Journal of Learning for Development 12(2), 2025, 290-312.

Monitoring Collaborative Interactions in Online Learning: Insights from Moodle Log Records

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Keywords

Moodle, Vector Space Model (VSM), collaborative learning, online interactions, learning analytics, online learning

Abstract

Interactions among students in online learning environments are difficult to monitor but can be crucial for their academic performance. Moodle is one of the best and most popular online learning platforms, where its log records can reveal important information on students' engagement and the respective performance. This study examines the degree of student participation and performance in online collaborative content creation activities, based on three iterative testing cycles: systematically designed Moodle forum discussions, group assignments, Wikis and Moodle workshops, specifically to obtain peer feedback. The abovementioned collaborative Moodle content creation and corresponding log record analysis was executed for four modules conducted at two higher education institutions from Sri Lanka and Brazil. Regression analysis on log records and student performance on four modules indicated a positive correlation, with R^2 values between 26% and 43.8%. A significant amount of data which remained unexplained were subjected to the Vector Space Model (VSM) data mining algorithm to uncover in-depth information. The results, indicating substantial influence on student performance by participation in online collaborative activities, provided vital insights into necessary improvements on instructional design. Accordingly, promoting productive student interactions could be significant in online learning environments, and the findings of this study underscore the importance of utilising the learning analytics data driven approaches to elevate student performance.

Introduction

Learning Management Systems (LMSs) are commonly used to create, manage, and distribute digital resources for both in-person and online delivery of educational instructions. These LMSs enable blending of conventional teaching techniques with digital learning resources to provide customised online learning opportunities for students (Aljawarneh, 2020; Corfman & Beck, 2019; Xie & Correia, 2024). Despite online learning having a long history, it gained much

Published by Commonwealth of Learning, Canada

popularity and a significant increase in usage only during the appearance of the Covid-19 pandemic in 2020, when on-site instruction in educational institutions was severely constrained by a global crisis (Dias et al., 2020; Raza et al., 2021). As a result, the learning environments were subject to a forced transformation from conventional modes of education, assessment, research, and scientific discourse dominated by physical interactions to distance learning mechanisms (Byrnes et al., 2020).

Nevertheless, LMSs have become increasingly important in STEM (Science, Technology, Engineering, and Mathematics) programme delivery over the decades. This has been facilitated by improved broadband internet connectivity and advancements in technologies for smoother online interactions among all stakeholders. To date, numerous educational institutions have successfully utilised LMSs and are interested in improving their effectiveness to create enhanced learning environments (Setiadi et al., 2021; Xie & Correia, 2024). However, studies that investigate utilising the maximum potential of LMSs to enhance the student experience and performance are limited. Moodle, being one of the prominent systems in use, provides a plethora of data on online student interactions, which could be effectively used to enhance the learner and teacher experience.

Literature Review

The available literature on monitoring online collaborative learning within a Moodle environment can be categorised into three distinct segments, each providing a deeper understanding of the respective scholarly evolution. These segments are the principles and practices of collaborative learning in online environments, the potential of Moodle as a collaborative environment, and the application of learning analytics for monitoring collaborative learning. Each segment offers in-depth information crucial to the development of research in this area. By examining these segments, researchers can gain a comprehensive view of the capabilities, challenges, and methodologies that inform the effective monitoring and facilitation of collaborative learning in Moodle.

Collaborative Learning in Online Environments

Collaborative learning has been a crucial paradigm in the field of education (Dillenbourg, 1999) and is rooted in Vygotsky's sociocultural theory, which regards learning as a social interaction process (Parker, 1979). Activities that are intended for collaborative and active learning demonstrate an improvement in students' understanding. Regardless of the teaching medium, all instructional design variables must be considered in higher education assessment. It is critical for faculty members to become acquainted with technology in order to build trust with their students. Because of the availability of online technology, it is possible to create interactive-based instructional designs, which play an important role in professional preparation.

Online instructions have become an essential element of effective teaching practices (Abuhassna & Alnawajha, 2023a; Corfman & Beck, 2019; Xie & Correia, 2024). Therefore, researchers are constantly seeking innovative methods to improve student education, especially in the realm of online classrooms. However, certain disciplines need hands-on activities and specialised training to develop the required skills, posing additional challenges for educators and course designers when incorporating online environments. Thus, the significance of instructional design (ID) has gained much attention in the field of education. In Asia, Africa, South Africa, and Europe, there is a need for more research on instructional design, according to a study by Abuhassna & Alnawajha (2023a). This study emphasised the significance of concentrating on instructional design steps and processes with various research models, frameworks, and theories to advance the field and improve educational practices in these regions. It is advised that close attention be paid to these factors.

Usually, student-system interactions are recorded by LMSs and Web 2.0 tools. These interactions cover a range of activities, including how frequently students access the course, participate in discussions, and the time they spend on these platforms (Peramunugamage et al., 2024). These data, which are also known as system logs, have become important sources for thorough analysis and synthesis, offering insightful information that could influence the learning process. As a result, the use of system logs in research has grown in popularity and is considered as a credible source of information (Cheung et al., 2021; Wei et al., 2024). Therefore, it is important to examine the potential impact of students' participation in collaborative Moodle activities and their academic performance.

Collaborative Learning Potential of Moodle

The online learning platforms that were widely used and researched during 2015-2020 included Edmodo, Moodle, Coursera, Udemy, and Google Classroom (Setiadi et al., 2021). Altinpulluk and Kesim's (2021) systematic review on LMS usage trends reveals that Moodle was the most widely used and preferred open-source LMS across a wide range of academic disciplines, including STEM education (Al-Ajlan & Zedan, 2008; Sergis et al., 2017)

Publications between 2015 and 2020 that contained the keyword "Moodle", and were categorised by discipline area, revealed that more than 60% of them were related to STEM subjects (Setiadi et al., 2021). A 250% increase in Moodle users from 78 million in 2015 (Singh, 2015) to over 294 million in 2021 (Moodle, 2022) depicts its remarkable growth in supporting learning environments. Moodle enables managing routine teaching tasks and exposing students to online collaborative interactions with the constructivism and social constructivism incorporated in version 2004 of the platform (Dai et al., 2022). Abuhassna and Alnawajha (2023a, 2023b) found that collaborative learning was discussed in 12% of the articles reviewed during 2012-2022. Several of these studies emphasised the use of Moodle's workshop tool, which allows students to evaluate the work of their peers, reducing the burden on the teaching staff. ArchMiller et al., (2017), Slee and Jacobs (2017), and Strang (2015) demonstrated how to use the 'workshop' for peer assessment purposes. Furthermore, according to Awofeso et al. (2016), the 'forum' activity within Moodle was found to be beneficial in enhancing problem-based learning through group projects.

