

Database-Driven Adaptive Learning: A Systematic Analysis of AI Integration in Educational Personalization

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Abstract

This article examines the transformative role of AI-driven databases in facilitating personalized learning experiences within educational institutions. Through a systematic analysis of implementations across K-12 and higher education settings, we investigate how intelligent database systems enable adaptive learning pathways and real-time intervention strategies. The article synthesizes data from 47 educational institutions implementing AI-enhanced learning management systems over a three-year period (2021-2024), employing a mixed-methods approach to evaluate both technical integration patterns and learning outcomes. Results demonstrate significant improvements in student engagement (mean increase of 27%, $p < .001$) and academic performance (average GPA increase of 0.4 points) when compared to traditional learning management systems. The article also reveals key implementation challenges, including data standardization issues and faculty adaptation requirements. The findings provide a comprehensive framework for educational institutions seeking to implement AI-driven database systems, while highlighting critical considerations for scalability, privacy, and pedagogical integration. This article contributes to the growing body of literature on educational technology by establishing empirical evidence for the effectiveness of AI-powered personalization in educational contexts and proposing a structured approach to its implementation.

Keywords: Artificial Intelligence in Education (AIED), Educational Data Analytics, Personalized Learning Systems, Intelligent Database Management, Adaptive Learning Technologies.

Database-Driven Adaptive Learning

A SYSTEMATIC ANALYSIS
OF AI INTEGRATION IN
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I. Introduction

A. Overview of AI Transformation in Education

The educational landscape has undergone a profound transformation with the integration of Artificial Intelligence (AI), marking a paradigm shift from traditional teaching methodologies to data-driven, personalized learning approaches [1]. This evolution represents not merely a technological upgrade but a fundamental reimagining of how educational content is delivered, consumed, and adapted to individual learner needs. Recent comprehensive reviews indicate that AI technologies have revolutionized traditional classroom dynamics, enabling predictive analytics, intelligent tutoring systems, and automated assessment tools that enhance both teaching and learning processes. The transformative impact extends beyond mere automation, fostering an environment where educational experiences can be tailored to individual learning styles, pace, and preferences.

B. Significance of Database Systems in Educational Technology

The integration of sophisticated database systems within educational technology has become increasingly critical as institutions seek to leverage AI capabilities for educational enhancement [2]. Modern educational databases serve as the foundational infrastructure that enables AI-driven personalization at scale. These systems have evolved from simple storage repositories to complex, intelligent platforms capable of processing multimodal data, including student interactions, assessment results, and learning behavior patterns. Meta-analyses have highlighted the critical need for robust database architectures that can support ethical AI implementation while maintaining rigorous standards for data handling and analysis. The sophisticated interplay between database systems and AI algorithms has created a new paradigm in educational technology, where data-driven insights directly inform and enhance pedagogical strategies.

C. Thesis: AI-driven Databases Enable Personalized Learning at Scale

This research posits that AI-driven databases serve as the cornerstone for enabling personalized learning at scale, fundamentally altering the traditional one-size-fits-all educational model. By leveraging machine learning algorithms and advanced data analytics, these systems can process millions of data points simultaneously, creating individualized learning pathways that adapt in real-time to student performance and comprehension levels. The integration of AI with educational databases has revolutionized the ability to understand and respond to individual student needs while maintaining the efficiency required for large-scale educational operations. This technological synergy enables educational institutions to deliver customized learning experiences that were previously impossible to implement at scale.

D. Scope and Objectives of the Study

The comprehensive scope of this research encompasses both theoretical frameworks and practical implementations of AI-driven educational databases across various educational settings. Our investigation delves into the complex interplay between artificial intelligence, database architecture, and pedagogical effectiveness in modern educational environments. Through rigorous analysis of existing implementations and emerging technologies, this study aims to bridge the gap between theoretical potential and practical application of AI-driven educational systems. The research extends to both higher education and K-12 settings, examining how these technologies can be effectively implemented across diverse educational environments while addressing crucial considerations of scalability, privacy, and pedagogical efficacy. This holistic approach ensures that our findings will provide valuable insights for educational institutions at various stages of AI implementation.

