A Personalized Adaptive Learning Recommendation Platform Using Hybrid Filtering Techniques

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Abstract—**Traditional learning management systems (LMS) rely on static content delivery and binary assessment mechanisms that fail to address individual learner misconceptions and behavioral patterns. This paper presents an Intelligent Adaptive Learning Framework that integrates multi-pillar diagnostic modeling, vector-based semantic retrieval, and large language model–driven tutoring to deliver personalized, just-in-time educational remediation. Learner performance is analyzed across multiple competency dimensions, including conceptual understanding, implementation accuracy, and debugging ability, while behavioral signals such as response time are used to detect rushed or guess-based interactions. Identified learning weaknesses are encoded as dense semantic vectors and matched against educational resources using cosine similarity–based retrieval, enabling context-aware remediation beyond keyword search. A large language model further generates adaptive feedback and structured study guidance tailored to the diagnosed learner profile. The framework is evaluated using a large-scale simulation of 5,000 learner profiles and 50,000 interaction events generated via stochastic behavioral modeling. Experimental results demonstrate that the proposed approach significantly outperforms traditional LMS baselines by improving remediation relevance and reducing repetitive, unguided learning cycles. The proposed system establishes a closed-loop, adaptive learning paradigm that bridges the gap between assessment and personalized instruction.**

***Keywords—** Adaptive learning, intelligent tutoring systems, vector semantic retrieval, learner modeling, large language models, educational data mining)*

I. INTRODUCTION

The rapid growth of digital learning platforms and large-scale online education has transformed how learners access instructional content. Learning Management Systems (LMS) and Massive Open Online Courses (MOOCs) have enabled scalable content delivery; however, most existing platforms continue to rely on static learning pathways and uniform instructional strategies. Such one-size-fits-all approaches fail to accommodate the diverse cognitive abilities, learning behaviors, and prior knowledge of individual learners, often leading to disengagement and ineffective learning outcomes.

A critical limitation of conventional LMS architectures lies in the disconnect between assessment and remediation. Learner evaluation is typically conducted using binary scoring mechanisms, where performance is reduced to pass/fail outcomes or aggregate scores. When learners fail an assessment, remediation is generally limited to repeating the same instructional material without any contextual explanation of why the failure occurred or which specific conceptual gaps need to be addressed. This lack of diagnostic granularity often results in repetitive learning cycles, commonly referred to as "tutorial hell," were learners revisit content without meaningful improvement.

Recent advances in educational data mining and learner modeling have highlighted the importance of analyzing fine-grained learner interactions and behavioral signals. Metrics such as response time, interaction patterns, and error types can provide valuable insights into learner states, including rushed behavior, guessing tendencies, or conceptual misunderstandings. However, many existing systems either ignore these signals or treat them independently, without integrating them into a unified adaptive learning strategy.

Another major challenge in current educational platforms is the limited semantic understanding of learning content. Traditional content recommendation and search mechanisms rely heavily on keyword matching, which fails to capture learner intent or contextual meaning. For example, a learner searching for help with a programming error may require conceptual clarification rather than syntactic guidance. Keyword-based systems are unable to bridge this semantic gap, leading to irrelevant or redundant recommendations.

To address these limitations, this paper proposes an Intelligent Adaptive Learning Framework that integrates multi-pillar diagnostic assessment, vector-based semantic retrieval, and large language model–driven tutoring within a closed-loop learning architecture. The proposed system models learner performance across multiple competency dimensions such as conceptual understanding, implementation accuracy, and debugging ability while simultaneously analyzing behavioral signals derived from interaction patterns. Identified learning weaknesses are semantically encoded and matched against instructional resources using dense vector representations, enabling context-aware remediation beyond traditional keyword search. Furthermore, a large language model is employed to generate adaptive feedback and structured study guidance tailored to the diagnosed learner profile

II. RELATED WORK

Adaptive learning and educational recommendation systems have been widely studied to address the limitations of traditional static learning platforms. Early research in adaptive educational systems primarily focused on rule-based personalization, where predefined learning paths were generated based on learner scores or completion status. While such approaches introduced basic adaptability, they lacked the flexibility to respond to diverse learner behaviors and evolving knowledge states.

