Student Engagement Tracking and Interpersonal Skills Development Analysis using Log Dataset

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***Abstract*— Migrating from traditional classroom learning to online platforms presents numerous challenges, particularly in determining suitable pedagogical designs for content delivery. Moodle log dataset analysis is one technique that addresses these challenges. Supported by visual analytics, this analysis helps teachers enhance educational outcomes, personalize learning experiences, and provide insights into student behavior. This study addresses one such challenge through the Research Question (RQ): "How can instructors enhance content delivery, student engagement, and analyze interpersonal skills development for skill-oriented courses?" To scientifically answer this RQ, instructors used various visual approaches aimed at improving pedagogical practices in a Design Thinking course. The study involved learners from two different cohorts, with Moodle log datasets collected to apply these visual approaches. Using the Tableau tool, diverse visualizations were developed to analyze student behavior regarding pedagogical practices in each cohort. Instructors then implemented changes in content delivery methods and pedagogical activities to improve interpersonal skills and performance. The results and discussions demonstrate that applying various visual approaches with student log data significantly aids instructors in effectively analyzing student behavior and engagement in Learning Management Systems (LMS), leading to improved student outcomes.**

***Keywords*— Learning Management System; Moodle Log Dataset; Pedagogical Practice; Visual Approach.**

***ICTIEE* Track*:* Technology Enhanced Learning**
ICTIEE Sub-Track: Learning Analytics in academic success and behavioural modelling

I. INTRODUCTION

GENAI and online learning platforms are becoming increasingly intertwined, offering a range of possibilities to enhance education through personalization, engagement, and efficiency. Integrating GenAI with online learning platforms like Moodle offers a transformative potential to enhance the educational experience. By providing personalized learning, intelligent tutoring, automated assessment, and data-driven insights, GenAI can help educators create a more effective, engaging, and inclusive learning environment. One effective solution that has emerged is 'Blended Learning,' which has been widely adopted by educational institutions. This approach helps in managing academic schedules and facilitating continuity in the education process. Educational institutes have readily embraced blended learning, with instructors adapting to online education. Many educators utilize Learning Management Systems (LMS) such as Canvas, Moodle, and Google Classrooms to distribute learning materials and administer activities such as assignments, discussion forums, and quizzes as part of the assessment process. Various factors including network bandwidth, access to devices, student attendance, and proficiency in online education significantly influence the learning experience (Byun et. al, Lin et. al).

Therefore, it is imperative for instructors to regularly monitor students' participation and performance in LMS activities and grades (Boca, 2021). If instructors observe a decline in students' performance and participation in LMS activities, they should motivate the students and adjust pedagogical activities accordingly based on the course's nature. Moodle, being an open-source LMS, is highly beneficial for instructors in managing online and offline classes, facilitating discussions, handling assignment submissions, and conducting quizzes effectively. Instructors can serve as course administrators and have privileges to access log reports.

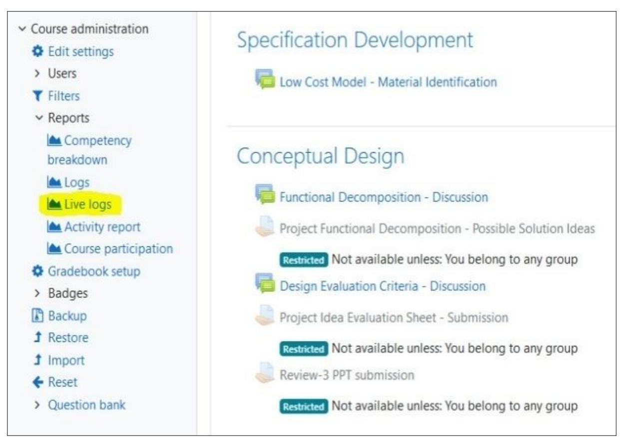

Fig. 1. Sample Moodle Page of Course

This feature of Moodle enables instructors to manage their courses at both macro and micro levels. Fig. 1 illustrates the

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course administrator page for Moodle log reports.

The Moodle mobile application is also accessible for both instructors and students. While instructors predominantly utilize the web application of Moodle, some students opt to access it through their mobile devices. Team activities play a crucial role in shaping students' character, thereby contributing to a balanced career progression. Additionally, these activities enhance their soft skills by fostering good practices such as timely submissions and the use of appropriate language during discussions, among others.

This work addresses the research question (RQ): "How can instructors enhance content delivery, student engagement and analyze interpersonal skills development for skill-oriented courses?". Various visual approaches are employed to analyze the behavior and performance of undergraduate engineering students in the Moodle log datasets of the Design Thinking (DT) course. By leveraging these visual approaches, instructors enhance their content delivery and organizational plan within the Learning Management System (LMS). The paper is organized as follows: section 2 discusses the literature review focused on this research topic, section 3 describes the methodology adopted in this work, section 4 explains the Moodle logs and visualizations with Tableau and section 5 concludes the paper with future scope for research.

II. Literature Review

The MOCLog project was implemented to analyze Moodle log data and visually represent it for stakeholders such as students, teachers, study program managers, and administrators (Mazza et. al., 2012). Student behavior was scrutinized using Moodle Log data to ascertain the correlation between Moodle usage and their grades (Kadoic et. al., Filipovic et. al., Zhang et. al.). Clustering and association rule mining were conducted on Moodle log parameters including course views, forum and quiz participation, assignment submissions, and grades, and then compared with students' overall performance (Rachel et. al., Mtebe et. al). Prediction models for portability were developed for different course sets using various attributes of Moodle logs to forecast students' performance (Zambrano et. al., 2020). Additionally, a novel data integration method was devised using Moodle logs and a pivot table to analyze students' behaviors via a time series cross-section table, enabling teachers to identify students who have not accessed learning materials (Konomu, 2017).