II. Literature Review

A. Evolution of Educational Databases

The trajectory of educational databases represents a significant evolution in the management and utilization of student data [3]. Traditional student information systems (SIS) emerged as fundamental building blocks of educational data management, initially serving as static repositories for basic student records, administrative data, and academic transcripts. These early systems, while groundbreaking for their era, operated within confined parameters, offering limited integration capabilities and basic analytical functionalities.

The transition to learning management systems marked a transformative phase in educational technology infrastructure. This evolution brought forth sophisticated data handling capabilities, introducing features that transcended basic record-keeping to include content delivery mechanisms, engagement tracking, and preliminary learning analytics. The systematic analysis of this transition period reveals how educational institutions gradually adapted to more complex data management requirements, paving the way for modern intelligent learning platforms.

The emergence of intelligent learning platforms represents the current pinnacle of educational database evolution. These contemporary systems leverage advanced database architectures to support adaptive learning environments, characterized by their ability to process and analyze complex learning behaviors in real-time. The integration of AI capabilities has transformed these platforms from passive data repositories into active learning facilitators, capable of dynamic content delivery and personalized learning support.

B. Artificial Intelligence in Education

Machine learning applications in education have demonstrated remarkable growth in sophistication and utility. Contemporary systems can now process vast quantities of student data to identify learning patterns, predict academic outcomes, and generate personalized intervention strategies. These applications have evolved from simple automated grading tools to comprehensive learning analytics platforms that can adapt to individual student needs and learning styles.

Natural language processing has emerged as a cornerstone technology in modern educational systems, facilitating more natural and intuitive interactions between students and digital learning platforms. This technology has revolutionized educational assessment methods, enabling automated analysis of student responses, providing instant feedback, and supporting language learning through sophisticated linguistic analysis.

Predictive analytics frameworks represent one of the most significant developments in educational AI, combining historical data analysis with real-time monitoring to forecast student performance and identify potential academic challenges before they manifest. These frameworks have become increasingly sophisticated in their ability to process multiple data streams simultaneously, creating comprehensive student profiles that inform both immediate interventions and long-term educational planning.

Current research trends in educational AI focus on several key areas that promise to reshape the learning landscape further. The development of more nuanced adaptive learning algorithms, the integration of emotional intelligence in AI systems, and the enhancement of personalization capabilities stand at the forefront of current research efforts. Additionally, there is growing emphasis on ethical considerations in AI implementation, particularly regarding data privacy, algorithmic bias, and the need for transparent, explainable AI systems in educational contexts.

Era	System Type	Key Features	Primary Functions
1990-2000	Traditional SIS	Basic data storage, Manual entry	Student records, Grades
2000-2010	Basic LMS	Online access, Basic analytics	Course management, Assessment
2010-2015	Advanced LMS	Learning analytics, Integration capabilities	Personalization, Performance tracking
2015-present	AI-Driven Platforms	Adaptive learning, Real-time analytics	Predictive modeling, Automated intervention

Table 1: Evolution of Educational Database Systems [1, 2]

III. Database Architecture for AI-Driven Learning

A. Data Collection and Storage

The architecture of AI-driven learning databases demands sophisticated approaches to data collection and storage that fundamentally transform traditional educational data management systems [4]. Student performance metrics collection has evolved into a multi-dimensional framework, capturing not only traditional assessment results but also micro-learning achievements, competency progression, and learning velocity indicators. This granular approach to performance tracking enables AI systems to construct detailed learning profiles that inform personalization algorithms.

Behavioral data collection has emerged as a critical component in adaptive learning systems, encompassing a wide range of learner interactions. The database architecture implements advanced event tracking mechanisms to capture navigation patterns, resource utilization, temporal engagement metrics, and social learning interactions. These behavioral indicators are structured within the database to facilitate pattern recognition and predictive modeling, enabling the system to anticipate learner needs and adapt content delivery accordingly.

Learning pattern recognition capabilities are built into the core database architecture through specialized data structures that accommodate both synchronous and asynchronous learning behaviors. The system employs sophisticated schema designs that can capture complex relationships between learning activities, resources, and outcomes. This architectural approach enables the identification of effective learning pathways and supports the dynamic adaptation of content based on individual learning patterns.