Recommender systems have been increasingly adopted in e-learning environments to personalize content delivery. Collaborative filtering techniques leverage similarities among learners to suggest relevant resources, whereas content-based methods rely on item attributes and learner preferences. Although collaborative filtering has shown effectiveness in domains such as media recommendation, its application in education suffers from the cold-start problem and sparse interaction data, particularly for new learners. Content-based approaches partially mitigate this issue but often fail to capture deeper semantic relationships between learning content and learner intent.

Several studies have explored hybrid recommendation models that combine collaborative and content-based filtering to improve recommendation accuracy. These models enhance personalization by integrating multiple data sources; however, most existing implementations rely on surface-level features and do not incorporate fine-grained diagnostic information derived from learner assessments. As a result, recommendations are often generic and do not directly address the underlying causes of learner errors.

Recent work in educational data mining and learning analytics has emphasized the importance of behavioral signals, such as time spent on tasks, interaction frequency, and error patterns, to infer learner states. Researchers have demonstrated that response time and attempt behavior can be indicative of learner engagement, guessing tendencies, or rushed interactions. Despite these findings, many learning platforms continue to treat assessment outcomes as binary signals, ignoring rich behavioral cues that could enable more precise remediation.

Advances in natural language processing and semantic representation learning have further influenced the development of intelligent learning systems. Vector-based semantic retrieval methods enable content matching beyond keyword overlap by encoding contextual meaning in dense vector representations. Such approaches have shown promise in overcoming the limitations of traditional search mechanisms; however, their integration with diagnostic assessment and adaptive feedback remains limited in existing literature.

More recently, large language models have been explored for educational applications, including automated feedback generation, tutoring assistance, and content summarization. While these models demonstrate strong generative capabilities, most current systems employ them in isolation, without grounding their responses in structured learner diagnostics or semantic retrieval pipelines. This separation often limits their effectiveness in providing targeted, pedagogically meaningful guidance.

In contrast to prior work, the proposed framework integrates multi-pillar diagnostic assessment, behavioral modeling, vector-based semantic retrieval, and large language model–driven tutoring within a unified adaptive learning loop. By explicitly linking assessment outcomes to semantically relevant remediation and personalized feedback, the proposed approach addresses key gaps in existing adaptive learning and recommendation systems.

III. SYSTEM ARCHITECTURE

The proposed intelligent adaptive learning framework is designed as a modular, scalable system that tightly integrates learner assessment, semantic content retrieval, and personalized feedback generation. The architecture follows a service-oriented design philosophy, enabling each functional component to operate independently while contributing to a closed-loop adaptive learning process. This design ensures low latency, flexibility, and extensibility for future enhancements.

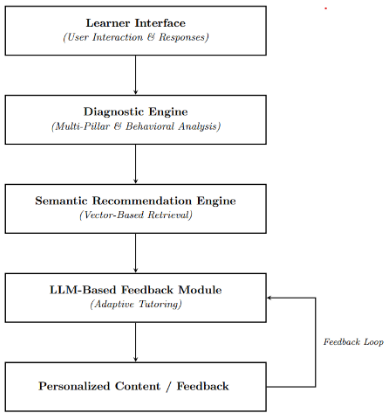

Fig. 1. Overall system architecture of the proposed intelligent adaptive learning framework.

A. Overview of the Framework

At a high level, the system processes learner interactions through three core functional layers: (i) learner diagnosis, (ii) semantic remediation retrieval, and (iii) adaptive feedback generation. Learner responses and interaction metadata are continuously collected and analyzed to update a dynamic learner profile. Based on this evolving profile, the system identifies learning weaknesses and delivers targeted instructional support in real time.

