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Research Article

A Sustainable Learning Behavior Analytics Framework for Customized Learning Management Systems

Marwan Ali Shnan[1], Munef Abdullah Ahmed[2,*]

[1] Faculty of Computer Systems & Software Engineering (FSKKP) UMP, Malaysia

[2] Electronics Department, Alhawija Technical Institute, Northern Technical University, Iraq

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ABSTRACT

The Learning Management System (LMS) has emerged as a key platform for e-learning and as an agent to create massive amounts of data about learners' interactions, which can be used for educational decision making. Yet, many LMS systems that are in place today only capture students' behaviors, but fail to make them relevant to the context of behavioral analysis. Based on the above, this study is proposing the Enhanced Learning Behavior Analytics Framework (LBAF) that could be embedded in a customized LMS to systematically collect, organize and analyze the learners' behavior data during the online learning process. The proposed framework was designed adhering to the ADDIE instructional design model and involves several behavioral indicators such as; course participation, content exploration, interaction with the video, involvement in the discussion forum, performance in assessment, and engagement with the learner. It was implemented and evaluated by analyzing the behavioral data collected from 45 undergraduate students, and by conducting structured evaluation questionnaires with students and instructors. Based on the experimental results, the proposed framework is able to support the monitoring of the learner's engagement and the assessment of instruction and analysis of the behavior of the learner in the customized LMS is successful. The students' and instructors' perceptions of the usability of the system and flexibility of the communication and overall learning experience were positive. The proposed framework offers a viable solution to integrate learning behavior analytics into customized LMS for evidence-based instruction decision making, effective online learning environment, and sustainable digital education in line with SDG 4 (Quality Education).

1. INTRODUCTION

The rapid development of digital technologies has greatly changed the face of the Higher Education Industry, and Learning Management Systems (LMSs) are a key platform for the provision of online and blended learning. The modern LMS are designed to offer flexible access to educational resources, communication between teachers and students, and a variety of activities for learning and assessment. Therefore, higher education institutions are increasingly looking towards custom LMS solutions to improve education accessibility, flexibility and quality [1].

Higher education institutions are expected to contribute to educational sustainable development as well as digital learning technologies are being rapidly adopted. The United Nations Sustainable Development Goal 4 (SDG 4) focuses on achieving inclusive, equitable and quality education, and promoting lifelong learning opportunities for everyone. In the context of sustainable digital education, LMS and learning behaviour analysis can help with ongoing monitoring of learners, inform evidence-based decision making on programme, facilitate learner engagement and enhance the quality of the online learning environment [2].

Besides delivering content, LMSs also produce a lot of behavioral data pertinent to students' learning activities, including login time, content access, video viewing time, forum interaction, assessment performance, and more. Studying these interactions of behavior has been identified as a critical aspect of Learning Analytics (LA) that can help teachers to gain insights into student engagement, identify evidence of learning progress, and make effective instructional decisions [3, 4]. Although much of the data gathered by any existing LMS platform is of an interaction nature, many LMS platforms are merely gathering these data for administration purposes, not converting these data into some actual behaviour indicator. This limitation hinders the ability of instructors to observe student involvement in online learning and to gauge student learning in full during online classes [5].

*Corresponding author email: muneef_hwj@ntu.edu.iq
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To address this challenge, the following study proposes an Enhanced Learning Behavior Analytics Framework (ELBAN) which can be integrated into a LMS. New proposal to extend current learning behaviour monitoring to a number of interactions, and to structure the monitoring of learning behaviour into indicators of learning behaviour for tracking engagement or measuring instruction. It has been realised following an instructional design model called ADDIE, which makes systematic development and integrates it into the LMS environment. The main conclusions of the study are summarized below:

1. Development of an Enhanced Learning Behavior Analytics Framework.
2. Integration of structured behavioral indicators.
3. Validation using real educational data.
4. Support for learner monitoring and instructional evaluation.

2. LITERATURE REVIEW

Learning Management Systems have revolutionized higher education by offering flexible and accessible online learning experiences. Today's LMS systems also enable course management, content delivery, communication, course assessment, collaboration, and collect a wealth of learner interaction data. These digital footprints have become useful tools to understand the learning behaviors of students and to enhance educational quality and make decisions based on data analysis [6].

Learning Analytics is a new and developing research field that examines how to gather, quantify, analyze and interpret educational data to improve the learning and teaching process. Learning Analytics differs from the traditional methods of activity logging in that it attempts to convert the way a learner interacts with content into behaviour so that the teacher can track engagement, learning progress and enhance the effectiveness of instruction [7,8]. In recent studies, it has been found that behavioral information like login frequency, content access, video interactions, forum participation, and assessment performance gives valuable information of the learning engagement and academic achievement of the students [9].

