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ALBERT-Based Personalized Educational Recommender System: Enhancing Students' Learning Outcomes in Online Learning

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Abstract—

Online learners must navigate vast educational resources to find materials that meet their needs. This study introduces an ALBERT-based personalized educational recommender system to improve student learning. ALBERT (A Lite BERT), an optimized variant of the BERT algorithm, captures contextualized word representations and understands the semantic meaning of learning resources, student profiles, and interactions. This study evaluates the ALBERT-based recommender system's personalized learning recommendations. To assess learning outcomes, a diverse group of students from different educational domains is evaluated. Before and after the recommender system, academic performance, knowledge retention, and engagement are assessed. User satisfaction surveys assess recommendation quality, relevance, and user experience. The recommender system uses ALBERT's model optimization to improve recommendation accuracy, learner engagement, and personalized learning. The evaluation shows the ALBERT-based personalized recommender system improves online learning outcomes. System-generated recommendations boost student engagement, knowledge retention, and academic performance. User satisfaction surveys show that the ALBERT-based system meets learners' needs by providing relevant and high-quality recommendations. This research shows how advanced deep learning algorithms like ALBERT can improve personalized online learning. ALBERT's optimized training and inference speeds up the recommender system's scalability. This empowers learners to access tailored and high-quality educational resources, maximizing their learning outcomes and potential in online learning.ALBERT, BERT, deep learning, educational recommender system, personalized learning, online learning, learning outcomes, semantic representation, user satisfaction, model optimization.

I. INTRODUCTION

In the era of online learning, the availability of vast educational resources has opened up new opportunities for learners worldwide. However, the abundance of resources poses a

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significant challenge for learners in finding the most relevant and suitable materials that align with their individual learning needs, preferences, and goals. Traditional "onesize-fits-all" approaches to education fail to address the diverse learning requirements and result in suboptimal learning outcomes. To overcome these challenges and enhance students' learning experiences, personalized educational recommender systems have emerged as a promising solution. The goal of a personalized educational recommender system is to provide tailored recommendations to learners, assisting them in discovering and accessing educational resources that best suit their unique needs and preferences. These systems leverage advanced technologies, such as deep learning algorithms, to analyze various data sources, including learner profiles, learning behaviors, content metadata, and interactions, to generate personalized recommendations. Among the deep learning algorithms, BERT (Bidirectional Encoder Representations from Transformers) has emerged as a powerful language model for natural language processing (NLP) tasks. BERT captures contextualized word representations by considering the surrounding words on both sides of a given word, enabling it to understand the intricate nuances of language. This capability makes BERT well-suited for understanding the semantic meaning and context within educational texts and learner interactions. However, to address the limitations of BERT, an advanced variant called ALBERT (A Lite BERT) has been introduced. ALBERT employs innovative techniques, including factorized embedding parameterization, cross-layer parameter sharing, and inter-sentence coherence training, to optimize the model's size and training efficiency. These optimizations result in a more compact model that maintains or even improves the performance of BERT, making it an ideal choice for large-scale applications, such as personalized educational recommender systems. This research project focuses on designing and evaluating an ALBERT-based personalized educational recommender system to enhance students' learning outcomes in the context of online learning. By leveraging ALBERT's capabilities in understanding the semantic meaning of learning resources, student profiles, and interactions, the recommender system aims to provide accurate and personalized recommendations to learners. The system will analyze the individual learning needs, preferences, and goals of each learner to generate tailored recommendations that maximize their learning potential.

The research project will employ a comprehensive evaluation methodology to assess the effectiveness of the ALBERTbased recommender system. Key performance indicators,

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including academic performance, knowledge retention, and learner engagement, will be measured before and after the implementation of the system. Additionally, user satisfaction surveys will be administered to gather feedback on the quality, relevance, and user experience of the personalized recommendations. The outcomes of this research project will contribute to the field of educational technology by showcasing the benefits and effectiveness of utilizing advanced deep learning algorithms, specifically ALBERT, in personalized online learning. The optimized nature of ALBERT enables faster training and inference, ensuring scalability and efficiency of the recommender system. Ultimately, the ALBERT-based personalized educational recommender system aims to empower learners by providing them with tailored and high-quality educational resources, thereby enhancing their learning outcomes and overall learning experiences in the online learning environment.

