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PERSONALISED LEARNING USING DEEP LEARNING TECHNIQUES

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ABSTRACT

With the growing popularity of online learning and e-education platforms, the importance for adaptive learning as per individual learning needs has been increasing. Although existing solutions have come a long way, they still lack the ability to capture a wide range of learning styles and truly deliver personalized learning experiences. This project suggests a comprehensive framework combining sentiment analysis and knowledge graph technologies to enhance personalization in educational platforms. With the use of advanced models such as BERT-Bi-LSTM-Attention for analyzing course reviews and knowledge graphs to represent user interaction, course relationships and store user preferences, the system can break cold-start issues and ensure that course recommendations are more transparent. The methodology includes an approach to leverage learner motivation and learning outcomes by delivering a more responsive and personalized digital education environment. The solution also includes a feedback loop and dynamically generates quizzes based on completed courses helping students assess their progress and identify areas for improvement, offering a scalable model that can be utilized to adapt to various educational environments and offers continuous enhancement in personalized learning.

Keywords: *Personalization, Course Recommendations, BERT-Bi-LSTM-Attention, Knowledge Graph, Feedback Mechanism.*

1. INTRODUCTION

The abrupt shift towards digital and online education has brought the requirement for intelligent educational platforms that can deliver personalized learning experience according to certain goals, interest, and learning style. Although Ed-tech is expanding, most traditional systems struggle to handle the wide differences in how students learn. This often leads students to lose interest, feeling less motivated [3].

One of the key limitations of existing recommendation systems is their inability to serve new users effectively—a challenge known as the cold-start problem. Lacking few or no data, these systems cannot offer thoughtful and relevant learning materials to new users [2]. Secondly, while students provide feedback such as ratings, reviews, and comments—contain valuable information, the existing sentiment analysis models often fail to understand the exact emotional tone or context. This can lead to misclassification and may provide recommendations that fail to engage users [1].

These limitations highlight the need for a more flexible and adaptable style of personalized learning. To obtain this advanced machine learning method, contextual sentiment analysis, and intelligent user profiling must be combined not just to deliver content but also provide motivation and guidance to learners. Algorithmic personalization has been shown to improve motivation and learning performance as it aligns with the learning pattern of individual learner [3].

To address the sparsity problem of the data, this project integrates the use of collaborative knowledge graph attention models [2]. These models

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facilitate the extraction of sophisticated relationships with a deep understanding of learners' needs. Additionally, a deep learning architecture—e.g., BERT with Bi-LSTM and attentions—permits more focused sentiment analysis on student comments, which assists teachers in developing course material as well as teaching routines [1].

The proposed research focuses on creating adaptive learning models responsive to diverse educational needs, thereby enhancing participation and outcomes. It involves the creation of interpretable and accurate recommendation systems using knowledge graph networks and deep sentiment analysis to derive actionable knowledge from learner feedback. The ultimate long-term objective of the project is to create inclusive and dynamic systems responsive to diverse learning environments, thereby enhancing increased accessibility and more effective personalized learning outcomes. Real-world experiments will validate the strength and applicability of the models.

1.1 Problem Statement - Overview

Greater reliance on e-learning platforms heightens the need for adaptive platforms that can meet the unique needs of learners. Nonetheless, traditional methods and technologies are inadequate to fully address multiple learning modalities, leading to disengagement and compromised academic performance [3]. Also, most of the recommendation systems are hampered by the cold-start problem, limiting them from being capable of suggesting perfect content to new users based on a lack of historical data [2]. Despite this, whenever a student provides feedback as a review or a comment, even though its relevant input, most sentiment models fail to understand the emotional and contextual meaning of such input [1]. Overall, these limitations make it challenging to create explainable, adaptive, and sufficiently personalized learning platforms.

1.2 Motivation

Overcoming these limitations brings immense advantages to learners and instructors. Smart learning materials based on machine learning technology have been shown to improve student learning and achievement by matching resources to personal learning styles [3]. Embedding collaborative knowledge graph attention networks can counter sparsity and deliver more accurate recommendations that are capable of learning user preferences [2]. Additionally, using deep models such as BERT, Bi-LSTM along with attention models for sentiment analysis can extract beneficial feedback from the sentiments of the students to better empower teachers with strategy-making to further enhance overall course performance [1]. These advancements do not merely bridge necessary voids in education technology, but they open avenues towards making educational settings even more inclusive as well as productive.

