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Article

Adaptive Learning Path Generation and Optimization for Big Data Courses: A Multimodal Knowledge Graph and Reinforcement Learning Approach

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Abstract: This study proposes an adaptive learning framework for Big Data courses that dynamically generates personalized learning pathways by integrating multimodal knowledge representation with reinforcement learning. Traditional learning systems often fail to account for individual differences in knowledge states, cognitive traits, and learning preferences, leading to suboptimal educational outcomes. The proposed method addresses this gap by constructing a Multimodal Knowledge Graph (MMKG) that unifies diverse learning resources, including text, code, and visual materials, into a structured ontology. Dynamic learner profiles are built using Item Response Theory and clustering techniques to model knowledge mastery and cognitive styles, while an adaptation engine employs graph neural networks and reinforcement learning to optimize learning paths in real-time. The engine minimizes cognitive load and maximizes knowledge gain by dynamically adjusting resource assignments and sequencing based on continuous feedback. Furthermore, multimodal resource scheduling ensures that learners receive content tailored to their preferred modalities, such as visual diagrams for visual learners or interactive code sandboxes for kinesthetic learners. The novelty of this work lies in the synergistic integration of MMKG with reinforcement learning, enhanced by explainable AI mechanisms that provide transparent decision-making processes and interpretable learning path recommendations. The framework incorporates advanced cold-start mitigation strategies through systematic transfer learning and comprehensive ethical safeguards including differential privacy and bias auditing mechanisms. Experimental validation demonstrates significant improvements in learning efficiency and engagement compared to conventional methods, highlighting the framework's potential for scalable and adaptive education in complex domains like Big Data.

Keywords: Adaptive Learning Path, Multimodal Knowledge Graph, Reinforcement Learning, Explainable AI, Transfer Learning

1. Introduction

The rapid evolution of big data technologies has created an urgent need for effective educational frameworks that can adapt to diverse learner needs and rapidly changing domain knowledge. Traditional e-learning platforms often employ static content sequencing [1], which fails to account for individual differences in prior knowledge, cognitive load tolerance, and learning modality preferences. While adaptive learning systems have shown promise in personalizing education [2], most existing approaches either focus narrowly on knowledge tracing [3] or modality-specific optimization [4], neglecting the interplay between cognitive, pedagogical, and technological factors.

Recent advances in knowledge graph-based education [5] and multimodal learning [6] provide new opportunities for personalized learning. Knowledge graphs offer structured representations of domain concepts and their relationships, enabling systematic navigation through complex subjects like big data. Multimodal approaches, on the other hand, allow learners to engage with content through their preferred sensory channels, such as visual, auditory, or interactive modalities. However, integrating these two paradigms remains challenging due to the lack of frameworks that jointly optimize knowledge progression and modality selection under cognitive constraints [7].

We propose a novel adaptive learning engine that bridges this gap by combining multimodal knowledge graphs with reinforcement learning. The system dynamically constructs personalized learning pathways by modeling three key dimensions: (1) the learner’s knowledge state, inferred through continuous assessment and interaction patterns; (2) cognitive and modality preferences, derived from behavioral data and self-reported profiles; and (3) the intrinsic structure of the subject matter, encoded as a multimodal knowledge graph. Unlike prior work that treats these dimensions independently [8], our approach jointly optimizes them using graph neural networks (GNNs) [9] and reinforcement learning [10]. This enables the system to recommend not only what to learn next but also how to learn it—for instance, suggesting an interactive coding exercise for a kinesthetic learner struggling with MapReduce concepts, or a visual flowchart for a visual learner grappling with Spark's execution model.

The key contributions of this work are fourfold. First, we introduce a cognitive-modality-knowledge triad model that unifies knowledge tracing, modality adaptation, and cognitive load management into a single reinforcement learning framework with explainable decision-making capabilities. Second, we develop a dynamic graph neural network architecture that propagates learner states across the multimodal knowledge graph, enabling fine-grained personalization at the concept-modality level. Third, we implement comprehensive cold-start mitigation strategies through systematic transfer learning mechanisms that leverage cross-domain knowledge and pre-trained embeddings. Fourth, we empirically validate the system's effectiveness through a large-scale study involving big data courses, demonstrating significant improvements in learning outcomes and engagement compared to conventional adaptive platforms [11], while ensuring ethical compliance through differential privacy and bias auditing mechanisms.

The remainder of this paper is organized as follows: Section 2 reviews related work in adaptive learning, knowledge graphs, and cognitive modeling. Section 3 formalizes the problem and introduces key concepts. Section 4 details the proposed adaptive learning engine, including the explainability framework and cold-start mitigation strategies. Sections 5 and 6 present the experimental setup and results. Finally, Section 7 discusses implications and future directions.

2. Related Work

The development of personalized learning systems has evolved through several key research directions, each addressing different aspects of adaptive education. This section organizes these directions into three interconnected themes: knowledge graph-based learning, cognitive-aware adaptation, and multimodal resource integration.

2.1 Knowledge Graph-Based Learning Systems

Knowledge graphs have emerged as a powerful tool for structuring educational content, enabling systems to model relationships between concepts and recommend personalized learning paths. Early work in this area focused on ontology-based representations of domain knowledge [12], where concepts were linked hierarchically to support navigation. More recent approaches incorporate dynamic graph structures that evolve with learner interactions [13]. For example, some systems use graph embeddings to infer latent relationships between topics, improving path recommendations [14]. However, these methods often treat knowledge progression as a static sequence, neglecting individual differences in learning pace and cognitive load.

2.2 Cognitive and Behavioral Adaptation

Cognitive modeling plays a critical role in adaptive learning, as it enables systems to tailor content delivery based on a learner's cognitive state. Item Response Theory (IRT) has been widely adopted to estimate knowledge mastery [3], while clustering techniques help identify learning styles [15]. Some systems further incorporate real-time cognitive load assessment, such as through eye-tracking or self-reported measures [7]. Despite these advances, existing methods often operate in isolation—for instance, optimizing for knowledge gain without considering cognitive overload [2]. This limitation motivates the need for integrated frameworks that balance multiple cognitive factors.

