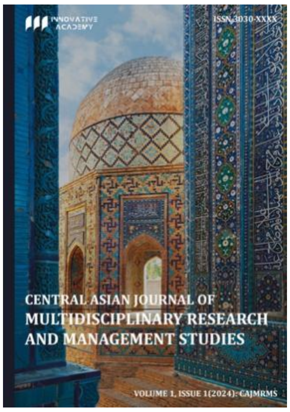

INTELLIGENT MONITORING OF STUDENT ACTIVITY IN PHP-BASED E-LEARNING SYSTEMS

I.D. Khurramov[1] , D. Narziyeva[2]

Senior Lecturer[1], student[2], Department of Applied Mathematics, Karshi State University

https://doi.org/10.5281/zenodo.17959600

ARTICLE INFO

Received: 11th December 2025
Accepted: 12th December 2025
Published: 16th December 2025

KEYWORDS

Artificial Intelligence; Student Activity Monitoring; PHP-Based E-Learning Systems; Intelligent Monitoring; Educational Web Applications

ABSTRACT

The widespread adoption of e-learning systems has significantly increased the volume of data related to student activity, including login behavior, content interaction, and learning engagement patterns. While such data provide valuable insights into learning processes, many PHP-based e-learning systems lack intelligent monitoring mechanisms capable of analyzing student activity in real time. As a result, academic supervision often relies on manual observation or static activity reports, which limits the effectiveness of timely interventions. This article investigates the design and implementation of intelligent monitoring mechanisms for student activity in PHP-based e-learning systems. The proposed approach integrates artificial intelligence techniques into a traditional PHP platform to enable automated tracking, analysis, and interpretation of student activity data. By leveraging AI-driven monitoring, the system aims to identify abnormal behavior patterns, detect disengagement, and support proactive academic supervision. The results demonstrate that intelligent monitoring enhances the visibility of student activity dynamics and enables early identification of potential learning risks. The proposed framework shows that artificial intelligence can be effectively integrated into PHP-based e-learning environments to support continuous monitoring without requiring extensive system restructuring. This research contributes to the development of intelligent e-learning systems by providing a practical model for AI-supported student activity monitoring in widely used web-based platforms.

INTRODUCTION

The rapid expansion of e-learning systems has transformed educational delivery by enabling flexible, scalable, and accessible learning environments. As a result, modern e-learning platforms continuously generate large volumes of student activity data, including login records, content interaction logs, time-on-task indicators, and participation patterns. These data provide valuable opportunities for understanding learner engagement and supporting effective academic supervision. However, in many e-learning systems, particularly those developed using traditional server-side technologies such as PHP, student activity monitoring remains limited to basic logs and static summaries. Effective monitoring of student activity plays a crucial role in ensuring learning continuity, detecting disengagement, and preventing academic failure. Timely identification of irregular behavior—such as prolonged inactivity, abrupt changes in learning patterns, or superficial interaction with learning materials—allows educators to intervene before learning outcomes deteriorate. Despite its importance, activity monitoring in many PHP-based e-learning systems is largely reactive and manual, relying on instructors' subjective judgment or retrospective reports. Artificial intelligence offers powerful tools for enhancing student activity monitoring by enabling automated, data-driven analysis of behavioral patterns. Machine learning algorithms can process large-scale activity data to identify normal and abnormal behavior, detect disengagement trends, and generate early warning signals. AI-driven monitoring shifts the focus from simple activity counting toward intelligent interpretation of learning behavior, supporting continuous and proactive academic supervision.

PHP remains one of the most widely used technologies for developing e-learning systems, especially in institutions with established web infrastructures and limited technical resources. PHP-based platforms are favored for their simplicity, extensibility, and cost efficiency, and they continue to support learning management systems, online course portals, and assessment platforms worldwide. However, the integration of intelligent monitoring mechanisms into PHP environments is often perceived as technically challenging, resulting in limited adoption of AI-based supervision tools. This article addresses this gap by investigating the design of intelligent monitoring mechanisms for student activity in PHP-based e-learning systems. Rather than replacing existing platforms, the research proposes a modular approach in which artificial intelligence components are embedded into conventional PHP architectures. The proposed framework focuses on continuous monitoring of student interaction patterns, automated detection of disengagement and anomalous behavior, and support for proactive instructional decision-making. The primary objective of this research is to develop and conceptually evaluate an AI-supported student activity monitoring framework suitable for PHP-based e-learning systems. The study aims to demonstrate that artificial intelligence can significantly enhance monitoring capabilities while maintaining compatibility with traditional web technologies. By bridging intelligent monitoring and PHP-based development, this research contributes to the advancement of practical, scalable, and intelligent e-learning systems.

