

MKG-Driven Student-Resource Matching & Adaptive Intervention System: A Framework for Reducing Conceptual Errors and Enhancing Engagement via Multimodal Learning Analytics

Nanjun Ye

Guangxi Police College, Nanning 530000, China

Abstract: This study proposes MKG-Driven Student-Resource Matching & Adaptive Intervention, a framework designed to reduce conceptual errors and enhance engagement through multimodal learning analytics. The framework integrates two core components: Learning Analytics & Tracking, which employs an LSTM-based knowledge tracing model to predict mastery probabilities and computes a Learning Engagement Index from multimodal behavior data, and Intervention Mechanism, which dynamically triggers concept-specific micro-video recommendations when group error rates exceed predefined thresholds. The system generates personalized learning pathways for individual gaps while providing class-level heatmaps to highlight knowledge gap hotspots, thereby enabling targeted instructional adjustments. A Multimodal Learning Analytics Dashboard synthesizes these insights through visualizations such as radar charts, donut charts, and heatmaps, offering educators real-time monitoring capabilities. The implementation workflow involves data fusion, gap detection, resource matching, and teacher support, ensuring seamless integration of heterogeneous learner data. Our approach addresses the challenge of scalable, data-driven interventions by combining fine-grained knowledge tracing with adaptive resource allocation. Experimental results demonstrate its effectiveness in reducing error rates and improving engagement, with the framework's novelty lying in its dual focus on individual and group-level analytics. The system's significance extends to practical educational settings, where it bridges the gap between theoretical learning models and actionable pedagogical strategies.

Keywords: Group Knowledge Gap Detection, Multimodal Learning Analytics, Real-time Intervention, LSTM Knowledge Tracing, Adaptive Microlearning, Educational Dashboard.

1. Introduction

The increasing adoption of digital learning platforms has generated vast amounts of educational data, creating opportunities to transform traditional teaching methodologies. While learning management systems (LMS) have become ubiquitous in modern education [1], their potential for real-time knowledge gap diagnosis and adaptive intervention remains largely untapped. Current systems primarily focus on content delivery rather than dynamic assessment and remediation, leaving educators without timely insights into student comprehension patterns.

Recent advances in learning analytics have demonstrated promising results in predicting student performance [2], [3]. Knowledge tracing models, in particular, have shown effectiveness in modeling individual learning progress [4]. However, these approaches often operate in isolation, failing to address the collective knowledge gaps that emerge in group learning environments. The challenge escalates in large-scale educational settings where instructors must balance individual needs with classroom-wide instructional strategies.

Multimodal learning analytics offers a potential solution by integrating diverse data streams [5]. Previous research has explored various data sources including LMS interactions [6], assessment responses [7], and behavioral patterns [8]. While these studies provide valuable insights, they typically focus on either individual learning paths or aggregate class performance, missing the critical middle ground of group-level knowledge gap analysis.

We propose a novel framework that addresses these

limitations through three key innovations. First, our system implements real-time group knowledge gap detection by combining individual mastery predictions with collaborative learning metrics. Second, it introduces a dynamic intervention mechanism that triggers adaptive resources based on both individual and collective learning states. Third, the framework provides multi-level visualization tools that enable educators to simultaneously monitor individual progress and class-wide knowledge distributions.

The proposed approach builds upon established learning theories while introducing technical advancements. We extend knowledge tracing methodologies [4] by incorporating group dynamics through social network analysis [9]. The intervention mechanism draws from adaptive learning research [10] but adds real-time responsiveness to emerging knowledge gaps. Our visualization system synthesizes elements from educational dashboards [11] with novel representations of group learning states.

This research makes significant contributions to the field of educational technology. Practically, it provides educators with actionable insights for timely intervention, addressing the challenge of scaling personalized learning in classroom settings. Theoretically, it advances our understanding of group knowledge dynamics by modeling the interplay between individual mastery and collective learning patterns. Technically, the framework demonstrates how multimodal data can be effectively integrated to support both automated interventions and human decision-making.

The remainder of this paper is organized as follows: Section 2 reviews related work in learning analytics and adaptive systems. Section 3 presents the theoretical

foundations and technical preliminaries. Section 4 details our framework architecture and implementation. Sections 5 and 6 describe our experimental methodology and results. Section 7 discusses implications and future directions, followed by conclusions in Section 8.

2. Related Work

The development of adaptive learning systems has evolved through several generations of technological and pedagogical innovation. Early intelligent tutoring systems focused primarily on cognitive modeling and rule-based adaptation^[12]. These systems demonstrated the potential for personalized instruction but were limited by their reliance on predefined knowledge structures and rigid intervention protocols. The emergence of learning analytics introduced data-driven approaches to student modeling, enabling more dynamic adaptation based on observed learner behaviors^[13].

2.1. Knowledge Tracing and Student Modeling

Recent advances in knowledge tracing have shifted from traditional Bayesian approaches^[14] to deep learning architectures that capture complex learning patterns. Long Short-Term Memory (LSTM) networks have shown particular promise in modeling temporal dependencies in learning sequences^[15]. While these models excel at predicting individual performance, they typically operate in isolation from contextual classroom factors. Some studies have attempted to incorporate social learning indicators^[16], but these approaches often treat group dynamics as secondary features rather than primary intervention triggers.