With the rapid progress of digital learning technologies, sustainable education has emerged as a key research field of higher education in recent years. SDG 4 (Inclusive and Equitable Quality Education) focuses on providing inclusive and equitable education and on improving the teaching and learning process continually. The concept of learning analytics has been emphasized recently to help sustainable digital education in various ways, such as facilitating learners' engagement, facilitating data-driven decisions, optimizing educational resources, and continuous improvement of online learning quality in digital learning environments [10-12].

Student engagement is a factor that has been consistently identified as one of the best predictors of successful online learning. Various factors such as active engagement in learning activities, constant interaction with the educational resources, and continuous communication in online courses all have a favorable impact on learning that affects the rate of course completion [10]. Many current LMS still maintain activity logs with only descriptive logs without establishing detailed analytical indicators that help to guide teachers to assess students' engagement during the learning process [11].

A number of recent studies have suggested learning analytics dashboards and behavioural monitoring systems that would allow to visualize the activities that learners undertake and their educational performance. While these methods enhance access to behavioral data, virtually all of them are designed to visualize behavioral data in a static manner and/or to report on a single metric.

In this study, authors propose an Enhanced Learning Behavior Analytics Framework integrated with a customised Learning Management System, driven by these limitations. The proposed framework is an extension of the existing concept of tracking learning behaviors that is framed in a single framework of behaviors that provides learners with a single reference when evaluating learning engagement, monitoring the learning process, and making continuous improvements in learning.

The literature over the last few years has shown great advances on the application of learning analytics and behavioral monitoring in Learning Management Systems (LMSs) Learner engagement, learning data analysis, learning analytics dashboards, and behavioral prediction have been investigated in different ways to enhance online learning experiences. But most current solutions are limited to behavioral measures or descriptive analytics that do not incorporate a learner interaction, but rather are working in isolation. Table I provides an overview of some selected studies indicating their methodology, contribution and limitations, highlighting the research gaps in the proposed framework. Furthermore, recent research indicates that integrating learning behavior analytics into LMS platforms supports sustainable digital education by facilitating continuous educational quality improvement and evidence-based teaching practices.

TABLE I. COMPARISON OF RECENT STUDIES ON LEARNING BEHAVIOR ANALYTICS AND LMS

Ref.	Year	Method / Approach	Main Contribution	Limitation
[13]	2022	Learning Analytics	Improved learning performance analysis using educational data	Limited behavioral indicators
[14]	2023	Higher Education Learning Analytics	Reviewed recent learning analytics applications in higher education	Focused on literature review without implementation
[15]	2023	Systematic Literature Review	Identified trends and challenges in learning analytics	No practical framework proposed

[16]	2023	Educational Data Mining	Analyzed learner interaction patterns	Focused mainly on predictive analysis
[17]	2024	Learning Analytics Framework	Proposed analytics techniques for educational improvement	Limited integration with customized LMS
[18]	2024	Student Engagement Analytics	Evaluated learner engagement using LMS logs	Considered only engagement metrics
[19]	2024	LMS Dashboard	Developed visualization dashboard for instructors	Did not integrate comprehensive behavioral analytics
[20]	2025	Behavioral Learning Analysis	Investigated online learning behaviors using interaction records	Limited scalability and practical deployment
Proposed Work	2026	Enhanced Learning Behavior Analytics Framework	Integrates structured behavioral indicators within a customized LMS to support learner engagement monitoring and instructional evaluation	Limited to a single institution and descriptive behavioral analytics

3. METHODOLOGY

3.1 Framework Overview

This study presents an Enhanced Learning Behavior Analytics Framework (LBAF) integrated into a personalized LMS and on an online learning platform, to collect, group and analyze students' learning behaviors in online learning. The framework draws upon the current monitoring of learning behavior, but introduces a new feature – structured behavioral analytics indicators that allow teachers to monitor and track student engagement and progress in learning. It is a five-step framework that follow the ADDIE instructional design process: Analysis, Design, Development, Implementation, and Evaluation. This model provides a systematic approach to design the education system with a uniform approach to the system implementation and evaluation between the goals of the system and the implementation of the system.

Students engage with the LMS via different learning activities, such as: content access, viewing videos, participating in forums, and assessments, as shown in Figure 1. The interactions are captured by the behavior collection module, and analyzed as part of the Learning Behavior Analytics Layer, which groups them into pre-defined behavioral indicators. The data analysed then is used in the behavioural database and on the instructor dashboard, to monitor learner progress and assess instruction. The overall set-up might be a useful addition to the existing LMS features, without requiring changes to the system architecture.