The statistical analysis conducted on Moodle log files identified four crucial factors affecting student performance: learning time zone, access times for optional learning material, completeness of course material, and assignment submission time (Tan et. al, 2021). Machine learning algorithms, such as random forest classifierswere employed to predict students at risk using Moodle log reports (Ljubobratović et. al., Tamada et. al). Classification and clustering algorithms were utilized to distinguish between excellent and at-risk students based on their Moodle usage (González et. al., 2020). The Vector Space Model was utilized to generate visualizations for Moodle logs, enabling the study of student behavior about Moodle participation and grades (Estacio et. al., 2017). Additionally, behavioral analysis of students was conducted using techniques such as dotted chart analysis, fuzzy miner, and social network miner, recommending appropriate organization of course terials to enhance access counts for low-performing students (Arpasat et. al., 2021).

Moodle log data was examined to investigate the relationship between students' activities in Moodleand their performance (Ademi et. al., 2019). A classifier model was constructed using the decision tree classifier to predict students' performance in the subsequent year. Another model was developed by integrating data from the student information system, Moodle logs, and students' interactions during online classes to analyze student behavior alongside their performance (Hasan et. al, 2021). Furthermore, a motivation-based model was devised for Chinese students learning English as a foreign language, highlighting intrinsic motivation as the most significant factor supporting the learning environment (Peng et. al., 2021). The Achievement Emotions Questionnaire (AEQ) was employed to analyze students' emotions, with most expressing positive feelings toward online quizzes compared to tests. The authors concluded that these positive emotions toward assessment contributed to students' self-sustainability (Riegel et. al., 2021). Additionally, active learning strategies implemented within the classroom served as an alternative method to traditional lectures, enhancing student performance (Shoufan, 2020). The behavior of students in the eLearning platform was studied using their learning patterns and the DBSCAN clustering algorithm (Andrés et. al., 2023). Temporal analysis was done using Moodle logs to assist learning community to make easy interpretation (Rotelli et. al., 2023).

From the literature review, it is apparent that the majority of the research endeavors have relied on machine learning algorithms such as classification and clustering to analyze student behavior. However, there has been a dearth of focus on visualizing the data for easier interpretation. If instructors were equipped with advanced data visualization tools, the time required for analyzing reports could be significantly reduced. This paper delineates various activities employed in the Design Thinking course and assesses the effectiveness of students' participation in Moodle activities.

III. Methodology

This section outlines the series of pedagogical activities implemented to enhance students' design thinking skills through the Design Thinking course. These activities encompass a variety of engaging solo and team tasks, which are elaborated upon in subsequent subsections. Moodle served as the Learning Management System (LMS) for the course, and the necessary data were derived from its log reports. Initially, the course instructor developed a comprehensive instructional design document detailing individual and team activities, along with assessment rubrics, guidelines, and presentation templates. Students were given orientation for problem selection under Sustainable Development Goals (SDGs), such as quality education, clean energy, and good health. The themes list was explained briefly and shared with all students. Team details, including team size, roles, responsibilities, problem domain, and technical mentor, were gathered using Google Forms. Each team followed three major phases: project identification, specification development, and conceptual design. All team discussions and document submissions were done in Moodle. Projects underwent evaluation in three stages using the rubrics. Fig. 2 illustrates the structure of the proposed methodology.

A. Project Identification

- 5W1H Activity: Each participant was tasked with contemplating the problem and its functions from various perspectives, including Who, What, When, Where, Why, and How. Their insights were documented in the discussion forum.
- Focus Group Discussion: The chosen problem underwent further exploration, and stakeholders were identified during a brainstorming session.
- Code of Cooperation: The instructor elucidated the concept of the Code of Cooperation (CoC) in the class. This CoC was expected to be adhered to by each individual within the team as well as among teams throughout the project. It was subsequently submitted as an assignment.
- Stakeholders Interaction: Project teams utilized survey questionnaires, interview approaches, and field studies to interact with stakeholders and gather requirements. Evidence of these interactions was submitted in Moodle.
- Requirements Development: All teams identified both functional and non-functional requirements and then prepared requirements specification documents for the initial review stage.