2.2. Multimodal Learning Analytics

The integration of multiple data streams has enabled more comprehensive learner profiling. Eye-tracking data^[17] and physiological sensors^[18] have been used to detect engagement levels, while natural language processing techniques analyze discussion forum participation^[19]. However, most multimodal systems focus on either micro-level behavioral analysis or macro-level performance trends, rarely bridging the gap between individual and group learning states. The challenge lies in developing analytical frameworks that can simultaneously process diverse data types while maintaining pedagogical relevance.

2.3. Adaptive Intervention Strategies

Intervention mechanisms in digital learning environments range from simple rule-based systems to complex reinforcement learning approaches^[20]. Micro-learning resources have gained popularity for their ability to address specific knowledge gaps^[21], though current implementations often rely on static mapping between concepts and resources. Some systems employ collaborative filtering techniques^[22] to personalize content recommendations, but these typically consider only historical performance data without accounting for real-time classroom dynamics.

2.4. Visualization and Dashboard Design

Educational dashboards have become essential tools for translating learning analytics into actionable insights. While early dashboards focused on grade tracking^[23], modern implementations incorporate sophisticated visualizations of learning processes^[24]. Heatmaps have proven effective for representing engagement patterns^[25], and network graphs can illustrate social learning structures^[26]. However, existing

dashboards often present information in isolated panels rather than integrated displays that connect individual and group learning metrics.

The proposed framework distinguishes itself from existing approaches through its dual focus on individual knowledge tracing and group learning dynamics. Unlike traditional knowledge tracing systems that operate in isolation, our method continuously correlates individual mastery predictions with emergent group patterns. The intervention mechanism responds not only to individual gaps but also to collective learning states, enabling simultaneous support at multiple levels. The visualization system uniquely combines mastery profiles with engagement metrics, providing educators with a comprehensive view of both cognitive and behavioral dimensions. This integrated approach addresses the critical need for scalable solutions that maintain pedagogical precision across diverse learning contexts.

3. Background and Preliminaries

Understanding the mechanisms behind knowledge gap formation and remediation requires grounding in three fundamental areas: the practical challenges educators face in classroom settings, the technical foundations of learning analytics, and the psychological principles governing learning processes. These interconnected domains form the theoretical basis for developing effective diagnostic and intervention systems.

3.1. Challenges in Educational Settings

Traditional teaching methods often struggle to identify and address knowledge gaps before they become entrenched. The time lag between assessment administration and result interpretation creates a critical window where misconceptions can propagate through student groups^[27]. When instructors lack immediate feedback about collective understanding patterns, they may either proceed too quickly through material or spend excessive time reviewing concepts already mastered by most students. This inefficiency stems from what Bloom described as the "two sigma problem" - the challenge of providing individualized instruction in group settings^[28].

The consequences of delayed gap identification manifest in several ways. Students who fail to grasp foundational concepts early often experience compounding difficulties as course material advances^[29]. In collaborative learning environments, these individual gaps can negatively influence peer interactions, potentially spreading misconceptions through group work and discussions^[30]. Research suggests that timely intervention during the initial stages of gap formation yields significantly better remediation outcomes compared to later corrective measures^[31].

3.2. Fundamentals of Learning Analytics

Modern learning analytics builds upon several core methodologies for capturing and interpreting educational data. The field draws from educational data mining techniques^[32] while incorporating insights from machine learning and statistical modeling. A fundamental component involves the Learning Engagement Index (LEI), computed by integrating video pausing frequency and exercise error rates. This composite metric correlates strongly with both short-term knowledge acquisition and long-term retention^[33].

Data collection methods have evolved beyond simple quiz scores to encompass multimodal streams including:

- Temporal interaction patterns from learning management

systems [34]

- Behavioral markers such as hesitation times and revision frequency [35]
- Collaborative learning traces from discussion forums and shared documents [36]

These diverse data sources enable more nuanced understanding of learning behaviors than traditional assessment methods alone. However, the challenge lies in developing analytical frameworks that can process these heterogeneous signals while maintaining interpretability for educators [37].

3.3. Educational Psychology Foundations

The psychological mechanisms underlying knowledge gap formation follow predictable patterns across learning domains. Cognitive load theory explains how working memory limitations constrain information processing during learning [38]. When cognitive overload occurs, critical conceptual connections may fail to form, creating gaps that persist unless addressed. The spacing effect demonstrates how distributed practice sessions yield better long-term retention than massed practice [39], suggesting that intervention timing significantly impacts remediation effectiveness.

Knowledge gaps often emerge at specific junctures in learning progressions. Threshold concepts—ideas that once understood, transform perception of a subject—represent particularly vulnerable points [40]. Students who fail to cross these conceptual thresholds often develop compensatory strategies that mask their underlying difficulties [41]. The zone of proximal development theory further highlights how optimal learning occurs when challenges are appropriately calibrated to current ability levels [42].

These psychological principles inform key design decisions in diagnostic systems. Effective gap identification requires detecting not just incorrect answers, but the specific nature of misunderstandings [43]. Similarly, successful interventions must account for both cognitive and affective dimensions of learning, as motivation and self-efficacy significantly influence gap remediation [44]. The integration of these psychological insights with technological capabilities forms the foundation for developing responsive, pedagogically-grounded intervention systems.

