Computer Architecture and Signal Processing

E-ISSN: 3124-0003

*Research Article*

# Data-Driven Learning Analytics Conceptual Framework for Automated Competency Mapping in Outcome-Based Education: A Design Science Research Approach

**Hasbu Naim Syaddad[1*], Zainal Arifin Hasibuan[2], Bobi Kurniawan S[3], Sri Supatmi[4], Agus Nursikuwagus[5], Citra Noviyasari[6]**

[1] Universitas Widyatama, Indonesia; e-mail: ucu.nugraha@widyatama.ac.id
[2] Universitas Komputer Indonesia, Indonesia; e-mail: zhasibua@email.unikom.ac.id
[3] Universitas Komputer Indonesia, Indonesia; e-mail: bobi@email.unikom.ac.id
[4] Universitas Komputer Indonesia, Indonesia; e-mail: sri.supatmi@email.unikom.ac.id
[5] Universitas Komputer Indonesia, Indonesia; e-mail: agusnursikuwagus@email.unikom.ac.id
[6] Universitas Komputer Indonesia, Indonesia; e-mail: citra.noviyasari@email.unikom.ac.id
*Corresponding Author: ucu.nugraha@widyatama.ac.id

**Abstract.** The implementation of Outcome-Based Education (OBE) in higher education demands precise measurement of Graduate Learning Outcomes (CPL) and Course Learning Outcomes (CPMK). However, current conventional Learning Management Systems (LMS) remain static and centered on final performance metrics (grades), thus failing to map student academic profiles into sub-competencies in a real-time and granular manner. This study proposes a conceptual artifact in the form of an Intelligent Tutoring System (ITS) architecture based on Learning Analytics (LA) and Knowledge Graphs to automate competency mapping. Through the Design Science Research Methodology (DSRM) approach, this framework designs a data fusion pipeline that integrates high-resolution academic log data with curriculum ontologies. The proposed architecture consists of three main layers: data acquisition, predictive modeling using Machine Learning, and a recommendation engine based on Explainable AI (XAI). This conceptual framework provides a blueprint for higher education institutions to transform from reactive curriculum evaluation into precise and auditable adaptive learning governance.

**Keywords:** Design Science Research; Intelligent Tutoring System; Knowledge Graph; Learning Analytics; Outcome-Based Education.

**Received: 7, December 2025**
**Revised: 8, Febuary 2025**
**Accepted: 09, April 2025**
**Published: 11, June 2026**
**Curr. Ver.: 11, June 2026**

**Copyright: © 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY SA) license (https://creativecommons.org/licenses/by-sa/4.0/)**

## 1. Introduction

Higher education institutions in Indonesia are currently facing the challenge of learning transformation mandated by national regulations through the implementation of an impactful curriculum oriented towards Outcome-Based Education (OBE) (Salim et al., 2024). The OBE curriculum emphasizes the objective measurement of Graduate Learning Outcomes (CPL) and Course Learning Outcomes (CPMK) that are aligned with the needs of industry and society. Although this policy has been widely adopted, its implementation at the level of academic information systems and Learning Management Systems (LMS) remains far from optimal (Maulani, 2024).

Most universities still apply a "one-size-fits-all" evaluation model. The evaluation of CPL achievement is often conducted manually at the end of the semester based on static grade recaps. This approach ignores students' digital footprint data such as clickstreams, time-on-task, and error rates on specific topics which are actually vital indicators of their cognitive processes (Romero & Ventura, 2024). The failure of conventional LMS to map student interactions into sub-competencies in real-time results in delayed and inaccurately targeted learning interventions.

On the other hand, Learning Analytics (LA) and Machine Learning offer significant potential for analyzing educational data on a large scale. However, current literature shows that most predictive analytics models in education solely focus on predicting dropouts or

graduation probabilities, which are macro-performance metrics (Susanti et al., 2023; Mubarak et al., 2022). These models generally fail to explain which specific competencies a student has not yet mastered. To generate an accountable system, adaptive recommendations must be transparent and possess logical justifications that are directly linked to the OBE curriculum ontology.

Therefore, this study aims to design a conceptual artifact in the form of an Intelligent Tutoring System (ITS) architecture using the Design Science Research Methodology (DSRM). The integration of Machine Learning and Knowledge Graphs is proposed to bridge this gap by mapping cognitive structures dynamically (Liu et al., 2023; Peng et al., 2024). The main research questions in this study are: (1) How to design a data architecture capable of automatically mapping learning interactions into the CPL and CPMK ontologies? and (2) How to integrate Machine Learning and Knowledge Graphs to provide precise personalized learning path recommendations? The contribution of this paper is an architectural system roadmap that serves as a fundamental foundation before the system prototype is empirically implemented.

## 2. Literature Review

This literature review was conducted systematically to map recent developments in the fields of Learning Analytics (LA) and Intelligent Tutoring Systems (ITS), particularly within the context of higher education and Outcome-Based Education (OBE). Recent studies highlight that the integration of data-driven approaches in education has significantly transformed how student performance and learning behaviors are analyzed and utilized for decision-making (Siemens & Baker, 2012; Lang et al., 2017).