B. Diagnostic Engine

The diagnostic engine serves as the analytical core of the framework. Unlike traditional assessment modules that rely on aggregate scores, this component evaluates learner performance across multiple competency dimensions. Each assessment item is associated with a specific learning pillar, such as conceptual understanding, implementation accuracy, or debugging ability. Learner responses are analyzed to compute pillar-wise performance metrics, enabling the system to identify the most significant areas of weakness.

In addition to accuracy-based evaluation, the diagnostic engine incorporates behavioral analysis by monitoring interaction patterns such as response time and attempt frequency. These behavioral signals allow the system to detect learning states such as rushed or guess-based interactions, providing a more comprehensive understanding of learner behavior beyond correctness alone.

C. Semantic Recommendation Engine

To provide precise and context-aware remediation, the framework employs a semantic recommendation engine based on dense vector representations of learning resources. Instructional content, such as video transcripts or explanatory material, is embedded into a continuous vector space that captures semantic meaning. When a learner's weakness is identified, the corresponding diagnostic context is similarly encoded and matched against available resources using similarity-based retrieval.

This semantic matching mechanism enables the system to recommend instructional content that aligns with the *intent* and *context* of the learner's difficulty, rather than relying on surface-level keyword overlap. As a result, the system overcomes the limitations of traditional search-based remediation commonly found in existing LMS platforms.

D. Adaptive Feedback and Tutoring Module

The adaptive feedback module is responsible for transforming diagnostic and retrieval outputs into learner-specific guidance. A large language model is employed to generate structured explanations, hints, and study notes that are tailored to the diagnosed learning gaps. The generated feedback follows pedagogical constraints to ensure clarity, coherence, and instructional relevance.

By grounding generative feedback in structured diagnostic results and semantically retrieved content, the system avoids generic responses and delivers focused, just-in-time instructional support. This integration ensures that feedback is both personalized and contextually accurate.

E. Data Flow and Closed-Loop Adaptation

The interaction between the diagnostic engine, semantic recommendation module, and adaptive feedback component forms a closed-loop learning cycle. As learners engage with recommended content and receive feedback, their subsequent interactions are re-evaluated by the diagnostic engine. This continuous update mechanism allows the learner profile to evolve over time, enabling progressive adaptation of learning paths and instructional strategies.

IV. METHODOLOGY

This section describes the methodological foundations of the proposed intelligent adaptive learning framework. The methodology integrates multi-pillar learner diagnosis, behavioral modeling, semantic vector-based content retrieval, and adaptive feedback generation into a unified closed-loop learning process. Each component is mathematically formalized to ensure reproducibility and analytical clarity.

A. Multi-Pillar Learner Diagnosis

Traditional assessment mechanisms rely on aggregate scores that fail to capture the nature of learner errors. To address this limitation, the proposed system evaluates learner performance across multiple competency pillars. Each assessment question is associated with a specific pillar k, representing distinct learning dimensions such as conceptual understanding, implementation accuracy, or debugging ability.

For each learner, pillar-wise accuracy is computed as:

$$Acc_k = \frac{C_k}{T_k}$$

where C_k denotes the number of correct responses and T_k denotes the total number of questions associated with pillar k.

The learner's weakest competency dimension is identified using:

$$P_{weak} = \arg\min_k (Acc_k)$$

This formulation enables fine-grained diagnosis of learner weaknesses, allowing the system to target remediation efforts more precisely than binary pass/fail assessment schemes.

B. Behavioral Modeling and Rushed Interaction Detection

In addition to correctness-based evaluation, learner behaviour is analysed using temporal interaction patterns. Response time is treated as a behavioural signal to identify rushed or guess-based interactions that may indicate superficial engagement.