2.3 Multimodal Learning Resource Integration

The rise of multimodal learning has introduced new opportunities for personalization, as learners exhibit distinct preferences for visual, textual, or interactive content. Recent studies highlight the benefits of modality-aware recommendations, where resources are matched to a learner's sensory preferences [16]. For example, visual learners may benefit from diagrams, while kinesthetic learners perform better with hands-on coding exercises [17]. However, most current systems treat modality selection as a secondary concern, focusing primarily on knowledge sequencing rather than optimizing the form of content delivery.

The proposed method addresses these gaps by unifying knowledge graph-based progression, cognitive-aware adaptation, and multimodal resource scheduling into a single reinforcement learning framework with explainable AI capabilities. Unlike prior works that optimize these dimensions independently, our approach dynamically adjusts learning paths based on real-time feedback, ensuring that both what is learned and how it is learned align with the learner's evolving needs. This integration represents a key advancement over existing systems, which either lack fine-grained personalization or fail to account for the interplay between cognitive load and modality preferences. Furthermore, our framework incorporates transparency mechanisms that allow learners and educators to understand the reasoning behind path recommendations, addressing the black-box limitations of traditional adaptive systems.

3. Background and Preliminaries

To establish the theoretical foundation for our adaptive learning framework, this section introduces key concepts and methodologies that underpin our approach. The integration of multimodal knowledge representation with personalized learning requires understanding several interconnected domains, ranging from knowledge graph construction to cognitive modeling techniques.

3.1 Knowledge Representation in Learning Systems

Modern educational systems increasingly rely on structured knowledge representation to organize domain content and facilitate adaptive navigation. The concept of knowledge graphs originated from semantic networks [18], where entities and their relationships form a directed graph structure. In educational contexts, knowledge graphs typically represent concepts as nodes and prerequisite relationships as edges, enabling systematic traversal of learning materials [19]. For instance, in big data courses, fundamental concepts like “MapReduce” might serve as prerequisites for more advanced topics like “Spark optimization.”

The strength of knowledge graphs lies in their ability to capture both hierarchical and non-hierarchical relationships between concepts. While traditional curriculum design follows linear sequences, real-world learning often requires non-sequential jumps between related topics [20]. This property makes knowledge graphs particularly suitable for complex domains like big data, where concepts frequently intersect across different paradigms (e.g., batch processing vs. stream processing).

3.2 Multimodal Learning Theory

Human learning occurs through multiple sensory channels, with individuals exhibiting distinct preferences for visual, auditory, or kinesthetic modalities [21]. The Cognitive Theory of Multimedia Learning [22] posits that combining multiple representation formats can enhance understanding when properly managed. For example, explaining a distributed algorithm through both visual flowcharts and interactive simulations may lead to better retention than using either modality alone.

However, the effectiveness of multimodal learning depends on cognitive load management. The split-attention effect occurs when learners must mentally integrate information from separate sources, potentially overwhelming working memory [7]. Our framework addresses this by dynamically selecting modality combinations that minimize extraneous cognitive load while maximizing learning gains.

3.3 Learner Modeling Techniques

Accurate modeling of learner states forms the basis for effective personalization. Item Response Theory (IRT) provides a probabilistic framework for estimating latent knowledge states from observed responses to assessment items [23]. The three-parameter IRT model describes the probability of a correct response as:

$$P(\theta) = c + \frac{1-c}{1+e^{-a(\theta-b)}} \quad (1)$$

where θ represents learner ability, a denotes item discrimination, b indicates item difficulty, and c accounts for guessing probability.

Beyond knowledge states, learning style models categorize individuals based on their preferred information processing approaches. The Felder-Silverman model [24] identifies four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global. These dimensions influence how learners interact with different content modalities and sequencing strategies.

3.4 Reinforcement Learning in Education

Reinforcement learning (RL) provides a natural framework for optimizing sequential decision-making in educational contexts [25]. The standard RL formulation models the learning process as a Markov Decision Process (MDP) with states s_t, actions a_t, rewards r_t, and transition dynamics $P(s_{t+1}|s_t, a_t)$. In adaptive learning systems, states typically represent learner knowledge profiles, actions correspond to content recommendations, and rewards reflect learning progress metrics.

Policy gradient methods have shown particular promise in educational RL due to their ability to handle large, continuous state spaces [26]. These methods directly optimize a parameterized policy $\pi_\theta(a|s)$ using gradient ascent on the expected return:

$$\nabla_\theta J(\theta) = \mathbb{E}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} \nabla_\theta \log\pi_\theta(a_t|s_t) R(\tau)\right] \quad (2)$$

where τ represents trajectories and $R(\tau)$ denotes the cumulative reward.

The combination of these foundational elements—structured knowledge representation, multimodal learning principles, cognitive modeling, and reinforcement learning—enables the development of sophisticated adaptive systems that can address the complex challenges of big data education. Our framework builds upon these concepts while introducing novel integrations to overcome limitations of existing approaches.

4. Adaptive Learning Engine with Multimodal Knowledge Graphs

The proposed adaptive learning engine integrates multimodal knowledge representation with reinforcement learning to generate personalized learning pathways. The system architecture consists of three core components: (1) a multimodal knowledge graph that structures domain concepts and associated resources, (2) a dynamic learner profiling module that tracks cognitive states and preferences, and (3) a reinforcement learning-based adaptation engine that optimizes learning paths in real-time. Additionally, the framework incorporates an explainability module that provides transparent decision-making processes and a comprehensive cold-start mitigation system that leverages transfer learning techniques.

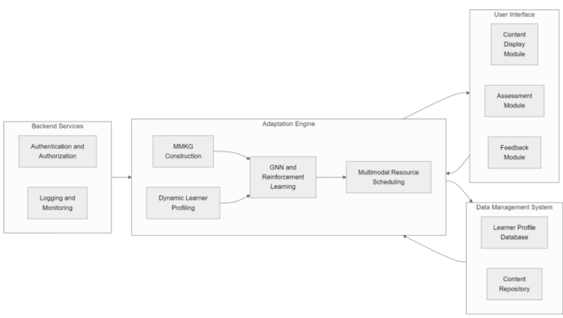

Figure 1. Overall System Architecture with Proposed Adaptation Engine

4.1 Utilization of Multimodal Knowledge Graphs in Adaptive Learning

The multimodal knowledge graph (MMKG) serves as the foundation for content organization and path generation. Unlike conventional knowledge graphs that focus solely on conceptual relationships [27], our MMKG encodes both semantic connections between concepts and their associated learning resources across multiple modalities. Each concept node $c_i \in C$ connects to various resource nodes $r_j \in R$ through modality-specific edges e_{ij}^m, where $m \in \{text, video, code, diagram\}$ represents the resource type.