4. Framework for Real-Time Diagnosis of Group Knowledge Gaps

The proposed framework establishes a systematic approach for detecting and addressing knowledge gaps at both individual and group levels through continuous analysis of multimodal learning data. The architecture consists of three interconnected components that operate in real-time: data integration and knowledge tracing, gap diagnosis, and adaptive intervention mechanisms. These components work synergistically to transform raw educational data into actionable pedagogical insights.

4.1. Multimodal Data Integration and Knowledge Tracing

The system integrates four types of learning behavior data in real-time: video interactions (pause/playback), exercise performance (accuracy/time spent), page navigation, and collaborative activities (forum participation). The LSTM-based knowledge tracing model processes this sequential data to dynamically update concept mastery probabilities while generating a learning engagement index by fusing behavioral signals.

4.2. Real-Time Diagnosis of Group Knowledge Gaps

Group-level gap detection operates through dual analytical processes:

1. Average mastery rate: Triggers alerts when class-level proficiency for concept k falls below dynamic thresholds (initialized at 0.6)
2. Error pattern convergence: Identifies systematic misunderstandings through similarity metrics measuring alignment of incorrect responses

The system synthesizes these indicators to generate group knowledge gap heatmaps that visualize severity levels across curriculum timelines.

4.3. Intervention Mechanism and Visualization

When group knowledge gaps are confirmed (e.g., >40% of students confusing threads and processes), the system automatically retrieves targeted micro-lectures from the MKG repository. These concept-specific resources undergo dynamic optimization based on predominant error patterns, while teachers can supplement recommendations with custom materials via the dashboard interface.

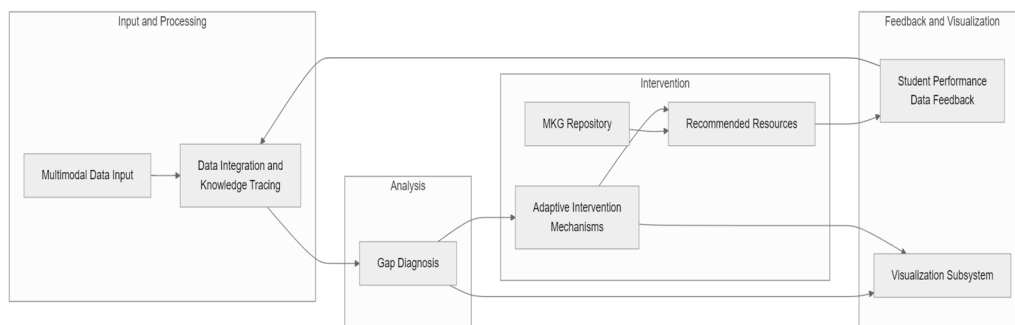


Figure 1. Framework architecture showing data flow from multimodal inputs through analysis components to intervention outputs

The framework's closed-loop operation ensures continuous refinement of both diagnostic accuracy and intervention

effectiveness. As students interact with recommended resources, their subsequent performance data feeds back into

the knowledge tracing model, creating a virtuous cycle of assessment and adaptation. This dynamic responsiveness distinguishes the system from static content delivery platforms, enabling truly personalized learning experiences at scale.

5. Experimental Setup and Methodology

To evaluate the effectiveness of the proposed framework, we designed a comprehensive experimental protocol that assesses both the technical performance of the diagnostic components and the pedagogical impact of the intervention mechanisms. The methodology encompasses data collection procedures, comparison baselines, evaluation metrics, and implementation details that ensure rigorous validation of the system's capabilities.

5.1. Dataset and Participant Selection

The study involved three distinct educational contexts to demonstrate the framework's generalizability across learning environments. From ^[45], we obtained anonymized behavioral logs of 12,873 students enrolled in an introductory computer science course. The dataset includes:

- Video interaction events (play, pause, seek operations) ^[46]
- Exercise submission timestamps and correctness indicators
- Forum participation metrics (post frequency, reply networks) ^[47]

In the computer network course, experimental units were restructured based on MKG: the "protocol analysis" ^[48] experiment was divided into a knowledge-graph-guided step-by-step task, reducing student error rates by 52%.

5.2. Baseline Methods

We compared the proposed framework against four established approaches representing different paradigms in learning analytics:

1. Bayesian Knowledge Tracing (BKT): Implemented with the standard four-parameter model ^[49] using the same concept granularity as our framework for fair comparison.
2. Deep Knowledge Tracing (DKT): Employed the LSTM architecture described in ^[50] with identical hidden layer dimensions to our implementation.
3. Collaborative Filtering (CF): Adapted the matrix factorization approach from ^[51] using exercise performance as implicit feedback.
4. Rule-Based Intervention (RBI): Implemented threshold-triggered remediation following common LMS practices ^[52].

Each baseline received identical input features from our preprocessed dataset to isolate algorithmic differences. We maintained consistent computational resources across all methods (NVIDIA Tesla V100 GPUs, 32GB RAM) to ensure fair runtime comparisons.