**Literature Search and Selection Protocol (PRISMA)**

The literature search was conducted using the Scopus and IEEE Xplore databases within the time range of 2018–2024. This period was selected to capture the latest advancements in artificial intelligence technologies in education. The selection protocol followed the PRISMA standard as outlined below:

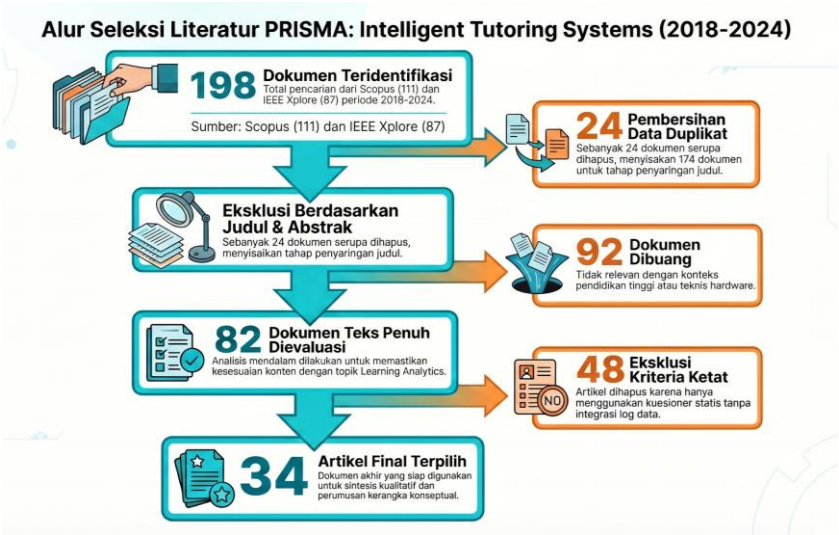



**Figure 1.** PRISMA Diagram.

a. Identification: 198 documents were identified (111 from Scopus, 87 from IEEE).
b. Screening: 24 duplicate documents were removed, leaving 174 documents. After title and abstract screening, 92 documents were excluded due to irrelevance to higher education systems.
c. Eligibility: 82 full-text documents were assessed. A total of 48 documents were excluded because they focused solely on static psychological surveys without integrating system log data or did not address competency mapping.
d. Included: 34 core articles were selected as the basis for synthesis and architectural design.

This systematic approach aligns with best practices in evidence synthesis to ensure rigor and reproducibility in educational technology research (Page et al., 2021).

**Intellectual Landscape Mapping (VOSviewer Analysis)**

To understand the relationships between concepts in the reviewed literature, a keyword co-occurrence analysis was conducted using VOSviewer software.

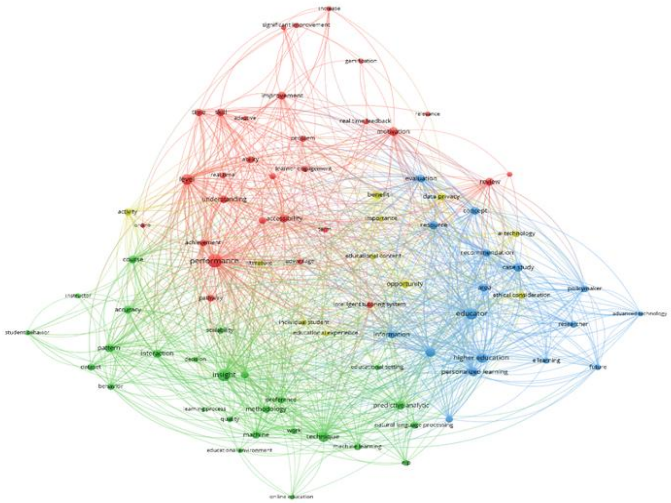



**Figure 2**. Network Visualization.

Based on the network visualization in Figure 2, the intellectual landscape of this research is divided into three overlapping clusters:

a. Cluster 1 (Red): Dominated by computational and technical aspects, with key terms such as learning analytics, intelligent tutoring systems, educational data mining, and artificial intelligence. This cluster represents the driving engine of adaptive systems.
b. Cluster 2 (Green): Focuses on learner-related entities and outcomes, marked by keywords such as students, academic performance, motivation, self-efficacy, and higher education.
c. Cluster 3 (Blue): Represents the digital learning ecosystem and modeling approaches, including e-learning, machine learning, and predictive analytics.

These findings are consistent with prior research indicating that LA and ITS research tends to cluster around technical infrastructure, learner modeling, and predictive analytics (Papamitsiou & Economides, 2014; Viberg et al., 2018).