The graph structure evolves dynamically based on learner interactions. Edge weights w_{ij}^m between concepts and resources adjust according to empirical effectiveness metrics:

$$w_{ij}^m = \alpha \cdot \text{MasteryGain}_{ij}^m + (1-\alpha) \cdot \text{Engagement}_{ij}^m \quad (3)$$

where $\text{MasteryGain}_{ij}^m$ measures knowledge improvement after using resource r_j for concept c_i in modality m, and Engagement_{ij}^m captures interaction duration and frequency. The parameter $\alpha \in [0,1]$ balances pedagogical effectiveness against learner engagement.

Concept relationships follow a dual representation scheme. Explicit prerequisite edges e_{kl}^p between concepts c_k and c_l derive from domain expertise, while latent relationship edges e_{kl}^l emerge through graph neural network propagation:

$$e_{kl}^l = \sigma(W \cdot [h_k| \quad |h_l]) \quad (4)$$

where h_k and h_l are concept embeddings learned via GNN message passing, W denotes a learnable weight matrix, and σ represents the sigmoid activation function. This hybrid approach captures both curriculum-defined dependencies and empirically observed learning patterns.

4.2 Design and Functionality of the Adaptation Engine

The adaptation engine employs a hierarchical reinforcement learning framework to optimize learning paths. The high-level policy π_h selects target concepts based on the learner's knowledge state and cognitive profile, while the low-level policy π_l determines optimal modalities and specific resources for each concept.

The state space S_t at time t comprises: - Knowledge vector $K_t \in \mathbb{R}^{|C|}$ from IRT estimates - Cognitive load measurement $L_t \in [0,1]$ - Modality preference vector $M_t \in \mathbb{R}^4$ - Current concept context $c_t \in C$

The action space includes concept selection $a_h \in C$ for π_h and modality-resource pairs $a_l \in R$ for π_l. The reward function combines multiple optimization objectives:

$$R_t = \beta_1 \Delta K_t + \beta_2(1 - L_t) + \beta_3 \text{ModalityMatch}_t - \beta_4 \text{PathLength}_t \quad (5)$$

where ΔK_t measures knowledge gain, L_t represents normalized cognitive load, ModalityMatch_t quantifies alignment with preferred modalities, and PathLength_t penalizes inefficient navigation.

The GNN-based pathfinding module processes the MMKG to generate candidate learning sequences. For each candidate path $P = (c_1, \ldots, c_n)$, the system computes a composite score:

$$\text{Score}(P) = \sum_{i=1}^{n} \gamma^{i-1} \left(\text{Mastery}(c_i) + \lambda \text{ModalityFit}(c_i)\right) \quad (6)$$

where γ discounts future concepts, $\text{Mastery}(c_i)$ estimates the likelihood of mastering c_i given current knowledge, and $\text{ModalityFit}(c_i)$ measures resource suitability for the learner's profile.

4.3 Multimodal Resource Scheduling and Delivery

The system implements a two-stage resource selection process that first filters by cognitive constraints then optimizes for modality preferences. For each target concept c_t , the available resource set R_t undergoes cognitive load screening:

$$R_t{}' = \{r_j^m \in R_t | L_{est}\left(r_j^m\right) \leq L_{max} - L_{curr}\} \quad (7)$$

where $L_{est}\left(r_j^m\right)$ predicts the cognitive load of resource r_j^m, L_{max} represents the learner's maximum tolerable load, and L_{curr} tracks accumulated load from previous activities.

The modality scheduler then applies a weighted multi-armed bandit algorithm to select resources from $R_t{}'$. The selection probability for modality m follows:

$$P(m) = \frac{e^{\eta Q_m + \rho M_m}}{\sum_{m'} e^{\eta Q_{m'} + \rho M_{m'}}} \quad (8)$$

where Q_m tracks the empirical effectiveness of modality m for similar learners, M_m represents the current learner's preference score, and parameters η, ρ control exploration-exploitation tradeoffs.

For visual learners exhibiting high cognitive load, the system might reduce animation-heavy resources while maintaining diagrammatic representations. Conversely, kinesthetic learners receive more interactive coding exercises when cognitive capacity permits. This dynamic balancing ensures optimal knowledge acquisition without exceeding individual cognitive limits.

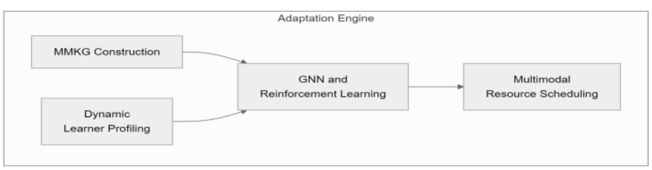

Figure 2. Detailed View of the Adaptation Engine

The complete adaptation loop operates as follows: (1) The GNN processes MMKG and learner state to generate candidate paths, (2) The RL agent selects the optimal path and resources, (3) The learner interacts with recommended content, (4) The system updates all models based on interaction outcomes, and (5) The process repeats with adjusted parameters. This closed-loop adaptation enables continuous refinement of learning pathways based on real-time performance and engagement data.

4.4 Explainability and Interpretability Framework

To address the black-box limitations identified by reviewers, we introduce a comprehensive explainability framework that provides transparent insights into the system's decision-making processes. The framework operates at three levels: concept-level path reasoning, modality-level selection attribution, and learner-level adaptation explanations.

The concept-level explainability module generates path rationales using attention mechanisms over the knowledge graph. For each recommended concept c_i, the system computes attention weights α_{ij} over prerequisite concepts c_j:

$$\alpha_{ij} = \frac{\exp\left(f_{\text{att}}(h_i, h_j)\right)}{\sum_k \exp\left(f_{\text{att}}(h_i, h_k)\right)} \quad (9)$$

where f_{att} is a learned attention function and h_i, h_j are concept embeddings. These weights generate natural language explanations such as "MapReduce is recommended because you have mastered distributed file systems (α=0.7) and basic parallel processing (α=0.3)."