1.3 Scope & Objectives

This project seeks to innovate personalized learning systems by solving major challenges in responding to the needs of individual learners. The emphasis is on creating adaptive machine learning models that can react to diverse learning styles, making students more engaged and improving academic performance [3]. One of the central aspects of this work is creating sophisticated recommendation systems based on collaborative knowledge graph attention networks, which allow for improved and interpretable suggestions of educational materials [2]. In addition, the research utilizes deep learning architecture—BERT-Bi-LSTM with attention mechanism—to conduct sentiment analysis of students' feedback, allowing for the extraction of subtle emotional and contextual information to guide instructional refinement [1]. The solutions proposed are meant to be scalable and flexible in diverse learning environments to ensure universal accessibility and inclusivity across various learner profiles. The overall goals are to construct dynamic learner-based models, create explainable recommendation structures, deciphering student sentiment accurately, and verify the proposed methods using real-world datasets to measure their performance and trustworthiness.

2. RELATED WORK

2.1 Sentiment Analysis based on Deep-Learning

Use of Deep Learning methodologies has enhanced sentiment analysis considerably, particularly in the learning environment. Shuqin and Raga [1] introduced a deep learning-powered model that draws on course review to evaluate the sentiment of learners with better performance compared to past methods. Bi-LSTM architectures and Transformer-based models like BERT have become popular because they are capable of handling long dependencies and contextual meanings in text.

Hybrid models using the combination of BERT and Bi-LSTM together with attention have improved sentiment classification even further. Khan et al. [12] used sentiment analysis to complement personal learning systems using learner feedback analysis, and Zhang et al. [4] utilized knowledge graphs in addition to sentiment analysis to engage in more expressive learner modeling.

2.2 Attention Mechanisms in NLP

Attention mechanisms have played a crucial role in NLP in highlighting salient regions of the input. With attention mechanisms incorporated in deep learning models, more interpretable and accurate sentiment labeling is possible. For example, Yang et al. [14] investigated multi-modal systems in which attention mechanisms were crucial in handling various education materials to improve recommendation performance.

Shao et al. [17] also pointed to hybrid models that rely on the application of attention to enhance personalization in recommendation making, validated in real-world applications to learning settings.

2.3 Knowledge Graph-Based Recommendation Systems

Knowledge graphs (KGs) yield semantic relationships between entities like courses, teachers, and students. Bai et al. [11] used KGs in online learning recommendation systems and showed how entity relationship can improve recommendation performance. Wang and Yue [2] also developed a collaborative knowledge graph attention model for enhancing recommendation accuracy and context of recommendations for learning resources.

The application of GNNs and attention-based spreading in KGs facilitates personalized suggestions by giving weights to various neighbors. It was also complemented by Zhang et al. [4], who highlighted simultaneous utilization of sentimental information and KGs to enrich learner profiles.

2.4 Course Recommendation and Hybrid Systems

Course recommendation frameworks have progressed from collaborative filtering towards hybrid models that combine multiple information sources. Gupta et al. [8] and Yuan et al. [23] proposed Hybrid recommendation frameworks with consideration of learner behavior, course content, and learner feedback to provide personalized suggestions .

Current work has centered on the incorporation of user preference and sentiment-aware methods. Chen et al. [10] used deep neural networks to optimize recommendation of content, while Chen and Liu [24] optimized recommendation efficiency using MOOC-related sentiment information.

In addition, other studies such as Cheng et al. [6] and Liu et al. [21] explored the use of collaborative filtering and learner modeling for adapting learning pathways. Others, such as Rao et al. [19] and Nguyen et al. [9], studied reinforcement learning and predictive analytics for adjusting recommendations in the long term.

2.5 Adaptive and Intelligent Learning Systems

Current trends in adaptive learning revolve around adapting course recommendations in real-time using feedback. Zhou et al. [16] proposed a method that utilizes real-time feedback to make adaptive course recommendations. Xu et al. [20] and Jiang et al. [22] proposed AI-based methods that leverage knowledge graphs and sentiment analysis to recommend personalized learning routes.