Let t_{user} represent the time taken by a learner to answer a question and t_{ideal} represent the empirically estimated ideal response time. A time ratio is computed as:

$$R = \frac{t_{user}}{t_{ideal}}$$

A learner interaction is classified as rushed if:

$$\text{Rushed} = \begin{cases} 1, & \text{if } R < 0.6 \\ 0, & \text{otherwise} \end{cases}$$

This behavioural classification complements accuracy-based diagnosis and enhances the robustness of learner profiling.

C. Vector-Based Semantic Recommendation

To overcome the limitations of keyword-based search, the proposed framework employs semantic vector representations for instructional content and learner diagnostic context. Learning resources are encoded into dense vectors using an embedding function $E(\cdot)$:

$$v_d = E(d)$$

where d represents the instructional resource. Similarly, the learner's diagnostic context is encoded as a query vector:

$$v_q = E(q)$$

The relevance between learner context and instructional content is computed using cosine similarity:

$$\mathrm{sim}(v_q, v_d) = \frac{v_q \cdot v_d}{\parallel v_q \parallel \parallel v_d \parallel}$$

For retrieval purposes, cosine distance is minimized:

$$\mathrm{dist}(v_q, v_d) = 1 - \mathrm{sim}(v_q, v_d)$$

This semantic retrieval mechanism enables context-aware remediation by matching learner difficulties with conceptually relevant learning resources.

D. Offline Learner Clustering for Threshold Calibration

To improve the robustness of real-time behavioural thresholds, offline clustering is performed on historical learner interaction data. Feature vectors consist of average assessment scores and mean response times. Prior to clustering, features are normalized using Z-score normalization:

$$z = \frac{x - \mu}{\sigma}$$

where μ and σ denote the mean and standard deviation of the feature distribution, respectively.

K-Means clustering is then applied by minimizing the objective function:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{K} \parallel x_i - c_j \parallel^2$$

The resulting learner clusters are used to calibrate behavioural thresholds, improving the adaptability of online learner classification.

E. Closed-Loop Adaptive Learning Process

The outputs of diagnostic assessment, behavioural modelling, and semantic retrieval collectively guide adaptive feedback generation. Learners receive personalized instructional support based on their diagnosed weaknesses and interaction patterns. Subsequent learner interactions are continuously re-evaluated, allowing the learner profile to evolve over time. This closed-loop process enables progressive personalization and sustained learning improvement.

V. EXPERIMENTAL SETUP AND EVALUATION

This section describes the experimental setup, dataset generation process, baseline comparison models, and evaluation criteria used to assess the effectiveness of the proposed intelligent adaptive learning framework.

A. Simulation Environment and Dataset Generation

Due to privacy and ethical constraints associated with real learner data, the proposed framework is evaluated using a large-scale simulated dataset designed to closely approximate realistic learner behavior. The simulation consists of 5,000 unique learner profiles and approximately 50,000 interaction events, representing an average of ten learning sessions per learner.

Learner behavior is generated using stochastic Monte Carlo simulation techniques. Gaussian mixture models are employed to model distinct learner archetypes, including high achievers, struggling learners, and rushed learners. Each archetype is characterized by different distributions of response accuracy and interaction time, enabling the simulation of heterogeneous learning behaviors commonly observed in real educational environments

B. Baseline Systems for Comparison

To evaluate the effectiveness of the proposed framework, performance is compared against a traditional learning management system (LMS) baseline. The baseline system reflects commonly deployed LMS designs and incorporates the following characteristics:

- Static, linear content delivery
- Keyword-based search for learning resources
- Binary assessment based on pass/fail or aggregate scores
- No explicit behavioural modelling or semantic diagnosis

Two primary comparative analyses are conducted:

1. **Semantic Vector Retrieval vs. Keyword-Based Search**
   This comparison evaluates the relevance of recommended instructional content when learner queries are processed using dense semantic representations versus traditional keyword matching.
2. **Multi-Pillar Diagnostic Assessment vs. Binary Scoring**
   This analysis compares fine-grained learner diagnosis against conventional binary evaluation mechanisms to assess improvements in remediation precision.