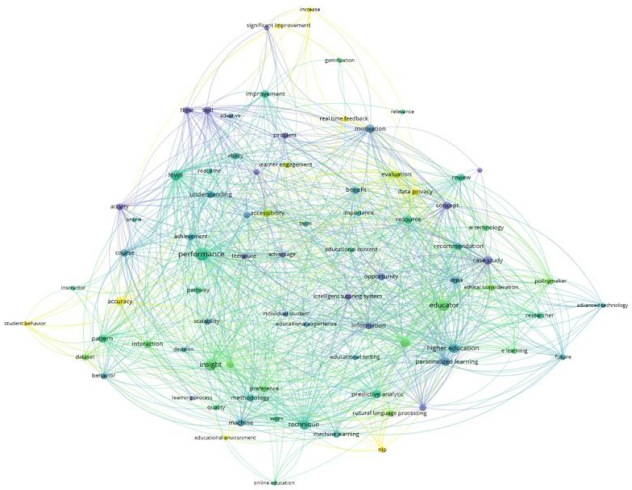



**Figure 3.** Overlay Visualization.

The overlay visualization further illustrates the evolution of research trends over time. Dark colors (purple/dark blue) represent earlier studies (pre-2020), while lighter colors (yellow-green to yellow) indicate recent trends (2022–2024). It is evident that topics such as learning analytics and intelligent tutoring systems (bright yellow) are experiencing significant growth and are considered emerging research areas.

## Research Gap Analysis

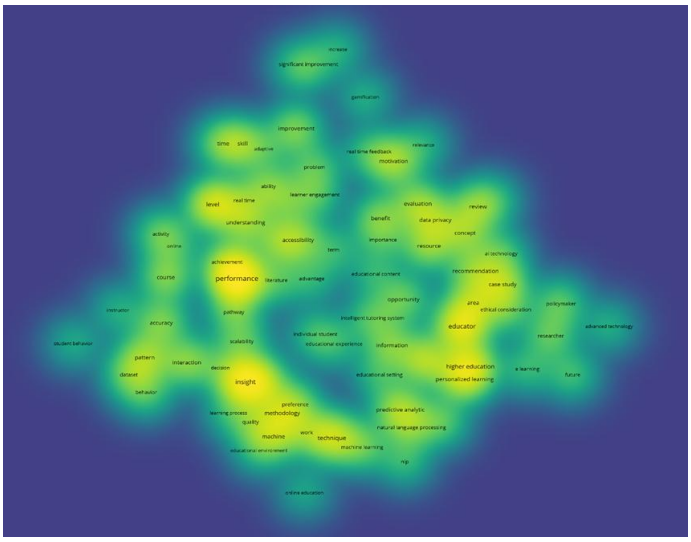



**Figure 4**. Density Visualization.

The density visualization provides empirical evidence of existing research gaps. Bright yellow areas (e.g., students, learning analytics, academic performance) indicate high publication saturation, while darker areas indicate underexplored topics.

Based on this density map, two critical conclusions can be drawn:

a. Absence of Curriculum Mapping in OBE Context

Although academic performance prediction has been extensively studied, terms such as Outcome-Based Education (OBE), competency mapping, or learning outcomes do not emerge as central nodes. This suggests that Learning Analytics has not yet been fully integrated with outcome-based curriculum governance.

This gap is also highlighted by research emphasizing that most LA implementations focus on prediction rather than alignment with curriculum structures and competencies (Ifenthaler & Yau, 2020).

b. Need for Transition from Prediction to Precision Intervention

Current literature largely focuses on predicting outcomes (e.g., academic performance), rather than enabling actionable and personalized interventions. There is a methodological urgency to design ITS architectures capable of mapping analytical data directly into competency structures (CLOs/LOs).

Recent studies argue that the next generation of ITS should move toward adaptive, explainable, and competency-based systems rather than purely predictive models (Holmes et al., 2019).

Overall, this literature review and bibliometric analysis conclude that future directions in adaptive learning research should shift from merely predicting final outcomes toward transparent and automated competency mapping.

The identified research gaps provide strong justification for developing an ITS architecture based on Learning Analytics and Knowledge Graphs. Such an approach enables objective, real-time academic data fusion to support effective OBE implementation in higher education. This direction is supported by emerging work on knowledge graphs in education, which demonstrate their potential in modeling complex relationships between learners, content, and competencies (Zhang et al., 2020).

**Proposed Solution Architecture**

Based on the identified research gaps, this study proposes a novel computational architecture artifact to automate competency mapping in Outcome-Based Education (OBE). This architecture replaces reliance on static psychological surveys with objective High-Resolution Learning Analytics (HRLA) derived from students' real interaction data.