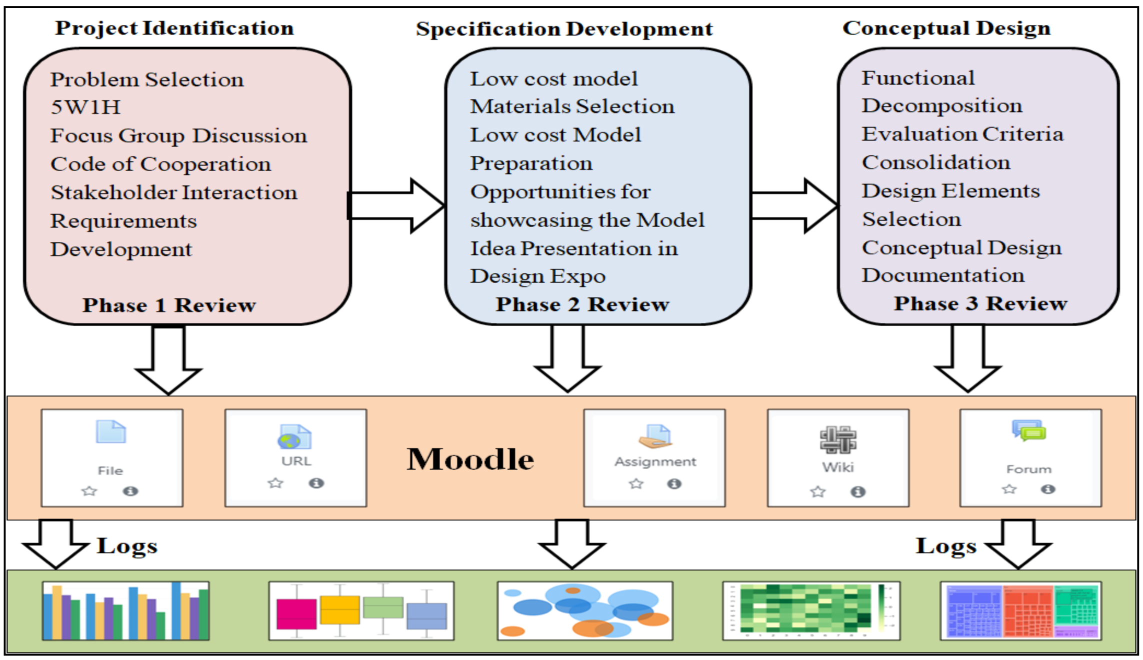

Fig. 2. Customized Course Plan and Visualization Tools

B. Specification Development

- Low-cost model material selection and preparation: Teams deliberated on the materials needed, such as charts, paper, etc., to illustrate their concepts. Then, they proceeded to prepare project specifications.
- Showcasing ideas: All teams were asked to identify the opportunities for showcasing their ideas/solutions/products to the customers or stakeholders by exploring the market. Videos were recorded during the design and development of the model, which were then presented at the Design Expo.

C. Conceptual Design

- Functional Decomposition: Functional Decomposition: All project teams engaged in discussions regarding both functional and non-functional requirements, leading to the compilation of a list of modules necessary for the product.
- Evaluation Criteria Selection: During team discussions, each group generated a set of evaluation criteria tailored to their specific application. For instance, criteria for application projects might include usability, aesthetics, user-friendliness, and satisfaction, while algorithm-based projects might consider factors like accuracy, error rate, and execution time. With guidance from the instructor, evaluation parameters for the design were finalized for the class and shared with all teams.
- Design Document Development: Teams crafted design documents utilizing various design diagrams such as Unified Modeling Language (UML), Data Flow Diagrams (DFDs), and User Interface Design (UID) with the aid of drawing tools. Each team implemented their design and showcased it during the third review.

D. Moodle Activities

All project teams documented their individual and/or team performance on Moodle through various means such as forums, assignment submissions, or wikis. The forum activity facilitated all students to read posts, provide responses, and engage in peer assessments. Assignment submissions allowed them to upload or update their documents, while wikis enabled them to create pages and record facts and their perspectives.

E. Visualization Techniques for Moodle Logs

Moodle generates log files in various formats, including comma-separated values (CSV), Excel, and others. These files are then utilized in tools such as Microsoft Excel, where pivot tables are employed to filter features, tabulate data, and generate graphs for visualization purposes. Additionally, more visually appealing and informative visuals are created using applications like Tableau. Column or bar charts are utilized for comparing data in two dimensions, while stacked bar charts are employed to compare data across three dimensions. Bubble charts are effective for comparing data, with larger bubbles indicating higher participation and vice versa. Box plots aid in identifying outliers, and distinguishing under-performing or over-performing students. Treemaps are utilized to determine the percentage of participation for all students, while heat maps are instrumental in illustrating the relationships between data points.

IV. Experimental Results

The Design Thinking course was offered to second-year B.Tech Information Technology students. Moodle served as the primary Learning Management System (LMS) tool, where students were assigned various graded activities. Students formed different project teams, with each team consisting of 3-4 members, as detailed in Table I. These activities were scrutinized using Moodle log reports and their effectiveness was assessed through visualization techniques. This study encompassed the analysis of log reports from two consecutive academic years, namely Batch 1 and Batch 2.

TABLE I
DESIGN THINKING COURSE DETAILS

Academic Year	Batch	Number of Students	Number of Project Teams
AY 1	Batch 1	Boys: 40, Girls: 22	16
AY 2	Batch 2	Boys: 39, Girls: 22	20

All project teams were instructed to document their discussion points in the Discussion Forum/Wiki and submit assignments through Assignment activities. Log reports for both batches were initially downloaded in Excel format from the Moodle server. Rows of administrators and course instructors were removed from the dataset. The log report for Batch 1 contained 21,156 rows, while Batch 2 contained 17,774 rows. MS Excel's pivot table functionality was utilized to extract data from the log reports. The extracted details of Moodle log parameters for both batches, Batch 1 and Batch 2 are provided in Table II.

Typically, the semester spans a 90-day (3-month) period, during which the planned pedagogical activities are implemented by the course faculty. Table III presents the list of activities, the type of Moodle activity, and the log parameters for both batches.