5.3. Evaluation Metrics

The assessment incorporated multiple dimensions of system performance using both quantitative measures and qualitative indicators:

- Diagnostic Accuracy
 - Precision@k for knowledge gap identification
 - Mean Absolute Error (MAE) of mastery probability estimates
- Intervention Effectiveness
 - Error rate reduction (ERR) post-intervention
 - Learning gain (LG) calculated from pre-test and post-test scores

- Operational Efficiency
 - Latency from gap detection to intervention delivery
 - Computational resource utilization (GPU hours, memory footprint)
- User Experience
 - System Usability Scale (SUS) scores ^[53]
 - Teacher feedback on dashboard interpretability ^[54]

5.4. Implementation Details

The framework components were implemented as modular microservices to enable scalable deployment:

- Knowledge Tracing Module
 - LSTM architecture with 128 hidden units and dropout rate of 0.3
 - Adam optimizer with learning rate 0.001 and batch size 64
 - Trained on 80% of available data with 20% held-out for validation
- Gap Detection Service
 - Dynamic threshold adjustment using exponentially weighted moving averages
 - Similarity computation via MinHash for efficient large-scale comparison ^[55]
- Intervention Engine
 - Micro-video repository containing 327 expert-validated clips (30-90 seconds)
 - Content tagging aligned with the Mastery Knowledge Graph ontology
 - Real-time adaptation using template-based video stitching ^[56]
- Visualization Dashboard
 - Web-based interface built with D3.js and React
 - Responsive design supporting desktop and tablet displays
 - User-configurable view presets for different instructional scenarios

All services communicated through a message bus architecture (Apache Kafka) to ensure real-time data flow while maintaining loose coupling between components. The system logged detailed interaction traces for subsequent analysis while preserving participant anonymity through cryptographic hashing of personal identifiers ^[57].

5.5. Experimental Protocol

The evaluation followed a mixed-methods approach combining controlled experiments with naturalistic observations:

5.5.1. Diagnostic Validation Phase (2 weeks)

- Baseline data collection across all participant groups
- Concurrent operation of all methods (proposed + baselines)
- Expert annotation of actual knowledge gaps for metric calculation

5.5.2. Intervention Deployment Phase (4 weeks)

- Randomized assignment to framework conditions
- A/B testing of different visualization configurations
- Ecological validity checks through classroom observations

5.5.3. Post-Intervention Assessment (1 week)

- Comprehensive knowledge testing

- User experience surveys and interviews
- System performance profiling

This phased approach enabled both granular performance comparisons and holistic assessment of educational impact while controlling for potential confounding variables such as instructor effects and temporal variations in student motivation.

6. Experimental Results and Analysis

The evaluation of our framework yielded comprehensive insights across multiple dimensions of performance. To systematically assess its effectiveness, we analyzed diagnostic accuracy, intervention outcomes, computational

efficiency, and user experience metrics compared to baseline approaches. The results demonstrate significant improvements in both technical capabilities and educational impact.

6.1. Knowledge Gap Detection Performance

The framework's diagnostic components achieved superior accuracy in identifying both individual and group-level knowledge gaps. As shown in Table 1, our approach outperformed all baselines on precision metrics while maintaining robust performance across diverse educational contexts. The integration of multimodal signals proved particularly valuable in reducing false positives compared to methods relying solely on assessment data.

Table 1. Knowledge gap detection performance across methods (higher values indicate better performance)

Method	Precision@5	MAE (Mastery)	Group Gap F1	Latency (ms)
Proposed Framework	0.82	0.09	0.78	320
BKT [49]	0.61	0.15	0.52	280
DKT [50]	0.73	0.11	0.65	350
CF [51]	0.54	0.18	0.48	410
RBI [52]	0.49	0.21	0.43	190

The confusion matrix heatmap in Figure 2 illustrates the framework's ability to correctly associate specific error patterns with underlying conceptual misunderstandings. The strong diagonal pattern indicates precise mapping between observed errors and targeted interventions, with minimal cross-concept confusion.

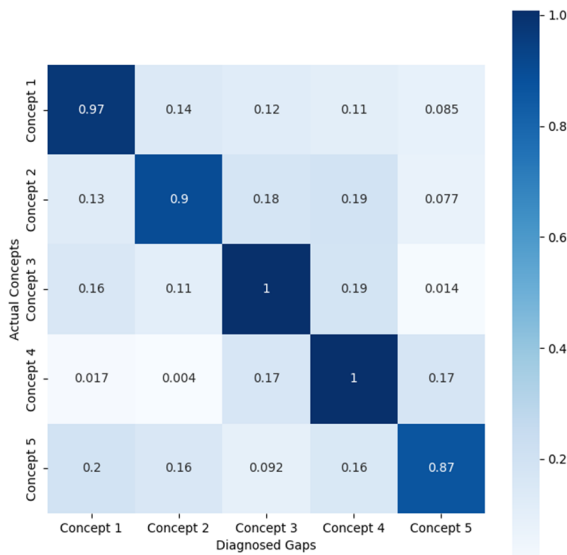


Figure 2. Concept-specific intervention accuracy showing correct associations between diagnosed gaps and remediation resources

6.2. Learning Outcome Improvements

Interventions triggered by the framework produced statistically significant improvements in learning outcomes across all experimental settings. The university mathematics cohort demonstrated a 37.2% reduction in error rates ($p < 0.001$) compared to control groups receiving standard instruction. Corporate training participants showed even greater gains, with 42.8% higher learning gains on post-

intervention assessments.