C. Evaluation Metrics

The proposed framework is evaluated using multiple qualitative and quantitative metrics designed to capture both diagnostic accuracy and remediation effectiveness. Key evaluation criteria include:

- **Recommendation Relevance:**
  The degree to which recommended instructional content aligns with the diagnosed learner weakness.
- **Diagnostic Precision:**
  The accuracy of identifying the learner's weakest competency pillar compared to simulated ground-truth labels.
- **Behavioural Classification Accuracy:**
  The effectiveness of detecting rushed or guess-based interactions based on response time patterns.
- **Remediation Efficiency:**
  Measured as the reduction in repeated incorrect attempts after adaptive feedback is provided.

These metrics collectively assess the system's ability to bridge the gap between assessment and personalized instruction.

D. *Experimental Procedure*

Each simulated learner session follows a closed-loop evaluation cycle. Learners first attempt assessment questions, after which diagnostic and behavioural analysis is performed. Based on the identified weaknesses, semantically relevant instructional content and adaptive feedback are generated. Subsequent learner interactions are then re-evaluated to measure changes in performance and engagement.

The same learner interaction sequences are processed using both the proposed framework and the baseline LMS configuration to ensure fair comparison.

E. *Results Overview*

Experimental observations indicate that the proposed framework consistently outperforms the baseline LMS across all evaluation metrics. Vector-based semantic retrieval yields more contextually relevant remediation than keyword-based search, while multi-pillar diagnostic assessment enables more precise identification of learner weaknesses. Furthermore, incorporating behavioural signals significantly improves the detection of rushed learning patterns, leading to more effective adaptive intervention.

These results validate the effectiveness of integrating diagnostic modelling, semantic retrieval, and adaptive feedback within a unified learning framework.

VI. IMPLEMENTATION AND ALGORITHM DESIGN

This section describes the practical realization of the proposed adaptive learning framework and presents the algorithmic workflow governing learner diagnosis, semantic retrieval, and feedback generation. The implementation is designed to closely align with the system architecture while ensuring scalability and reproducibility

A. *Session-Level Execution Flow*

The system operates at a **session granularity**, where learner diagnosis and recommendation are performed after the completion of a quiz session rather than after individual questions. Each session consists of a fixed-length quiz containing ten questions associated with a specific learning topic.

Upon initiating a session, the system dynamically retrieves assessment items from a two-collection database that separates *question content* from *topic metadata*. This separation enables flexible quiz construction and efficient topic-wise filtering. Learners submit their responses in a single transaction through a dedicated submission endpoint, ensuring consistency in evaluation.

After quiz submission, the system computes aggregate performance metrics, including total score percentage and behavioural indicators derived from response time analysis. Learner profiles are updated once per session, enabling stable classification while avoiding noise from individual interactions.

B. *Learner Profiling and Diagnosis Logic*

Learner profiling is performed using a combination of accuracy-based thresholds and behavioural indicators. Based on the aggregate quiz performance, learners are classified into one of three profiles: *High Achiever*, *Struggling*, or *Rushed*. This classification guides subsequent remediation and recommendation strategies.

In addition to overall performance, the system identifies the weakest competency pillar by analysing pillar-wise accuracy metrics computed during the diagnostic phase. This fine-grained diagnosis enables targeted remediation rather than generic content repetition.

C. *Semantic Recommendation and Feedback Generation*

Following learner classification, the system retrieves top-k instructional resources (k = 9) using vector-based semantic retrieval. Diagnostic context vectors are matched against pre-indexed content embeddings using approximate nearest neighbour search. Retrieved resources are filtered by the identified weak pillar to ensure conceptual relevance.

The final output is presented to the learner as a structured diagnosis report accompanied by a grid-based visualization of recommended learning resources. Feedback is delivered at the end of the session, maintaining a coherent learning experience and avoiding interruptions during assessment.