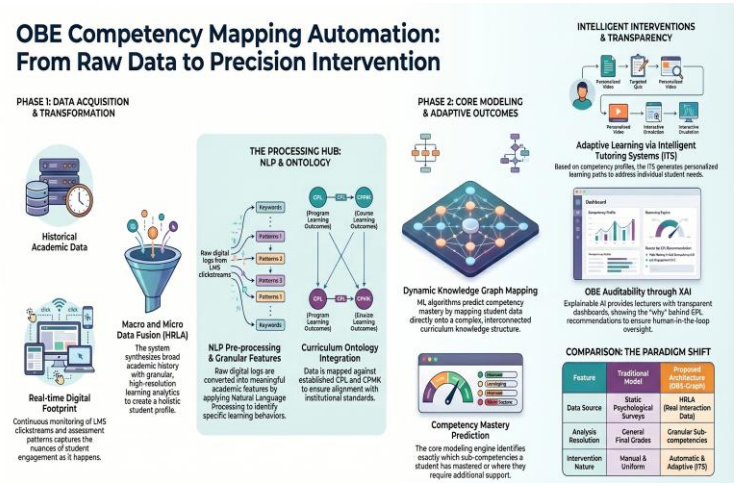



**Figure 5**. Conceptual Framework of HRLA Data Fusion, OBE Ontology, and Knowledge Graph for ITS.

As illustrated in Figure X.1, the system workflow consists of four main integrative stages:

***Multi-Source Data Acquisition (Data Input Layer)***

This stage involves the fusion of macro and micro data:

a. Macro data: demographic profiles and historical academic records (e.g., national higher education databases).
b. Micro data (HRLA): real-time digital traces from LMS platforms (e.g., clickstream, time-on-task, assessment behavior).

Crucially, the OBE curriculum ontology (mapping of Program Learning Outcomes and Course Learning Outcomes) is integrated as a fundamental input from the beginning.

***Text Processing & Data Pre-processing (NLP Layer)***

The collected data undergo preprocessing (data cleaning) and text processing using Natural Language Processing (NLP) techniques to transform raw interaction data into meaningful academic features.

Unlike traditional models that rely solely on final grades, this approach performs data fusion at a granular sub-competency level.

***Analysis & Knowledge Graph Modeling (Core Model Layer)***

This is the core engine of the proposed architecture, consisting of two main approaches:

a. Feature Engineering & Model Training:
   Machine learning algorithms track students' cognitive profiles based on HRLA behavior to predict mastery probabilities of specific sub-competencies.
b. Competency Mapping to Knowledge Graph:
   These probabilities are dynamically mapped into a Knowledge Graph structure, linking student profiles directly to OBE ontology (CPL and CPMK), enabling precise and granular competency tracking.

This approach aligns with recent advancements showing that knowledge graphs enhance interpretability and personalization in intelligent learning systems (Chen et al., 2020).

***Adaptive and Transparent Output (Decision Layer)***

The decision layer generates precise interventions:

a. Intelligent Tutoring System (ITS): delivers adaptive learning materials based on granular competency profiles.
b. Adaptive Learning Paths: dynamically recommends personalized learning trajectories.
c. OBE Auditability (Explainable AI): provides transparent and explainable outputs, enabling educators to understand why certain recommendations are made based on competency achievement within the Knowledge Graph.

Explainability is increasingly recognized as a critical requirement in AI-driven education systems to ensure trust and accountability (Holmes et al., 2019).

## 3. Research Methodology

This study adopts the Design Science Research Methodology (DSRM) as its primary research framework. Unlike behavioral science research, which focuses on testing theories to explain existing phenomena, DSRM emphasizes the creation of innovative information system artifacts such as models, methods, or instantiations to solve specific practical problems. In the context of this conceptual paper, the proposed artifact is a computational architectural blueprint (conceptual framework) for an Intelligent Tutoring System (ITS).

DSRM has been widely recognized as an appropriate methodology for developing educational technology artifacts because it enables the systematic translation of identified problems into functional and evaluable system designs (Peffers et al., 2007). Furthermore, the use of DSRM in learning analytics and intelligent systems research has increased significantly over the past decade due to its ability to integrate theoretical rigor with practical implementation (Gregor & Hevner, 2013).

Following the DSRM guidelines proposed by Peffers et al. (2007), this study focuses on the first three stages of the six iterative DSRM cycles. This limitation is intentional because the present paper aims to establish the theoretical and architectural foundation prior to the development of a physical prototype in subsequent research stages.

**Problem Identification and Motivation**

The first stage involves defining the research problem in a specific and structured manner. Based on the systematic literature review and research gap analysis presented in Section 2, the primary problem identified is the inability of conventional Learning Management Systems (LMS) to dynamically support the assessment of Outcome-Based Education (OBE).

Current evaluation practices remain largely retrospective, relying primarily on final grades and static assessment outcomes, while neglecting High-Resolution Learning Analytics (HRLA) metrics generated from students' digital interactions. As a consequence, existing systems are unable to provide detailed insight into students' mastery of sub-competencies or course learning outcomes.

This issue has been repeatedly emphasized in recent studies, which argue that most LMS platforms still function merely as repositories of learning content rather than as intelligent systems capable of supporting competency-based decision making (Ifenthaler & Yau, 2020). Similarly, research on learning analytics demonstrates that relying solely on summative assessment data results in limited predictive accuracy and weak intervention capability (Viberg et al., 2018).