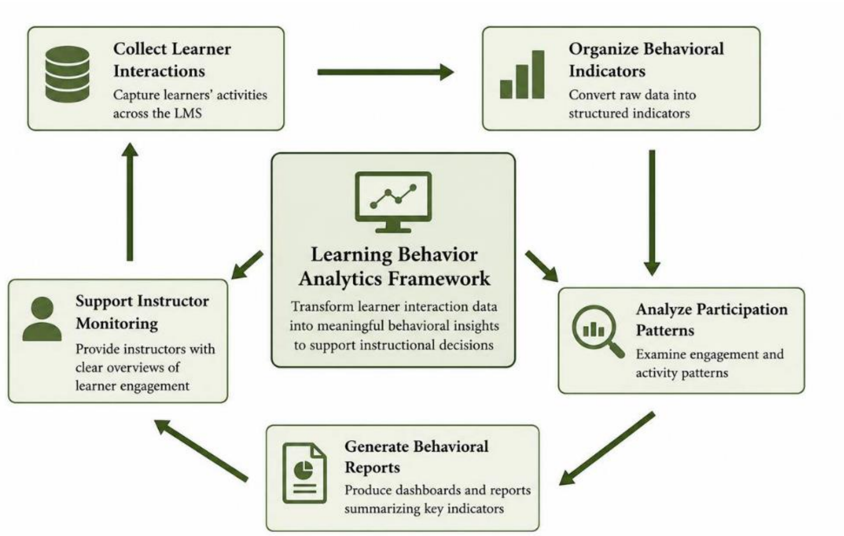

Fig. 1. Overview of the Proposed Learning Behavior Analytics Framework

3.2 Analysis Phase

The Analysis phase sets the groundwork for the development of the proposed Learning Behavior Analytics Framework (LBAF), which identifies the educational goals and target users, the system requirements and the indicators of behavioral analytics needed for effective learner monitoring. This phase is to make sure that the proposed framework matches both instructional objectives and users' needs and to allow a thorough analysis of students' learning behaviors.

It is developed for undergraduate students in higher education institutions who are taking online courses. In this stage, the functional needs of the customized Learning Management System (LMS) were mapped covering Learner Registration; Course Management; Course Content Delivery; Assessment and Behavioral Data Collection. Besides, it was identified that the behavioral indicators should be used for learning analytics evaluation of learners' engagement and participation during the learning process. The idea of structure is explained at three complementary levels of analysis of learner activities:

1. **Course Level:** monitors students' interactions with course materials, assessments, and learning resources.
2. **Student Level:** records individual behavioral indicators such as learning activities, participation, and academic progress.
3. **Environment Level:** evaluates learners' interactions with the customized LMS and the surrounding learning environment.

The results of this phase will be the basis for the next stage of design and implementation as well as the functional requirements of the framework. The most important results obtained during the analysis phase are summarized in Table II, which lists the objectives, target users and functional requirements of the proposed framework.

TABLE II. SUMMARY OF THE ANALYSIS PHASE

Analysis Component	Description
Target Users	Undergraduate students using the customized LMS
Educational Objective	Improve learner engagement through learning behavior analytics
Course-Level Analysis	Course access, learning materials, assessments
Student-Level Analysis	Learning activities, participation, engagement indicators
Environment-Level Analysis	LMS interaction and learning environment
Expected Outcome	Structured behavioral analytics supporting instructional evaluation

3.3 Design Phase

In the Design phase, the general structure and functionality of the proposed Learning Behavior Analytics Framework (LBAF) in the customized Learning Management System (LMS) are being developed. In this stage, the system architecture, users and roles, behavior-based analytics features, and assessment processes were mapped out to allow for a harmonized interaction between the learners, teacher, and the LMS.

Three user roles in the customized LMS were created: visitors, students, and instructors. Specific permissions are granted to each role to allow for secure and efficient access to a system's functions. Students own the access to learning materials, the completion of learning assessments, learning activities, and the review of behavioral analyses created by the framework; while instructors own course content, student progress, and review the student behavioral analyses. The framework also specifies the learning contents and learning activities that are provided in the LMS, such as Learning Materials, Instructional videos, Quizzes, Assignments, Discussion Forums, and Evaluation surveys. The Learning Behavior Analytics Layer uses these learning activities as primary data sources for learning behavior data collection, which are then processed.

To evaluate the effectiveness of the proposed framework, an evaluation module was added to the system. The evaluation is carried out using a structured post-course questionnaire, which aims to assess the satisfaction of the users of the system, the level of engagement of the learners, the usability of the system, the effectiveness of the learning, and the performance of the system. Table III presents key roles of users and permissions for each role in the customised LMS.

TABLE III. USER ROLES AND PERMISSIONS

Function	Visitor	Student	Instructor	Administrator
Register/Login	✓	✓	✓	✓
View Course Content	✗	✓	✓	✓
Participate in Learning Activities	✗	✓	✓	✓
Download Learning Materials	✗	✓	✓	✓
Manage Course Content	✗	✗	✓	✓
Manage Assessments	✗	✗	✓	✓
Manage Users	✗	✗	✗	✓

The proposed framework's functional design and the interactions between users, learning resources, and the behavioral analytics layer are displayed in Figure 2.