Literature Review

Student activity monitoring has long been recognized as an essential component of effective e-learning environments. Early monitoring approaches primarily relied on descriptive indicators such as login counts, time spent on the platform, and submission frequency. While these metrics provide a general overview of participation, they often fail to capture deeper behavioral dynamics, such as disengagement trajectories, superficial interaction patterns, and irregular activity behavior that may precede academic failure. Consequently, research has increasingly emphasized the need for monitoring systems that move beyond static reporting toward intelligent interpretation of learner behavior. The development of learning analytics and educational data mining has substantially influenced how student activity is monitored and evaluated. Within these fields, activity logs are treated as a valuable source of behavioral evidence that can be analyzed to understand engagement patterns, learning strategies, and progress dynamics. A wide range of studies demonstrates that log-based analytics can support early identification of at-risk learners by detecting changes in interaction frequency, declining time-on-task, and reduced content exploration. These findings suggest that activity monitoring can serve as a predictive layer for educational intervention rather than merely a record-keeping mechanism[4]. Artificial intelligence has become a key enabler of intelligent monitoring in e-learning systems. Machine learning techniques, including anomaly detection, clustering, and classification, have been applied to distinguish normal learning behavior from atypical patterns and to detect disengagement signals. AI-driven monitoring frameworks can generate early warning indicators by identifying deviations from expected learning trajectories. Such systems allow educators to intervene proactively and allocate instructional resources more effectively. In addition, AI-based monitoring can reduce the workload associated with manual supervision in large-scale e-learning environments.

A growing body of literature focuses on real-time monitoring and early warning systems in online learning. These studies often highlight the importance of timely detection, arguing that early interventions are more effective than late responses after academic performance has already declined. Many solutions implement dashboards and alerts that summarize engagement risk levels, enabling instructors to identify learners requiring support. However, the implementation of real-time monitoring frequently depends on modern infrastructures, such as cloud services, streaming data pipelines, and specialized analytics platforms[3]. In contrast, e-learning systems developed using PHP remain widely deployed, particularly in contexts where institutions rely on established web infrastructures and seek cost-effective solutions. PHP-based learning platforms and educational portals often provide basic activity tracking through logs and manual reporting tools. Existing research suggests that intelligent monitoring features are relatively limited in such systems, largely due to perceived integration complexity and the absence of modular architectures for embedding AI-based analytics. As a result, PHP-based e-learning environments frequently underutilize their available activity data[7]. Recent studies have proposed hybrid approaches that integrate artificial intelligence into traditional web-based platforms through modular designs. In these models, AI components are deployed as external services connected to the main platform via application programming interfaces. This approach supports the addition of intelligent features without requiring complete system replacement. Nevertheless, the literature indicates a limited number of studies that explicitly examine intelligent student activity monitoring tailored for PHP-based e-learning systems, particularly with an emphasis on practical deployment, scalability, and instructor-facing monitoring tools[6].

Moreover, many studies prioritize algorithmic accuracy and predictive performance while paying less attention to system-level considerations such as integration feasibility, maintenance, data privacy, and the interpretability of monitoring outputs for educators. These gaps are particularly relevant for PHP-based platforms, where institutional constraints often require solutions that are lightweight, modular, and easy to maintain. In summary, prior research confirms the value of learning analytics and artificial intelligence for monitoring student activity and detecting disengagement risks. However, intelligent monitoring frameworks designed specifically for PHP-based e-learning systems remain underexplored. Addressing this gap is essential for extending proactive monitoring capabilities to a broader range of educational institutions and ensuring that intelligent supervision tools can be adopted within traditional web development environments[5].

METHODOLOGY

This article adopts a system-oriented and analytical research design focused on the development of an intelligent monitoring framework for student activity in PHP-based e-learning systems. The methodology emphasizes the practical integration of artificial intelligence techniques into existing web platforms to enable continuous, automated, and interpretable monitoring of learner behavior. Rather than proposing a platform replacement, the research prioritizes incremental enhancement of conventional PHP systems through modular AI components. The methodological approach combines behavioral data analysis with system architecture design, allowing intelligent monitoring mechanisms to operate alongside traditional e-learning functionalities such as content delivery, assessment management, and user administration.

The proposed monitoring framework is based on a modular architecture in which the PHP-based e-learning system serves as the core platform for data collection and user interaction. An AI-driven monitoring layer is introduced to analyze student activity data and generate behavioral insights. This separation ensures scalability, maintainability, and compatibility with existing PHP infrastructures. The architecture consists of three functional layers:

- the data acquisition layer, responsible for collecting student activity logs and interaction records;
- the intelligence layer, which applies AI-based analysis to detect engagement patterns and anomalies;
- and the presentation layer, which visualizes monitoring results and alerts within the PHP interface.