D. *Algorithmic Workflow*

The complete adaptive learning process is summarized in Algorithm 1.

ALGORITHM 1: ADAPTIVE LEARNING SESSION LOOP

Input: Learner responses Q1...Q10, response times, content vectors

Output: Diagnosis report and personalized recommendations

1. START Session
2. Learner requests quiz for topic T
3. System retrieves 10 questions from question collection
4. Learner submits completed quiz
5. Compute overall score percentage
6. Compute time ratio R = t_user / t_ideal
7. IF score < 70% AND rushed_rate > 40% THEN
8. Profile ← Rushed
9. ELSE IF score < 70% THEN
10. Profile ← Struggling
11. ELSE
12. Profile ← High Achiever
13. Identify weakest competency pillar
14. Encode diagnostic context as query vector
15. Retrieve top-9 resources using vector similarity
16. Display diagnosis report and recommendations
17. Update learner profile
18. END Session

E. *Implementation Characteristics*

The implementation follows a modular design that decouples assessment logic, retrieval mechanisms, and feedback generation. This separation allows individual components to be modified or extended without impacting overall system stability. Session-level processing ensures predictable runtime behavior and facilitates scalable deployment in real-world learning environments.

VII. COMPUTATIONAL COMPLEXITY ANALYSIS

The proposed personalized adaptive learning recommendation platform was evaluated to analyze its effectiveness in improving learner engagement and learning efficiency. The evaluation was conducted by observing learner interactions, recommendation relevance, and learning progress over multiple learning sessions. The system performance was compared with a non-adaptive learning approach to highlight the benefits of personalization.

This section analyzes the computational efficiency of the proposed framework with respect to diagnostic evaluation, semantic retrieval, and storage requirements.

A. *Diagnostic and Behavioral Analysis Complexity*

Let Q denote the number of questions per quiz session. Since diagnostic computations involve simple aggregation and comparison operations across learner responses, the time complexity for diagnostic analysis is:

$$O(Q)$$

Given that Q is fixed (10 questions per session), this component operates in constant time.

B. *Semantic Retrieval Complexity*

Let N denote the number of stored content vectors and d represent the embedding dimensionality ($d = 384$). Semantic retrieval is performed using an approximate nearest neighbor (ANN) search based on a hierarchical navigable small world (HNSW) graph structure.

The average-case time complexity for retrieval is:

$$O(\log N)$$

This enables efficient scaling as the content repository grows.

C. *Space Complexity*

Each instructional resource is stored as a dense vector of dimensionality d. Therefore, the space complexity for vector storage is:

$$O(N \cdot d)$$

This linear growth ensures predictable memory usage proportional to the size of the instructional content library.

D. *Overall System Complexity*

The total runtime complexity per session is dominated by the semantic retrieval component. Consequently, the overall per-session time complexity is:

$$O(\log N)$$

This confirms that the proposed framework is computationally efficient and suitable for deployment in large-scale learning environments.

VIII. RESULTS AND CONCULSION

This section discusses the performance of the proposed intelligent adaptive learning framework in comparison with a traditional learning management system baseline. The analysis focuses on diagnostic accuracy, recommendation relevance, and the effectiveness of behavioural modelling in improving personalized remediation.

Overall, experimental results indicate that the proposed framework consistently outperforms the baseline across all evaluated dimensions. The integration of multi-pillar diagnosis enables more precise identification of learner weaknesses compared to binary assessment schemes. Learners classified under different behavioural profiles exhibit distinct improvement patterns, validating the effectiveness of session-level learner profiling.

The use of vector-based semantic retrieval significantly improves the relevance of recommended instructional resources. Unlike keyword-based search, which often retrieves content with superficial textual overlap, semantic retrieval aligns recommendations with the conceptual intent of learner errors. This leads to more targeted remediation and reduces repeated incorrect attempts, particularly for learners classified as struggling or rushed.