Reinforcement learning [9], clustering techniques [15], and cognitive modeling [18] have also been shown to be promising in improving learner personalization and adaptability.

3. METHODOLOGY

The suggested methodology combines sentiment analysis and recommendation systems to develop a learner-focused educational system based on learner's flexibility to demands. The system combines course review comments, user-resource interaction information, and dynamic feedback to give correct recommendations.

3.1 Knowledge Graph BERT Bi-LSTM Attention Mechanism Model Framework

3.1.1 Input Layer

The system enhances course suggestions based on sentiment analysis of comments and user behavior patterns. The methodology considers both action and tone of user comments, which results in tailored suggestions.

To get the data ready for model use, a standardized preprocessing pipeline is used. This involves tokenization (splitting text into words or sub-words), noise removal (removing redundant characters, HTML tags, and stop words), and data normalization (normalizing case, spell correction, etc.). All these reduce input variability and increase model accuracy.

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The data is preprocessed to make it ready to satisfy the input requirements of deep learning models such as BERT-Bi-LSTM with attention for sentiment analysis. This enables the model to learn user comments and text to suggest appropriate courses.

3.1.2 Knowledge Graph Construction Module

The system forms a dynamic graph of important entities such as courses, instructors, schools, and user interests. It collects data from different sources with a bottom-up strategy and employs Neo4j to structure the relationships between these entities. This allows mapping interactions, for example, between courses and instructors, schools, and user interests. The functionality of Neo4j allows effective exploration of these relationships, facilitating personalized recommendations based on relationships and tracked behavior.

1. Knowledge Graph Buildup: The knowledge graph is built based on entities like courses, instructors, students, schools, subjects, and YouTube videos, linked through significant relations such as "taught by", "offered at", "interested in", and "related to". Each node is an entity, and edges represent their interactions or dependencies. This ordered representation allows the system to capture higher-order semantic relationships that are hard to encode using conventional recommendation systems.

2. Attention Mechanism: To distinguish the different relevance of nearby nodes in the knowledge graph, an attention mechanism is used when passing messages. Not all the nearby nodes play an equal role in comprehending a target entity (e.g., some courses might be more impactful than others for a learner). The attention layer provides adaptive weights to nearby nodes depending on their contextual significance, higher weights are assigned to meaningful information. This allows for more relevant information to be propagated during embedding learning, hence enhancing the expressiveness and interpretability of node representations.

3. Embedding Propagation: Each graph node (learners, courses, instructors, etc.) is initially encoded as a low-dimensional vector (embedding). By multi-hop propagation, these embeddings are updated by summing information from neighboring nodes and their corresponding attention weights. This enables the model to capture higher-order structural information and relations within the graph. The embeddings are increasingly improved at each layer, capturing deeper interactions like a learner's indirect preferences through common instructors or comparable courses.

4. Prediction Layer: Following the embedding of propagation, the system calculates the inner product between learner and course embeddings at the final time step to predict the interaction probability, which is the probability of a learner interacting with a given course or video. The interaction scores are utilized for ranking and recommending resources to individuals based on their own preferences. The model is trained on a loss function like binary cross-entropy or Bayesian Personalized Ranking (BPR), depending on whether interaction data is explicit or implicit feedback.

Figure 1: Construction of Knowledge Graph [2]

3.1.3 Sentiment Analysis Module

BERT-Bi-LSTM-Attention (BBA) Model: Captures rich contextual and emotional relationships from text data.

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1. BERT Layer: Our architecture's first component is the Bidirectional Encoder Representations from Transformers (BERT), which is a transformer model pre-trained on a vast text corpus using masked language modeling and upcoming sentence prediction. We employ in our framework a pre-trained BERT model (e.g., BERT-base-uncased) to represent each of our input comments as a sequence of dense contextualized embeddings. BERT learns deep bidirectional contextual representations by looking at the whole sentence in both directions at once, effectively capturing word-level relationships and contextual subtleties that are essential for sentiment understanding.