TABLE II
DETAILS OF MOODLE LOG PARAMETERS

Moodle Log Parameters	Number of Rows in Log Reports	
	Batch 1	Batch 2
Unique users	62	61
Component	10	6
Event Context	26	16
Event Name	41	29
Origin –web	19261	16229
Origin –ws (Mobile App)	1895	1545
IP Address	1903	1615
Days	119	130
Total Instances	21156	17774

TABLE III
MOODLE ACTIVITIES AND LOG PARAMETERS

Activities	Type	Log Parameters
5W1H	Discussion Forum	Discussion Subscription Created (DSC), Discussion Subscription Deleted (DSD), Post Deleted (PD), Post Updated (PU)
Stakeholder Interview - Survey Plan (SISP)	Discussion Forum	
Study of Existing Solutions (SES)	Discussion Forum	
Code of Cooperation (CoC)	Assignment	Submission Created (SC), Submission Updated (SU)
Evaluation Sheet (ES)	Assignment	

One interesting log parameter is "Origin," which provides data on whether students accessed Moodle via the web (web) or Moodle MobileApp (ws). This parameter, along with the IP Address, allows instructors to monitor student activity and quiz submissions. Table IV illustrates how students utilized the web and mobile applications for participation and submission in Moodle. It appears that participants predominantly utilized the web application for their activities. However, among all components, students used the MobileApp for three activities—assignment, forum, and system (for file view)—to some extent in both batches.

TABLE IV
MOODLE WEB VS MOODLE MOBILEAPP ACCESSES

Moodle Log Component	Batch 1		Batch 2	
	Origin - web	Origin - ws	Origin - web	Origin - ws
Assignment	5406	421	5986	633
File	13	6	45	9
File submissions	542	22	514	56
Forum	6251	846	5649	549
Online text submissions	154	6	220	24
Submission comments	9	-	-	-
System	5661	476	3815	274
URL	155	21	-	-
User report	1	5	-	-
Wiki	1069	92	-	-
Total	19261	1895	16229	1545
Grand Total	21156		17774	

A. Visual Approaches and Discussions

The dataset file in CSV format was imported into the Tableau tool for various visualization approaches. One of the simple visual types used was the highlight table, which allowed for viewing the number of student participation in each activity in greater detail, as shown in Fig. 3. The visualization reveals that more team interactions and submissions occurred in Moodle for Batch 1 compared to Batch 2. This disparity can be attributed to Batch 1being conducted entirely online during the city's full lockdown, resulting in more submissions in Moodle during class hours compared to Batch 2. Given that the course aims to develop Design Thinking skills through teamwork, it was observed that more submissions occurred outside class hours. Consequently, a slight process change was implemented by the instructor for the subsequent batch, Batch 2 based on the visual analysis of Batch 1. The modification involved instructing all teams to submit a single document per activity, facilitated by the team leader following team discussions. Batch 1encountered difficulties accessing the internet during class hours, prompting the instructor to permit and encourage submissions outside class hours. This adjusted approach successfully addressed their issue.

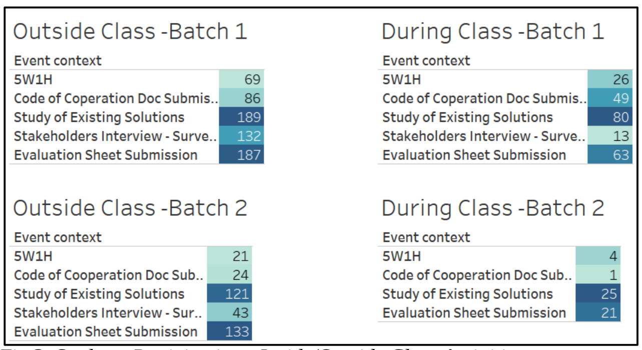

Fig.3. Students Participation - Inside/Outside Class Activities

Table V provides insights into the percentage of student participation in both inside and outside class activities for both batches. For instance, 91% of Batch 1students accessed the Moodle for Stakeholder Interview and Survey Plan (SISP) activity after class hours, while 100% of Batch 2 students accessed it after class hours. Additionally, the table indicates that a majority of students from the Batch 2 accessed Moodle items after their class hours, suggesting that they engaged in discussions related to the course, activities, and projects with their team members outside of working hours. With the process change implemented by the instructors, as described earlier, the Batch 2 performed more comfortably and effectively.

TABLE V
STUDENTS' PARTICIPATION IN CLASS ACTIVITIES

Activities	Batch 1		Batch 2	
	Access during Class Hour (%)	Access during outside Class Hour (%)	Access during Class Hour (%)	Access during outside Class Hour (%)
5W1H	27	73	16	84
CoC	36	64	4	96
SES	30	70	17	83
SISP	9	91	0	100
ES	25	75	14	86

The instructor may be interested in further details regarding student participation, such as the specific hours during which students were most active, whether in the early morning or late evening. Tableau's Stacked Bar Chart feature would be beneficial for visualizing this data. Fig. 4(a) illustrates the hourly participation details for all activities. In Batch 2, it is observed that 10-24% of students accessed Moodle during late evening hours (7 p.m. to 11 p.m.), whereas 8-14% of students accessed Moodle in Batch 1. Given that Batch 1was conducted entirely online, it is likely that students spent their day hours for participating and making submissions.