Despite the enhanced features of Moodle, a comprehensive analysis of the design of collaborative activities and monitoring of students' interactions was lacking. Gamage et al. (2022) examined: (i) Moodle adoption; (ii) innovative and effective methods used in online teaching and learning; and (iii) concerns, trends, and gaps in educational software developments during the previous six years, as presented in 155 articles published in 104 journals from 55 countries across ten different disciplines. The findings highlighted the need for qualitative research into educators' perspectives on Moodle usage and recommended incorporating educational theories to inform the design of courses in Moodle. Further, the need for an in-depth examination of educators' experiences and insights to improve their understanding and effective use of Moodle in educational settings was also a timely requirement (Dai et al., 2022).

Learning Analytics for Monitoring Collaborative Learning

Numerous studies have revealed that collaborative learning is helpful for learners' cognitive development (Long & Mclaren, 2024; Sung et al., 2017), improvement of metacognitive skills (Kim et al., 2019), and behaviours (Sung et al., 2017). Currently, various kinds of emerging technologies extend the possibilities of collaboration and provide promising learning opportunities in richer ways. In informal learning settings, advanced technologies also facilitate collaborative learning through flexible and instant feedback (Rambe & Bere, 2013). Previous studies indicated social media, tangible interaction techniques, virtual learning platforms, mobile devices, and augmented reality tools can serve as vehicles to support collaborative learning in informal learning settings.

However, learning analytics is a powerful tool that can help educators understand how students learn and interact in collaborative activities (Cheung et al., 2021; Johar et al., 2023; Tong & Zhan, 2023). By analysing data from online collaborative learning environments, researchers can identify patterns of student behaviour and engagement (Pekrun et al., 2011; Tong & Zhan, 2023), and use this information to improve the design of collaborative activities. Learning analytics is an emerging and expanding field that leverages students' online activities to enhance learning outcomes and academic performance (Kew & Tasir, 2022; Saqr et al., 2017). By monitoring student interactions, it is possible to identify potential areas of concern and implement proactive measures to mitigate the risk of academic struggles (Karaoglan & Yilmaz, 2020). Educators and institutions can effectively employ learning analytics to track student activities, analyse instructional contexts, and gather valuable feedback, thereby enriching and optimising the learning process.

Tekin and Oztekin (2018), in their review of published literature on educational data mining from 2006 to 2016, concluded that most studies focused on academic achievement, and some explored the impact of online learning environments within specific courses. Similar research by Bulca and Demirhan (2020) showed the impact of online learning environments on achieving student learning outcomes for a particular course. The objective of a study conducted by Tlili et al. (2018) was to model learners' personalities using a cutting-edge approach to learning analytics called intelligent Moodle (iMoodle). The outcomes of this strategy were contrasted with those of the more conventional approach, which models learners' personalities using questionnaires. Another study was conducted by Xiao and Rahman (2017), and aimed at building a mathematical model based on the analysis of student learning behaviour that could be used to automatically identify learning styles. Subsequent studies used educational data mining techniques to investigate and predict students' attitudes toward learning. Johar et al. (2023) recommended in their systematic literature review that future studies should focus on investigating student engagement in online settings and explore how the outcomes of engagement analysis can be leveraged to develop interventions aimed at addressing learning challenges, such as high dropout rates and poor learning performance.

Theoretical Framework

Garrison (2019) emphasised that effective online course design is crucial for ensuring that learners achieve their desired learning outcomes and develop the skills and knowledge they need to succeed in their academic or professional pursuits. It is also a difficult task to provide learners with engaging, accessible, and high-quality learning experiences that meet their needs and objectives (Anderson & Garrison, 1995; Garrison, 2019).

Gilly Salmon's Five-Stage Model (Ruzmetova, 2018; Salmon et al., 2010) serves as a distinctive and widely recognised framework for designing and delivering online courses. This model is widely recognised for its emphasis on socialisation, interaction, and constructivist pedagogy, making it a valuable tool for teachers and instructional designers aiming to create effective and engaging online learning environments. The model's structure not only facilitates participants' comfort and familiarity with both online and in-person modalities but also ensures a gradual and supportive learning experience that enhances learner engagement and success.

Salmon's model underscores the importance of interaction not only between learners and instructors but also with the course content throughout the learning process. The model's structured approach ensures that learners are gradually introduced to the online environment, supported in building relationships, and guided through increasingly complex tasks, all of which contribute to a positive and effective learning experience. Therefore, Gilly Salmon's Five-Stage Model was adopted as a theoretical framework for this study, since it provides a comprehensive and well-established approach to creating engaging and effective online learning experiences that promote active participation, collaboration, and meaningful learning outcomes.

Methods

Research Methodology

The primary research approach employed in this study was the educational design research technique (van den Akker et al., 2006). Within educational practice, design research is a systematic and flexible process aimed at enhancing educational practices through iterative analysis of needs, design, development, and implementation (Wang & Hannafin, 2011). The research incorporated the design-based research methodologies introduced by Reeves (Amiel & Reeves, 2008; Herrington et al., 2007). Design experiments were conducted as a means of formative research, providing insights into the next steps to be taken.

Population and Sample

The participants selected for the implementation of the study were final-year (Semester 8), first-year (Semester 2) and third-year (Semester 5) Engineering undergraduates enrolled for the modules indicated as M1-S8, M2-S2 and M3-S5 during 2020-2022, in which the student numbers were 48, 59 and 58, respectively, at a state university in Sri Lanka. The participant population included a mix of male and female students in the age range of 18-22 and were divided into groups of 4-5 members to conduct the activities. The M1, M2, and M3 modules underwent three rounds of iterative testing and refinements. Following this, the M4-S8 module was applied to evaluate the final intervention in a distinct context, involving 93 Computer Science undergraduates from Brazil. Course details are listed in Table 1. Moodle log records were used to collect data in terms of student interactions and participation in activities.

Table 1: Main Characteristics of the Modules Involved in the Research

Characteristics	Module 1 [M1]	Module 2 [M2]	Module 3 [M3]	Module 4 [M4]
University	UoM	UoM	UoM	USP
Credits	2	2	2	2
Compulsory (C), Elective (E) or Optional (O)	C	C	E	O
Level of Study (year)	4	1	3	4
Semester	S8	S2	S5	S8
Continuous Assessment (CA) %	30	60	100	50
Written Examination (WE) %	70	40	0	50
Access Mode	Online	Online	Online	Hybrid
Number of Students (n)	48	59	58	93
Number of Groups	12	12	15	32

Data Collection

Enhancing students' interactions can be achieved through the implementation of a diverse range of collaborative learning activities. These activities encompass various approaches, including: (i) engaging students in pair or group discussions; (ii) fostering cooperation through activities such as matching, sorting, or rating; (iii) incorporating competitive games like bingo, drama, and role-playing; (iv) promoting information exchange through activities like jigsaw puzzles and barrier games, as well as (v) assigning small group tasks (Gehringer, 2007; Jabbar & Hasmy, 2020; Swid et al., 2018).