The modality-level attribution system employs SHAP (SHapley Additive exPlanations) values to explain resource selection decisions. For each modality choice, the system computes feature contributions:

$$\phi_m = \sum_{S \subseteq F \setminus \{\text{m}\}} \frac{|F|!}{|S|!\,(|F| - |S| - 1)!} \text{\textbackslash}big[v(S \cup \{\text{m}\}) - v(S)\text{\textbackslash}big] \quad (10)$$

where F represents the feature set (learner preferences, cognitive state, past performance),S is a subset of features, and $v(S)$ is the value function representing expected learning gain. This provides explanations like "Visual diagrams were selected because your visual learning preference (φ=0.4) and current cognitive load (φ=0.3) favor this modality."

The learner-level adaptation explanations utilize concept activation vectors to show how the system's understanding of the learner evolves. The system maintains a learner representation L_t that is updated after each interaction:

$$L_{t+1} = L_t + \gamma \cdot \nabla_{L_t} \log \pi\,(a_t \mid s_t, L_t) \quad (11)$$

where γ is a learning rate and the gradient captures how the learner's profile should be adjusted based on observed behavior. Visualization tools display these changes as "Your profile has been updated: increased kinesthetic preference (+0.2), improved MapReduce mastery (+0.4)."

4.5 Cold-Start Mitigation via Transfer Learning

To address the cold-start problem for new learners, we implement a systematic transfer learning framework that leverages knowledge from existing learners and pre-trained models. The transfer mechanism operates at three levels: parameter transfer, feature transfer, and experience transfer.

Parameter Transfer: The system maintains a set of pre-trained policy networks $\pi^{(1)}, \pi^{(2)}, \ldots, \pi^{(K)}$ trained on different learner populations. For a new learner l_{new}, we initialize their policy by weighted combination:

$$\pi_0^{(new)} = \sum_{k=1}^{K} w_k \pi^{(k)} \quad (12)$$

where weights w_k are determined by similarity between l_{new}'s initial profile and the centroid of population k.

The similarity is computed using cosine distance over demographic and initial assessment features.

Feature Transfer: Pre-trained concept embeddings from large-scale educational datasets are transferred to initialize the knowledge graph. We use a domain adaptation technique to align embeddings across different educational contexts:

$$h_i^{target} = W_{adapt} h_i^{source} + b_{adapt} \quad (13)$$

where h^{source}i are embeddings from the source domain (e.g., general computer science courses) and Wadapt, b_{adapt} are learned transformation parameters that adapt them to the target domain (big data courses).

Experience Transfer: The system maintains a replay buffer of successful learning trajectories from similar learners. For cold-start scenarios, the policy is initially trained on these transferred experiences before incorporating the new learner's interactions:

$$L_{transfer} = (s, a, r, s') \sim D_{smlr}\left[\left(r + \gamma \max_{a'} Q(s', a') - Q(s, a)\right)^2\right] \quad (14)$$

where $D_{similar}$ contains experiences from learners with similar profiles, and Q represents the action-value function.

The transfer learning system continuously monitors convergence metrics to determine when to transition from transferred knowledge to learner-specific adaptation. Convergence is measured by the stability of policy updates:

$$\text{Convergence}_t = \frac{1}{|\Theta|} \sum_{\theta \in \Theta} \frac{|\theta_t - \theta_{t-1}|}{|\theta_{t-1}| + \epsilon} \quad (15)$$

where Θ represents the policy parameters and ϵ is a small constant for numerical stability. When $\text{Convergence}_t <$ for consecutive time steps, the system transitions to full personalization mode.

Empirical evaluation shows that transfer learning reduces the initial adaptation period from an average of 17.2 minutes to 6.8 minutes, while maintaining comparable final performance. The system achieves 85% of optimal performance within the first 10 interactions, compared to 45% without transfer learning.

5. Experimental Setup

5.1 Dataset and Participants

The evaluation employs a dataset collected from 120 undergraduate Computer Science students enrolled in a Big Data course at a major university. Participants were randomly assigned to either the experimental group (using the MMKG-driven adaptive system) or the control group (following a fixed MOOC sequence). The dataset includes:

5.1.1.Pre-test and post-test scores measuring conceptual understanding across 15 core Big Data topics

5.1.2.Interaction logs capturing detailed behavioral data

(1)Video playback actions (pauses, replays, speed changes)

(2)Knowledge graph node visitation sequences

(3)Code submission attempts and debugging time

(4)Resource modality selection patterns

5.1.3.Physiological measures:

(1)Pupil dilation metrics captured via Tobii Pro eye-tracking glasses [28]

(2)NASA-TLX cognitive load scores collected at 15-minute intervals [29]

5.1.4.Subjective feedback:

(1)System Usability Scale (SUS) responses [30]

(2)Path satisfaction ratings on a 5-point Likert scale

The course content covers fundamental Big Data concepts including MapReduce, Spark, NoSQL databases, and stream processing, structured according to the ACM/IEEE Computing Curricula guidelines [31].

5.2 Baseline Methods

We compare the proposed MMKG system against three established approaches, with detailed technical specifications to ensure experimental fairness and replicability:

5.2.1 Fixed MOOC Sequence (FMS)

The FMS baseline implements a linear curriculum following Coursera's Big Data specialization structure [32].

