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From logs to insights: A comprehensive framework for data-driven learning insights

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ABSTRACT

This study develops a theoretical framework for learning analytics utilizing data from the Moodle Learning Management System (LMS). Despite Moodle's extensive use in educational settings, its potential for learning analytics remains underutilized. This research aims to design a predictive framework for identifying learning difficulties through Moodle's internal analytics, incorporating various data points such as activity completion, attendance logs, social interactions, and learner habits. The study employs a research and development methodology with three main stages: (1) needs analysis and learning component identification, (2) theoretical framework design, and (3) validation through focused group discussions with learning experts. The framework integrates predictive modeling for learning retention, task load analysis, and personalized learning style assessments based on the VARK model. Results demonstrate that the framework effectively uses Moodle's default logs for analyzing learner behavior, although it is limited to online interactions within the LMS. Validation confirms its alignment with Moodle's architecture and online learning theories, with minor adjustments for task load components. The framework offers a scalable solution for institutions managing large student populations and varied learning models, serving as a foundation for early intervention and improved learning outcomes. Future studies could expand the framework's scope to include offline and face-to-face interactions.

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INTRODUCTION

Moodle has become the choice of many learning organizations, from primary education to higher education. The implementation of Moodle LMS also varies, initially as a tool for organizing online learning (Irawan & Surjono, 2018), to hybrid learning (Nugroho, et al., 2024; Nugroho, et al., 2024; Siswanto et al., 2023). The variety of topics taught also varies, ranging from language (Rokhmah et al., 2022) and science (Irawan & Surjono, 2018; Rizki & Daniamiseno, 2019) to vocational learning (Kusumaningrum & Marpanaji, 2014). These various implementation scenarios also illustrate that Moodle has become a reliable LMS that can be implemented in various scenarios (Gunawan et al., 2024).

Although there have been many implementations of learning with various innovative scenarios (Saputra & Putra, 2021), the potential of Moodle as a Learning Management System (LMS) is still not fully explored. The use of Moodle is still limited to facilitating learning to support distance learning and independent learning. Moodle holds various potentials, such as an activity completion feature that can track learners' activities towards the content in Moodle, an attendance plugin that tracks learners' attendance, chat with peers through Moodle, public discussion on learning forums, to system log records that track and store all activities and behaviors of LMS users (Molins & García, 2023; Peraić & Grubišić, 2022; Verdú et al., 2021).

One form of advanced implementation of Moodle is in the development of a learning analysis system. By default, Moodle has a feature that can send alerts to teachers if there are students who have the potential to not pass a lesson. This feature is less flexible and cannot be customized without having to make changes to the main Moodle source code. The implementation of learning analytics has been done in many higher education institutions, and various results have been obtained such as recommendations for improving courses in the LMS, variables that affect learner achievement, and visualization of learner behaviors (Einhardt et al., 2016; Mwalumbwe & Mtebe, 2017; Yassine et al., 2016).

There have been many studies on Moodle. Molins & García (2023) utilize Moodle as a learning environment that promotes learning regulation ability. In promoting learning regulation, a learning design is developed that can be personalized according to the learners' wishes. The result of the personalization is used in learning analysis. The process of monitoring learning is done through monitoring the completeness of learners' learning activities. In addition, the research with the theme of social interaction, which was conducted by Verdú et al., (2021), demonstrates the capability of Moodle as a system that can seamlessly connect learning in virtual and non-virtual environments. This research also provides insight for educators into the learning process of learners through the aspect of communication both with peers and with learning content.

This study aims to develop an analytical framework for learning based on the components within a learning management system (LMS). In prior research conducted by various scholars, the assembly process among learning component variables was primarily based on gaps identified in empirical studies. However, no comprehensive framework has yet been established to fully integrate all variables and LMS components into a cohesive learning analytics system. The expected outcome of this research is a theoretical framework that can serve as a guideline for designing evaluation techniques for learning conducted through LMS platforms.