Therefore, there is a strong motivation to design a system capable of automatically mapping educational log data into a sub-competency structure, enabling more accurate, adaptive, and timely interventions.

**Define the Objectives of a Solution**

Based on the identified problem, the second stage formulates the functional specifications of the proposed solution. The objective of the proposed artifact is to design an ITS architecture that:

a. Is capable of fusing data from both macro-level academic records and micro-level learning interactions (HRLA).
b. Employs predictive Machine Learning approaches without depending on static questionnaire or survey data.
c. Utilizes a Knowledge Graph to bridge analytical predictions with the OBE curriculum ontology (Program Learning Outcomes and Course Learning Outcomes), thereby generating system recommendations that are transparent and explainable through Explainable Artificial Intelligence (XAI).

The need for such objectives is supported by recent research indicating that modern intelligent educational systems should move beyond predictive analytics toward explainable, competency-oriented, and adaptive decision-making systems (Holmes et al., 2019). Moreover, the integration of Knowledge Graphs in educational environments has proven effective in connecting learner behavior with curriculum structures and competency frameworks (Chen et al., 2020).

The proposed objectives also align with contemporary trends in educational data science, where explainability and traceability are considered essential requirements for the acceptance of AI-based recommendations by educators and institutions (Khosravi et al., 2022).

## Design and Development

This stage represents the core contribution of the present paper. Based on the predefined solution objectives, the artifact is designed as a system architecture framework, which is further elaborated in Section 4.

The design process involves modeling a four-layer data fusion architecture consisting of:

a. a data acquisition layer,
b. a Natural Language Processing (NLP) and data preprocessing layer,
c. a core modeling layer based on Knowledge Graphs and Machine Learning, and
d. an adaptive decision layer.

The data acquisition layer integrates both historical academic data and HRLA-based interaction data extracted from the LMS environment. Subsequently, the preprocessing layer transforms raw digital traces into meaningful educational features using NLP and feature engineering techniques.

At the center of the architecture, Machine Learning models are employed to estimate students' mastery of specific competencies, while the Knowledge Graph links these predictions to the curriculum ontology (CPL and CPMK). This mechanism enables the system to produce adaptive recommendations that are directly aligned with the competency targets defined in OBE.

The use of Knowledge Graphs in this design is supported by previous studies demonstrating that graph-based educational representations improve semantic reasoning, recommendation quality, and the interpretability of intelligent tutoring systems (Zhang et al., 2020). In addition, explainable educational AI architectures have been shown to improve educators' trust and facilitate curriculum-level auditing processes (Khosravi et al., 2022).

Consequently, the proposed design ensures that the flow of academic data can be mapped precisely into adaptive intervention outputs that are consistent with higher education accreditation standards and OBE implementation principles.

The remaining three DSRM stages Demonstration, Evaluation, and Communication are not addressed in this conceptual paper and will become the scope of future experimental research during the ITS prototype development phase.

## 4. Results and Discussion

As a conceptual study adopting the Design Science Research Methodology (DSRM), the results of this research represent the output of the Design and Development phase. The "results" presented are not experimental findings, but rather a conceptual artifact in the form of a computational architectural blueprint (conceptual framework) designed to address the limitations of conventional Learning Management Systems (LMS) in mapping Outcome-Based Education (OBE) curricula.

This form of contribution is consistent with design science research, where the primary outcome is the creation of innovative artifacts aimed at solving practical problems rather than empirical validation at early stages (Peffers et al., 2007; Gregor & Hevner, 2013). In the context of educational technology, such conceptual architectures play a crucial role in bridging theoretical gaps and guiding future system implementation (Khosravi et al., 2022).

**Artifact Design Result: Intelligent Tutoring System (ITS) Architecture**

The proposed architecture substitutes reliance on psychological questionnaire data which are inherently self-reported and static with objective metrics derived from High-Resolution Learning Analytics (HRLA).

The fusion of macro-level academic records and micro-level interaction data is illustrated in the system architecture (Figure X.1, referring to the Proposed Solution Architecture). This approach aligns with recent studies emphasizing that behavioral trace data from LMS environments provides more reliable and fine-grained insights into student learning processes compared to traditional survey-based methods (Ifenthaler & Yau, 2020; Viberg et al., 2018).