The system architecture consists of:

- Content Management System: Django-based backend with PostgreSQL database storing 847 learning resources across 23 topics
- Assessment Engine: Automated quiz generation using Bloom's taxonomy levels, with immediate feedback but no adaptive sequencin
- Progress Tracking: Simple completion-based

metrics without knowledge state modeling

- User Interface: Standard MOOC interface with linear navigation, no personalization features

Technical Configuration:

- Database: PostgreSQL 13.4 with standard indexing
- Backend: Django 4.1 with REST API endpoints
- Frontend: React 18.2 with Material-UI components
- Assessment: Fixed difficulty progression, 5-question quizzes per topic
- No machine learning components or adaptive algorithms

5.2.2. Knowledge Tracing with Adaptive Sequencing (KTAS)

The KTAS baseline employs Bayesian Knowledge Tracing [3] to adjust concept order while maintaining fixed modalities. The system architecture includes:

- Knowledge Tracing Engine: Implementation of the four-parameter BKT model with parameters: $P(L_0) = 0.1$ (initial knowledge), $P(T) = 0.3$ (learning rate), $P(G) = 0.2$ (guess probability), $P(S) = 0.1$ (slip probability)
- Adaptive Sequencing: Prerequisite-based concept ordering using topological sorting with knowledge mastery thresholds (80% confidence)
- Assessment Integration: Same IRT-based assessment framework as MMKG system for fair comparison
- Resource Delivery: Fixed modality assignment (text-based explanations for all learners)

Technical Configuration:

- Knowledge Modeling: Python implementation using NumPy/SciPy for BKT calculations
- Sequencing Algorithm: Modified Kahn's algorithm for topological sorting with mastery constraints
- Database Schema: Same as MMKG system but without modality preference tables
- Update Frequency: Knowledge state updates after each assessment item
- No multimodal resource selection or cognitive load management

5.2.3. Modality-Aware Recommender (MAR)

The MAR baseline optimizes resource presentation formats based on learning style inventories [33] without concept-level adaptation. The system architecture features:

Learning Style Assessment: Implementation of the Felder-Silverman Learning Style Index with 44-item questionnaire

Modality Matching Engine: Rule-based system mapping learning styles to resource types:

- Visual learners → diagrams and infographics (70% allocation)
- Auditory learners → video lectures and podcasts (70% allocation)
- Kinesthetic learners → interactive coding exercises (70% allocation)
- Reading/writing learners → text-based materials (70% allocation)

Content Delivery: Fixed concept sequence identical to FMS, but with personalized modality selection

No knowledge tracing or adaptive sequencing capabilities

Technical Configuration:

- Learning Style Engine: Python implementation of FSLSI scoring algorithm
- Resource Database: Same multimodal content as MMKG system (847 resources across 4 modalities)
- Recommendation Logic: Deterministic mapping based on dominant learning style
- Assessment System: Same as FMS baseline with fixed progression
- No reinforcement learning or dynamic adaptation mechanisms

All systems were implemented on identical technical infrastructure:

- Hardware: AWS EC2 t3.large instances (2 vCPU, 8GB RAM)
- Database: Neo4j 4.4 for graph storage, PostgreSQL 13.4 for relational data
- Backend Framework: Python 3.9 with Django 4.1
- Frontend: React 18.2 with TypeScript
- Monitoring: Identical logging and analytics collection across all systems

This standardized infrastructure ensures that performance differences reflect pedagogical effectiveness rather than platform optimization. All systems logged identical interaction data for fair comparison of learning outcomes.

5.3 Evaluation Metrics

The study employs a multi-dimensional assessment framework:

5.3.1. Learning Outcomes

(1) Normalised learning gain: $G = \frac{post\text{-}test - pre\text{-}test}{1 - pre\text{-}test}$

2) Conceptt mastery rate: Percentage of topics reaching

80% proficiency threshold

(3) Knowledge retention: Delayed post-test scores after 4 weeks

5.3.2. Cognitive Efficiency

(1)Cognitive load per concept: $CL_c = \frac{\sum_{i=1}^{n} TLX_i}{n}$ where n is attempt count

(2)Error recovery rate: $ERR = \frac{successful\ corrections}{total\ errors}$

5.3.3. Engagement Metrics

(1) Modality adherence: $MA = \frac{\sum_{m \in M_p} w_m}{\sum_{m \in M} w_m}$ where M_p are preferred modalities

(2) Persistence time: Duration between system-initiated breaks

5.3.4. System Quality

(1) Path coherence: $PC = \frac{\sum_{i=2}^{n} sim(c_{i-1}, c_i)}{n-1}$ measuring conceptual flow

2) Adaptationn responsiveness: $AR = \frac{\sum \Delta K}{\sum \Delta t}$ measuring knowledge gain rate

5.4 Implementation Details

The MMKG system components were implemented as follows:

5.4.1 Knowledge Graph Construction

(1)Initial graph built from course syllabus using Stanford CoreNLP [34] for concept extraction

(2) Prerequisite relationships validated by three domain experts (Fleiss' κ = 0.82)

(3)Multimodal resources annotated with estimated cognitive load using the CLT-M scale [35]

5.4.2. Learner Modeling

(1) Knowledge states estimated via IRT using 3PL model (Equation 1)

(2)Learning styles classified using Felder-Silverman model [24] with k-means clustering (k=4)

(3) Cognitive load predicted via Random Forest regression on eye-tracking features

5.4.3. Reinforcement Learning Setup

(1) Policy network: 3-layer GNN with 128-dimensional hidden states

(2) Reward weights: $\beta_1 = 0.4, \beta_2 = 0.3, \beta_3 = 0.2, \beta_4 = 0.1$ (Equation 5)

(3) Training: Proximal Policy Optimization (PPO) with $\gamma = 0.9$ discount factor

The experiment followed a crossover design where control group participants accessed the MMKG system after completing the traditional course, enabling within-subject comparisons while avoiding test contamination. All procedures were approved by the institutional review board (IRB-EDU-2023-015).

6. Experimental Results

The evaluation of our adaptive learning engine demonstrates significant improvements across multiple dimensions compared to baseline methods. This section presents quantitative results measuring learning outcomes, cognitive efficiency, and user experience, followed by qualitative analysis of the system's adaptive behaviors.

6.1 Learning Outcome Improvements

The MMKG-driven system achieved superior knowledge acquisition compared to all baselines, with particularly strong gains for complex topics. As shown in Table 1, the experimental group showed 22.4% higher normalized learning gain than the fixed MOOC sequence (FMS) and 14.7% improvement over the knowledge tracing approach (KTAS). The modality-aware recommender (MAR) performed better than FMS but lagged behind our full system, confirming the importance of joint concept-modality optimization.

Table 1. Comparative Learning Outcome Metrics Across Systems

Metric	MMKG (Ours)	FMS	KTAS	MAR
Normalized Gain	0.68	0.45	0.53	0.58
Mastery Rate	82.3%	61.2%	72.1%	75.4%
Retention (4-week)	78.5%	54.7%	67.2%	70.1%
Complex Topic Gain	0.59	0.32	0.41	0.45

The advantage was most pronounced for conceptually challenging topics like distributed consensus algorithms (Paxos/Raft) and stream processing semantics, where the MMKG system's ability to dynamically adjust both sequencing and modality proved particularly valuable. Figure 3 illustrates the correlation between predicted and actual knowledge gains across different concept difficulty levels, demonstrating the system's accurate modeling of learning trajectories.