To optimise collaborative activities in hybrid or online learning settings, Deris et al. (2012) and Paschalis (2017) suggested leveraging popular Moodle applications like assignments, quizzes, forums, and content creation to facilitate collaboration and communication between students and instructors, enabling effective engagement in hybrid or online learning environments. In this research, several Moodle-based learning activities were provided to monitor students' four types of interactions as listed in Table 2.

Table 2: Number of Activities Conducted for each Course

Activity	M1-S8 (n = 48) Total Activities	M2-S2 (n = 59) Total Activities	M3-S5 (n = 58) Total Activities	M4-S8 (n = 93) Total Activities	Interaction Type
Online Face-to-Face Sessions					
Zoom meeting /Google Meet	4	15	15	22	LT, LL
Seminar	1	0	0	2	LT, LL
Webinar	1	0	0	0	LT, LL
Learning Resources					
File Reading Material	10	5	10	8	LC
File Additional Resource-Video	6	8	2	20	LC
URL Additional Resources	5	0	0	5	LC
Lecture Materials	2	11	10	41	LC
Recorded Lectures/Labs	2	8	1	0	LC
Tutorial	1	0	2	9	LC
Tutorial Answers	1	0	0	0	LC
Coursework Template	1	0	1	1	LC
Online Moodle Tools					
Forum	2	4	1	1	LT, LL
Journal	2	0	0	0	LT
Virtual Lab	3	0	0	0	LT, LL, LC
Questionnaire	3	1	0	4	LC
Wiki	4	1	1	1	LT, LL
Workshop	1	2	0	0	LT, LL
Assignment	0	2	5	26	LT, LL
Turnitin Assignment	4	1	0	0	LT, LL
Quiz	0	2	1	0	LC
Questionnaire - Feedback	2	3	2	2	LC
Total Activities	55	63	50	142	

LL - learner-learner interaction; LT - learner-teacher interaction; LC - learner-content interaction; LI - learner-interface interaction

Lesson-by-lesson interactions together with the students' feedback were evaluated and incorporated for continuous improvements of the lesson plans. This process was conducted iteratively for the refinement of interventions and the collected data was analysed with quantitative measurements. Descriptive analysis was conducted to obtain an overview of the collaborative interactions. To explore how students' interactive behaviour correlated with their course grades, regression analysis was performed using the total marks students obtained in their final examinations against their Moodle access logs for each module. Additionally, to gain a deeper understanding of students' collaborative interactions, Vector Space Model (VSM) analysis was carried out. Further details are discussed in the results and discussion section.

Moodle has built-in features that produce useful statistics through log records that can be used to monitor student activities. These 'action logs' were used to obtain feedback on resources and activities that were accessed by each learner including, when, by which student, for how long, etc. For this study, logs of students' actions for the entire semester for each of the modules were collected and cleaned up. Each event record in the raw action log has nine attributes: time, user full name, affected user, event context, component, event name, description, origin, and IP address. This study focused on the user's full name, component, and event name. The event name attribute captured the actions initiated by students on different items accessible through Moodle, including assignments, quizzes or assessments, course content, forum discussions, Wikis, workshops, resources, and URLs. To monitor and analyse students' collaborative interactions, the research focused on events related to Wikis, comments, discussions, and posts in M1, M2 and M3 as outlined in Table 3. These specific types of events were considered essential for examining and understanding the collaborative dynamics among students in the study.

Table 3: Moodle Event Identifiers Related to the Collaborative Interactions

Log Activity	**Module 1** **(N =** 330,081) Number of actions (%)	**Module 2** **(N =** 593,791) Number of actions (%)	**Module 3** **(N =** 338,251**)** Number of actions (%)
Wiki			
Wiki diff viewed	68 (0.2%)	8 (< 0.1%)	48 (0.1%)
Wiki history viewed	419 (1.3%)	275 (0.5%)	768 (2.3%)
Wiki page created	57 (0.2%)	144 (0.2%)	73 (0.2%)
Wiki page locks deleted	271 (0.8%)	692 (1.2%)	1,224 (3.6%)
Wiki page map viewed	41 (0.1%)	225 (0.4%)	175 (0.5%)
Wiki page updated	249 (0.8%)	652 (1.1%)	1,161 (3.4%)
Wiki page version viewed	22 (< 0.1%)	17 (< 0.1%)	49 (0.1%)
Wiki page viewed	644 (2.0%)	3,666 (6.2%)	3,686 (11%)
Wiki version restored			2 (< 0.1%)
Comments			
Comment created	2 (< 0.1%)	5 (< 0.1%)	22 (< 0.1%)
Comment deleted	1 (< 0.1%)	139 (0.2%)	2 (< 0.1%)
Comments viewed	113 (0.3%)	1,068 (1.8%)	225 (0.7%)
Discussions			
Discussion created	5 (< 0.1%)	94 (0.2%)	3 (< 0.1%)
Discussion deleted	1 (< 0.1%)	16 (< 0.1%)	
Discussion subscription created	14 (< 0.1%)	52 (< 0.1%)	24 (< 0.1%)
Discussion subscription deleted	4 (< 0.1%)	21 (< 0.1%)	1 (< 0.1%)
Discussion viewed	142 (0.4%)	1,021 (1.7%)	165 (0.5%)
Posts			
Post created	2 (< 0.1%)	80 (0.1%)	25 (< 0.1%)
Post deleted	1 (< 0.1%)	16 (< 0.1%)	
Post updated	1 (< 0.1%)	20 (< 0.1%)	3 (< 0.1%)
Post created	2 (< 0.1%)	80 (0.1%)	25 (< 0.1%)
Feedback viewed	Not applicable	60 (0.1%)	
Forum	469 (1.4%)	2,925 (4.9%)	

N = Total action logs

Ethical Clearance

Ethical approval for this study was granted by the Ethics Review Committee of The Open University of Sri Lanka (OUSL). Throughout the research process, stringent ethical standards were adhered to, ensuring that all participants and stakeholders were fully informed, and their consent obtained. The study involved multiple stages, including content development and the collection of log records. At each stage, appropriate permissions were sought and granted by the relevant authorities. This process included informing both students and teachers about the nature of the research, their roles, and the potential impact on their participation. Consent was explicitly obtained for each research activity, ensuring that all participants were aware of the objectives and methodologies involved.