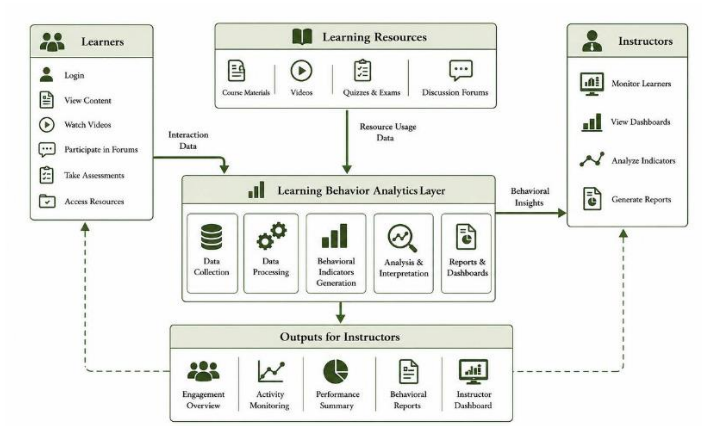

Fig. 2. Functional Design of the Proposed Framework

3.4 Learning Behavior Analytics Layer

The proposed framework is built on the foundation of the proposed Learning Behavior Analytics Layer that transforms raw interactions between learners and the system into structured indicators of learning behavior that can be used to analyze learning and monitor learners. This layer does not just track what students are doing, rather it collapses the behavioural data into meaningful metrics for students' engagement and learning progress, and allows the instructor to see a bigger picture to inform their teaching. The analytics layer captures learners' behavior as they interact with the customised LMS, such as accessing content, exploring content, watching videos, engaging in discussion forums, performing assessments, and interacting for a certain amount of time. The behavioral records are then processed and stored as pre-defined indicators that provide a summary of the students' learning activities over the course. Table IV shows the behavioral indicators that were collected and analyzed through the proposed framework.

TABLE IV. BEHAVIORAL ANALYTICS INDICATORS

Indicator	Description
Registered	Learner enrollment status
Viewed	Access to the LMS homepage or course
Explored	Completion of at least half of the available content
Number of Events	Total recorded learner interactions
Active Days	Number of days with LMS activity
Videos Viewed	Number of accessed videos
Chapters Viewed	Number of accessed chapters
Forum Posts	Number of discussion contributions
Grade	Assessment score
Certification Status	Course completion status

The Learning Behavior Analytics Layer shown in Figure 3 is responsible for collecting, processing and organizing the learner interaction data into behavioral indicators.

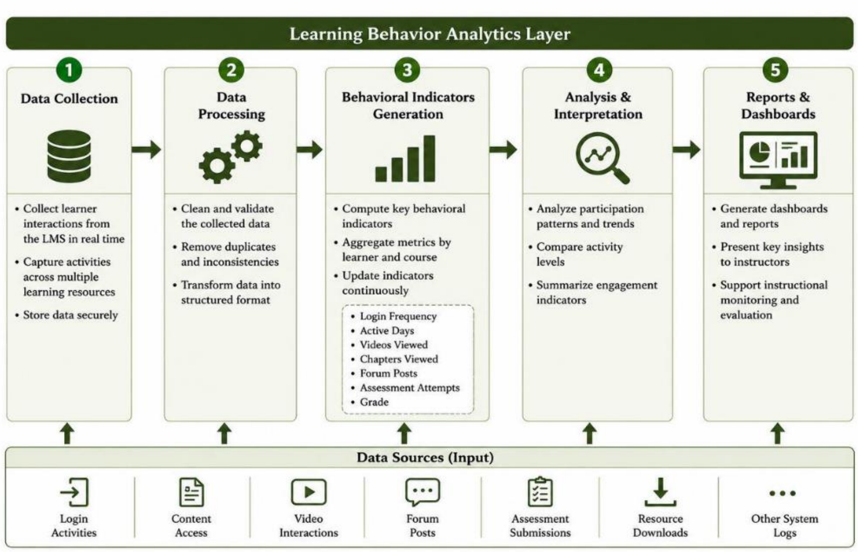

Fig. 3. Learning Behavior Analytics Layer.

3.5 Framework Implementation

To collect, manage and analyze students' learning behaviors during the whole process, a customized Learning Management System (LMS) was used to implement a Learning Behavior Analytics Framework (LBAF). The implementation includes course management features and behavioral analytics, allowing for ongoing monitoring of learner engagement. The framework has four primary roles of users: Administrator, Instructor, Student and Visitor. Specific permissions are given to each role depending on their role. Students engage with course content, take assessments, join in on discussion forums, and access the course materials; instructors manage course content, monitor learners' activities and review their behavior analytics on the instructor dashboard.