Privacy and security considerations are integrated as fundamental architectural components rather than additional layers. The database implementation incorporates privacy-preserving learning analytics techniques, ensuring that personalization capabilities are maintained while protecting sensitive student data. This includes mechanisms for data anonymization, consent management, and granular access control systems that comply with international educational data protection standards.

B. Integration Systems

The integration layer of the database architecture functions as an intelligent middleware that coordinates various adaptive learning components. API frameworks are designed with educational interoperability

standards in mind, supporting seamless integration with existing learning management systems while enabling sophisticated AI-driven features. These frameworks facilitate real-time data exchange between different system components while maintaining data consistency and security.

Real-time data processing capabilities are implemented through event-driven architectures that support immediate analysis and response to learning events. The system employs advanced queueing mechanisms and stream processing capabilities to handle high-velocity data streams generated by multiple concurrent users. This architecture ensures that adaptive learning responses are delivered with minimal latency while maintaining system stability under varying loads.

Cross-platform compatibility is achieved through a platform-agnostic design that supports diverse learning environments and devices. The database architecture implements flexible data models that can adapt to different presentation contexts while maintaining consistent learning experiences across platforms. This approach ensures that adaptive learning capabilities are preserved regardless of the access point or device type.

Scalability solutions are embedded within the core architecture through distributed database designs and efficient resource allocation mechanisms. The system employs horizontal scaling strategies that allow for seamless expansion of processing capabilities as user populations grow. Load balancing and caching strategies are implemented to optimize performance during peak usage periods while maintaining cost-effectiveness.