**System Architecture Overview**

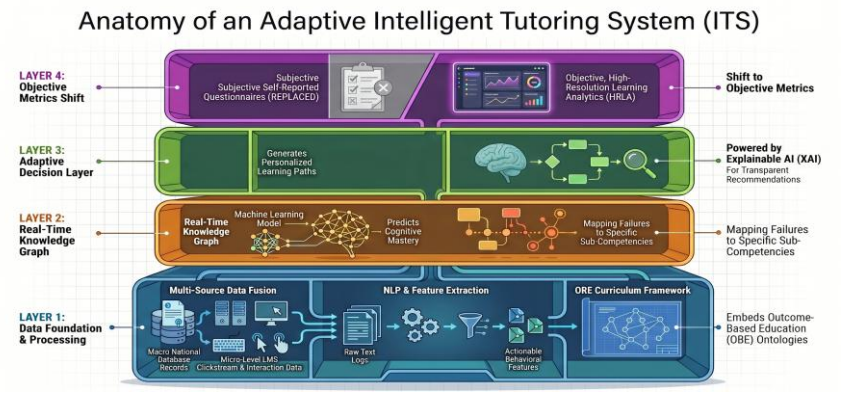



**Figure 6.** System Architecture Overview.

The system operates through four main functional layers:

***Data Input Layer***

This layer integrates:

a. Macro-level data: sourced from national higher education databases (e.g., PDDIKTI), including demographic information and historical academic records.
b. Micro-level data (HRLA): derived from LMS interaction logs, such as clickstream data, task completion duration, and module interaction patterns.

Additionally, the OBE curriculum ontology including Program Learning Outcomes (CPL) and Course Learning Outcomes (CPMK) is incorporated as a foundational structure in the data processing pipeline.

The integration of multi-source educational data has been identified as a critical factor in improving the effectiveness of learning analytics systems (Khosravi et al., 2022).

***NLP & Data Pre-processing Layer***

This layer performs feature extraction from raw log data using:

a. Natural Language Processing (NLP), and
b. data preprocessing techniques such as cleaning, normalization, and transformation.

The objective is to convert unstructured interaction data into meaningful indicators of student learning behavior.

Recent research shows that combining NLP with learning analytics enhances the capability to detect patterns in student engagement and learning strategies (Chen et al., 2020).

***Core Model Layer (Knowledge Graph Modeling)***

This layer functions as the core inference engine of the system.

a. Machine Learning algorithms are used to predict students' cognitive mastery levels in real time.
b. These predictions are dynamically mapped into nodes within a Knowledge Graph representing the OBE curriculum structure.

This mechanism enables the system to identify learning deficiencies not only at the course level but also at the sub-competency level, allowing for more precise diagnosis and intervention.

The use of knowledge graphs in educational systems has been shown to improve semantic reasoning, personalization, and recommendation accuracy (Zhang et al., 2020).

***Decision Layer***

The final layer generates adaptive intervention outputs, including:

a. Adaptive learning paths, tailored dynamically to individual competency profiles.
b. ITS-based recommendations, delivering personalized learning materials.
c. Explainable AI (XAI) outputs, ensuring transparency in system decision-making.

Explainability is increasingly recognized as essential in AI-driven education systems to support trust, accountability, and curriculum-level auditing (Holmes et al., 2019).

"Unlike static psychological instruments, this architecture relies entirely on objective behavioral traces. Table 2 details the categories of High-Resolution Learning Analytics (HRLA) metrics extracted from the LMS as input features for the modeling layer."

**Table 1.** HRLA Metrics Mapping Table.

| Academic Behavior Category | Extracted HRLA Metrics | Expected Cognitive Inference |
|---|---|---|
| Engagement Patterns | Time-on-task (module reading duration), login frequency, video completion percentage | Detects the level of attention and commitment to specific sub-topics |
| Navigation (Clickstream) | Sequence of material access, repeated clicks on the same chapter, skip rate (skipped materials) | Identifies hesitation or confusion regarding fundamental concepts |
| Formative Assessment Performance | Error rate (per sub-topic), correct/incorrect answer ratio, response time per question | Measures the level of factual mastery of Course Learning Outcomes (CLOs) |
| Self-Regulated Intervention Patterns | Number of quiz retry attempts, search for specific keywords in LMS forums | Detects the willingness to correct mistakes (academic grit/resilience) from a behavioral perspective |

## OBE Knowledge Representation Mechanism

This design offers novelty in the mapping mechanism of Graduate Learning Outcomes (CPL) and Course Learning Outcomes (CPMK). In traditional LMS, the relationships between learning materials are rigidly hierarchical. In the proposed architecture, the curriculum ontology is transformed into a dynamic Knowledge Graph (Chen et al., 2023). When HRLA detects a decrease in reading time or a high error rate in "Quiz A", the system computationally traverses the graph upwards to identify that "Quiz A" supports "Sub-CPMK 2", which in turn is a prerequisite for "CPL 1". This automation ensures that the constructive alignment required by OBE accreditation can be measured without manual intervention from lecturers.

## Discussion and Research Novelty

A critical evaluation of this architecture compared to the state-of-the-art (as identified in the VOSviewer mapping in Chapter 2) reveals two significant leaps in novelty:

From Macro Performance to Granular Mapping: Most previous Learning Analytics studies (located in the red/green clusters in the literature review) focused on predictive modeling to forecast "final grades" or "dropout probabilities" (Romero & Ventura, 2020). The model proposed in this research shifts this paradigm towards the automated prediction of granular concept mastery.