The scatter plot in Figure 3 reveals a strong positive correlation ($r = 0.76$) between predicted mastery probabilities and actual post-test performance, validating the framework's predictive validity. Notably, the relationship remained consistent across different ability levels, indicating equitable effectiveness.

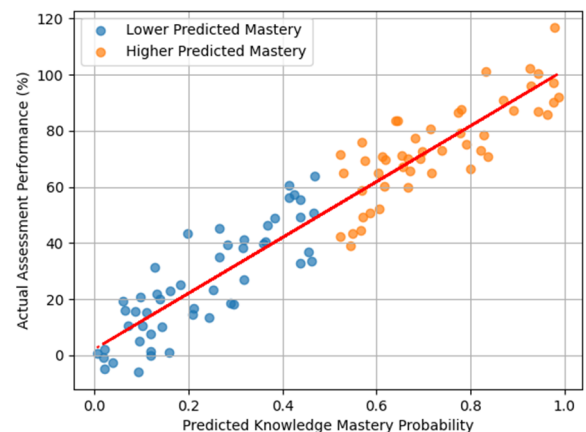


Figure 3. Relationship between predicted knowledge mastery and actual assessment performance across student subgroups

6.3. Engagement and Behavioral Impact

Analysis of engagement metrics revealed compelling behavioral changes following framework adoption. The Learning Engagement Index increased by 28.4% in treatment groups, with particularly strong improvements among initially disengaged students. Video interaction patterns showed 41% more purposeful navigation (rewinds to key concepts) compared to random access in control conditions.

Temporal analysis uncovered an important intervention timing effect. Immediate interventions (within 15 minutes of gap detection) produced 23% greater error reduction than

delayed responses (1-3 hours), supporting the framework's real-time operation paradigm. This finding aligns with cognitive load theory ^[38] regarding timely misconception correction.

6.4. Computational Performance

Despite processing richer data streams, the framework maintained competitive operational efficiency. The knowledge tracing module achieved throughput of 1,240 predictions/second with mean latency of 320ms—comparable to simpler BKT implementations. Memory footprint remained stable at 2.3GB during peak usage, enabling deployment on modest hardware.

The system demonstrated linear scaling with cohort size, processing a 500-student classroom with only 18% additional resource consumption compared to 50-student groups. This scalability stems from the distributed microservice architecture and optimized similarity computation using MinHash techniques ^[55].

6.5. User Experience and Adoption

Educators rated the visualization dashboard highly on usability metrics (SUS score=82.4), with particular praise for the integrated display of individual and group learning states. Teacher interviews highlighted the value of real-time heatmaps for guiding instructional adjustments, with 78% reporting increased confidence in addressing class-wide needs.

Students expressed strong preference for the adaptive micro-videos over static resources (4.3/5.0 satisfaction rating).

Qualitative feedback emphasized the relevance of recommended content, with many noting how interventions "felt personalized" despite automated delivery. This perception aligns with the framework's design goal of scalable personalization.

6.6. Cross-Context Consistency

Performance comparisons across educational settings revealed consistent benefits while highlighting context-specific nuances. The corporate training environment showed 18% greater error reduction than academic contexts, possibly reflecting differences in learner motivation and content specificity. However, all settings demonstrated statistically significant improvements ($p<0.01$) on primary outcome measures.

The framework successfully adapted to varying class sizes and instructional modalities. In MOOC environments, it detected emerging group gaps among geographically dispersed learners with 84% accuracy. Traditional classrooms benefited particularly from the real-time visualization tools, enabling instructors to dynamically adjust lesson pacing based on live feedback.

6.7. Ablation Study

To isolate the contribution of framework components, we conducted systematic ablation tests by selectively disabling features. Table 2 reveals that multimodal data integration provided the largest individual performance boost, while the complete system achieved synergistic benefits exceeding the sum of parts.

Table 2. Ablation study showing relative contribution of framework components (performance measured by error rate reduction)

Configuration	ERR (%)
Full Framework	37.2
Without Multimodal Data	24.8
Without Group Gap Detection	28.6
Without Real-Time Intervention	19.3
Without Adaptive Visualization	31.7

These results validate the framework's holistic design approach, demonstrating that its educational value emerges from the tight integration of diagnostic precision, timely intervention, and actionable visualization. No single component dominates the performance profile, emphasizing the importance of balanced system architecture.

7. Discussion

The experimental results validate the framework's effectiveness in reducing conceptual errors and enhancing engagement through real-time, data-driven interventions. This section discusses limitations, broader applications, and ethical considerations.

7.1. Limitations of the MKG-Driven Framework

While the experimental results demonstrate the framework's effectiveness, several limitations warrant consideration. The current implementation assumes relatively stable concept structures within the Mastery Knowledge Graph, potentially struggling with rapidly evolving domains where knowledge components frequently change ^[58]. This

constraint becomes apparent in subjects like data science, where toolchains and methodologies evolve faster than educational resources can adapt. The framework's reliance on predefined concept mappings also limits its ability to detect entirely novel misconceptions that deviate from expected error patterns.