Results and Discussion

A two-phase approach was utilised to follow the data mining process outlined by Romero et al. (2008). The initial preparation of data was followed by the use of data mining algorithms that transformed them into an acceptable form for interpretation and analysis. After normalising the data obtained for the four modules, the total counts for each action type for all courses were retrieved. For example, students in M1 often logged onto Moodle only to do assessment activities, with minimal access to instructional materials or participation. On the other hand, students in M2 seemed to connect via Zoom sessions, material access, and interaction with assessment activities more frequently. These visualisations might assist course administrators in determining the type of strategic interventions required for each activity to ensure that student engagements remain within the scope of the planned learning objectives. Additionally, Table 3 compares student participation in Moodle's collaborative activity, which showed a substantial difference in the amount of group work. Their access to collaborative work significantly improved, as can be seen from the examples of Wiki page views improving from M1-644 (2.0%) to M2-3,666 (6.2%) to M3-3,686 (11%), and Wiki pages updated from M1-249 (0.8%) to M2-652 (1.1%) and M3-1,161 (3.4%).

Moodle was developed to promote student-content interaction and, in addition to that, it enables learner-teacher and learner-learner interactions through its user-friendly interfaces (Alammary et al., 2014; Porter & Graham, 2016). Thus, by increasing student contact in a technology-mediated setting, we can foster information transfer, comment threads, involvement, inspiration, group work, group cohesiveness, and discussion. This encourages peer assessment and feedback will enhance the learning experience, allowing students to learn from each other and reflect on their own work.

Figure 1 is a graphical representation illustrating the students' participation in collaborative activities for modules M1, M2, and M3. The bar chart displays the number of events that occurred for each specific collaborative activity. Each module is represented by a different colour or bar in the graph, allowing for a visual comparison of student participation across the different modules. The X-axis represents the number of events, while the Y-axis indicates the different collaborative activities such as Wiki, comments, discussions, or other relevant activities. The height or length of each bar represents the frequency or number of events recorded for that particular activity in each module, providing insights into the level of student engagement and participation within the collaborative activities throughout the three modules.

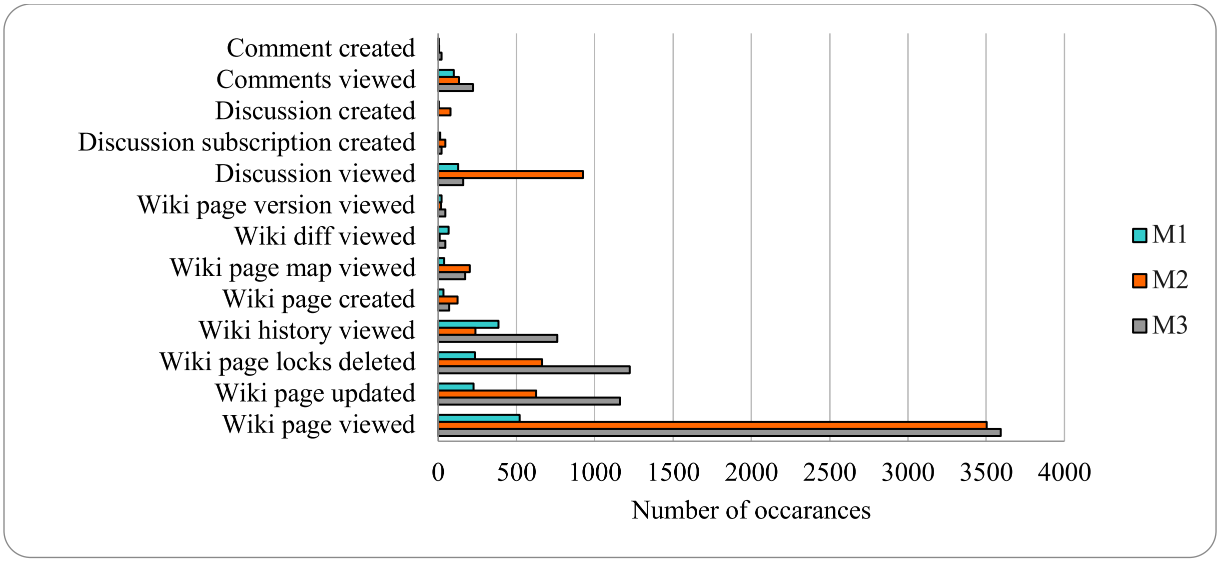


Figure 1: Total collaborative events performed in each module

To provide a comprehensive understanding of individual students' collaborative participation, Figures 2, 3, and 4 illustrate the student interactions within each module (M1, M2 and M3) based on different activities. These figures present a visual representation of how students engage and contribute to various collaborative activities throughout the modules. By examining these figures, researchers and educators can gain valuable insights into the level and nature of student participation, allowing them to assess the effectiveness of the collaborative learning approach and identify areas for improvement.