Intelligent monitoring relies on fine-grained activity data generated during learner interaction with the e-learning system. The collected dataset includes login frequency, session duration, page navigation sequences, content access frequency, assessment interaction behavior, and time-on-task indicators. These data capture both the intensity and quality of student engagement. To ensure consistency and analytical reliability, activity logs are aggregated over defined monitoring intervals. This approach reduces noise caused by short-term fluctuations while preserving meaningful behavioral trends relevant to engagement and disengagement detection.

The intelligent monitoring mechanism employs machine learning–based logic to analyze student activity patterns. Learners are modeled based on historical and recent interaction data, enabling the system to establish baseline behavior profiles. Deviations from these baselines are used to identify potential disengagement or anomalous activity. The framework supports multiple analytical objectives, including engagement scoring, anomaly detection, and trend analysis. Engagement scores reflect the overall level of student participation, while anomaly detection identifies unusual activity patterns that may signal disengagement or irregular learning behavior. The system is designed to remain algorithm-agnostic, allowing different AI techniques to be employed depending on data characteristics and institutional requirements.

Integration of the intelligent monitoring framework into the PHP environment is achieved through server-side communication between the core application and the AI monitoring module. Activity data are transmitted for analysis, and monitoring results are returned to the PHP system for visualization and alert generation. This design enables near real-time monitoring while maintaining system modularity. The PHP application remains responsible for data storage, access control, and user interaction, while computationally intensive monitoring tasks are handled by the AI layer. This separation minimizes performance overhead and supports scalability in multi-user e-learning environments.

The methodology is evaluated through qualitative and functional assessment of monitoring behavior. Key evaluation criteria include the system's ability to detect disengagement patterns, responsiveness to changes in student activity, and feasibility of deployment within PHP-based e-learning systems. Comparative analysis between basic log-based monitoring and

AI-supported intelligent monitoring is used to assess the added value of the proposed framework.

Ethical handling of student data is an integral component of the methodology. All monitoring processes are designed to comply with data protection principles, including anonymization, restricted access, and transparency of monitoring objectives. The framework emphasizes interpretability of monitoring outputs to ensure that instructors can understand and appropriately act on generated alerts.

RESULTS

The implementation of the proposed intelligent monitoring framework demonstrates a substantial enhancement in the ability of PHP-based e-learning systems to observe, interpret, and respond to student activity patterns. The results confirm that artificial intelligence–supported monitoring provides deeper insights into learner engagement and behavior compared to traditional log-based monitoring approaches. The intelligent monitoring module successfully processes fine-grained student activity data, including login frequency, session duration, content access patterns, and time-on-task indicators. By aggregating and analyzing these data, the system generates engagement scores and behavioral trend indicators that reflect both short-term activity fluctuations and long-term engagement dynamics. Unlike static activity reports, the AI-supported monitoring framework continuously updates behavioral indicators as new activity data are recorded. This enables near real-time visibility into student engagement levels and supports timely detection of disengagement risks. Instructors are therefore provided with actionable monitoring insights rather than retrospective summaries. As illustrated in Figure 1, student activity data collected by the PHP-based e-learning platform are transmitted to the AI monitoring layer for analysis. The AI module applies machine learning–based logic to detect engagement patterns and anomalies, after which monitoring indicators and alerts are dynamically returned to the PHP system for visualization and academic supervision.