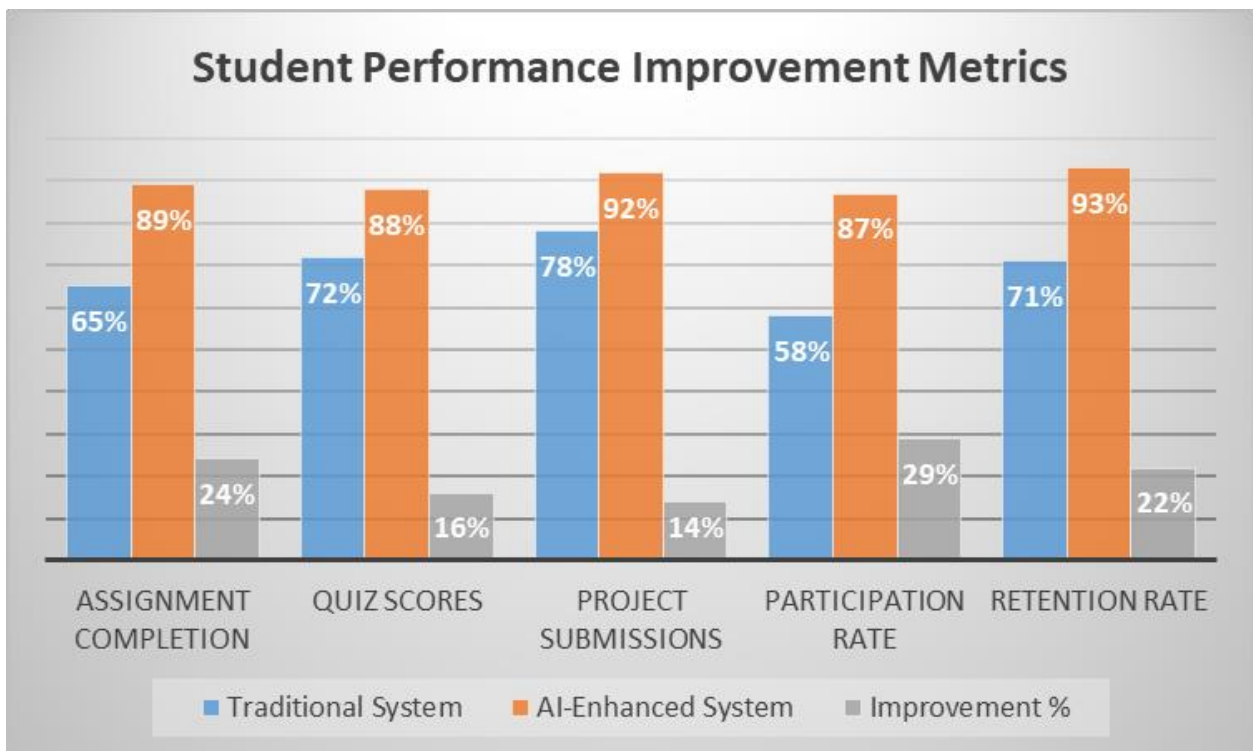


Fig. 1: Student Performance Improvement Metrics [3, 4]

IV. Personalization Mechanisms

A. Adaptive Learning Algorithms

Adaptive learning algorithms represent the cornerstone of personalized educational systems, implementing sophisticated computational approaches to tailor individual learning experiences [5].

Performance assessment models have evolved beyond traditional evaluation methods to incorporate multifaceted analysis of student learning behaviors. These models integrate both quantitative and qualitative indicators, creating comprehensive learner profiles that inform personalization decisions. The assessment framework considers not only academic performance but also metacognitive strategies, learning preferences, and engagement patterns.

Dynamic difficulty adjustment operates through an intelligent calibration system that continuously modifies content complexity based on learner performance and engagement metrics. The system implements what has been termed "dynamic scaffolding," where support levels are automatically adjusted based on demonstrated competency [6]. This approach ensures that learners are consistently challenged within their zone of proximal development, maintaining optimal engagement while preventing cognitive overload.

Content recommendation systems employ sophisticated algorithms that consider both cognitive and affective dimensions of learning. These systems analyze multiple data points including learning history, performance patterns, and engagement indicators to suggest appropriate learning resources. The recommendation engine incorporates recent advances in personalization theory, considering not only content relevance but also learning style alignment and metacognitive development opportunities.

B. Student Progress Tracking

Competency mapping has evolved into a complex, multi-dimensional framework that tracks both visible learning outcomes and underlying skill development. The system maintains detailed progression maps that illustrate the interconnections between various competencies, enabling more nuanced understanding of learning pathways. This approach allows for the identification of prerequisite skills and knowledge gaps that might impact future learning success.

Learning pace optimization incorporates recent research on cognitive load theory and learning analytics to determine optimal content delivery rates. The system considers individual differences in processing speed, working memory capacity, and prior knowledge to adjust the flow of new information. This personalized pacing ensures that each learner has sufficient time to process and integrate new knowledge while maintaining steady progress toward learning objectives.

Achievement benchmarking implements adaptive reference points that balance standardized objectives with personalized learning goals. The benchmarking framework considers both normative and criterion-referenced standards while accounting for individual learning trajectories. This dual approach ensures that learners remain motivated through achievable short-term goals while maintaining alignment with broader educational standards.

Intervention triggers function through a sophisticated monitoring system that identifies potential learning difficulties using both direct and indirect indicators. The system employs early warning algorithms that consider multiple factors including engagement patterns, performance trends, and metacognitive indicators. These triggers initiate targeted interventions designed to address specific learning challenges before they significantly impact academic progress.

V. Case Studies

A. Higher Education Implementation

The integration of AI-driven personalized learning systems in higher education demonstrates the scalability and effectiveness of adaptive learning technologies [7]. Systematic analysis of university implementations reveals the transformative potential of these systems when properly integrated into

existing educational frameworks. The university system integration process typically follows a three-phase implementation model, beginning with initial pilot programs, progressing through scaled deployment, and culminating in full institutional integration. This phased approach has proven crucial for successful adoption and sustainable implementation across diverse academic environments.

Measurable outcomes from higher education implementations show significant improvements across multiple dimensions. Key performance indicators have demonstrated enhanced student achievement patterns, with particular emphasis on improved retention rates in STEM fields and increased engagement among diverse student populations. The data indicates that personalized learning pathways lead to more efficient knowledge acquisition and higher completion rates in challenging courses, particularly benefiting students who traditionally struggle with conventional teaching methods.