Tableau's line chart offers a distinctive visual representation. Fig. 4(b) illustrates the hourly participation of students in assignment and forum activities. It appears that Batch 2 predominantly utilized late evening hours,particularly around 21 or 22. The width of the line indicates the number of participants, with wider lines indicating higher participation rates. This visualization provides insights into the timing of student engagement with assignment and forum activities, allowing instructors to understand peak participation periods throughout the day.

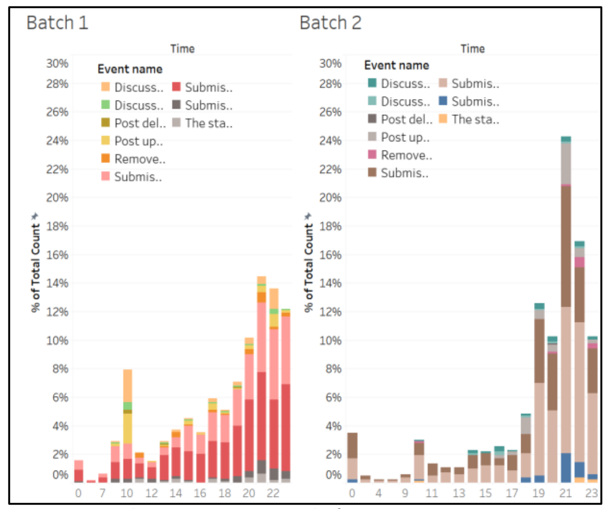

Fig. 4(a). Hourly Participation Details for Activities

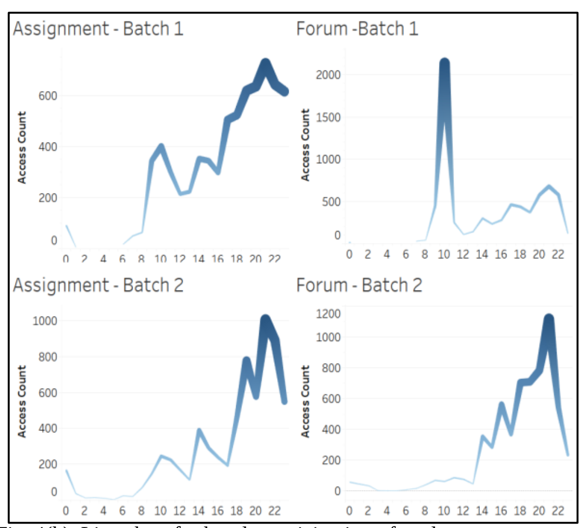

Fig. 4(b). Line chart for hourly participation of students

To quickly visualize any late submissions by the students, the instructor can utilize Excel's pivot table functionality by selecting appropriate filters and due dates for each activity. Table VI displays the number of submissions made by both batches before and after the due dates. This visualization allows the instructor to easily identify instances of late submissions and assess their frequency across different activities.

TABLE VI
TRACKING OF ASSIGNMENT SUBMISSIONS

Activity for Submissions	Number of Submissions Batch 1		Number of Submissions Batch 2	
	Before Due Date	After Due Date	Before Due Date	After Due Date
5W1H	51	11	58	3
SES	58	4	56	5
CoC	61	1	61	0
SISP	19	43	52	9
ES	49	13	42	19

To visualize potential outliers in the data, the instructor can utilize Tableau's box plot functionality. By selecting appropriate parameters for drawing this plot, the instructor can obtain valuable insights into student participation levels in Moodle activities. Fig. 5(a) illustrates the distribution of student participation in Moodle activities for both batches. It appears that more students from the Batch 2 actively engaged in assignments and forums compared to the Batch 1. This visualization allows the instructor to identify any potential outliers in student participation and compare participation levels between different batches.

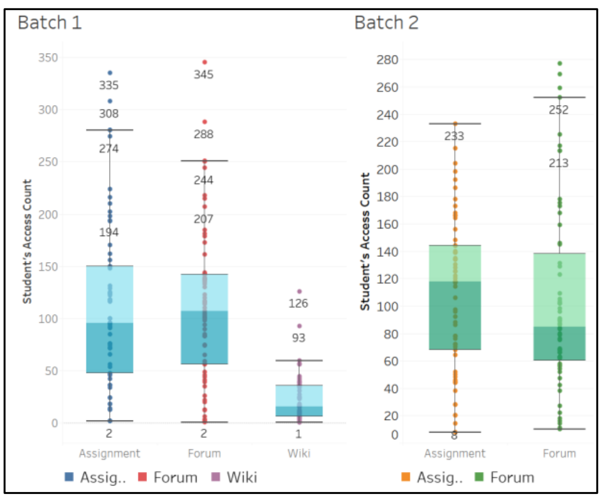

Fig. 5(a) Box Plot for Moodle activities (a) Access Count

To further segregate the details using demographic data such as gender, the instructor can utilize a box plot for visualization purposes, as shown in Fig. 5(b). This visualization reveals that girls accessed Moodle more frequently than boys. For instance, for one activity posted under the forum, girls in Batch 1 had an access count of 550, whereas boys had 425 accesses. However, the participation ratio of girls to boys in Batch 2 is almost equal and has improved from the previous batch. To achieve this improvement in participation, the instructor interacted with teams comprising less active boys and motivated them to participate in the forum activities.