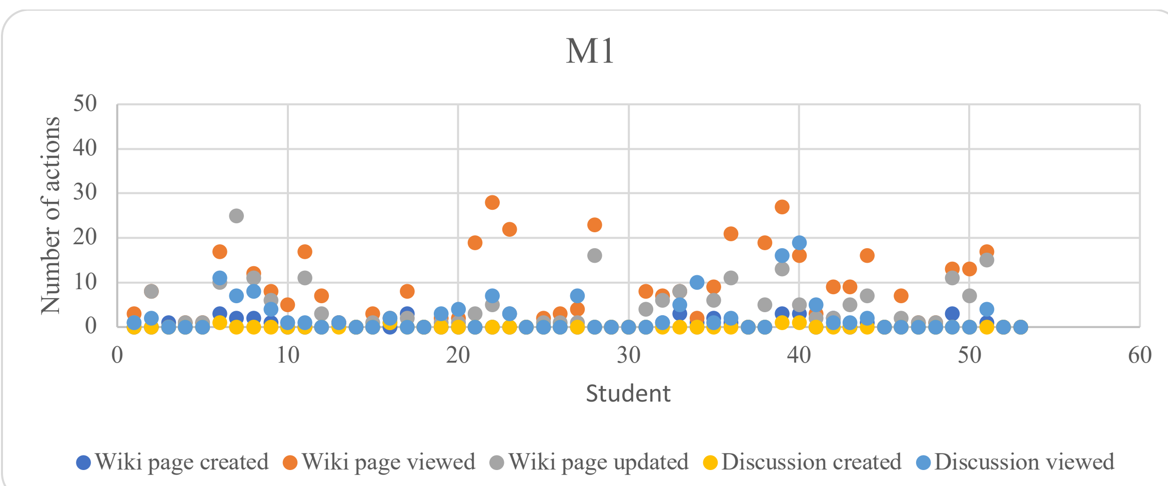


Figure 2: M1 Moodle collaborative events performed by each student

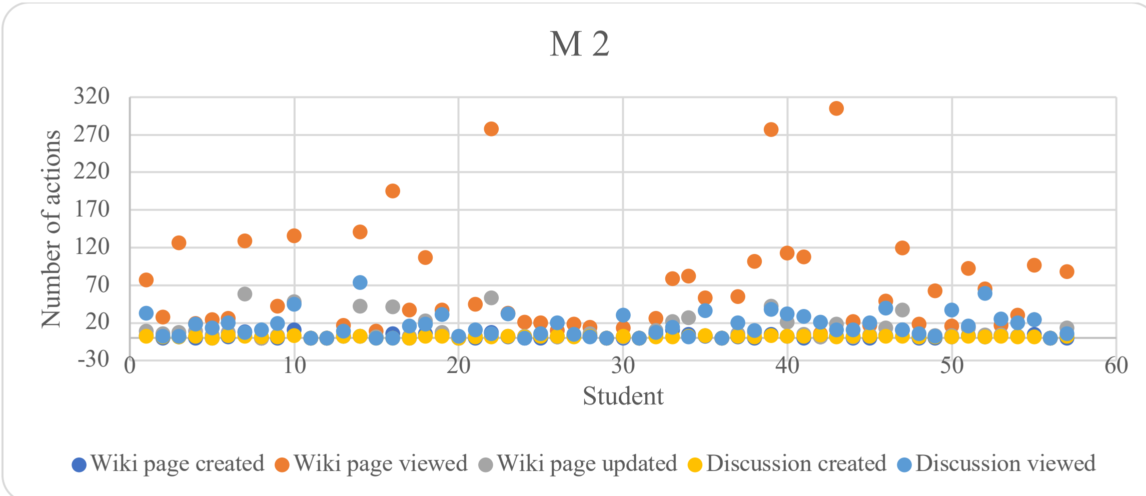


Figure 3: M2 Moodle collaborative events performed by each student

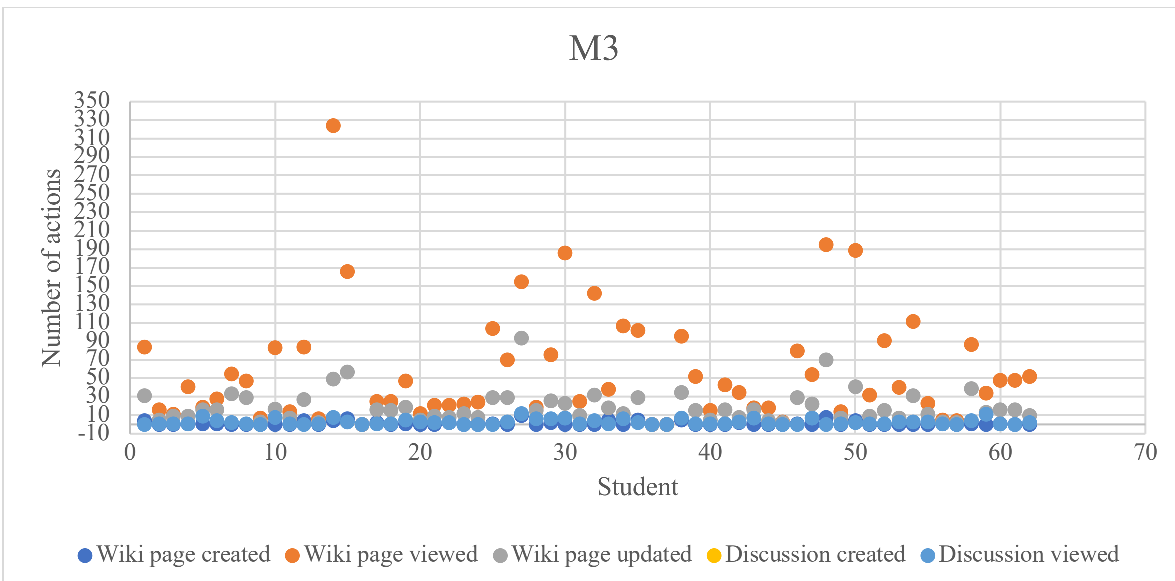


Figure 4: M3 Moodle collaborative events performed by each student

Regression Analysis

Before delving into detailed activity log analysis, it was crucial to examine if a connection existed between module access and students' course performance. The purpose was to get insight into how students' interactive behaviour correlated with their course grades, which evaluate both individual and group performance, providing a more comprehensive evaluation of student learning. To assess the importance, Pearson coefficient correlation (r) was employed. Regression Analysis performed with the M1 Total Marks that students obtained at their final examination vs the Moodle access logs for M1 were analysed to investigate whether a relationship existed between students' participation in online activities and their final grades.

As depicted in Figure 5, the R^2 value of 0.2604 indicates that the model explains 26% of the data. The significance F value of 0.0000003 suggests that the null hypothesis is rejected, supporting the presence of a positive relationship between student participation and final grades. However, since 74% of the data remains unexplained by the model, further analysis was conducted using data mining algorithms in subsequent sections of the study. These subsequent analyses aimed to uncover additional patterns or insights that may not have been captured by the initial regression analysis, with the goal of better understanding the factors influencing student performance in M1.

Regression Statistics	
Multiple R	0.510311549
R Square	0.260417877
Adjusted R Square	0.243218293
Standard Error	14.54525527
Observations	45

ANOVA	df	SS	MS	F	Significance F
Regression	1	3203.284701	3203.285	15.14094	0.0003419
Residual	43	9097.271392	211.5645		
Total	44	12300.55609			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	46.23522666	4.880281622	9.473885	4.34E-12	36.39320078	56.07725254
Access log	0.027625895	0.007099699	3.891136	0.000342	0.013307987	0.041943802