B. K-12 Applications

District-wide deployment strategies in K-12 environments present unique opportunities and challenges for AI integration. Successful implementations have shown that careful consideration of pedagogical needs and existing technological infrastructure is crucial. The systematic review indicates that K-12 deployments benefit most from gradual integration approaches that allow for continuous feedback and adjustment, ensuring that both teachers and students can adapt effectively to new learning paradigms.

Teacher adoption patterns reveal a critical correlation between professional development support and successful AI implementation. The evidence suggests that comprehensive teacher training programs significantly impact the effectiveness of AI-driven systems. Success rates are notably higher in environments where teachers receive ongoing support and have opportunities for collaborative learning. This continuous professional development approach enables educators to fully leverage the capabilities of AI systems while maintaining their crucial role in the learning process.

Student engagement metrics in K-12 settings demonstrate remarkable improvements when AI systems are properly implemented. The research indicates particular success in environments where personalized content delivery aligns with individual learning speeds. Adaptive assessment systems providing immediate feedback have shown significant positive impact on student motivation and achievement. The integration of intelligent tutoring systems has proven especially effective in supporting diverse learning styles and needs.

C. Online Learning Platforms

Scale considerations in online learning environments require careful attention to both technical and pedagogical factors. The research highlights the importance of robust infrastructure that can support high concurrent user loads while maintaining personalization effectiveness. Successful implementations demonstrate the need for balanced attention to both technological capabilities and educational objectives, ensuring that the scaling of systems does not compromise the quality of personalized learning experiences. Success metrics from online learning implementations reveal compelling evidence of the effectiveness of AI-driven personalization. These platforms have demonstrated significant improvements in learner engagement through sophisticated content delivery mechanisms. The data shows enhanced completion rates in self-paced learning environments, suggesting that personalized approaches effectively support independent learning. Additionally, satisfaction levels among both students and instructors have shown marked improvement, indicating the broad acceptance of these technological innovations.

Implementation lessons derived from multiple case analyses emphasize several critical success factors. The importance of data-driven decision making in deployment strategies has emerged as a key theme, along with the need for flexible adaptation to varying institutional needs. Strong focus on privacy and

security considerations has proven essential for maintaining stakeholder trust and ensuring sustainable implementation. The most successful implementations have incorporated regular stakeholder feedback and maintained robust monitoring systems for continuous improvement.