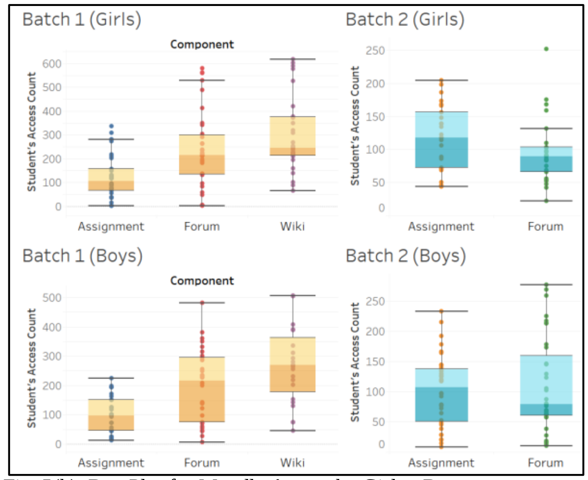

Fig. 5(b). Box Plot for Moodle Access by Girls - Boys

The next visual approach is the bubble chart, which provides a comprehensive view for instructors quickly. Each bubble represents events like forum, assignment or wiki. Number inside the circle represents the total count of access by the participants for a particular activity. By interpreting the size and color of the bubbles, the instructor can easily discern patterns in the data. Tableau's dashboard functionality facilitates the integration of data from two batches side by side, as depicted in Fig. 6(a). This allows for easy comparison between the two batches and provides a holistic understanding of student participation and engagement. It is evident that there are more equal-size bubbles in the Batch 2 compared to the Batch 1. This indicates a more balanced distribution of student access counts on forums and assignments in the second batch. Such balance was likely achieved due to the instructor providing clearer guidance regarding the Design Thinking processes. This visualization showcases details of highly participated students as well as those who participated less in both batches, as shown in Fig. 6 (b).

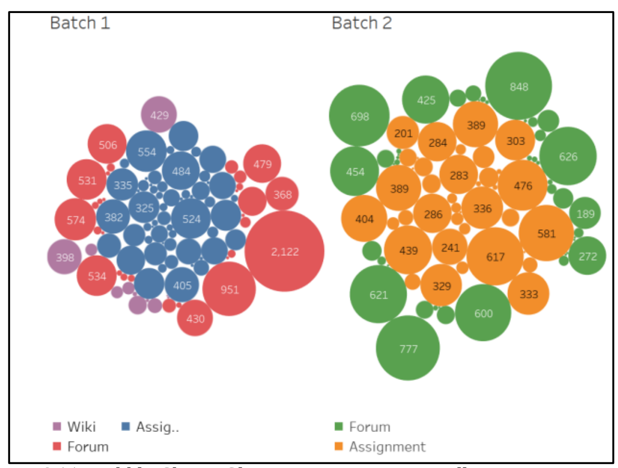

Fig. 6 (a). Bubble Chart - Class Participation in Moodle

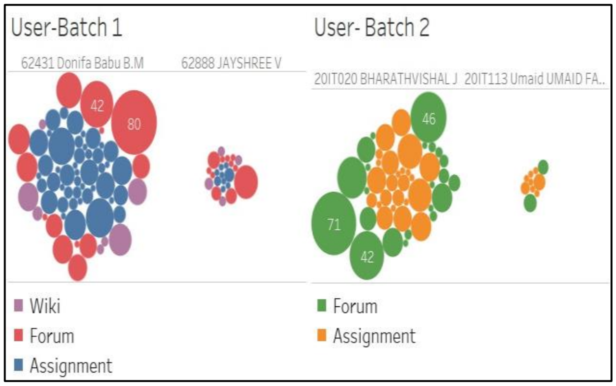

Fig. 6 (b) Bubble Chart - User Participation in Moodle

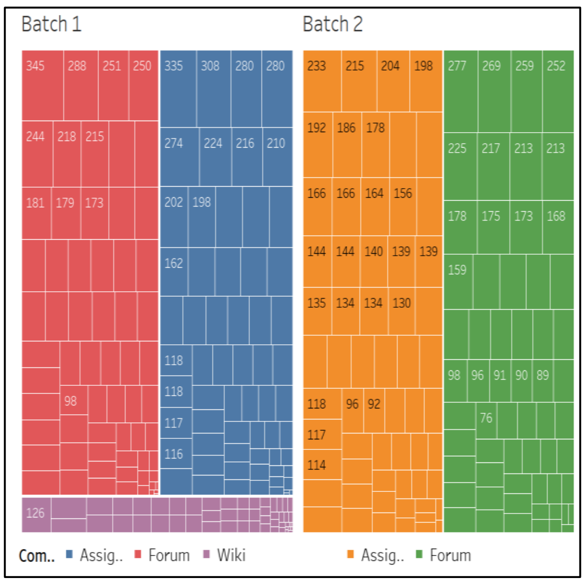

Fig. 7. Treemap – Percentage of Students Participation

The Treemap provides a deeper understanding of the overall data. Fig. 7 displays the percentage of participation of each student for each activity. Placing the cursor over a block provides details of a specific student. Treemap analysis followed by bubble chart analysis offers deeper insights into individual student participation, as shown in Fig. 6(b), including details of students with high and low participation.

The instructor conducted various activities to develop students' skills, attitudes, and knowledge, which can be assessed during reviews. In this course, reviews were conducted at three different stages. Microsoft Excel, a simple spreadsheet application, can be used to compare data through doughnut graphs and heat maps. Figures 8 and 9 illustrate how instructors can use Excel's features to analyze students' performance.