METHOD

This study is a research and development type with a product in the form of a theoretical framework intended to predict learning difficulties based on various data points sourced from Moodle LMS and other brand LMS. In this research, the development model adopted is the circular prototype model because it provides convenience in the process of developing technological designs (Pressman & Maxim, 2020), however, in this research, the circular stage is not carried out in full, but only emphasized on the product development stage of the theoretical framework. This research has three main stages, namely (1) Needs Analysis & Identification of Learning Components, (2) Design of the theoretical framework of the prediction model, and (3) Evaluation of the framework based on scientific literature review. The research procedure overview can be seen in Figure 1.

The stage of Needs Analysis and Component Identification is focused on the availability of learning components supported by internal LMS analytics. The availability of learning components on the LMS can significantly affect the model to be developed. In the theoretical framework design stage, it is the main process in the research stage. At this stage, the output is a draft design of the learning analytics framework that will be evaluated through a literature review. The findings or fundamental errors found in the third stage it is used as a reference in revising the draft that has been made. The flow of the second and third stages is circular. Circular stages open opportunities to improve and strengthen the developed model so that it can be used as a reference in building applicable products through the model that has been developed.

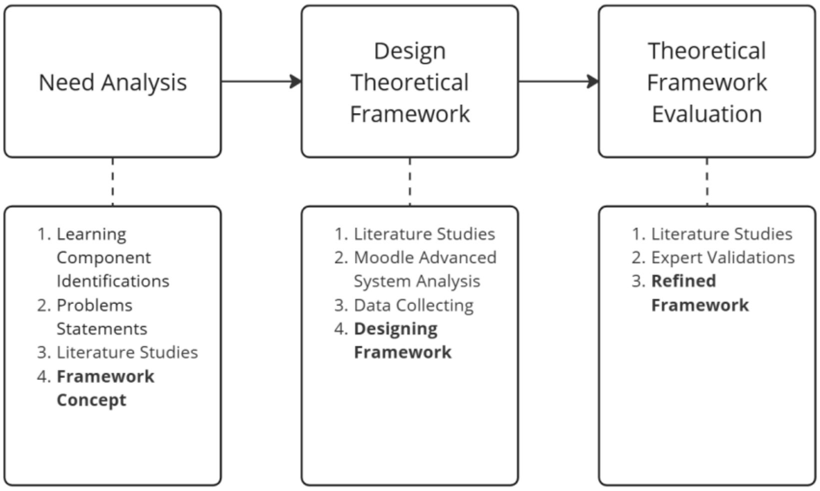

Figure 1. Research Procedure

The validation process for the developed framework is carried out through focused group discussions with a panel of learning experts. The validation process includes assessing the relevance and interconnection of components and aspects based on empirical studies, as well as their alignment with conventional and online learning theories. The panelists are entrusted with the mandate to provide the final decision regarding the accuracy of this framework based on the outcomes of discussions among researchers and participants.

The data sources used in this research are primary and secondary data. Primary data is system recording data or logs on SIPEJAR Moodle. Secondary data consists of scientific literature published in open access with topics in the scope of learner habits, learning strategies, learning outcomes, learning styles, use of AI in academic life, social learning relationships, self-determination theory, and self-regulated learning. The system records used in this study are RAW_LOGS data that have not been processed, so a cleaning & normalization process is needed so that it can be used in further research processes.

The final product of this research is a learning analysis construct model that can be used as an early warning system by institutions that have a massive number of students with various models of learning conducted in LMS.

RESULTS AND DISCUSSION

Results

Needs Analysis & Identification of Learning Components Stage

At the stage of analyzing learning needs and components, findings were obtained on the learning process at the State University of Malang through the SIPEJAR LMS. In general, the learning delivery process is carried out face-to-face and online. Face-to-face delivery of material is conducted in the classroom, while digital delivery is through SIPEJAR. However, few lecturers conduct asynchronous learning, which is fully conducted through SIPEJAR as a medium for delivering material, and students access it on demand through their respective devices at any place and time (Soepriyanto & Kuswandi, 2021).

In analyzing the learning components in the LMS, SIPEJAR supports many data points that can be used as a reference to assess the quality of learning carried out by learners. SIPEJAR supports data points such as duration spent in accessing and interacting with SIPEJAR, learning content downloaded and viewed, delay in collecting assignments, and social relationships between learners through forum discussions and private chats (see Table 1 SIPEJAR Data Point for the overview. In the context of learning components, SIPEJAR can support accommodating various learning components needed, but unfortunately, not all learners present learning components in SIPEJAR (Adi et al., 2024; Soepriyanto et al., 2021). This happens because the learning process carried out at the State University of Malang runs in a hybrid manner so that some components are presented in face-to-face meetings and the rest are presented in virtual meetings that run asynchronously (Soepriyanto et al., 2022).