During each learning session, students' interactions are automatically recorded by the behavior collection module. These interactions encompass logins, access to content, video viewing, chapter exploration, forum engagement, assessment attempts, and learning time. Collected data are then processed by the Learning Behavior Analytics Layer, which groups the data into learning behavior indicators, and then enters the learning behavior database for analysis. The process of implementing the system is sequential and starts from the authentication of learners, then continues with the participation of the course, collecting behavior data, creating analytics, and presenting learning reports on the instructor's dashboard. This process allows the teacher to make continual assessments of learner engagement as well as tracking students' learning progress throughout the course. The implementation process of the proposed framework is represented in Figure 4, which begins with learner authentication and progresses to generating learning analytics reports.

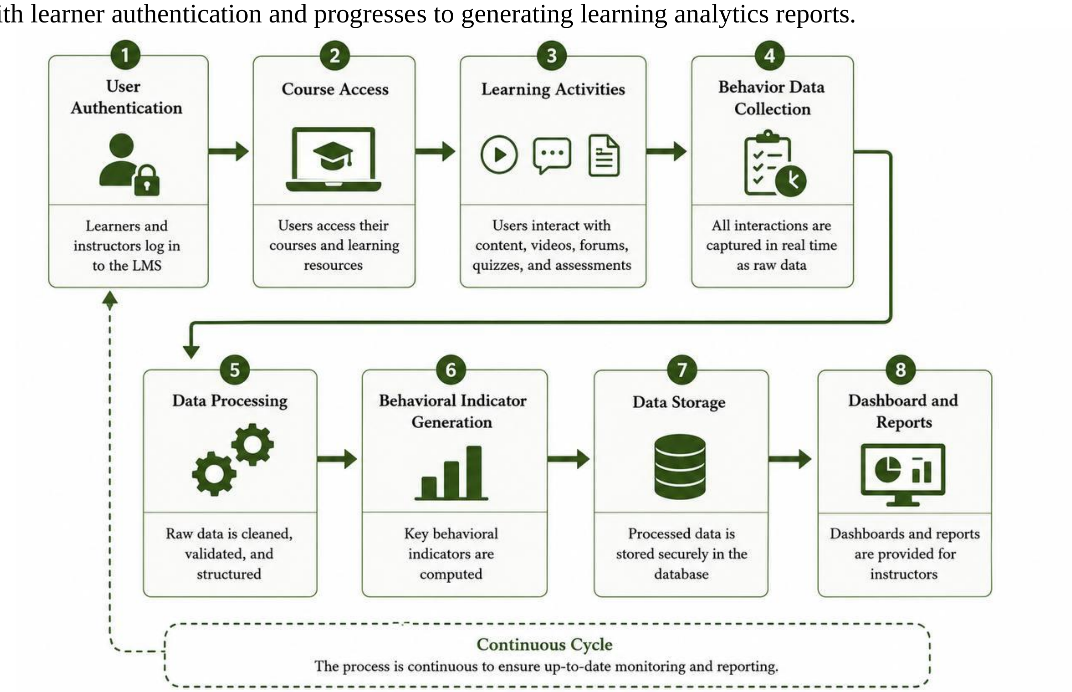

Fig. 4. Framework Implementation Workflow.

3.6 System Architecture

The proposed Learning Behavior Analytics Framework (LBAF) has a three-layer framework: presentation layer, application layer, and data layer, which offers a modular and scalable approach to incorporating the behavioral analytics in the customised Learning Management System. The presentation layer is the user interface that students, teachers, administrators, and visitors use to access the LMS. This is a layer which enables functions like navigation within courses, access to learning resources, assessments and visualization on the dashboard.

The main processing level of the framework is the application level. It offers user authentication, managing courses, recording behaviors, and the suggested Learning Behavior Analytics Layer. This layer depicts students' interactions and translates them into structured behavioral indicators, which help to monitor student engagement and assess the effectiveness of the instruction. The data layer handles all aspects of storing information about users, course materials, assessment results and behavioral analytics indicators. It provides for the efficient retrieval and management of the learning content and helps in continuous monitoring and reporting via the instructor dashboard. The proposed architecture can be implemented seamlessly with the customized LMS, with a light and scalable system structure well suited to the higher education environment, as a whole. The overall system architecture of the proposed framework will be shown in Figure 5, which shows the interaction among the presentation layer, application layer and data layer.