Fig. 8 displays the doughnut graphs showing the three review marks of two batches. The inner circle represents review 1, while the outermost circle represents review 3, facilitating comparison. It is observed that there was a slight decrease in the performance of Batch 1in review 3 compared to their review 2 marks. The activity Evaluation Sheet (ES) submission was done as an assignment, and the students' gains in this aspect were assessed in review 3. In response to this slight decrease, the instructor modified the content delivery for the subsequent batch, Batch 2, by introducing a forum for the Evaluation Criteria activity alongside assignment submission. This change helped Batch 2 students score better in review 3. The various modifications in the DT process and activities led to a significant improvement in the performance of Batch 2 compared to Batch 1. Sometimes, the instructor may wish to view the performance of each student at each stage.

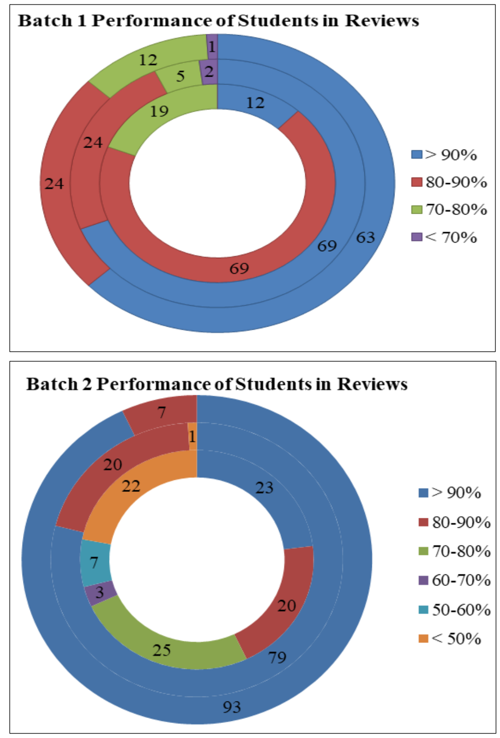

Fig. 8. Doughnut Graphs of Student's Performance

The heat map is an ideal choice for studying correlations between data. Fig. 9 illustrates the performance of a few students in all three reviews using a heat map. The varying color intensities help instructors easily interpret the data. This visualization is created using the Conditional Formatting and Color Scales features in MS Excel.

Student	Review 1	Review 2	Review 3
Stud 1	17	18	18.5
Stud 2	17.5	18	18
Stud 3	17	19	19
Stud 4	17	18	19
Stud 5	16.5	16	16
Stud 6	17	18	18.5
Stud 7	12	13	14.5
Stud 8	16	18	17.5
Stud 9	16	18	17.5
Stud 10	17	19	19

Fig.9 Heatmap for Students' Performance in Reviews

For example, Fig. 9 shows the three review marks of 10 students, with a maximum score of 20 for each review. A dark green shade represents the maximum score, while a bright red shade represents the minimum score. Intermediate values are assigned colors accordingly. These Excel-generated heat maps provide better visualization, enabling the instructor to quickly understand whether a student's performance is trending upward or downward.

B. Correlation Analysis

Figures 10 (a) and (b) display scatter plots illustrating the relationship between the count of Moodle access by all students and their average review marks. In these plots, the red line represents the mean count of access and average marks. The plots are divided into four quadrants, and the explored values are summarized in Table VII. This visualization allows instructors to identify any potential correlations between student engagement with Moodle activities and their performance in reviews.

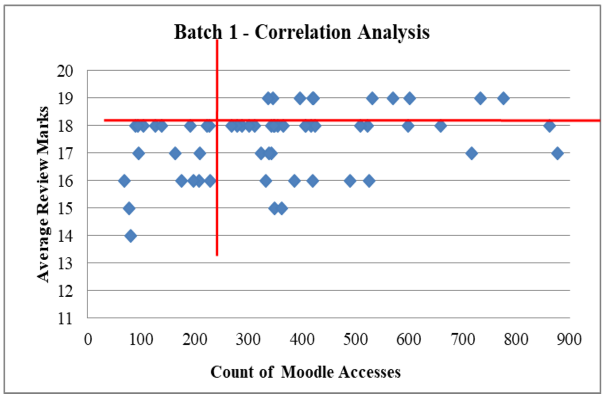

Fig. 10 (a).Batch 1 Correlation Analysis

Most students should fall within Quadrant Q2, indicating a balance between their access to Moodle activities and their average review marks. Table VII indicates that approximately 75% of students are located in Quadrants Q2 and Q3, which aligns with this preference. For the Batch 1, conducted in online mode, 40% of students (Quadrant Q3) scored above the mean despite having lower access to Moodle activities. This discrepancy may be attributed to various factors, such as individual performance not being adequately evaluated in an online setting. In team-based evaluations, instructors must pay close attention while assessing individual's performance.