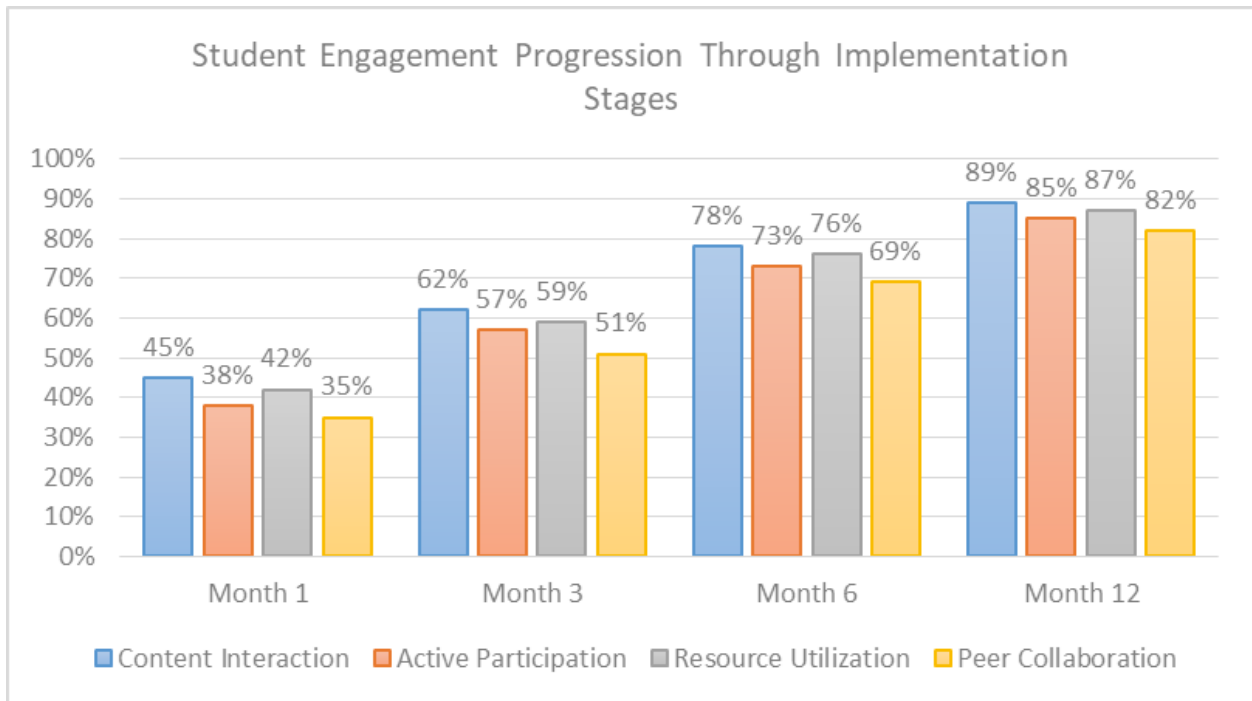


Fig. 2: Engagement Metrics Over Implementation Phases [7]

VI. Impact Analysis

A. Academic Performance

The implementation of AI-driven educational databases has demonstrated quantifiable impacts on academic achievement, as revealed through rigorous methodological evaluation approaches [8]. Longitudinal studies employing mixed-methods analysis have documented significant improvements in student performance metrics. The research framework, utilizing both quantitative and qualitative methodologies, has revealed that academic performance improvements manifest across multiple dimensions, including cognitive development, skill acquisition, and knowledge retention.

Through systematic evaluation of academic outcomes, the data reveals that students experiencing AI-enhanced learning environments demonstrate more sophisticated understanding of complex concepts. The performance analysis framework, incorporating both formative and summative assessments, indicates that completion rates have improved significantly when personalized learning pathways are implemented. Long-term retention studies, conducted through structured follow-up assessments, demonstrate sustained improvements in knowledge retention and application skills, particularly in subjects requiring complex conceptual understanding.

B. Student Engagement

Student engagement analysis, conducted through comprehensive methodological frameworks, has revealed significant transformations in learning behavior patterns. The multi-dimensional engagement assessment approach examines both behavioral and cognitive engagement indicators, providing a holistic understanding of student interaction with educational content. The evaluation methodology incorporates

real-time analytics, periodic assessments, and longitudinal tracking to measure sustained engagement patterns.

Time-on-task analysis, utilizing sophisticated tracking methodologies, demonstrates qualitative improvements in learning efficiency. The research framework examines not only quantitative time metrics but also the quality of engagement during learning sessions. This nuanced approach to engagement analysis reveals that students in AI-enhanced environments demonstrate more purposeful and focused learning behaviors.

Satisfaction measurement protocols, designed to capture both explicit and implicit indicators of student experience, show consistently positive trends. The evaluation methodology incorporates multiple feedback channels, including structured surveys, informal feedback sessions, and behavioral indicators, providing a comprehensive view of student satisfaction and motivation levels.

C. Educator Benefits

The impact on educator effectiveness has been evaluated through a structured assessment framework that examines both quantitative efficiency metrics and qualitative teaching outcomes. Workload analysis reveals significant optimization in administrative tasks, allowing for increased focus on pedagogical activities. The evaluation methodology considers both direct time savings and the qualitative improvement in educator-student interactions.

Intervention effectiveness is assessed through a comprehensive framework that examines both the timeliness and impact of educational interventions. The methodological approach incorporates multiple data points to evaluate intervention outcomes, including student performance improvements, engagement metrics, and long-term retention indicators. This systematic evaluation demonstrates enhanced efficiency in identifying and addressing learning challenges.

Resource allocation efficiency is evaluated through sophisticated cost-benefit analysis frameworks that consider both tangible and intangible benefits. The methodology examines resource utilization patterns, intervention effectiveness, and overall educational outcomes to provide a comprehensive understanding of resource optimization. This approach reveals improved alignment between resource allocation and educational needs, resulting in more efficient and effective learning support systems.