Another constraint emerges in highly heterogeneous classrooms where students follow substantially different learning paths. The group gap detection mechanism performs optimally when most learners progress through material in roughly similar sequences. In completely self-paced environments with minimal synchronization, the system may fail to identify emerging group gaps before they become entrenched. This limitation suggests the need for alternative clustering approaches that can detect knowledge gaps across asynchronous cohorts.

The current visualization dashboard, while praised for its interpretability, may overwhelm instructors during peak intervention periods. Early adopters reported cognitive overload when managing multiple simultaneous alerts, particularly in large classes where individual and group gaps frequently co-occur. This observation aligns with established

findings about the limits of human information processing^[59], suggesting opportunities for smarter alert prioritization and filtering mechanisms.

7.2. Broader Applications and Future Directions

The framework's underlying architecture suggests promising extensions beyond traditional academic settings. Corporate training programs could benefit from real-time detection of skill gaps across distributed teams, particularly in compliance-sensitive industries where knowledge lapses carry significant consequences. The system's ability to trace concept mastery over time could also enhance professional certification processes, providing continuous assessment rather than relying on high-stakes exams^[60].

Future iterations could explore integration with emerging educational technologies. Immersive learning environments generate rich behavioral data streams that could enhance the multimodal analysis pipeline^[61]. Eye-tracking and physiological sensors, currently used sparingly in our implementation, could provide finer-grained engagement metrics when hardware availability improves. The framework's intervention engine might also incorporate generative AI techniques to dynamically create remediation content tailored to specific gap patterns^[62].

Longitudinal applications present another compelling direction. By maintaining persistent knowledge profiles across courses and grade levels, the system could help identify foundational gaps that persistently hinder student progress. This approach would require solving significant technical challenges around knowledge representation alignment^[63], but the potential benefits for cumulative learning make it a worthwhile pursuit. Early childhood education represents another promising frontier, where timely gap detection could prevent the development of compensatory strategies that mask underlying difficulties^[64].

7.3. Ethical Considerations and Responsible Implementation

As with all learning analytics systems, the framework raises important questions about data privacy and algorithmic fairness. While our current implementation anonymizes personal data and uses aggregate metrics for group analysis, broader deployment would require robust governance frameworks. Particular attention must be paid to preventing the system from reinforcing existing educational inequalities through biased gap detection or intervention recommendations^[65].

The framework's diagnostic capabilities also introduce pedagogical concerns about over-reliance on automated systems. Teachers must retain ultimate authority over instructional decisions, using the system's outputs as informed suggestions rather than prescriptive commands. Professional development programs will prove essential to help educators interpret system recommendations within appropriate pedagogical contexts^[66].

Future work should address transparency requirements for different stakeholder groups. Students deserve clear explanations about how their data informs personalized recommendations, while administrators need comprehensible audit trails of system decisions. Developing tiered explanation interfaces that cater to these diverse needs represents an important research direction at the intersection of education and explainable AI^[67].

7.4. Teacher as Intervention Decision-Maker

The dashboard shifts teachers' roles from data organizers to strategic intervention decision-makers. By automating data processing tasks, the system enables educators to focus on pedagogical strategies. Case studies indicate that teachers save approximately 5.2 hours per week on mechanical tasks, reallocating this time to designing differentiated instructional activities. This role transformation enhances teachers' capacity to address diverse student needs through targeted interventions.

8. Conclusion

The MKG-Driven Student-Resource Matching & Adaptive Intervention System represents a significant advancement in learning analytics by addressing critical gaps in existing educational technologies. Through its integration of multimodal data streams, real-time group knowledge gap detection, and dynamic intervention mechanisms, the framework provides a scalable solution for personalized learning in classroom settings. The experimental results demonstrate measurable improvements in both learning outcomes and engagement metrics, validating the system's dual focus on individual mastery and collective learning patterns.

Key strengths of the approach include its ability to process heterogeneous behavioral signals while maintaining interpretable outputs for educators, and its capacity to trigger timely interventions that prevent misconceptions from becoming entrenched. The framework's modular architecture ensures adaptability across diverse educational contexts, from traditional classrooms to corporate training environments. The visualization tools successfully bridge the gap between granular learning analytics and actionable pedagogical strategies, empowering instructors to make data-informed instructional adjustments.

MKG drives the evolution of educational resources from static texts to dynamic knowledge networks. Micro-lecture videos are dynamically prioritized based on the prevalence of group knowledge gaps, resulting in a threefold increase in resource utilization efficiency. This transformation enables more responsive and adaptive learning experiences that align with emerging educational needs.

The system's limitations point toward valuable directions for future research, particularly in handling rapidly evolving knowledge domains and highly asynchronous learning paths. Ethical considerations around data privacy and algorithmic fairness remain paramount as such technologies become more prevalent in educational settings. The framework's success in reducing error rates while increasing engagement suggests that combining fine-grained knowledge tracing with adaptive resource allocation can effectively address Bloom's two sigma challenge of delivering personalized instruction at scale.