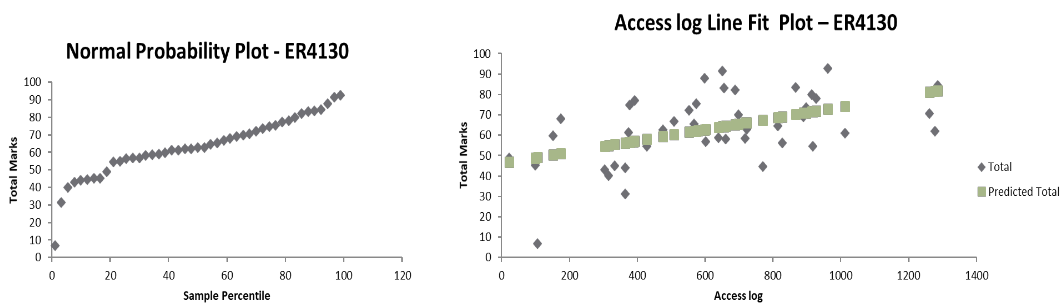


Figure 5: Regression analysis of M1 total marks vs Moodle access logs

Figures 6 and 7 display regression analysis results for M2 and M3, respectively. In M2, the model explains 41.3% of the data with an F value of 6.333E-07, indicating a positive relationship between Moodle activity access and final grades. Similarly, for M3, the model explains 3.2% of the data, also suggesting a positive relationship between Moodle activity access and final grades. These figures offer insights into how well the selected variables in the regression models explain grade variations in each module.

Regression Statistics	
Multiple R	0.642886
R Square	0.413303
Adjusted R Square	0.40082
Standard Error	11.352
Observations	49

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	4266.7419	4266.742	33.10944	6.33E-07
Residual	47	6056.7876	128.8678		
Total	48	10323.522			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	46.95504	4.505900507	10.42079	8.32646E-14	37.89033617	56.01974138
Access log	0.028471	0.00494796	5.754081	6.3295E-07	0.01851695	0.038424974

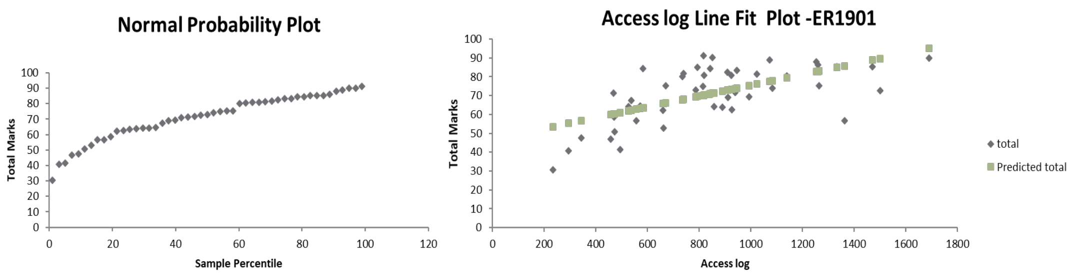


Figure 6: Regression analysis of M2 total marks vs Moodle access logs

Based on the preceding analysis, it was observed that the implementation of a Wiki improved student interaction. Consequently, the same procedure was applied to M4, which pertained to a distinct context. As indicated in Table 2, M4's activities were confined to M1, M2, and M3 because this course was chosen as a pilot run to investigate Moodle interactions in a different setting.

Regression Statistics	
Multiple R	0.179192844
R Square	0.032110075
Adjusted R Square	0.014826327
Standard Error	11.50604006
Observations	58

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	245.9547121	245.9547	1.857819	0.178332409
Residual	56	7413.781647	132.389		
Total	57	7659.736359			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	54.5770814	4.706593824	11.59588	1.63E-16	45.14864101	64.0055218
Access log	0.011565502	0.008485214	1.363018	0.178332	-0.005432424	0.02856343

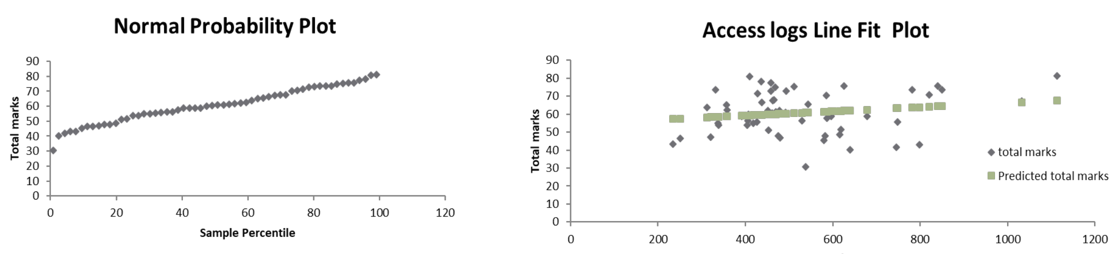


Figure 7: Regression analysis of M3 total marks vs Moodle access logs

Figure 8 displays regression analysis results for Module 4 (M4). The analysis indicates that the model explains 43.8% of the data, with an F value of 5.12E-13, revealing a positive relationship between Moodle activity access logs and final grades in M4. The selected variables in the model explain a significant portion of grade variations, emphasising Moodle activities' positive impact on academic performance.

Regression Statistics	
Multiple R	0.661781114
R Square	0.437954243
Adjusted R Square	0.431777916
Standard Error	23.36472843
Observations	93

ANOVA					
	df	SS	MS	F	Significance F
Regression	1	38709.711	38709.7112	70.908525	5.12059E-13
Residual	91	49677.858	545.910534		
Total	92	88387.569			

	Coefficients			Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	34.19076889	5.13348507	6.66034252	2.03195E-09	23.99373142	44.38781	23.99373	44.38781
Access log	0.133483673	0.015851812	8.420720028	5.12059E-13	0.101995995	0.164971	0.101996	0.164971

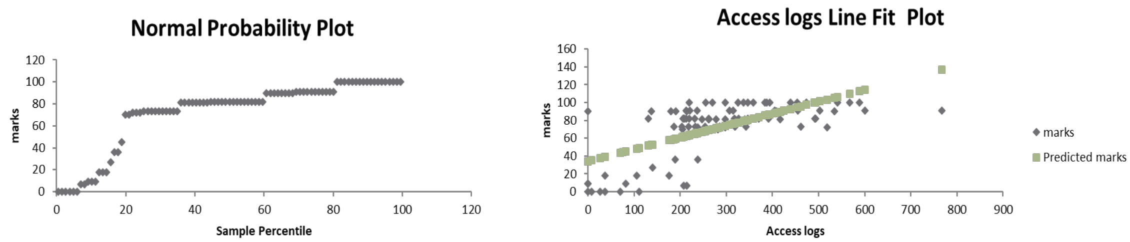
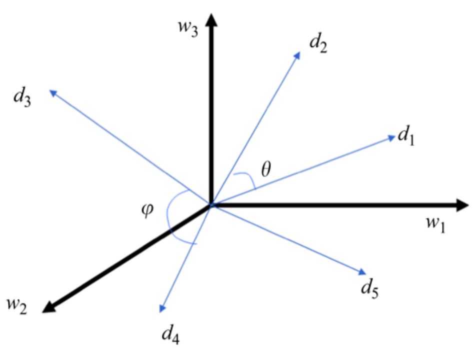


Figure 8: Regression analysis of M4 total marks vs Moodle access logs

Vector Space Modelling (VSM)

Data mining technologies allow for the extraction and display of activity patterns that may be used to predict student behaviour. Vector Space Modeling (VSM) (Jensen & Snodgrass, 2018) is a statistical model representation that is frequently utilised in the processing of documents in information retrieval. VSM's basic concept is to create vector representations for documents and then use these vectors to evaluate and compare the contents of each document. A vector is a labelled collection of data organised in a specific order.