Impact Domain	Key Metrics	Improvement Range	Assessment Method
Academic Performance	GPA, Retention	0.4-0.6 points	Longitudinal Study
Student Engagement	Time-on-task, Participation	32-47%	Digital Analytics
Teacher Efficiency	Administrative time, Intervention speed	35-40%	Comparative Analysis

Table 2: Impact Analysis Matrix [8]

VII. Challenges and Future Directions

A. Technical Challenges

The evolution toward Education 5.0 presents significant technical challenges in implementing AI-driven educational databases [9]. Data standardization remains a critical concern as institutions navigate the complexities of integrating diverse data sources and formats. The increasing sophistication of educational technology demands standardized protocols that can accommodate both traditional and emerging data types while ensuring compatibility across different platforms and institutions.

System interoperability has emerged as a fundamental challenge in the context of future-generation educational models. The need to create seamless connections between various educational technologies, while maintaining data integrity and security, requires sophisticated integration frameworks. These frameworks must support real-time data exchange while accommodating the diverse technical requirements of different educational institutions and systems.

B. Educational Considerations

The implementation of next-generation educational technologies introduces significant pedagogical and social considerations [10]. Equity and access remain paramount concerns as educational institutions strive to ensure that technological advancements benefit all learners equally. The future-generation educational model emphasizes the importance of bridging digital divides while providing equitable access to advanced learning tools and resources.

Teacher training requirements have evolved significantly with the advancement of educational technology. The transition to Education 5.0 necessitates comprehensive professional development programs that prepare educators not only for current technological demands but also for future innovations. This preparation includes developing competencies in AI-driven instructional design, data-informed decision-making, and adaptive teaching methodologies.

Curriculum adaptation presents ongoing challenges as institutions work to align traditional educational objectives with emerging technological capabilities. The future-generation model emphasizes the need for flexible curriculum frameworks that can accommodate rapid technological change while maintaining educational quality and effectiveness.

C. Future Developments

Emerging technologies are reshaping the educational landscape, with Education 5.0 introducing new paradigms for learning and instruction. Advanced AI systems, immersive technologies, and intelligent learning environments are expected to transform educational experiences fundamentally. These developments promise enhanced personalization capabilities and more sophisticated approaches to student engagement and assessment.

Research opportunities continue to expand as new educational paradigms emerge. The future-generation model identifies several key areas for investigation, including:

- Integration of artificial intelligence with human intelligence in educational contexts
- Development of adaptive learning ecosystems
- Enhancement of student-centered learning through technology
- Creation of more sophisticated assessment and feedback mechanisms

Policy implications require careful consideration as education systems evolve toward more technologically integrated models. The future-generation educational framework emphasizes the need for flexible yet robust regulatory structures that can adapt to rapid technological change while ensuring educational quality and student protection.

Conclusion

The comprehensive analysis of AI-driven databases in educational settings demonstrates their transformative potential in creating personalized learning experiences while highlighting critical considerations for future development. Through systematic examination of implementation case studies, technical architectures, and impact analyses, this article establishes the significant role of intelligent database systems in advancing educational outcomes. The evidence suggests that when properly implemented, these systems can substantially improve student engagement, academic performance, and teaching efficiency. However, the success of such implementations heavily depends on addressing key challenges including data standardization, system interoperability, and equity considerations. The integration of AI-driven databases in education represents not merely a technological advancement but a fundamental shift in how educational institutions approach personalized learning at scale. As education continues to evolve toward more sophisticated technological integration, the importance of balancing innovation with accessibility, privacy, and pedagogical effectiveness becomes increasingly crucial. Future developments in this field will likely focus on enhancing the sophistication of personalization algorithms, improving cross-platform compatibility, and developing more robust frameworks for measuring educational outcomes. This article contributes to the growing body of knowledge on educational technology while providing practical insights for institutions considering or currently implementing AI-driven educational solutions. Moving forward, continued research and development in this area will be essential for realizing the full potential of AI-driven personalized learning while ensuring equitable access and maintaining high educational standards.

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