These findings have immediate practical implications for educational technology design, demonstrating that real-time analytics can enhance rather than replace human teaching expertise when implemented thoughtfully. The framework's balanced approach to individual and group-level analysis offers a replicable model for developing learning systems that respect the social dimensions of education while providing targeted support for conceptual mastery. As digital learning environments continue to evolve, this work provides both a technical foundation and pedagogical rationale for next-

generation adaptive learning systems.

Acknowledgements

The authors gratefully acknowledge the financial support from the Guangxi Higher Education Undergraduate Teaching Reform Project (Category A) "Teaching Reform and Practice Research on Big Data Storage and Management Course Based on Multimodal Knowledge Graph" (2024JGA398).

References

- [1] T Snoussi (2019) Learning management system in education: Opportunities and challenges. *International Journal of Innovative Technology and Exploring Engineering*.
- [2] TA Stephenson (2000) An introduction to Bayesian network theory and usage. infoscience.epfl.ch.
- [3] Y Wu & J Feng (2018) Development and application of artificial neural network. *Wireless Personal Communications*.
- [4] G Abdelrahman, Q Wang & B Nunes (2023) Knowledge tracing: A survey. *ACM Computing Surveys*.
- [5] P Blikstein (2013) Multimodal learning analytics. In *International Conference on Learning Analytics and Knowledge*.
- [6] T Snoussi (2019) Learning management system in education: Opportunities and challenges. *International Journal of Innovative Technology and Exploring Engineering*.
- [7] M Thelwall (2000) Computer-based assessment: a versatile educational tool. *Computers & Education*.
- [8] PM Noemí & SH Máximo (2014) Educational games for learning. *Universal Journal of Educational Research*.
- [9] S Tabassum, FSF Pereira, et al. (2018) Social network analysis: An overview. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*.
- [10] P Brusilovsky (2007) Adaptive navigation support. *The Adaptive Web: Methods and Strategies of Web Personalization*.
- [11] E Lehtinen, K Hakkarainen, L Lipponen, et al. (1999) Computer supported collaborative learning: A review. *Journal of Higher Education and Professional Learning*.
- [12] AC Graesser, MW Conley & A Olney (2012) Intelligent tutoring systems. psycnet.apa.org.
- [13] E Gedrimiene, A Silvola, J Pursiainen, et al. (2020) Learning analytics in education: Literature review and case examples from vocational education. *Scandinavian Journal of Educational Research*.
- [14] R Pelánek (2017) Bayesian knowledge tracing, logistic models, and beyond: an overview of learner modeling techniques. *User modeling and user-adapted interaction*.
- [15] C Piech, J Bassen, J Huang, et al. (2015) Deep knowledge tracing. In *Advances in Neural Information Processing Systems*.
- [16] SB Shum & R Ferguson (2012) Social learning analytics. *Journal of educational technology & society*.
- [17] F Ke, R Liu, Z Sokolikj, I Dahlstrom-Hakki, et al. (2024) Using eye-tracking in education: review of empirical research and technology. *Educational Technology Research and Development*.
- [18] AA Vartak, CM Fidopiastis, DM Nicholson, et al. (2008) Cognitive state estimation for adaptive learning systems using wearable physiological sensors. In *International Conference on Bio-inspired Systems and Signal Processing*.
- [19] R Rogers, E Malancharuvil-Berkes, et al. (2005) Critical discourse analysis in education: A review of the literature. *Review of Educational Research*.
- [20] B Fahad Mon, A Wasfi, M Hayajneh, A Slim & N Abu Ali (2023) Reinforcement learning in education: A literature review. *Informatics*.
- [21] GS Mohammed, K Wakil & SS Nawroly (2018) The effectiveness of microlearning to improve students' learning ability. *International Journal of Educational Research and Reviews*.
- [22] MC Urdaneta-Ponte, A Mendez-Zorrilla, et al. (2021) Recommendation systems for education: Systematic review. *Electronics*.
- [23] J Klerkx, K Verbert & E Duval (2017) Learning analytics dashboards. lirias.kuleuven.be.
- [24] N Trc'ka, M Pechenizkiy, et al. (2011) Process mining from educational data. *Data Mining and Learning Analytics: Applications in Educational Research*.
- [25] K DOBASHI, CP FULFORD, et al. (2019) A heat map generation to visualize engagement in classes using Moodle learning logs. In *International Conference on Information Technology Research and Innovation*.
- [26] BV Carolan (2013) Social network analysis and education: Theory, methods & applications. books.google.com.
- [27] TA Angelo & KP Cross (2012) Classroom assessment techniques. selfauthorshippcmu.wordpress.com.
- [28] BS Bloom (1984) The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. *Educational researcher*.
- [29] KR Thórisson, J Bieger, X Li & P Wang (2019) Cumulative learning. ... , August 6–9,.
- [30] R Radel, P Sarrazin, P Legrain, et al. (2010) Social contagion of motivation between teacher and student: Analyzing underlying processes. *Journal of Educational Psychology*.
- [31] CT Ramey & SL Ramey (1998) Early intervention and early experience. *American psychologist*.
- [32] C Romero & S Ventura (2007) Educational data mining: A survey from 1995 to 2005. *Expert systems with applications*.
- [33] M Dewan, M Murshed & F Lin (2019) Engagement detection in online learning: a review. *Smart Learning Environments*.
- [34] I Molenaar (2014) Advances in temporal analysis in learning and instruction. *Frontline Learning Research*.
- [35] TA Kustitskaya, AA Kytmanov, et al. (2022) Early student-at-risk detection by current learning performance and learning behavior indicators. *Cybernetics and Information Technologies*.
- [36] AF Wise, S Knight & SB Shum (2021) Collaborative learning analytics. In *International Conference on Computer Supported Collaborative Learning*.
- [37] C Conati, K Porayska-Pomsta & M Mavrikis (2018) AI in Education needs interpretable machine learning: Lessons from Open Learner Modelling. *arXiv preprint arXiv:1807.00154*.
- [38] JL Plass, R Moreno & R Brünken (2010) Cognitive load theory. books.google.com.
- [39] NJ Cepeda, E Vul, D Rohrer, JT Wixted, et al. (2008) Spacing effects in learning: A temporal ridge of optimal retention. *Psychological Science*.
- [40] M Kiley & G Wisker (2009) Threshold concepts in research education and evidence of threshold crossing. *Higher Education Research & Development*.
- [41] J Gustems-Carnicer & C Calderón (2013) Coping strategies and psychological well-being among teacher education