Table 1. SIPEJAR Data Point

No.	SIPEJAR Learning Components	Data Points Availability
1	Duration Spent on LMS	Available Through Logs
2	Last Course Access	Available Through Logs
3	Learning Content Views	Available Through Logs
4	Delay in Submit Assignments	Available Through Logs
5	Social Interaction on Course via Forums	Available Through Logs
6	Private Social Interaction	Available Through Logs
7	Applied Learning Models	Not Available
8	Login Frequency	Available Through Logs
9	Presents Rate	Available Through Logs
10	Learning Content Download	Not Available Natively
11	Learning Content Shared	Not Available Natively
12	Work hours	Not Available Natively
13	Grades	Available Through Logs
14	Dropout Prediction	Opt-in Featured Natively

Developing the Learning Analytics Theoretical Framework Stage

The second stage is to develop the framework of the learning analysis system. The core structure used as “information nodes” is extracted from basic Moodle course Moodle logs & activity completion (Mwalumbwe & Mtebe, 2017). The prediction system modeling on learning retention uses data derived from attendance log records, frequency, and time spent on the LMS. The data is used to predict students' habits in accessing the LMS (Ademi et al., 2019). The basic rule used in this prediction is "if a learner does random access without any consistent time pattern, then the learner may be at risk of abandoning the learning process". The prediction model based on this pattern allows the analysis system to use a risk-based approach based on the anomaly or irregularity value of the student's activity. The higher the risk value, the more signals are sent to the "intervention" node.

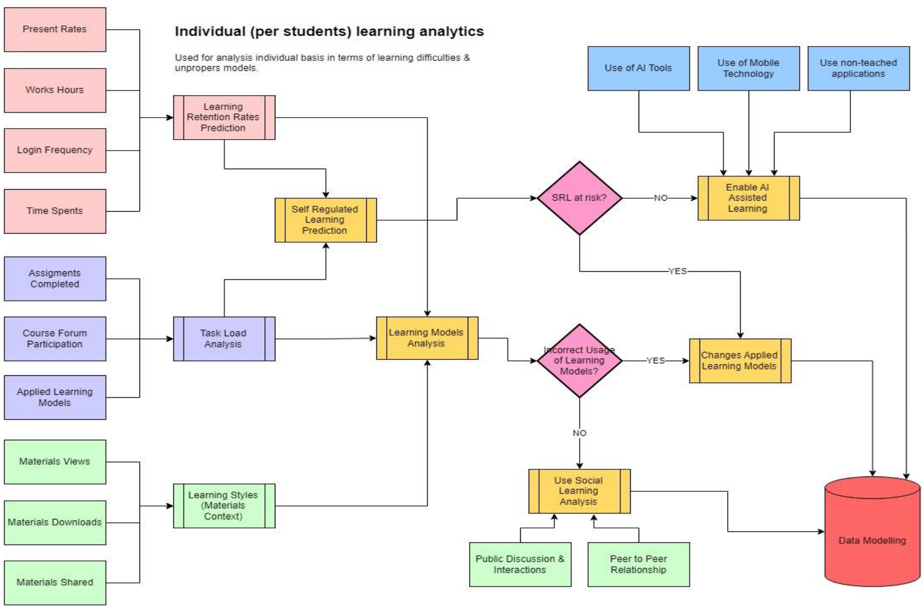

Figure 2. Learning Analytics Frameworks

The information needed in the task load analysis is the tasks completed, participation in learning forums, and learning models used. In the task completion node, the form of tasks, outcomes, and deadlines are significant considerations in determining the task load experienced by learners. The type of task, outcome, and deadline influence students' stress levels (Hidayat et al., 2021; Rahayu & Sari, 2023).