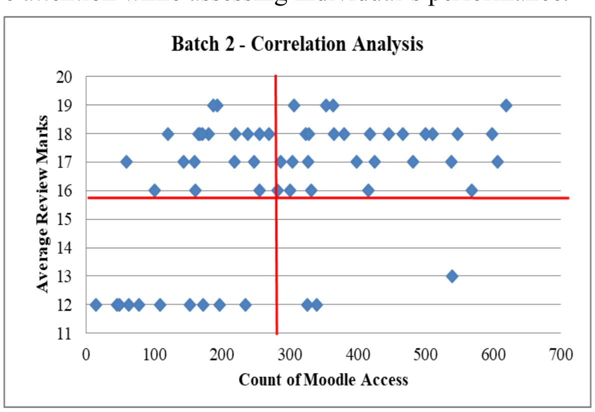

Fig. 10(b). Batch 2 Correlation analysis

TABLE VII

CORRELATION VALUES

Quadrant	Description	Number of Students Batch 1	Batch 2
Q1	Count of Access > Mean, Average Review Marks < Mean	6	3
Q2	Count of Access > Mean, Average Review Marks > Mean	21	26
Q3	Count of Access < Mean, Average Review Marks > Mean	24	21
Q4	Count of Access < Mean, Average Review Marks < Mean	8	11
	Mean of Count of Access	350	290
	Mean of Average Review Marks (max. 20 marks)	17	16

In contrast, for the Batch 2 (blended mode), strict monitoring and performance evaluation were implemented for all teams, resulting in a higher quality of work and performance improvement. Instructors should take measures to ensure that most students fall within Quadrant Q2, rather than other quadrants. Additionally, special attention should be given to students in Quadrants Q1 and Q4. Instructors must discuss the reasons for their low access to Moodle and low scores and provide support for their progression. Therefore, various visualization approaches serve as one of the solutions to address the research question. This is demonstrated through the analysis of Moodle log data from the design thinking course, utilizing various maps and charts to gain insights into student performance and engagement.

C. Moodle Team Participation (MTP) Grid

The correlation analysis leads to the development of Moodle-Team Participation (MTP) Grid, as shown in Fig. 11. It depicts the progress of interpersonal skills among students through their participation in Moodle activities and team projects. It likely showcases various aspects such as collaboration, communication, teamwork, and leadership skills that students acquire and demonstrate throughout the course.

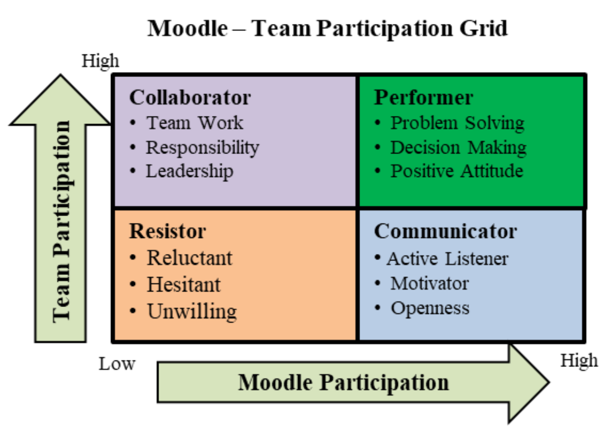

Fig. 11. Moodle–Team Participation (MTP) Grid

By analyzing Fig. 11, instructors can gain insights into the extent to which students engage with team-based activities and collaborate effectively to achieve project goals. This visualization highlights the importance of fostering interpersonal skills alongside academic knowledge, contributing to student's holistic development and preparedness for real-world challenges. The grid says *high* Moodle participation and *high* team. The grid categorizes students based on their level of participation in both Moodle activities and team projects, leading to different roles:

Performer: High participation in both Moodle activities and team projects indicates a student with problem-solving abilities, strong decision-making skills, and a positive attitude.

Collaborator: Effective participation in team projects suggests a student who develops leadership qualities, demonstrates teamwork and takes on responsibilities within the team.

Communicator: Active engagement in Moodle activities indicates a student who fosters communication skills, practices effective listening, and maintains openness to new ideas.

Resistor: Reluctance or hesitancy to participate in team projects or discussions characterizes a student who may lack engagement and participation in various activities.

By employing various visual approaches, instructors can regularly monitor each student's level of participation. Continuous motivation and support should be provided to students, especially when there is a decline in their engagement. This proactive approach ensures that students are actively involved in both Moodle activities and team projects, fostering the development of crucial interpersonal skills essential for their academic and professional success and thus addressing the research question.

Conclusion

The integration of GenAI with online learning platforms offers a transformative potential to revolutionize education. By personalizing learning experiences, providing intelligent tutoring, automating assessments, and delivering data-driven insights, GenAI can significantly enhance the effectiveness, engagement, and inclusivity of online learning environments. Most of the existing pedagogical practices and classroom teaching methods are not well suitable for online education.To assist instructors in enhancing their online content delivery mechanisms, a research question was formulated and various visual approaches were explored using students' Learning Management System (LMS) log datasets, particularly focusing on Moodle log reports. Through these approaches, instructors could gain insights into the challenges faced by students in one batch and implement corrective measures in subsequent batches of Design Thinking courses. The article discussed various data visualization techniques and effective strategies for managing classes using Moodle LMS. It demonstrated how students' activities could be reflected in their performance through these visual representations. Additionally, the article explained the characteristics of interpersonal skills of students based on their level of participation in Moodle activities and project teams, as depicted in the Moodle-Team Participation (MTP) grid.

Moving forward, the work will be extended to develop a customized visualization tool that supports instructors in periodically monitoring each activity in Moodle LMS, which in turn would facilitate for measuring the relevant Programme Outcomes like team work (PO9), communication (PO10), and life-long learning (PO12). Furthermore, addressing the challenges of online learning will involve designing activities while considering factors such as students' home environment, societal influences, access to information and communication technology (ICT), and financial support. By addressing these challenges and using effective visualization tools, educators can better facilitate engaging and effective online learning experiences for students.

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