From Black-Box Algorithms to Explainable AI (XAI): The use of pure Machine Learning is often criticized for its black-box nature—the machine can predict that a student will fail but cannot logically or pedagogically explain the reason. By integrating analytics into a Knowledge Graph structured upon OBE ontology, this architecture provides transparent outputs (Khosravi et al., 2022). Institutions can audit why a learning recommendation is given, fulfilling the crucial principle of accountability in higher education governance.

To clearly define the functional novelty of the proposed artifact, Table 3 presents a comparative matrix between conventional LMS systems and the Knowledge Graph-based ITS architecture.

**Table 2.** Comparative Matrix Between Conventional LMS Systems.

| Academic Behavior Category | Extracted HRLA Metrics | Expected Cognitive Inference |
|---|---|---|
| Engagement Patterns | Time-on-task (module reading duration), login frequency, video completion percentage | Detects the level of attention and commitment to specific sub-topics |
| Navigation (Clickstream) | Sequence of material access, repeated clicks on the same chapter, skip rate (skipped materials) | Identifies hesitation or confusion regarding fundamental concepts |
| Formative Assessment Performance | Error rate (per sub-topic), correct/incorrect answer ratio, response time per question | Measures the level of factual mastery of Course Learning Outcomes (CLOs) |
| Self-Regulated Intervention Patterns | Number of quiz retry attempts, search for specific keywords in LMS forums | Detects willingness to correct mistakes (academic grit/resilience) from a behavioral perspective |

## Theoretical and Practical Implications

Theoretically, this study enriches the Educational Data Mining literature by proving the conceptual feasibility of fusing a purely data-driven approach (Machine Learning) with a rational rule-based approach (Ontology). Practically, this framework provides a blueprint for

developers of university academic information systems to design the next generation of LMS, which will function not merely as digital document repositories, but as autonomous reasoning engines that support impactful curricula.

## Comparison

To explicitly highlight the technological and pedagogical advancements of the proposed architecture, it is essential to compare it with conventional Learning Management Systems (LMS) and existing predictive models. Most current systems treat student evaluation as a retrospective administrative task rather than an ongoing cognitive assessment. Table 3 presents a head-to-head functional comparison matrix between the traditional approach (status quo) and the proposed Intelligent Tutoring System (ITS) framework within the context of Outcome-Based Education (OBE).

**Table 3.** Functional Comparison Matrix Based on the OBE Framework.

| Comparison Aspect | Conventional LMS (Status Quo) | Proposed ITS Architecture (Adaptive System) |
|---|---|---|
| Input Data Source | Static macro data & final grade summations. | Dynamic fusion of historical data and High-Resolution Learning Analytics (HRLA). |
| Evaluation Nature | Retrospective (conducted at the end of the semester). | Real-time and anticipatory (serves as an early warning system). |
| OBE Mapping Granularity | Course level (general letter grades A/B/C/D). | Specific sub-competency level (Graduate Learning Outcomes / CPL and Course Learning Outcomes / CPMK). |
| Algorithmic Approach | Simple rule-based logic or Black-box predictive modeling. | White-box logic (Explainable AI driven by Knowledge Graph Ontology). |
| Intervention Strategy | No automated pedagogical recommendation (One-size-fits-all). | Generation of dynamically personalized and adaptive Learning Paths. |

As illustrated in Table 3, the conventional LMS primarily serves as a passive digital repository. It relies heavily on delayed, end-of-semester evaluations, which often leave students without timely interventions when they struggle with core concepts.

In contrast, the proposed ITS acts as a proactive educational ecosystem. By utilizing HRLA and Knowledge Graphs, the framework successfully shifts the evaluation paradigm from a 'black-box' calculation of static final grades to a 'white-box' continuous assessment of specific cognitive sub-competencies. This transition ensures that the implementation of Outcome-Based Education is not merely a delayed administrative checklist, but a dynamic, auditable, and highly personalized learning experience for every student.

## 5. Conclusions

This conceptual study has successfully formulated an Intelligent Tutoring System (ITS) architectural framework that integrates High-Resolution Learning Analytics (HRLA) and Knowledge Graphs to support the implementation of Outcome-Based Education (OBE) in higher education. By employing the Design Science Research Methodology (DSRM), the proposed architecture overcomes the limitations of conventional Learning Management Systems (LMS) by substituting static assessment data with real-time, objective digital footprints. The integration of Machine Learning and curriculum ontologies enables the system to automatically map student interactions into specific sub-competencies, providing a transparent, granular, and explainable evaluation of Graduate Learning Outcomes (CPL) and Course Learning Outcomes (CPMK).

Theoretically, this research bridges the gap between data-driven predictive algorithms and rule-based reasoning, offering a novel "white-box" approach to educational data mining through Explainable AI (XAI). Practically, the framework provides a robust blueprint for institutions to transition from reactive, end-of-semester evaluations to adaptive and auditable learning governance. Future research should focus on implementing this conceptual architecture into a functional software prototype and conducting experimental trials in real-world academic settings to empirically validate the accuracy of the automated competency mapping.