VSM requires the construction of activity vectors for each student (D1). An activity vector can be defined as a list of action types (w_1 to w_n) with their corresponding values depicting how many times each action was initiated by the student (Figure 9).



	w_1	w_2	w_3	$\cdots$	w_n
D_1	14	6	1	$\cdots$	0
D_2	0	1	3	$\cdots$	1
D_3	0	1	0	$\cdots$	2
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
D_K	4	7	0	$\cdots$	5

Table 4 shows a sample of activity vectors produced for each student to depict the student's collaborative activity using VSM. An activity vector is a collection of action types with values indicating how many times each action was started by the student. A value of 0 indicates that the action type was never begun. To compare the contents of action log documents, VSM determines how far their vector representations are located inside the semantic space. To assess how closely connected the topic of document D1 is to the topic of document D2, for example, VSM calculates the distance of D2 relative to the location of D1.

Table 4: Pre-processed Moodle Collaborative Activity Sample Vector

	Wiki diff viewed	Wiki history viewed	Wiki page created	Wiki page locks deleted	Wiki page map viewed	Wiki page updated	Wiki page version viewed	Wiki page viewed
Student 6	0	0	0	1	0	1	0	3
Student 7	0	1	0	8	0	8	0	8
Student 8	0	0	1	0	0	0	0	0
Student 9	0	0	0	1	0	1	0	1
Student 10	2	7	0	1	0	1	0	1
Student 11	0	1	3	10	2	10	0	17
Student 12	2	68	2	25	5	25	6	118

The cosine of the angle created between the two places is the most often used technique for determining this distance. The cosine angle is calculated using the following formula:

$$s(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|} = \frac{\sum_{i=0}^{n-1} x_i y_i}{\sqrt{\sum_{i=0}^{n-1} (x_i)^2} \times \sqrt{\sum_{i=0}^{n-1} (y_i)^2}}$$

Basically, for two vectors (x and y) with n values, this formula simply computes the scalar product of the two vectors for the numerator, and computes the product of the length or norm of the two vectors for the denominator.

The sample estimated cosine values for collaborative activities are shown in Table 5. The cosine formula gives a value between 0 and 1. The rule of VSM is that the higher the cosine value of two documents, the more similar their contents are. A cosine value of 1 indicates that two documents are identical, whereas a value of 0 indicates that they are completely disconnected. Any value in between represents the degree of similarity between documents; the greater the value, the more closely connected the documents. Cosine values compare students' collaborative activities to each other in order to group them based on how similar their level of activity is.

Table 5: Sample Cosine Calculation

	V4	V5	V6	V7	V8	V9	V10	V11	V12
4	1	0.082139	0.333333	0.099751	0	0	0	0.374634	0.05169
5	0.082139	1	0.646843	0.763525	0.391239	0.667378	0.652239	0.716411	0.839984
6	0.333333	0.646843	1	0.897758	0	0.666667	0.1557	0.967805	0.420908
7	0.099751	0.763525	0.897758	1	0	0.847883	0.267913	0.859513	0.544712
8	0	0.391239	0	0	1	0	0	0.162221	0.02558
9	0	0.667378	0.666667	0.847883	0	1	0.1557	0.65561	0.450445
10	0	0.652239	0.1557	0.267913	0	0.1557	1	0.196865	0.914044
11	0.374634	0.716411	0.967805	0.859513	0.162221	0.65561	0.196865	1	0.46476
12	0.05169	0.839984	0.420908	0.544712	0.02558	0.450445	0.914044	0.46476	1

To enhance our understanding of VSM applied to students' collaborative interactions in M1, M2, and M3, scatter plot diagrams were utilised. Figures 10, 11, and 12 present these scatter plots, illustrating the average cosine values generated by each student during their collaborative activities within their respective modules.

From the visualisations, M3 shows higher student interaction compared to M2 and M1. The average cosine values, closer to 1 in M3, suggest stronger alignment in collaborative interactions. Conversely, M2 and M1 exhibit lower average cosine values, indicating less interaction and alignment among students during collaboration. The scatter plot diagrams offer insights into collaborative interaction patterns and quality within each module. They aid in identifying variations in student engagement and collaboration levels across different modules.