2. Bi-LSTM Layer: Although BERT embeddings itself carry a lot of contextual information, we additionally encode it with a Bidirectional Long Short-Term Memory (Bi-LSTM) network. The Bi-LSTM layer learns long-term dependencies and sequential patterns in both directions, fine-tuning the contextual representations acquired from BERT. The Bi-LSTM layer is especially efficient in dealing with the variability and informality of social media text like using slang, abbreviations, and fragmentary sentences that are often present in YouTube comments.

3. Attention Mechanism: After the Bi-LSTM, we add an attention mechanism that dynamically weights every word in the sequence according to its importance towards sentiment classification. The attention layer improves the capability of the model to pay more attention to words and phrases containing sentiment and de-emphasize irrelevant or noisy data. This assists the model in identifying slight emotional indicators, emphasis markers, and negations, which are important for distinguishing between negative, positive, and neutral emotions. The attention weights are learned through training and enable interpretability by emphasizing important components of the input text.

4. Pooling and Classification Layers: Following attention-weighted features are calculated, we use a pooling layer, usually global average pooling or max pooling, to pool the sequence into a fixed-size vector representation. This representation is then passed through a fully connected (dense) layer followed by a sigmoid activation function to output the final sentiment score. For multi-class sentiment classification (positive, neutral, negative, etc.), the output layer can be modified to use a SoftMax function instead.

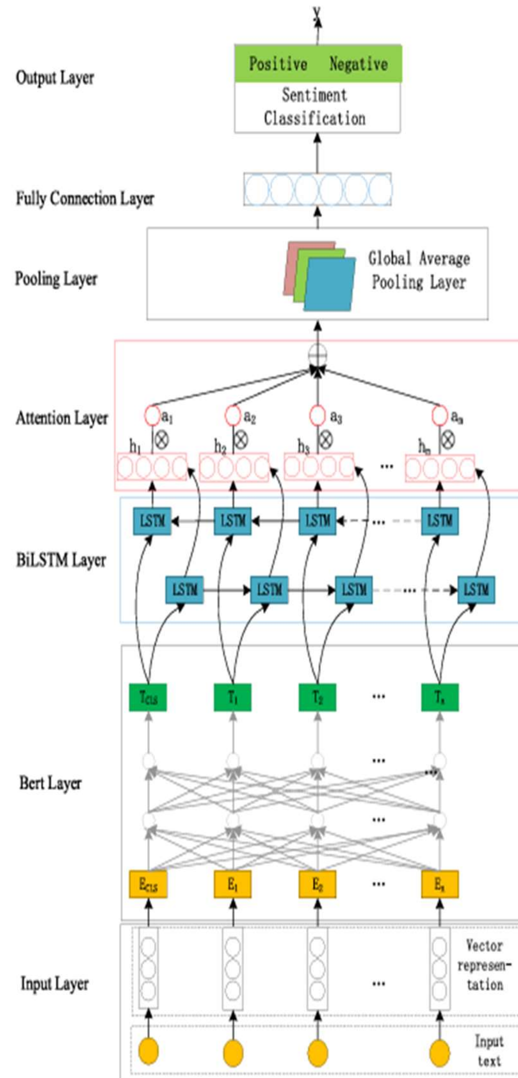


Figure 2: BBA Model Framework [1].

3.1.4 Unified Prediction Layer

Sentiment outputs trigger recommendation updates. For instance: Negative emotions may initiate suggestions for additional core or complementary material. Positive feelings may suggest more finely based on learner preference. Combines sentiment and knowledge graph outputs into a combined learner model.

3.2 Mechanism of Operation

The methodology adopted in this work combines sentiment analysis and knowledge graph-based recommendation with personalized course recommendations using the analysis of YouTube comments. The process can be divided into two main modules: sentiment analysis using BERT-Bi-LSTM-Attention (BBA) model and course recommendation using an attention-based knowledge graph.

3.2.1 Sentiment Analysis using BERT-Bi-LSTM-Attention

1. Input Preprocessing: Raw text from a few YouTube online courses is preprocessed and tokenized initially. Stop words, noise, and special characters are removed. Preprocessed text is tokenized again by BERT's tokenizer so that subword-level information can be maintained.

2. BERT Embedding Layer: The input passes through a pre-trained BERT model that provides deep contextual embeddings for each word. BERT has the capability of retaining rich bidirectional semantics and hence the complexities of sentiment are captured by the model.