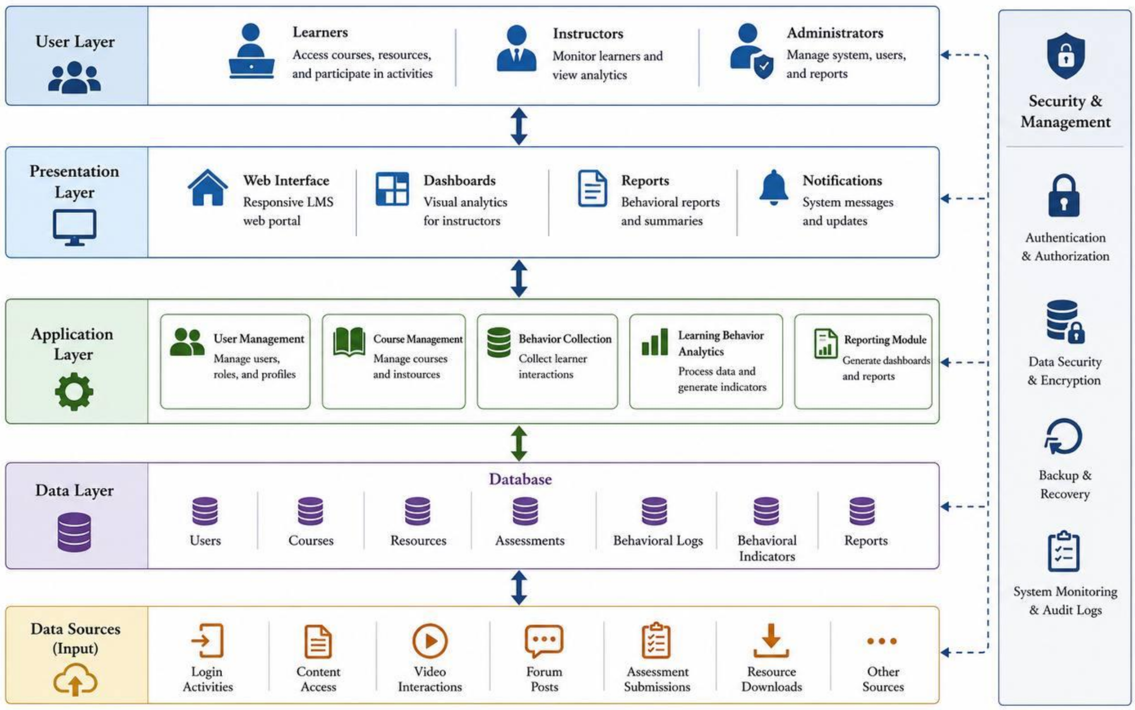

Fig. 5. System Architecture

3.7 Database Structure

The proposed Learning Behavior Analytics Framework (LBAF) utilizes a relational database to control academic information, learner interactions, and behavioral analytics in the customized Learning Management System. The database aims to store, retrieve and manage educational data efficiently, and also allows for ongoing monitoring of learner engagement. The database contains multiple sets of related components: Users, Courses, Learning Resources, Assessments, Behavioral Logs, and Behavioral Indicators. The user information is associated to the enrolment records of the courses, allowing course enrolment to be related to students' learning activities. The Learning Behavior Analytics Layer processes the behavioral interactions which are captured during an online learning session and returns structured behavioral indicators, which are recorded in the behavioral logs.

The relational design reduces data duplication, but adds the ability to query and report efficiently. The behavioral indicators that are created are used by the instructor dashboard to track learner engagement, assess learning progress, and inform instructional decision making. Table V shows the summary of the main entities in the relational database that is used to support the proposed framework.

TABLE V. MAIN DATABASE ENTITIES

Entity	Description
Users	Stores user information (students, instructors, administrators)
Courses	Contains course details and enrollment information
Learning Resources	Stores learning materials, videos, and documents
Assessments	Records quizzes, examinations, and grades
Behavioral Logs	Stores raw learner interaction records
Behavioral Indicators	Stores processed analytics indicators
Reports	Stores summarized learning analytics reports

The simplified data model and the relationships between the key entities that manage behavioral analytics information are shown in Figure 6.