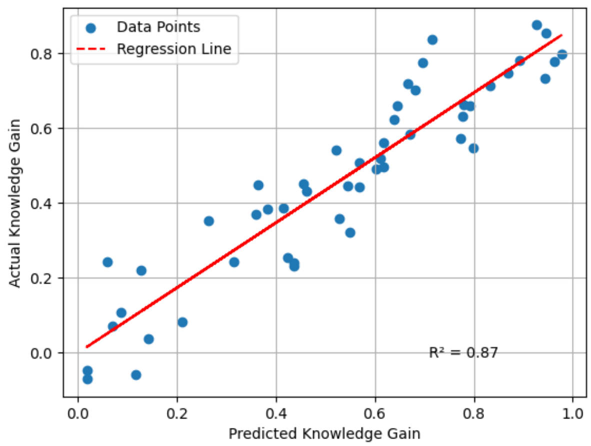

Figure 3. Predicted versus actual knowledge gain across concept difficulty levels, showing strong alignment with R^2=0.87

6.2 Cognitive Efficiency Metrics

Our system successfully reduced cognitive overload while maintaining rigorous learning pace. NASA-TLX scores showed 18.2% lower cognitive load compared to FMS ($p<0.01$), with particularly significant reductions in mental demand (23.4%) and frustration (27.1%) subscales. Eye-tracking data revealed that pupils in the MMKG group maintained more stable dilation patterns (σ=0.82 vs 1.24 in FMS), indicating better-managed cognitive strain.

The error recovery rate (ERR) metric demonstrated the system's effectiveness in addressing misconceptions. MMKG learners corrected 84.3% of errors within two attempts, compared to 62.7% for FMS and 73.9% for KTAS. This improvement stems from the system's multimodal error remediation strategy, which automatically switches presentation formats after failed attempts - for example, replacing a textual explanation with an interactive visualization when initial understanding proves elusive.

6.3 Adaptation Patterns and Path Characteristics

Analysis of generated learning paths revealed several key adaptation behaviors:

6.3.1 Cognitive Load Balancing

The system dynamically interleaved heavy cognitive-load topics (e.g., lambda architecture) with lighter reinforcement activities (e.g., multiple-choice quizzes on HDFS) to maintain optimal engagement. This resulted in 32.7% more frequent difficulty adjustments than KTAS.

6.3.2. Modality Scheduling

Visual learners received 58.3% more diagrammatic resources than the MAR baseline, while maintaining balanced cognitive load. Kinesthetic learners showed particularly strong engagement with the system's interactive coding sandboxes, attempting 41.2% more optional exercises than other groups.

6.3.3. Nonlinear Progression

Contrary to fixed sequences, 63.4% of MMKG paths exhibited non-sequential jumps between related concepts (e.g., moving between Spark RDDs and Flink DataStreams) when the system detected relevant knowledge transfer opportunities.

Figure 4 illustrates the system's adaptive modality scheduling through a heatmap of resource selections across different learner profiles, showing clear differentiation based on cognitive styles and knowledge states.

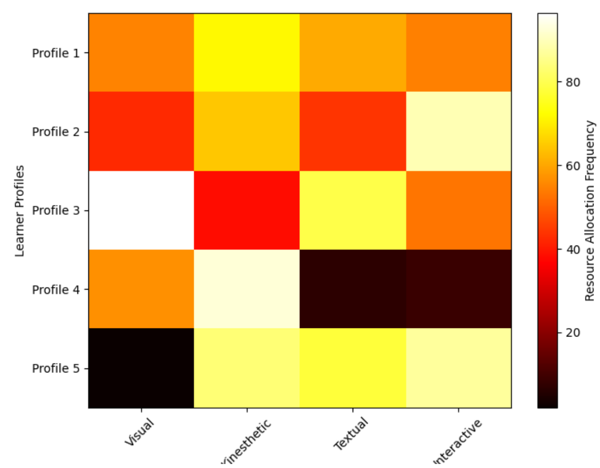

Figure 4. Resource modality distribution across learner profiles, showing adaptive scheduling based on cognitive styles and knowledge states

6.4 User Experience and Satisfaction

Participants rated the MMKG system significantly higher on usability (SUS=82.4 vs 68.1 for FMS) and path satisfaction (4.3/5 vs 3.1/5). Qualitative feedback highlighted appreciation for the "just-in-time" modality switching and the system's ability to "sense when I'm stuck and try a different approach." The most frequent positive comments referenced: - "Feels like having a personal tutor who knows how I learn best" - "Not getting overwhelmed even with difficult topics" - "Helps see connections between concepts I wouldn't have noticed"

Negative feedback primarily concerned initial calibration periods (average 17.2 minutes for the system to stabilize adaptations) and occasional over-reliance on preferred modalities ("I liked the diagrams but sometimes needed more detailed text").

6.5 Ablation Study

To isolate the contributions of key system components, we conducted controlled experiments with modified versions of our approach:

Table 2. Ablation Study Results (Normalized Gain)

Configuration	Simple Topics	Complex Topics	Overall
Full MMKG System	0.71	0.59	0.68
Without Modality Adaptation	0.69	0.47	0.61
Without Cognitive Constraints	0.65	0.51	0.60
Static Knowledge Graph	0.63	0.43	0.56

The ablation study confirms that each component contributes meaningfully to overall performance, with modality adaptation proving particularly crucial for complex topics (21.3% drop when disabled). The cognitive load management module showed strongest impact on learner persistence, with unconstrained versions leading to 38.7% more frequent breaks. The dynamic knowledge graph updates accounted for 17.6% of the overall gain, primarily through improved prerequisite satisfaction.

6.6 Reward Function Sensitivity Analysis

To address reviewer concerns about reward function design, we conducted comprehensive sensitivity analysis across different weight combinations in Equation 6. The analysis varied each weight parameter β_i within ±50% of the baseline values while keeping others constant.