3. Bi-LSTM Layer: BERT output is fed to a Bi-LSTM layer. The layer handles the text sequentially in both directions forward and backward and learns temporal and contextual dependencies.

4. Attention Mechanism: There is an attention layer added on top of Bi-LSTM outputs. There is a module that imparts different weights to different segments of the text in such a way that the model is keen on sentiment-carrying points and is not aware of unnecessary points. It speeds up the process of sentiment classification and it is simpler to comprehend.

5. Classification Layer: The weight of the attention is weighted and accumulated and fed into a fully connected sigmoid activation function layer to generate the sentiment classification of three classes: Positive, Neutral, and Negative.

6. Sentiment Storage: All comment predicted sentiment scores are stored into the system database and mapped into corresponding course entities.

3.2.2 Knowledge Graph-Based Course Recommendation

1. Knowledge Graph Construction: A heterogeneous graph of information is constructed over entities such as learners, courses, instructors, platforms, and subjects. Semantic relations such as "enrolled_in", "taught_by", and "has_topic" are modeled with edges.

2. Graph Embedding and Attention: Node features (such as sentiment ratings and interaction history) are embedded into vector representations. Scaled neighboring node contribution through an attention mechanism allows the model to pay attention to more useful entities (such as top-rated courses or most-loved instructors). Information is distributed across the entire graph using multi-hop message passing, detecting indirect and distant relationships such as similarly instructed courses by other instructors or like-minded individuals.

3. Learner Representation Generation: The representation of each learner is learned in real time by data gathering from proximal entities such as favorite courses, rated instructors, and interests.

4. Prediction Layer: Probability of a student engaging with a course is computed by inner product of corresponding embeddings. The better the score, the more appropriate the recommendation.

5. Recommendation Output: Top N courses with top N highest interaction probabilities are returned and shown to the student. Recommendations are contextually appropriate by considering historical preference and sentiment cues of social feedback.

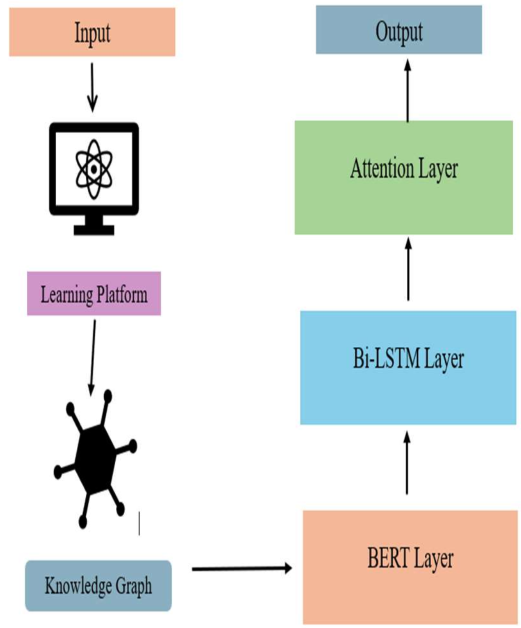


Figure 3: Methodology Flow

4. DATASET DESCRIPTION

The dataset has 500 comments on YouTube, which are used to perform sentiment analysis. The main intention of this dataset is to categorize the sentiments of the comments as negative, neutral, and positive into three classes. The dataset is prepared to train and test sentiment analysis models with machine learning and deep learning algorithms like BERT, Bi-LSTM, and Attention Mechanisms. Dataset Columns:
1.Comments: This column holds textual comments from YouTube videos. Each comment is a user's opinion, feedback, or response to a video. The comments are varied in language, usually including informal language, internet slang, emojis, and sometimes abbreviations.
2.Labels: The sentiment label for each respective comment is included in this column. The labels are given according to the sentiment expressed in the comment. There are three possible labels:
0: Negative Sentiment (The comment conveys dissatisfaction, dislike, or a negative opinion regarding the video.)
1: Neutral Sentiment (The comment shows neither strong positive nor strong negative sentiment, typically being indifferent or neutral.)
2: Positive Sentiment (The comment is an expression of praise, positive comment, or a positive opinion regarding the video.)