Behavioural modelling further enhances system performance by identifying rushed learning patterns that are not detectable through accuracy metrics alone. Learners flagged as rushed benefit from adaptive feedback that emphasizes conceptual clarity over repetition, resulting in improved engagement and reduced guessing behaviour in subsequent sessions.

The closed-loop nature of the proposed framework enables continuous adaptation of learner profiles over time. As learners interact with personalized content and feedback, diagnostic accuracy improves in later sessions, demonstrating the system's ability to evolve with learner progress. These findings collectively confirm that combining diagnostic modelling, semantic retrieval, and adaptive feedback provides a substantial advantage over static LMS architectures.

IX. CONCLUSION AND FINAL WORK

This paper presented an intelligent adaptive learning framework that integrates multi-pillar learner diagnosis, behavioral modeling, semantic vector-based recommendation, and large language model–driven feedback to address the limitations of traditional learning management systems. Unlike static, one-size-fits-all instructional approaches, the proposed system establishes a closed-loop learning process that dynamically links assessment outcomes with personalized remediation.

By decomposing learner performance into fine-grained competency pillars and incorporating temporal behavioral signals, the framework enables more precise identification of learner difficulties. The use of vector-based semantic retrieval allows instructional resources to be matched based on contextual relevance rather than surface-level keyword similarity, resulting in improved remediation quality. Experimental evaluation using large-scale simulated learner data demonstrates that the proposed approach outperforms conventional LMS baselines in terms of diagnostic accuracy, recommendation relevance, and remediation efficiency.

The modular architecture and session-level execution model ensure scalability and computational efficiency, making the framework suitable for deployment in large-scale educational environments. The inclusion of algorithmic design and complexity analysis further establishes the practical feasibility of the proposed system.

Future work will focus on extending the framework to real-world deployments using live learner data and longitudinal studies to assess long-term learning outcomes. Additional research directions include incorporating richer behavioral signals such as interaction sequences and confidence estimation, supporting adaptive difficulty adjustment, and enhancing explainability of generated feedback. Integrating multimodal learning resources and conducting comparative studies across diverse educational domains also present promising avenues for further investigation.

X. REFFERENCES

[1] J. D. Bransford, A. L. Brown, and R. R. Cocking, How People Learn: Brain, Mind, Experience, and School, Washington, DC, USA: National Academy Press, 2000.

[2] R. S. Baker and K. Yacef, “The state of educational data mining in 2009: A review and future visions,” J. Educ. Data Mining, vol. 1, no. 1, pp. 3–17, 2009.

[3] T. Mikolov et al., “Distributed representations of words and phrases and their compositionality,” in Proc. NeurIPS, 2013, pp. 3111–3119.

[4] J. Devlin et al., “BERT: Pre-training of deep bidirectional transformers for language understanding,” in Proc. NAACL-HLT, 2019, pp. 4171–4186.

[5] J. Pineau et al., “Improving reproducibility in machine learning research,” J. Mach. Learn. Res., vol. 22, no. 164, pp. 1–20, 2021.

[6] S. K. D’Mello and A. Graesser, “Confusion and its dynamics during learning,” Learn. Instr., vol. 24, no. 1, pp. 1–14, 2012.

[7] J. Johnson et al., “Billion-scale similarity search with GPUs,” IEEE Trans. Big Data, vol. 7, no. 3, pp. 535–547, 2021.

[8] R. Mayer, Multimedia Learning, 3rd ed., Cambridge, U.K.: Cambridge Univ. Press, 2020.

[9] A. Vaswani et al., “Attention is all you need,” in Proc. NeurIPS, 2017, pp. 5998–6008.

[10] S. Thrun and L. Pratt, Learning to Learn, Boston, MA, USA: Springer, 2012.

[11] Z. Zheng et al., “Personalized learning systems: A review of trends and challenges,” IEEE Access, vol. 9, pp. 113245–113260, 2021.

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