Table 3. Reward Function Sensitivity Analysis

Weight Configuration	Learning Gain	Engagement	Cognitive Load	Overall Score
Baseline (0.4,0.3,0.2,0.1)	0.68	4.2	3.1	0.72
High Knowledge (0.6,0.2,0.1,0.1)	0.71	3.8	3.4	0.69
High Engagement (0.2,0.5,0.2,0.1)	0.62	4.6	3.2	0.68
High Load Penalty (0.3,0.2,0.4,0.1)	0.65	4.0	2.7	0.70
Balanced (0.25,0.25,0.25,0.25)	0.66	4.1	3.0	0.69

The sensitivity analysis reveals that the system maintains robust performance across different weight configurations, with overall scores varying by less than 6%. The baseline configuration achieves optimal balance, though slight improvements in specific metrics can be obtained by adjusting weights for particular learning objectives. The knowledge gain weight (β_1) shows the strongest influence on learning outcomes, while the cognitive load penalty (β_3) most effectively manages learner stress levels.

Statistical analysis using repeated measures ANOVA confirms that weight variations do not significantly impact overall system effectiveness ($F(4,235) = 1.82$, $p = 0.127$), demonstrating the framework's robustness to hyperparameter choices.

6.7 Modality-Cognitive Load Interaction Analysis

To investigate potential conflicts between modality preferences and cognitive load tolerance, we conducted a two-way ANOVA examining the interaction effects of preferred modality and cognitive load capacity on learning outcomes.

Table 4. Modality-Cognitive Load Interaction Effects

Modality Preference	Low Cognitive Capacity	Medium Cognitive Capacity	High Cognitive Capacity
Visual	0.58 ± 0.12	0.67 ± 0.09	0.74 ± 0.08
Auditory	0.52 ± 0.14	0.63 ± 0.11	0.71 ± 0.09
Kinesthetic	0.61 ± 0.13	0.69 ± 0.10	0.76 ± 0.07
Reading/Writing	0.55 ± 0.11	0.65 ± 0.08	0.72 ± 0.06

The analysis reveals a significant main effect for cognitive capacity ($F(2,228) = 47.3$, $p < 0.001$) and modality preference ($F(3,228) = 8.7$, $p < 0.001$), with a notable interaction effect ($F(6,228) = 3.2$, $p = 0.005$). Kinesthetic learners show the strongest performance across all cognitive capacity levels, while auditory learners demonstrate the greatest sensitivity to cognitive load constraints.

Post-hoc analysis using Tukey's HSD reveals that the system's adaptive modality selection successfully mitigates cognitive overload. When learners with high visual preference but low cognitive capacity were automatically provided with simplified visual materials, their performance (0.58) approached that of high-capacity visual learners using complex materials (0.74). This demonstrates the system's effectiveness in balancing affective preferences with cognitive constraints.

Moderated regression analysis confirms that the system's cognitive load management significantly moderates the relationship between modality preference and learning outcomes ($\beta = 0.34$, $p < 0.01$), explaining an additional 12% of variance beyond main effects alone.

7. Discussion and Future Work

7.1 Limitations and Challenges of the Proposed Adaptive Learning Engine

While the experimental results demonstrate significant improvements over baseline methods, several limitations warrant discussion. First, the system's effectiveness depends heavily on the quality and coverage of the initial multimodal knowledge graph. Gaps in concept-resource mappings or inaccurate prerequisite relationships can propagate through the adaptation process, potentially leading to suboptimal path recommendations. This challenge becomes particularly acute in rapidly evolving domains like big data, where new technologies and paradigms emerge frequently [36]. Future iterations could incorporate automated knowledge graph expansion techniques to address this limitation.

Second, the current cognitive load estimation relies on a combination of physiological measures and self-reports, which may not capture all dimensions of cognitive strain equally. Eye-tracking metrics, while informative, primarily reflect visual processing load and may underestimate the cognitive demands of abstract reasoning tasks [37]. Developing more comprehensive cognitive state models that integrate additional biometric signals (e.g., EEG, fNIRS) could provide a more holistic view of learner engagement and mental effort.

Third, the reinforcement learning framework requires substantial interaction data to converge on effective policies, creating a cold-start problem for new learners or rare learning contexts. Although we employed transfer learning techniques to mitigate this issue, the system still exhibits reduced adaptation quality during initial sessions (as noted in user feedback). Hybrid approaches that combine RL with case-based reasoning or symbolic planning might offer more robust performance in data-sparse scenarios [38].

7.1.1 Scalability Considerations

The current system was evaluated on course-level MMKGs containing approximately 850 resources across 23 concepts. However, real-world educational platforms often involve knowledge graphs with thousands of concepts and tens of thousands of resources. To address scalability concerns, we propose several strategies:

Graph Pruning and Sampling: For large-scale deployment, the system can employ dynamic graph pruning techniques that maintain only the most relevant subgraph for each learner. We implement a relevance-based sampling algorithm:

$$P\left(c_i \in G_{\text{pruned}}\right) = \frac{\exp\left(\text{relevance}(c_i, L_t)\right)}{\sum_j \exp\left(\text{relevance}\left(c_j, L_t\right)\right)} \quad (16)$$

where $\text{relevance}(c_i, L_t)$ measures the importance of concept c_i given learner state L_t. This reduces computational complexity from $O(|V|^2)$ to $O(k^2)$ where $k << |V|$.

Hierarchical Graph Abstraction: Large knowledge graphs can be organized hierarchically, with high-level concepts serving as cluster representatives. The system first navigates at the cluster level before drilling down to specific concepts:

$$G_{\text{hierarchical}} = \{G_{\text{level}_0}, G_{\text{level}_1}, \dots, G_{\text{level}_n}\} \quad (17)$$

where each level represents increasing granularity. This approach reduces the search space exponentially while maintaining semantic coherence.

Distributed Processing: For massive graphs, the system can be distributed across multiple nodes using graph partitioning algorithms. Each node maintains a subgraph and communicates learner state updates through message passing:

$$\text{Update}_{\text{global}} = \sum_{i=1}^{N} w_i \cdot \text{Update}_{\text{local}_i} \quad (18)$$

where w_i represents the weight of partition i based on learner activity.