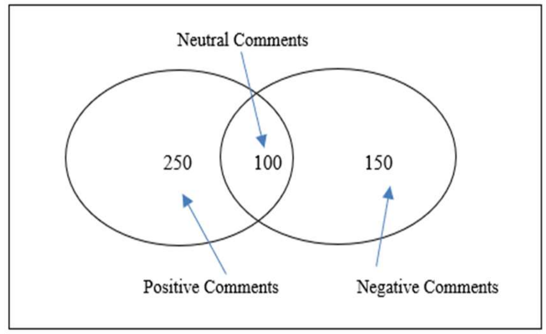


Figure 4: Dataset Visualization.

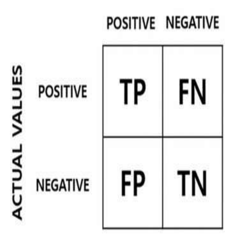
5. RESULTS

The BBA recommendations can be compared with the integration of BBA with knowledge for personalized recommendations.

5.1 Evaluation Metrics

Accuracy, F1-Score, Recall, Precision (sentiment analysis) and AUC, F1-Score, and Top K metrics (recommendation) to measure performance. Testing actual-world usability (user satisfaction).

The corresponding formula is as follows:



$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where TP, TN, FP and FN respectively represent the positive samples are projected by the model to be in the positive class, negative samples are anticipated to be in the negative class, the negative samples are anticipated to be in the positive class and positive samples are projected by the model to be in the negative class.

Metrics (%)	Score (%)
Accuracy	93.0
Precision	93.7
F1 Score	92.86

TABLE 1: EVALUATION METRICS.

5.2 Findings

The BBA model alone based recommendation system gives generalized course recommendations to all the users. These recommendations are identical to all users and lack personalization for specific users.

Integrating Knowledge graph has leveraged personalized course recommendations to each specific user based on their learning styles. To demonstrate this, multiple users were created with different learning preferences which are stored to knowledge graph, when searched for the same query by different users, the model was successfully able to provide tailored recommendations to individual users.

Thus, we achieved the goal of generating personalized course recommendations to different users based on their learning patterns.

5.3 Discussion

These findings demonstrate how sentiment only models fail to provide tailored recommendations to specific users, by integrating BBA model with Knowledge graph we can leverage the system to be more adaptive and provide dynamic recommendations.

The Knowledge graph captures contextual meaning by storing relationships among users, instructors, ratings etc. This hybrid model not only gives relevant recommendations but also generates dynamic quizzes with preferred difficulty level, aligning learning path with their preferences and improving learner satisfaction.

6. FUTURE SCOPE

1. Cross-Industry Application: Extend the model to diverse industries like corporate training, health education, and vocational courses. This can be done by formulating the model to suit sector-specific data to make it apply across various contexts.

2. Combination of Multiple Input Sources: Embed multiple media like video transcripts, recorded lectures, and interaction history in addition to text inputs for improved sentiment perception and recommendation accuracy.

3.Scalable Solutions: Leverage distributed computing resources and cloud infrastructure to efficiently process large datasets, support mass platforms, and facilitate processing from global users.

4.Fairness and Bias Reduction: Apply features that detect and eliminate biases in sentiment analysis and recommendation engines to facilitate fairness and ethical decision-making throughout the platform.

5.Gamification Driven Engagement: Using the recommended information and sentiment metrics to generate customized, learning environments to enhance learner motivation, engagement, and retention

7. CONCLUSION

The proposed architecture combines state-of-the-art sentiment analysis with knowledge graph integration to enhance personalized recommendation techniques and enrich digital learning platforms. It employs a BERT-Bi-LSTM-Attention model to extract in-depth emotional and contextual understanding from course reviews, complemented with data augmentation and noise-handling techniques to enhance the accuracy in processing noisy data. A dynamically updated knowledge graph models important entities like courses, teachers, and user interests, supporting accurate and explainable recommendations through a Knowledge Graph. The integrated prediction layer combines sentiment analysis and recommendation outputs, providing adaptive and personalized learning experiences. This design overcomes issues of interpretability, real-world applicability, and user satisfaction. Future innovations will be aimed at real-time personalization, cross-domain adaptability, multimodal integration, and reducing ethical biases, enabling dynamic, inclusive, and effective educational systems that develop in sync with advances in AI and technology.

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