In the learning style analysis section, the VARK framework (visual, auditory, reading, and kinesthetic) is used to determine the learning style of the learners. The selection of VARK as a learning style prediction modeling framework is because Moodle Logs supports logs that can record the material access behavior used by learners (Chung & Ackerman, 2015; Karagiannis & Satratzemi, 2018). The use of VARK in learning style analysis has also been widely done, especially in presenting personalized learning in the organization of learning content (Ikawati et al., 2020; Papanikolaou & Boubouka, 2020).

In addition to enabling social learning scope for the analytics Moodle, the logs must be extracted from the "site-wide" logs system that makes user communication in other than course-related space to be included in the analysis. Social interaction in online learning, especially in LMS, has a significant role in learners' knowledge construction. By analyzing social interaction in LMS, it is possible to know the exchange of knowledge and information between learners in the online learning environment (Hernández-García & Conde-González, 2016; Kaliisa et al., 2019; Saqr & Alamro, 2019).

In the sake of accommodating the use of Artificial Intelligence, its used another data point used for measuring students attitude toward AI (Chai et al., 2024; Suh & Ahn, 2022; Wang & Chuang, 2024). The use of AI in the learning process has become widespread, even deliberate, to assist the learning process (Maningtyas & Kusumadewi, 2023; Murcahyanto, 2023; Suharmawan, 2023; Wibowo et al., 2023).

Framework Model Validation Stage

After the model framework was developed, it was validated through focus group discussions with panelists and peers to ensure that the framework was in line with the Moodle architecture and the learning process. The result is that the framework is valid within the scope of the Moodle architecture but needs minor adjustments to the task load analysis. The adjustment needed is to remove the node 'quiz/final semester exam load' because it is beyond the control of the learner. The result can be seen in Figure 2 as a valid modeling framework that is suitable to be used as an analysis framework.