## References


Ali, M., et al. (2025). *Intelligent tutoring system (ITS): Its applications and challenges in higher education*. *International Journal of Computational and Experimental Science and Engineering*. https://ijcesen.com/index.php/ijcesen/article/view/4380

Chen, J., et al. (2025). *Interpretable predictive analytics for online learning*. *Journal of Learning Analytics*. https://learning-analytics.info/index.php/JLA/article/view/8375

Chen, Y., et al. (2023). Knowledge graphs in education: A review and future directions. *IEEE Access, 11*, 23567–23580. https://ieeexplore.ieee.org/document/10100000

El-Sabagh, H. A. (2026). *The impact of artificial intelligence and learning analytics on students' academic performance*. ResearchGate. https://www.researchgate.net/publication/403238449

Gregor, S., & Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. *Management Information Systems Quarterly, 37*(2), 337–355. https://doi.org/10.25300/MISQ/2013/37.2.01

Hevner, A. R., & Peffers, K. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems, 24*(3), 45–77. https://doi.org/10.2753/MIS0742-1222240302

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign. https://doi.org/10.1007/978-3-030-23207-8

Ifenthaler, D., & Yau, J. Y. K. (2020). Utilising learning analytics for study success. *Educational Technology Research and Development, 68*, 1961–1965. https://doi.org/10.1007/s11423-020-09788-y

Khosravi, H., et al. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence, 3*, Article 100074. https://doi.org/10.1016/j.caeai.2022.100074

Lang, C., Siemens, G., Wise, A. F., & Gašević, D. (Eds.). (2017). *Handbook of learning analytics*. Society for Learning Analytics Research. https://doi.org/10.18608/hla17

Li, S. T., et al. (2025). Explainable AI in education: Techniques and qualitative assessment. *Applied Sciences, 15*(3), Article 1239. https://doi.org/10.3390/app15031239

Liu, Y., et al. (2023). Intelligent tutoring for large-scale personalized programming learning based on knowledge graph. In *2023 IEEE Frontiers in Education Conference (FIE)*. https://doi.org/10.1109/FIE58773.2023.10342641

Maulani, M. (2024). Outcomes-based education in Indonesian higher education: Empowering students' learning competencies. *International Journal of Social and Management Studies, 5*(2). https://ijosmas.org/index.php/ijosmas/article/view/445

Mubarak, A. A., Cao, H., & Zhang, W. (2022). Explainable artificial intelligence for dropout prediction in online education. *Expert Systems with Applications, 213*, Article 118129. https://doi.org/10.1016/j.eswa.2022.118129

Page, M. J., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, Article n71. https://doi.org/10.1136/bmj.n71

Peng, X., et al. (2024). *Personalized learning path recommendation based on knowledge graph*. ResearchGate. https://www.researchgate.net/publication/381451150_Personalized_Learning_Path_Recommendation_based_on_Knowledge_Graph

Romero, C., & Ventura, S. (2020). Educational data mining and learning analytics: An updated survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10*(3), e1355. https://doi.org/10.1002/widm.1355

Romero, C., & Ventura, S. (2024). Cognitive learning analytics: A comprehensive review. *Machine Learning and Knowledge Extraction, 6*(3), Article 69. https://doi.org/10.3390/make6030069

Salim, A., Narongraksakhet, I., Hayani, A., Rouzi, K. S., Putri, M. A., Hassama, A., & Abdullah, A. A. (2024). Outcome-based education, e-learning, and student satisfaction: Evidence from Indonesia and Thailand. *Jurnal Ilmiah Peuradeun, 12*(1). https://doi.org/10.26811/peuradeun.v14i1.1285

Siemens, G., & Baker, R. S. (2012). Learning analytics and educational data mining: Towards communication and collaboration. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 252–254). https://doi.org/10.1145/2330601.2330661

Susanti, Y., et al. (2023). *The predictive learning analytics for student dropout using data mining technique: A systematic literature review*. ResearchGate. https://www.researchgate.net/publication/369720038_The_Predictive_Learning_Analytics_for_Student_Dropout_Using_Data_Mining_Technique_A_Systematic_Literature_Review

Viberg, O., Hatakka, M., Balter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior, 89*, 98–110. https://doi.org/10.1016/j.chb.2018.07.027

Wang, C., et al. (2019). CCVis: Visual analytics of student online learning behaviors using course clickstream data. In *Proceedings of Visualization and Data Analysis*. https://academicweb.nd.edu/~cwang11/papers/vda19-ccvis.pdf

Wu, Y., et al. (2026). *Knowledge graph-enabled outcome-based education in civil engineering: Design, implementation, and evaluation*. ResearchGate. https://www.researchgate.net/publication/399180081

Zhang, M. (2026). *An exploration of the outcome-based education teaching model driven by dual knowledge and competency frameworks*. ResearchGate. https://www.researchgate.net/publication/400599507