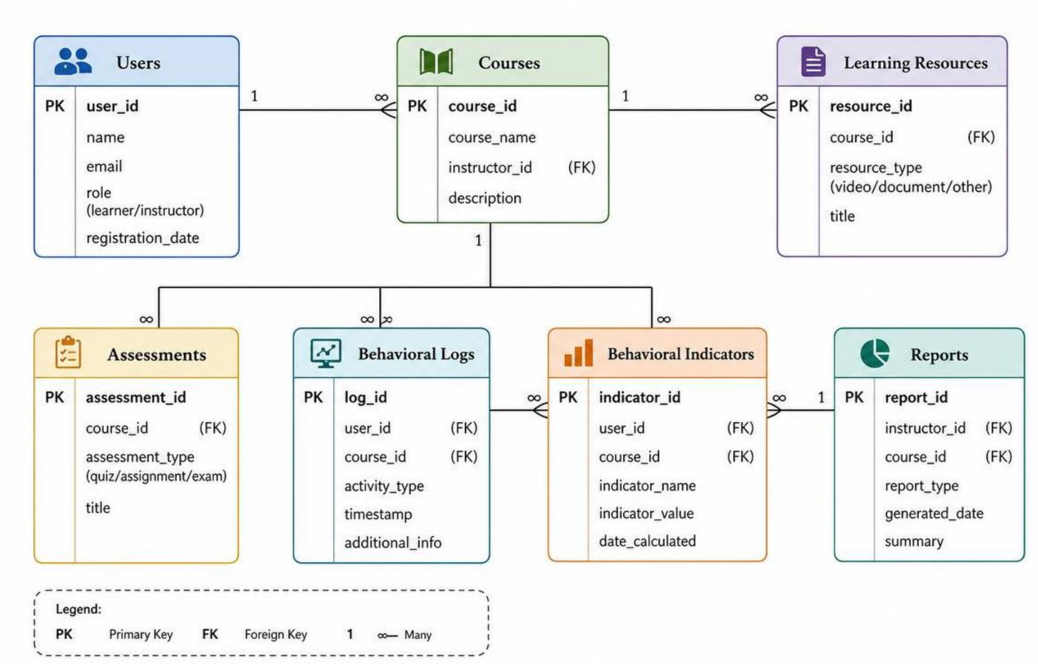

Fig. 6. Simplified Database Structure

4. RESULTS AND DISCUSSION

4.1. Learning Behavior Analytics Results

Collected behavioral data were also examined to determine the patterns of involvement, resource use, engagement, and performance in assessment. These behavioural analytics give teachers valuable feedback on student learning and engagement during the course. The proposed framework produces the following behavioral analytics in tabular format as seen in Table VI. Collected indicators are: learner registration, content exploration, learning activities, video interactions, participation in a discussion forum, completion of the online course, assessment performance and overall engagement in the online course.

TABLE VI. SUMMARY OF LEARNING BEHAVIOR ANALYTICS RESULTS

#	Behavior Record	Maximum / Positive Value	Minimum / Negative Value	Total Count
1	Registered	Positive Count (45)	Negative Count (0)	45 Rows
2	Viewed	Positive Count (45)	Negative Count (0)	45 Rows
3	Explored	Positive Count (37)	Negative Count (8)	45 Rows
4	N_events	Largest Count (201)	Smallest Count (10)	2405 Event
5	N_days_active	Largest Count (55)	Smallest Count (14)	58 Day
6	N_videos	Largest Count (6)	Smallest Count (1)	6 Videos
7	N_chapters	Largest Count (8)	Smallest Count (1)	8 Chapters
8	N_forums	Largest Count (21)	Smallest Count (0)	243 Posts
9	LoE	Largest Count (0)	Smallest Count (0)	45 Rows
10	Certified	Largest Count (1)	Smallest Count (0)	45 Rows
11	Grade	Largest grade (100)	Smallest Grade (0)	45 Rows
12	Rate of course Difficulty	Easy (62%)	Difficult (38%)	45 Rows
13	Passing rate	Passed (28)	Failed (17)	45 Rows

The gathered behavioral data shows that all the enrolled students were able to access the learning platform and most of the participants were actively using the learning resources. The student interaction logs also show significant differences in the amount of learning activities on the content, the participation in the discussions, assessment performance and time spent actively learning. These differences in behavior offer insights into the engagement of the learners and an example of how the framework can be used to track students' learning activities throughout the course. Overall, the generated behavioral analytics give teachers a full picture of students' engagement, allowing them to monitor the engagement of their students in real time and support evidence-based teaching evaluation.

4.2. Framework Evaluation

The efficiency of the proposed Learning Behavior Analytics Framework (LBAF) was tested by a structured post-implementation questionnaire filled by students and instructors. The evaluation was conducted on several aspects of the customized LMS, such as the system's performance, its usability, the learning resources, the flexibility of the communication process, the engagement of the learners, and the instructional support. After removing students who did not complete their responses and those who answered outside of the range, 41 valid responses were obtained over two evaluation sessions. Five instructors were also involved in the evaluation and shared their opinions on the ease of using and effectiveness of the proposed framework.

4.2.1. Students' Evaluation

Table VII summarizes the average evaluation scores obtained from students during the two evaluation phases.

TABLE VII. STUDENTS' EVALUATION RESULTS

Evaluation Criterion	Phase 1	Phase 2
Overall System Performance	4.0	4.2
Web Interface Appearance	3.8	4.0
Course Content Quality	3.6	4.2
Communication Flexibility	4.5	4.4
Learning Material Relevance	4.5	4.0
Instructor Support	4.5	3.5
Resource Availability	3.8	4.1
Feeling of Isolation / Disengagement	3.1	3.2
Technology Accessibility	3.2	4.0
Financial Support	3.0	2.1
Work and Family Responsibilities	1.9	1.9

The results show a fairly positive attitude towards the proposed framework. The overall system performance got high feedback points from the students, as well as communication flexibility, learning materials and teaching assistance. It was also found that the customized LMS helped in the engagement of learners and helped to create a structured online learning environment. However, scores were relatively low for technology accessibility and financial support, suggesting that there could be external factors impacting the student's online learning experience.

4.2.2. Instructors' Evaluation

Table VIII presents the instructors' evaluation of the proposed Learning Behavior Analytics Framework.