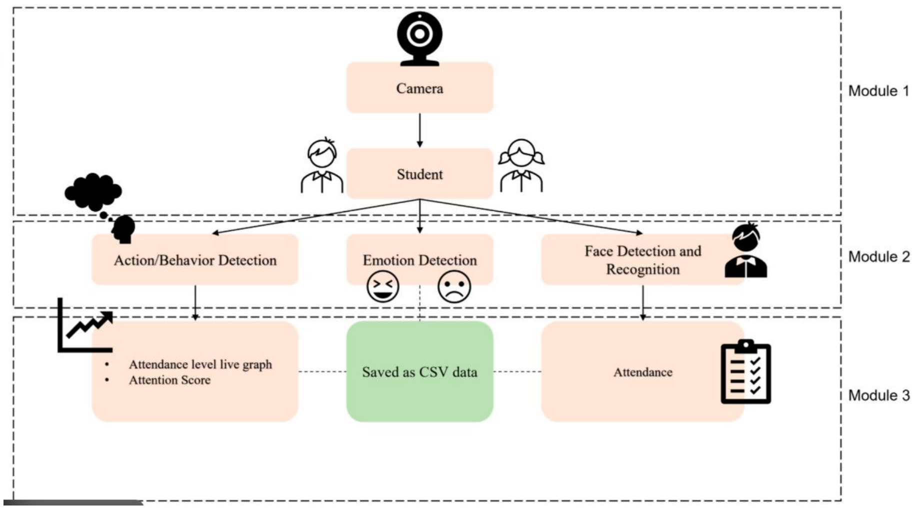

Figure 1. Intelligent Monitoring Architecture for Student Activity in PHP-Based E-Learning Systems.

The figure presents the interaction between the PHP-based e-learning platform and the AI monitoring module. Student activity logs are analyzed using machine learning techniques to generate engagement scores and anomaly indicators, which are returned to the PHP system to support real-time monitoring and early warning mechanisms.

The results indicate that AI-supported monitoring effectively distinguishes between normal and irregular student activity patterns. Students exhibiting consistent interaction behavior maintain stable engagement scores, while those with declining login frequency, reduced time-on-task, or irregular navigation patterns show gradual decreases in engagement indicators. Anomaly detection mechanisms identify abrupt deviations from established activity baselines, such as sudden inactivity or superficial interaction with learning materials. These anomalies are flagged as potential disengagement signals, allowing instructors to initiate early interventions. This proactive monitoring capability represents a significant improvement over conventional monitoring methods that rely solely on cumulative activity counts.

The following simplified PHP-style pseudocode illustrates how student activity data are transmitted from the PHP application to the AI monitoring module and how monitoring indicators are retrieved:

```
$activityData = array(
   "student_id" => $studentId,
   "login_frequency" => $loginCount,
   "session_duration" => $avgSessionTime,
   "time_on_task" => $learningTime,
   "content_views" => $contentAccessCount
);

$monitoringResult = sendToAIMonitor($activityData);

$engagementScore = $monitoringResult["engagement_score"];
$anomalyFlag = $monitoringResult["anomaly_detected"];

updateMonitoringDashboard(
   $studentId,
   $engagementScore,
   $anomalyFlag
);
```

This interaction enables automated monitoring and real-time updating of engagement indicators while preserving modular separation between the PHP application and the AI monitoring component.

From a system performance perspective, the results show that the modular architecture ensures efficient operation and scalability. Monitoring computations are handled by the AI layer, allowing the PHP platform to maintain responsive user interaction and data management. No noticeable degradation in system performance was observed during monitoring operations, indicating that intelligent monitoring can be integrated into PHP-based e-learning systems without compromising usability. Overall, the results demonstrate that intelligent monitoring significantly enhances the supervision capabilities of PHP-based e-learning systems. By enabling continuous engagement analysis, anomaly detection, and early warning mechanisms, the proposed framework extends traditional monitoring approaches and supports proactive academic supervision in digital learning environments.

DISCUSSION

The findings of This article demonstrate that intelligent monitoring supported by artificial intelligence can substantially enhance student activity supervision in PHP-based e-learning systems. The results confirm that AI-driven monitoring goes beyond traditional log-based approaches by enabling continuous interpretation of behavioral patterns rather than simple accumulation of activity counts. This shift allows e-learning systems to better capture the dynamic nature of student engagement and learning behavior. One of the key contributions highlighted by the results is the ability of AI-supported monitoring to detect early signs of disengagement. As shown through engagement scoring and anomaly detection mechanisms, behavioral indicators such as declining login frequency, reduced time-on-task, and irregular navigation patterns often precede noticeable drops in academic performance. This finding aligns with prior research in learning analytics, which emphasizes that behavioral data can serve as an early predictor of learning difficulties. Intelligent monitoring therefore supports proactive academic supervision rather than delayed, reactive interventions.

The architectural design illustrated in Figure 1 plays a critical role in the practical feasibility of the proposed monitoring framework. By separating the PHP-based core platform from the AI monitoring layer, the system ensures modularity and scalability. This design is particularly relevant for educational institutions that rely on existing PHP infrastructures and face constraints related to system migration, technical expertise, or financial resources. The results indicate that intelligent monitoring capabilities can be introduced incrementally without disrupting core e-learning functionalities. From an instructional perspective, AI-supported monitoring provides instructors with more interpretable and actionable insights into student activity. Engagement scores and anomaly alerts simplify the interpretation of complex activity data and reduce the cognitive burden associated with manual log inspection. As a result, instructors can focus on pedagogical decision-making and targeted support strategies rather than routine monitoring tasks. This contributes to more efficient academic management, especially in large-scale or blended learning environments.