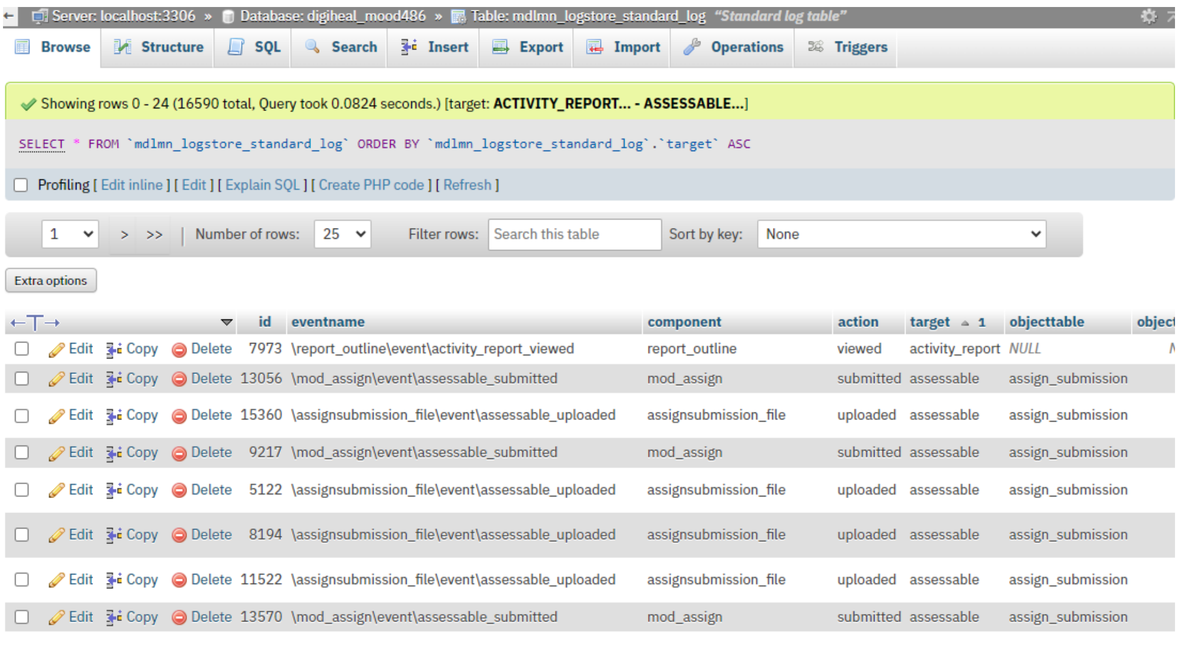

Figure 3. Raw Unprocessed Moodle Logs Data

Learning Analytics Framework Implementation on SQL

To perform the analysis, SQL Query is used as a tool to run the processing of the raw data contained in the Moodle logs database. In the Logs database, all system activities are recorded without any filter, therefore, SQL Query is used to filter the activities that will be used in the process of predicting learner behaviors. One of the examples in Figure 3 is the filter result of assignment collection activities from various courses and students enrolled in Moodle. Many tools can be used in processing system logs from Moodle, but the use of SQL is the most appropriate choice. SQL is the native query language of the database used in Moodle. Besides SQL, the use of high-level technology services such as Google Cloud NLP is a promising option to perform sentiment analysis on messages published on forums or Moodle courses (Baharuddin & Naufal, 2023; Baihaqi & Munandar, 2023; *Cloud Natural Language*, n.d.; Jazuli et al., 2023; Nugroho, et al., 2024).

Discussion

This research has developed a basic framework that empowers Moodle Logs as a data source for analyzing the learning styles of learners. The data sources used are nodes that are available by default in Moodle without any special modifications. Please note that the framework that has been developed is a basic framework created from scientific literature related to learning styles and student success, so there are still parts that can be further developed. The biggest drawback of this framework is that it is still unable to consider interactions that occur outside the LMS, offline activities, and face-to-face interactions with learners. However, this framework will be useful for learning that is specifically organized online, and the interaction is done entirely through the LMS.

Although the analysis process is complex to perform in-house, plugins that power the Moodle Logs in real-time can be used. This study was conducted by Kadoic & Oreski (2018) in the context of higher education at the University of Zagreb. The result was that learner success had a significant correlation with the number of logins and time spent on the Moodle LMS. In addition to interaction with the features of Moodle, Lerche & Kiel (2018) analyzed the learners' interaction with the computer through the cognitive framework through keystrokes on the keyboard, mouse presses, and independence in using the LMS. It was found that physical activity with computer input devices does not significantly affect self-reliance in managing learning on the LMS, which is the main factor to achieve success. The design of the LMS must also be adjusted to the learning objectives. Soepriyanto et al., (2021) because it has a high correlation with learner learning outcomes.

This research does not discuss the algorithm used to find the sweet spot of the predictions used in the analysis, but rather the relationship between the components in Moodle Logs and learning behavior. Tamada et al., (2021) tested several algorithms that can be used to predict learner performance through Moodle Logs with the input of learning duration on the LMS. Through various duration parameters and student groups with low and high risk, it is found that the Random Forest algorithm has the best performance in predicting learner performance. Ademi et al., (2019) compared algorithms between Decision Tree, Bayesian Network, and Support Vector Machine to find the correlation between system activity on Moodle Logs and learner success. The result is that the Decision tree has the highest prediction accuracy. Conijn et al., (2017) also made the same prediction with more courses and a massive number of students with blended learning implementation. The result is that it is not enough to rely on LMS data in blended learning. The predicted results do not have similar results and even seem to have their characters between the courses that have been analyzed. From these two studies, Log data on Moodle cannot necessarily be used in all learning contexts and implementations.

CONCLUSION

This research aims to develop a learning analysis system framework that can be used to analyze learner behavior. This study is conducted through a literature study that discusses components in the LMS that can be used to predict learning outcomes, behavior, and the use of artificial intelligence in the learning process. In the end, a learning analytics system framework is produced with the data source coming from Moodle system log records. This framework model is a theoretical framework and needs to be further investigated in real and massive learning environments such as universities and Moodle-based MOOCs. The weakness of this framework is that it focuses on student activities on Moodle; it still does not accommodate learning models that allow students to learn outside the LMS system. So, it is necessary to develop a more appropriate framework to measure the behavior of learners outside the LMS objectively and measurably. For future research, we can consider activities outside the LMS in building a learning behavior analysis framework. The use of simple algorithms can help build a simple prediction system for behavioral nodes. Considering the cognitive load that is present in both the material presented by the lecturer and the analysis of the difficulty of quizzes and exams.

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