TABLE VIII. INSTRUCTORS' EVALUATION RESULTS

Evaluation Criterion	Average Score
Overall System Performance	4.8
Web Interface Appearance	4.2
Course Content Quality	4.0
Communication Flexibility	4.8
Learning Material Relevance	4.6
Instructor Support	4.8
Resource Availability	4.2

The number of evaluations that the instructors conducted indicated that they are very satisfied with the proposed LBAF. Overall System Performance (4.8 points), Communication Flexibility (4.8 points) and Instructor Support (4.8 points) were the scores with the highest averages, showing that the framework helps both the students to monitor their learning and manage the course. Furthermore, positive ratings for Course Content Quality, Learning Material Relevance, and Resource Availability suggest that the framework can help to create a conducive and engaging online learning environment. The instructors' feedback is mainly positive and supportive of the proposed framework to improve learning behaviour analytics in custom-made LMS in general.

4.3. Discussion

The experimental results show that the proposed Learning Behavior Analytics Framework (LBAF) is able to capture and structure students' learning interactions within the customized Learning Management System. The identified behavioral cues indicated that there were significant differences between students' participation, engagement in learning, and academic performance, thus supporting the ability of this framework to offer valuable insights into the learning behaviors in online learning. The findings of behavioral analytics showed that students who had more interactions with content (such as frequent access to content, participation in discussion forums, frequent viewing of videos, and frequent participation in learning activities) tended to have better learning outcomes. The results of this study correspond with the recent research which focused on the positive correlation between the engagement of learners and their academic performance in online learning environments.

Further evidence of the effectiveness of the proposed framework is the evaluation process carried out by both students and teachers. Learners' perceptions of the usability of the system, communication flexibility, and learning resources were positive, and instructors reported that learners were able to monitor their own learning and evaluate the system's implementation. The results indicate that using behavioral analytics in personalized LMS can be an effective way to aid instructors to better understand the degree of participation that learners demonstrate in the system without adding to the complexity of the system. While the proposed framework is practical to monitor the learning behaviors, it is mostly related to descriptive behavioral analytics and does not focus on the predictive analytics. Therefore, it can be used as a decision support tool for teacher and offer structured behavioural data that can help in recognizing the patterns of student engagement and be used to inform educational interventions at an opportune time. In sum, the proposed framework portrays that the integration of structured behavioral analytic into customized Learning Management Systems can improve the quality of learner monitoring, learner instructional evaluation, and the quality of online learning.

In addition to educational and analytical gains, the proposed framework also has potential to promote sustainable digital education through sustainable teaching and learning. The framework is guided by well-documented evidence of learner behaviour and systematically monitors it, while being linked to the Sustainable Development Goal 4 (Quality Education) which highlights inclusive, equitable and quality education. The proposed framework has the potential to enhance educational quality over time, foster the sustainability of digital learning environments by fostering learner engagement patterns, and support teachers in optimizing their instructional approach.

5. CONCLUSION

In this study, an Enhanced Learning Behavior Analytics Framework (LBAF) embedded in a customized Learning Management System (LMS) was presented for enhancing monitoring and evaluation of students' learning behaviors in OL. The proposed framework captured and categorized learner interaction in a systematic fashion and in the form of structured behavioral indicators to assist teachers in assessing learner engagement, participation, and learning. The implementation and results of the evaluation showed that the proposed framework was effective in monitoring students' learning activities and giving meaningful insights in the behavioral patterns in the customized LMS. Positive feedback from both the students and the instructors further validated the usability and viability of the framework as well as its feasibility in evidence-based instructional decision making. The proposed framework enhances the tracking of conventional learning behavior with structured learning behavior analytics, and does not mandate any radical changes in the existing LMS infrastructures. It would therefore serve as a useful tool for higher education institutions to use and improve learner monitoring, and to better equip online learning environments. In addition, the proposed framework is designed to promote sustainable digital education by facilitating ongoing monitoring of the learner, implementing evidence-based teaching methods, and enhancing online learning spaces in general. The contributions are aligned with the goals of the United Nations Sustainable Development Goal (SDG 4): Inclusive, equitable and quality education in the effective use of digital technologies and innovation in education.

6. LIMITATIONS AND FUTURE WORK

The proposed framework showed good results but there were some limitations that should be discussed. The sample size in the experimental evaluation was relatively small (3nd-grade undergraduate students from a single higher education institution) so the results may not be generalized to the broader population. Secondly, the framework concentrates mainly on descriptive learning behavior analytics, and it lacks predictive and adaptive learning techniques. Lastly, behavioral records and questionnaire responses were relied upon primarily as a source of data for the evaluation, and other educational data sets might provide further support to the analysis.

The proposed framework can be further extended in the future by incorporating other advanced learning analytics techniques to detect at-risk students in the early stages of learning, adaptive learning mechanisms to adapt the educational content and the validation of the framework in other institutions and academic fields. Furthermore, future studies could consider the use of intelligent educational technologies to further strengthen how the learners engage with the teaching process and make decisions on learning in the custom-made LMS.

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