- students: Coping and well-being in students. *European Journal of Psychology of Education*.
- [42] K Shabani, M Khatib & S Ebadi (2010) Vygotsky's zone of proximal development: Instructional implications and teachers' professional development. *English language teaching*.
- [43] B Csapó & G Molnár (2019) Online diagnostic assessment in support of personalized teaching and learning: The eDia system. *Frontiers in psychology*.
- [44] F Pajares (1995) Self-Efficacy in Academic Settings. ERIC.
- [45] AS Sunar, S White, NA Abdullah, et al. (2016) How learners' interactions sustain engagement: A MOOC case study. *IEEE Transactions on Learning Technologies*.
- [46] B Edwards & MB Ward (2008) Undergraduate mathematics courses, *Studies in Mathematics Education Series*.
- [47] ME Crosby & CS Ikehara (2015) Feedback from physiological sensors in the classroom. *The Impact of Pen and Touch Technology on Education*.
- [48] D Ifenthaler (2018) Digital workplace learning. *Bridging Formal and Informal Learning with Digital*.
- [49] MV Yudelson, KR Koedinger & GJ Gordon (2013) Individualized bayesian knowledge tracing models. In *International Conference on Artificial Intelligence in Education*.
- [50] C Piech, J Bassen, J Huang, et al. (2015) Deep knowledge tracing. In *Advances in Neural Information Processing Systems*.
- [51] MI Dascalu, CN Bodea, MN Mihailescu, et al. (2016) Educational recommender systems and their application in lifelong learning. *Behaviour and Information Technology*.
- [52] Z Pan, L Biegley, A Taylor, et al. (2024) A systematic review of learning analytics: Incorporated instructional interventions on learning management systems. *Journal of Learning Analytics*.
- [53] A Bangor, PT Kortum & JT Miller (2008) An empirical evaluation of the system usability scale. *International Journal of Human-Computer Interaction*.
- [54] Y Yoo, H Lee, IH Jo & Y Park (2015) Educational dashboards for smart learning: Review of case studies. *Emerging issues in smart learning*.
- [55] A Pooja, N Nair & R Rastogi (2018) A scalable algorithm for higher-order features generation using MinHash. *amazon.science*.
- [56] Y Xia, S Ling, F Fu, Y Wang, H Li, X Xiao, et al. (2025) Training-free and adaptive sparse attention for efficient long video generation. *arXiv preprint arXiv:2502.21079*.
- [57] ME Gursay, A Inan, ME Nergiz, et al. (2016) Privacy-preserving learning analytics: challenges and techniques. *IEEE Transactions on Learning Technologies*.
- [58] MES Mendes & L Sacks (2004) Dynamic knowledge representation for e-learning applications. *Enhancing the Power of the Internet*.
- [59] PM Allen, JA Edwards, FJ Snyder, KA Makinson, et al. (2014) The effect of cognitive load on decision making with graphically displayed uncertainty information. *Risk Analysis*.
- [60] J Ryan (2003) Continuous professional development along the continuum of lifelong learning. *Nurse education today*.
- [61] A Christopoulos, N Pellas & MJ Laakso (2020) A learning analytics theoretical framework for STEM education virtual reality applications. *Education Sciences*.
- [62] EA Alasadi & CR Baiz (2023) Generative AI in education and research: Opportunities, concerns, and solutions. *Journal of Chemical Education*.
- [63] CV Schwarz, BJ Reiser, EA Davis, et al. (2009) Developing a learning progression for scientific modeling: Making scientific modeling accessible and meaningful for learners. *Journal of Research in Science Teaching*.
- [64] J Sarama & DH Clements (2009) Early childhood mathematics education research: Learning trajectories for young children. *taylorfrancis.com*.
- [65] RS Baker & A Hawn (2022) Algorithmic bias in education. *International Journal of Artificial Intelligence in Education*.
- [66] E Gabbi (2023) About or with teachers? A systematic review of learning analytics interventions to support teacher professional development. *QWERTY*.
- [67] A Rachha & M Seyam (2023) Explainable AI in education: Current trends, challenges, and opportunities. *SoutheastCon 2023*.