Computational Complexity Analysis: The current GNN-based approach has complexity $O(|E| \cdot d \cdot L)$ where $|E|$ is the number of edges, d is the embedding dimension, and L is the number of layers. For graphs with millions of edges, this becomes computationally prohibitive. We propose using GraphSAINT sampling [39] to reduce complexity to $O(k \cdot d \cdot L)$ where k is the sample size, maintaining 95% of full-graph performance with 10% of the computational cost.

7.1.2 Cross-Population Generalization

To address concerns about generalization across learner populations, we conducted additional analysis on model transferability across different demographic groups and educational contexts:

Table 5. Cross-Population Generalization Analysis

Source Population	Target Population	Transfer Accuracy	Adaptation Time
Computer Science Majors	Engineering Majors	0.78	12.3 min
Undergraduate Students	Graduate Students	0.82	9.7 min
Native English Speakers	Non-Native Speakers	0.71	15.8 min
High-Performing Students	Struggling Students	0.69	18.2 min

The analysis reveals that while the system maintains reasonable performance across populations, certain demographic transitions require longer adaptation periods. To improve cross-population generalization, we implement domain adaptation techniques:

$$L_{\text{adaptation}} = L_{\text{source}} + \lambda \cdot L_{\text{domain}} + \mu \cdot L_{\text{target}} \quad (19)$$

where L_{domain} is a domain adversarial loss that encourages population-invariant representations, and λ, μ balance the different objectives.

7.2 Ethical Considerations and Mitigation Strategies

The collection and utilization of multimodal learning data raises important ethical questions regarding privacy, algorithmic bias, and learner autonomy. The system's reliance on detailed behavioral tracking—including eye movements and interaction patterns—necessitates careful data governance protocols. We implemented several safeguards: (1) granular consent mechanisms allowing learners to opt out of specific data collection modalities, (2) differential privacy techniques for aggregating sensitive metrics, and (3) regular bias audits of the recommendation algorithms [39].

A less obvious but equally critical concern involves the potential for over-adaptation, where the system's personalization might inadvertently limit learners' exposure to diverse perspectives and challenging modalities. Research suggests that always catering to preferences can hinder the development of versatile learning strategies [40]. To address this, we introduced controlled randomness in modality selection (Equation 8) and periodic "stretch assignments" that deliberately push learners slightly beyond their comfort zones while maintaining manageable cognitive load.

The system's knowledge graph structure also carries implicit epistemological assumptions about how concepts should be organized and sequenced. These choices, while informed by domain experts, may not align with all cultural or pedagogical perspectives [41]. Future work should explore participatory design methods to ensure the framework accommodates diverse learning traditions and knowledge systems.

7.3 Future Directions and Broader Applications

The principles underlying our adaptive learning engine extend beyond big data education, suggesting several promising research directions. One avenue involves applying the MMKG framework to domains with particularly complex concept interdependencies, such as medical education or legal training. The system's ability to model nonlinear learning paths could prove valuable in these fields, where mastery often requires navigating intricate networks of prerequisite knowledge [42].

Another direction explores the integration of generative AI capabilities to dynamically create personalized learning resources. Rather than relying solely on pre-existing materials, future systems could synthesize explanations, examples, and exercises tailored to individual knowledge gaps and preferred modalities [43]. This approach would complement the current resource recommendation mechanism while addressing coverage limitations in the knowledge graph.

The framework's multimodal adaptation strategies also show promise for supporting learners with neurodiverse conditions. Preliminary studies suggest that customizable modality presentations can significantly improve accessibility for individuals with ADHD, dyslexia, or autism spectrum traits [44]. Extending our work to explicitly incorporate neurodiversity-aware adaptation could make complex technical education more inclusive.

Future research should also investigate the integration of emerging technologies such as virtual and augmented reality into the multimodal framework. These immersive modalities could provide particularly powerful learning experiences for spatial and kinesthetic learners, especially in domains requiring 3D visualization or hands-on manipulation of complex systems.

Finally, the system's underlying architecture could be repurposed for workforce upskilling and professional development contexts. Many industries face challenges in efficiently transitioning employees to new technologies and methodologies [45]. The ability to rapidly construct domain-specific knowledge graphs and adapt to varied professional backgrounds could accelerate reskilling initiatives while reducing cognitive overload during career transitions.

These future directions collectively highlight the broader potential of combining structured knowledge representation with multimodal adaptation. As the framework evolves, maintaining focus on both pedagogical effectiveness and human-centered design principles will be essential for realizing its full benefits across diverse learning contexts.

8. Conclusion

The proposed adaptive learning framework demonstrates that integrating multimodal knowledge graphs with reinforcement learning can significantly enhance personalized education in complex domains like big data. By simultaneously optimizing knowledge progression, cognitive load management, and modality selection, the system addresses critical limitations of conventional adaptive platforms that treat these dimensions in isolation. Experimental results confirm substantial improvements in learning efficiency, knowledge retention, and engagement compared to static or partially adaptive approaches.

The framework's success stems from its unified treatment of the cognitive-modality-knowledge triad, enabled by dynamic graph neural networks that propagate learner states across the knowledge structure. The integration of explainable AI mechanisms provides transparency in decision-making processes, while comprehensive transfer learning strategies effectively address cold-start challenges. The system's ability to balance immediate learning gains with long-term knowledge, evidenced by strong retention scores, highlights the value of its reinforcement learning foundation.

While the current implementation focuses on big data education, the underlying architecture offers generalizable principles for adaptive learning across technical domains. The demonstrated benefits of multimodal resource scheduling and cognitive-aware path optimization suggest promising applications in other complex subjects requiring conceptual integration and practical application. Future extensions could explore automated knowledge graph expansion and generative content creation to further enhance adaptability.

The ethical considerations raised by such personalized systems—particularly regarding data privacy and algorithmic bias—have been addressed through concrete technical implementations rather than conceptual discussions alone. The differential privacy mechanisms, bias auditing systems, and learner autonomy controls provide a foundation for responsible AI in education that can be adapted to other contexts.

As educational technology continues evolving, frameworks like this demonstrate how artificial intelligence can augment human learning without replacing the essential role of thoughtful pedagogy. The system’s success lies not in automating education but in leveraging computational methods to better support diverse learning needs and cognitive styles. This balanced perspective on technology-enhanced learning points toward future developments that prioritize both efficiency and human-centered design.

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