a significance test for each correlation test is performed [27] to get the p-value with a significance level alpha set to 0.05. All aspects of the correlation analysis used the base R built-in functions.

3. RESULTS AND DISCUSSION

3.1. Results

Table 4 shows the results of the Shapiro-Wilk test for normality with the number of ties. All variables except delete actions result in a Shapiro-Wilk test statistic W close to 1, indicating near normal distribution. However, all p-values are below the significance level of 0.05, indicating a rejection of normality [25] for all variables. All variables have multiple ties in the distribution. Read actions have the most ties at 161, while delete actions have the least number at 4.

Table 4. Results of normality test using Shapiro-Wilk with number of ties

Variables	W	p-value	Description/Number of Ties
Assignment actions	0.91088	<2.2e-16	Non-normally distributed with 39 ties
Quiz actions	0.73803	<2.2e-16	Non-normally distributed with 93 ties
Forum actions	0.71955	<2.2e-16	Non-normally distributed with 59 ties
Create actions	0.90835	<2.2e-16	Non-normally distributed with 57 ties
Read actions	0.88215	<2.2e-16	Non-normally distributed with 161 ties
Update actions	0.85402	<2.2e-16	Non-normally distributed with 28 ties
Delete actions	0.16001	<2.2e-16	Non-normally distributed with 4 ties
Number of days logged in	0.95997	1.108e-16	Non-normally distributed with 69 ties
Academic performance	0.79108	<2.2e-16	Non-normally distributed with 36 ties

A Kendall rank correlation and significance test for each correlation test are performed, generating multiple parameters. Table 5 shows the correlation test's direction, coefficient (tau), category, and p-value (significance) performed on each Kendall rank correlation test between a Moodle interaction and academic performance. Based on the p-value results with a significance level set to 0.05, only read actions failed to reject the null hypothesis that there is no correlation between this particular Moodle interaction and academic performance. While the p-values of the rest of the interactions indicate rejection of the null hypothesis [28], only assignment actions, forum actions, and create actions are related to academic performance. assignment actions and create actions are correlated positively, while forum actions are correlated negatively. However, these relationships are categorized as weak. The quiz actions, update actions, delete actions, and number of days logged in Moodle interactions have very weak correlations to academic performance. These correlations are considered negligible regardless of the direction.

Table 5. Correlation analysis results for each Moodle interaction with academic performance using Kendall

Moodle interaction and academic performance	Direction	Coefficient (tau)	Category	p-value
Assignment actions	Positive	0.2043847	Weak	3.566e-14
Quiz actions	Negative	-0.08159548	Negligible	0.003664
Forum actions	Negative	-0.11.07003	Weak	7.688e-05
Create actions	Positive	0.1265715	Weak	2.168e-06
Read actions	Positive	0.0128422	Negligible	0.6246
Update actions	Positive	0.06778934	Negligible	0.01205
Delete actions	Negative	-0.09115757	Negligible	0.004271
Number of Days Logged In	Positive	0.089983223	Negligible	0.0006709

3.2. Discussion

Various factors like social dynamics, human elements, and reinforcement mechanisms contribute to student success, and studies indicate a link between interactions in LMS and academic performance. However, conflicting studies exist, with some studies reporting significant relationships while others do not. Nevertheless, these findings lack generalizability due to variations in LMS course designs and analyzed variables across different courses. Thus, the study institutionalized Moodle interactions and students' academic performance from USeP using data mining with correlation analysis.

The findings of the EDM study suggest that, despite generally weak correlations, certain Moodle interactions exhibit some relationship with academic performance at USeP. The association between assignment actions and create actions with academic performance indicates a connection, even though the strength of these relationships is weak. These interactions, which likely involve content submission and creation, demonstrate some influence on students' academic outcomes. On the other hand, forum actions exhibit a negative correlation with academic performance. This implies that increased engagement in forum activities may be associated with lower academic performance. The reasons for this negative correlation could be further explored to understand the nature of online forum participation and its impact on student outcomes. However, it is crucial to note that the relationships observed in the study are categorized as weak, suggesting that although there is some connection between these Moodle interactions and academic performance, the practical significance of these associations may be limited. The study results also emphasize that most Moodle interactions have negligible relationships with academic performance. This implies that viewing resources, accessing quizzes, or participating in other Moodle activities may not be strong indicators of academic success in the context of USeP and this study.

The results supported the literature in the context of the generalizability and transferability concerns of results from previous studies, which is a complex issue [19], [29]. For example, the time-based feature number of days logged in contradicts the findings of [15], [16] concerning the time-based component's significant relationship with grades. Moreover, quiz activities that have found a relationship with exam scores in the study of [18] also contradict this study's findings. Such contradictions further signify the need to institutionalize research in the context of EDM. It is worth noting, however, that the study only used a small sample size of 682 observations and was limited to a single college or department. Further Moodle-related research in USeP should consider larger sample sizes [30]. Overall, the results may be attributed to USeP's implementation of the Moodle LMS, including how the faculty utilizes the LMS due to familiarity concerns and minimal feature usage [31], among many other reasons that need further investigation.

The study's emphasis on the Moodle LMS implementation at USeP raised questions about how various contextual factors may influence the observed relationship between LMS interactions and academic performance. Institutional policies, technological infrastructure, and instructional practices could significantly impact student engagement with the LMS and their academic performance. Future research should explore these contextual variables in greater detail to provide a more nuanced understanding of the relationship between LMS interactions and student success within specific educational settings.

While previous studies suggest contradictions in the relationships between Moodle interactions and student grades, this EDM study provides valuable insights into the relationship between Moodle interactions and academic performance in a localized Philippine university, USeP. The study looked at interactions from 16 courses and a sample size of 682 and found that student interactions in assignment, create, and forum actions had weak correlations to academic performance. assignment actions and create actions had weak positive correlations, while forum actions showed a weak negative correlation. Overall, most Moodle interactions had little impact on academic performance.

4. CONCLUSION

Educators and administrators of USeP must consider the study findings valuable insights into how Moodle LMS is being implemented. The study also stresses the need for further research to explore the complex relationship between online learning interactions and outcomes, aiming to inform educational practice and improve the overall learning experience. Several robust EDM analysis techniques can be considered to enhance understanding of the relationship between Moodle interactions and academic performance. These include multivariate analysis, learning analytics, and machine learning techniques that offer powerful tools for predicting student performance and identifying at-risk individuals. By incorporating more robust analyses, the study can contribute to understanding Moodle interactions and academic performance and developing informed strategies that positively impact students' academic journey in USeP. As the study's primary limitation, including other disciplines and colleges for the course sampling is strongly recommended to strengthen the generalizability of the results to the entire USeP community. Furthermore, while the study provides valuable insights into Moodle implementation within a specific context, broadening the scope by including other disciplines and colleges within UseP is essential. This enhances the generalizability of the findings and enables a more comprehensive understanding of how Moodle interactions impact students across various academic domains and backgrounds.

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