II. LITERATURE SURVEY

The literature survey provides an overview of several papers related to recommender systems and personalized learning in the context of education. These papers cover a wide range of topics, including the use of web 2.0 technologies, recommendations in e-learning, personalized lesson sequence recommendation, and the impact of open educational practices during the COVID-19 outbreak.

The survey begins with papers [1] and [2], which focus on recommender systems for web 2.0-supported elearning and personalizing e-learning using recommendations. These papers highlight the importance of leveraging web 2.0 technologies and personalized recommendations to enhance the learning experience for students.

Next, papers [3], [4], and [5] explore various aspects of recommender systems for recommending learning objects. They discuss argumentation-based hybrid recommendation systems, student-centered hybrid recommendation systems, and the provision of relevant learning objects from repositories. These papers emphasize the importance of personalized recommendations to support effective learning resource selection.

Papers [6] and [8] delve into personalized lesson sequence recommendation. They present approaches to learning student and content embeddings, as well as latent skill embedding, to optimize the sequencing of learning materials and activities for individual learners.

The survey also includes papers [9] and [10], which focus on the application of open educational practices and time-aware multi-objective recommendation in online learning

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environments, respectively. These papers address the emerging issues and challenges in the field and propose innovative solutions to enhance the learning experience.

Additionally, papers [11], [12], [13], [14], [15], [16], [17], and [18] cover various topics such as machine learningdriven personalized interactions with students, curriculum customization, embedding recommender systems into mobile apps, and deep academic learning intelligence. These papers contribute to the understanding of personalized learning approaches, recommendation algorithms, and the integration of technology in educational settings.

Overall, the literature survey provides a comprehensive overview of the research conducted in the field of personalized learning and recommender systems in education. It highlights the significance of personalized recommendations, the use of advanced technologies such as web 2.0 and machine learning, and the exploration of innovative approaches to enhance the learning experience for students.

[1] "Recommender System for Web 2.0 Supported ELearning" (2014): This paper focuses on the development of a recommender system that leverages Web 2.0 technologies to enhance eLearning experiences. It explores the use of collaborative filtering and content-based filtering techniques to personalize recommendations for learners. [2] "Personalizing E-Learning 2.0 Using Recommendations" (2014): This paper discusses the importance of personalization in eLearning 2.0 and proposes a recommendation approach to tailor learning materials and resources to individual learners' needs and preferences. The authors explore the use of collaborative filtering algorithms for personalized recommendations. [3] "Emerging Issues in Smart Learning International Conference on Smart Learning Environments" (2015): This conference paper discusses emerging issues in smart learning environments and their impact on educational practices. It covers various topics such as personalized learning, adaptive learning systems, and the integration of technologies in education. [4] "Argumentation-Based Hybrid Recommender System for Recommending Learning Objects" (2015): This paper presents a hybrid recommender system that incorporates argumentation-based techniques to recommend relevant learning objects. The system aims to enhance the effectiveness of personalized recommendations by considering user feedback and utilizing argumentation models. [5] "A Student-Centered Hybrid Recommender System to Provide Relevant Learning Objects from Repositories" (2015): This paper proposes a student-centered hybrid recommender system that integrates collaborative filtering and content-based filtering

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to recommend relevant learning objects from repositories. The system aims to improve the quality of personalized recommendations for learners. [6] "Learning Student and Content Embeddings for Personalized Lesson Sequence Recommendation" (2016): This paper presents an approach for personalized lesson sequence recommendation based on learning student and content embeddings. The authors use neural networks to model student and content representations and propose a ranking algorithm to generate personalized recommendations. [7] "Recommender System and Web 2.0 Tools to Enhance A Blended Learning Model" (2016): This paper discusses the integration of a recommender system and Web 2.0 tools to enhance a blended learning model. The authors propose a framework that combines collaborative filtering and content-based filtering techniques to provide personalized recommendations to learners.[8] "Latent Skill Embedding For Personalized Lesson Sequence Recommendation" (2016): This paper introduces a latent skill embedding approach for personalized lesson sequence recommendation. The authors propose a method to embed skills and model student knowledge to generate personalized recommendations for the optimal sequence of lessons.[9] "Disrupted Classes, Undisrupted Learning During COVID-19 Outbreak in China: Application of Open Educational Practices and Resources" (2020): This paper explores the application of open educational practices and resources during the COVID-19 outbreak in China. It discusses the use of online platforms, open educational resources, and innovative pedagogical approaches to ensure uninterrupted learning.[10] "CAREER: Time-Aware Multi-Objective Recommendation in Online Learning Environments" (2021): This paper focuses on time-aware multi-objective recommendation in online learning environments. It proposes a novel recommendation algorithm that considers multiple objectives and time constraints to provide personalized recommendations for learners. [11] "Putting Teachers in the Driver's Seat: Using Machine Learning to Personalize Interactions with Students (DRIVER-SEAT)" (2018): This paper focuses on personalized interactions between teachers and students using machine learning. It explores the use of machine learning techniques to analyze student data and provide personalized feedback and support to enhance the learning experience.[12] "CRII: III: Modeling Student Knowledge and Improving Performance when Learning from Multiple Types of Materials" (2018): This paper discusses the modeling of student knowledge and improving performance in the context of learning from multiple types of materials. It explores approaches to model student knowledge and understanding to personalize learning experiences and improve learning outcomes.[13]