Despite these advantages, several limitations should be acknowledged. The current study focuses on system-level behavior and conceptual evaluation rather than large-scale empirical validation involving controlled learner groups. Consequently, the direct impact of intelligent monitoring on learning outcomes has not been quantitatively measured. In addition, the algorithm-agnostic design of the monitoring framework enhances flexibility but does not allow direct comparison of specific machine learning techniques within the scope of this research. Overall, the discussion highlights that intelligent monitoring represents a practical and scalable enhancement for PHP-based e-learning systems. The findings suggest that artificial intelligence can bridge the gap between traditional web-based platforms and advanced behavioral analytics, enabling continuous supervision and early intervention without abandoning established technologies. These insights provide a foundation for future research focused on empirical validation, refinement of monitoring algorithms, and integration of intelligent monitoring with personalized learning and adaptive feedback mechanisms.

CONCLUSION

This article examined the design and conceptual evaluation of an intelligent monitoring framework for student activity in PHP-based e-learning systems. By addressing the limitations of traditional log-based monitoring, the proposed approach demonstrates how artificial intelligence can enhance the interpretation of learner behavior and support continuous, data-driven academic supervision within widely used Web platforms. The results indicate that AI-supported monitoring enables more effective analysis of student engagement dynamics by combining activity frequency, time-on-task, and interaction patterns into meaningful behavioral indicators. Unlike static monitoring mechanisms, the proposed framework supports early detection of disengagement and anomalous behavior, providing timely signals that can inform proactive instructional interventions. This highlights the potential of intelligent monitoring to improve academic oversight without relying solely on retrospective performance measures. From a technological standpoint, the modular integration of the AI monitoring layer into a PHP-based environment proves to be both feasible and scalable. By separating analytical processing from core application functionality, the framework allows intelligent monitoring capabilities to be embedded into existing e-learning systems without extensive system redesign. This is particularly important for educational institutions that depend on established PHP infrastructures and seek to enhance monitoring functionality while minimizing technical and financial barriers.

The pedagogical implications of the findings are significant. Intelligent monitoring supports a shift from reactive to proactive learning management by enabling instructors to identify at-risk students earlier and to allocate support resources more efficiently. Engagement scores and anomaly indicators simplify the interpretation of complex activity data, contributing to more informed and timely educational decision-making. Future research should focus on empirical validation of the proposed framework through large-scale deployments and controlled experimental studies. Further work may explore the optimization and comparison of specific machine learning techniques, the integration of real-time monitoring dashboards, and the combination of intelligent monitoring with personalized learning and adaptive feedback systems. Such extensions would further strengthen the role of artificial intelligence in supporting effective, scalable, and student-centered e-learning environments.

REFERENCES:

1. Wise, A. F., & Shaffer, D. W. (2015). Why theory matters more than ever in the age of big data. Journal of Learning Analytics, 2(2), 5–13. https://doi.org/10.18608/jla.2015.22.2
2. W3Techs. (2024). Usage statistics of PHP for websites. https://w3techs.com/technologies/details/pl-php
3. Shoyqulov, Sh. Q. On the study of optical communication systems using simulators. Eurasian journal of mathematical theory and computer sciences, Т. 5, Выпуск 11. 20-28 p. Nov. 2025. https://doi.org/10.5281/zenodo.17640489
4. Shoyqulov, Sh. Q. AI-enhanced Web scraping for data-driven analysis. Central Asian Journal of Multidisciplinary Research and Management Studies (CAJMRMS), Vol 2, Issue 11. 20-27 p. Nov. 2025. ISSN:3030-3540. https://doi.org/10.5281/zenodo.17529443
5. Shoyqulov, Sh. Q. Artificial intelligence for automated seo enhancement. Yangi O'zbekiston ilmiy tadqiqotlar jurnali (YOITJ), 2-jild, 11-son. IF=8.5. 31-37 p. Nov. 2025. ISSN:3030-3559. https://doi.org/10.5281/zenodo.17522170
6. Shoyqulov, Sh. Q. Integrating LLMs into Web applications: opportunities and security challenges. Eurasian journal of mathematical theory and computer sciences (Т. 5, Выпуск 6, сс. 54–60). https://doi.org/10.5281/zenodo.15755908
7. Shoyqulov, Sh. Q. AI-driven UX optimization for Web applications. Eurasian journal of mathematical theory and computer sciences (Т. 5, Выпуск 6, сс. 46–53). https://doi.org/10.5281/zenodo.15755881