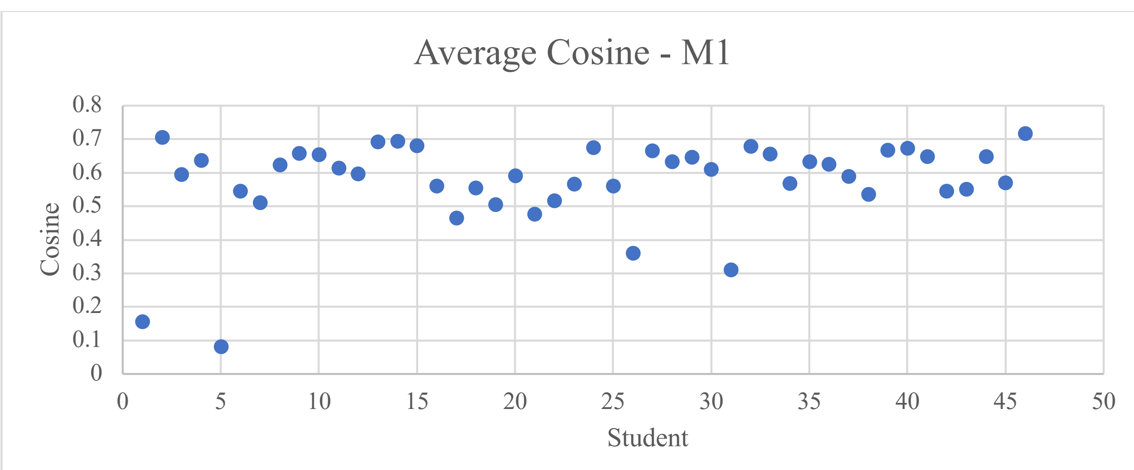


Figure 10: Visualisation of M1 collaborative activity logs analysed through VSM

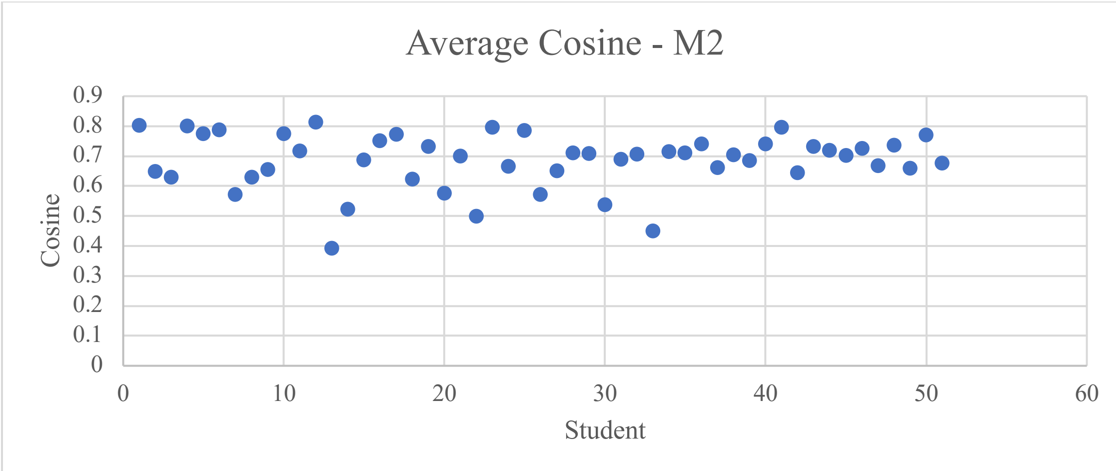


Figure 11: Visualisation of M2 collaborative activity logs analysed through VSM

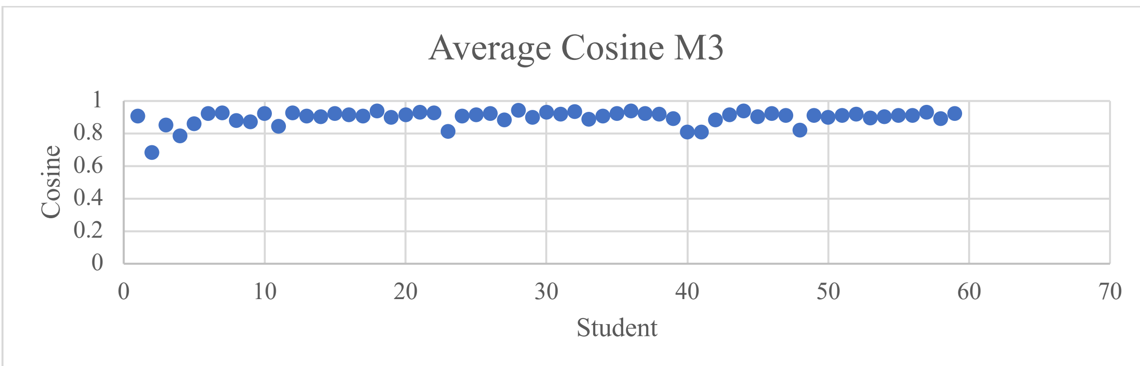


Figure 12: Visualisation of M3 collaborative activity logs analysed through VSM

Conclusions

Analysing Moodle logs provided valuable insights into students' participation, engagement, and collaboration in the online learning environment. Practitioners can make maximum use of Moodle's features to facilitate collaboration, such as setting up discussion forums, creating group assignments, and using Wikis for collective content creation. Systematically designed collaborative activities encourage student engagement and deepen understanding. Combining face-to-face instruction with online collaborative activities can create a more flexible and effective learning environment. Tasks requiring teamwork on complex problems have proven especially effective in enhancing interactions and improving learning outcomes.

Regression analysis and VSM indicated positive relationships between student participation in Moodle activities and their final grades and highlighted the importance of promoting active engagement and interaction among students through collaborative activities on the Moodle platform. This study demonstrated the utility of learning analytics in identifying which students engage most in collaborative activities, effective student groups, and engaging task types, allowing practitioners to continuously evaluate the effectiveness of collaborative learning activities and make data-driven improvements. Real-time feedback provided to students and teachers can identify areas for support, which is especially important in online collaborative environments where students may feel isolated.

This study demonstrated how active participation in collaborative learning activities can boost student motivation and retention rates by creating a strong learning community and enhancing the learning experience for students. Systematically designing collaborative activities and leveraging Moodle tools like assignments and forums can enhance collaboration, communication, and knowledge sharing. Such instructional design approaches, combined with learning analytics, create more engaging and effective online learning environments, improving student interactions and outcomes. By promoting collaborative learning, practitioners can empower students to take ownership of their learning, fostering independence and self-regulation. Moreover, by leveraging Moodle tools such as assignments, quizzes, forums, and content creation, instructors can foster collaboration, communication, and knowledge exchange among students. Overall, the use of learning analytics in online collaborative learning environments can help to enhance student interactions, improve learning outcomes, making courses more interactive and dynamic.

Recommendations for Future Work

It is important to note that user behaviour in LMS can vary over time. Therefore, future studies should incorporate a temporal model that tracks changes in user behaviour over time, providing real-time data to system analysts about the current state of the system rather than just an overall summary of system usage. Testing the stability of user behaviour is crucial, as behaviours may change throughout the course.

Integrating Artificial Intelligence (AI) into Moodle could enhance this analysis by offering predictive insights and personalised recommendations. AI could analyse student interactions with course materials in Moodle, offering deeper insights for optimising course design. Additionally, AI-powered analytics could track assessment effectiveness in real-time, enabling instructors to make data-driven decisions to better evaluate student understanding. The future of Moodle data analytics lies in harnessing the power of AI to create a more personalised and effective learning experience for students. AI can continuously adapt to user behaviour changes, providing educators with valuable insights to improve teaching and course design dynamically.

Acknowledgement: We acknowledge the financial support received from the Organisation for Women in Science for the Developing World (OWSD) and the Swedish International Development Cooperation Agency (SIDA) to conduct the research.

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Cite as: Peramunugamage, A., Ratnayake, U.W., Karunanayaka, S.P., Barbosa, E.F., de Deus, W.S., Jayawardena, C.L., de Silva, R.K.J. (2025). Monitoring collaborative interactions in online learning: Insights from Moodle log records. *Journal of Learning for Development*, *12*(2), 290-312.