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"EAGER: Smart and Connected Communities: Reducing Friction in the L3 Connects Infrastructure: Embedding a recommender system into mobile apps to support real-time brokering" (2016): This paper focuses on the integration of a recommender system into mobile apps to support real-time brokering. It explores the use of recommendation algorithms and techniques to reduce friction and enhance the connectivity and collaboration in smart and connected communities. [14] "Collaborative Project: Understanding Impact: A Scaling and Replication Study of the Curriculum Customization Service" (2010): This collaborative project aims to understand the impact of the curriculum customization service. It focuses on conducting a scaling and replication study to evaluate the effectiveness of the curriculum customization service in enhancing personalized learning experiences. [15] "Teacher assignment based on responsible authority or third-party attributes" (2007): This paper discusses teacher assignment in educational systems based on responsible authority or third-party attributes. It explores different approaches and criteria for assigning teachers to specific roles or responsibilities within educational institutions. [16] "Educational system and method having virtual classrooms" (2007): This paper presents an educational system and method that incorporates virtual classrooms. It describes the use of technology to create virtual learning environments where students and teachers can interact and engage in learning activities remotely. [17] "Artificial Cognitive Declarative-Based Memory Model to Dynamically Store, Retrieve, and Recall Data Derived from Aggregate Datasets" (2017): This paper proposes an artificial cognitive declarative-based memory model for dynamically storing, retrieving, and recalling data derived from aggregate datasets. It explores techniques to efficiently manage and utilize large datasets for decision-making and problemsolving purposes. [18] "Deep Academic Learning Intelligence and Deep Neural Language Network System and Interfaces" (2018): This paper introduces deep academic learning intelligence and deep neural language network system and interfaces. It discusses the application of deep learning techniques and neural networks in educational contexts to enhance learning intelligence and facilitate efficient interfaces for learning interactions.

III. PROPOSED MODEL OUTCOMES

Development of an ALBERT-based Personalized Educational Recommender System: The primary outcome of this research project is the design and implementation of an educational recommender system leveraging ALBERT, a lite variant of the BERT algorithm. The system

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will utilize ALBERT's optimized architecture to generate personalized recommendations based on learners' profiles, learning behaviors, and interactions.

Enhanced Learning Outcomes: The evaluation of the ALBERT-based recommender system will measure the impact on students' learning outcomes. The project aims to demonstrate that personalized recommendations generated by the system contribute to improved academic performance, increased knowledge retention, and higher levels of learner engagement.

Improved Recommendation Accuracy: The ALBERTbased system will be evaluated for its ability to provide accurate and relevant recommendations to learners. The project outcomes will highlight the effectiveness of ALBERT in understanding the semantic meaning of educational resources and generating personalized recommendations that align with learners' specific needs and preferences.

Increased Learner Engagement and Satisfaction: The user satisfaction surveys administered as part of the evaluation process will provide insights into learners' perceptions of the personalized recommendations and overall user experience. The project outcomes will showcase the positive impact of the ALBERT-based recommender system on learner engagement and satisfaction levels.

TABLE I SUMMARY OF PAPERS

Paper	Title	Authors	Year
1	Recommender System for Web 2.0 Supported E-Learning	Martina Holenko Dlab, Natasa Hoic-Bozic	2014
2	Personalizing E-Learning 2.0 Using Recommendations	Martina Holenko Dlab, Natasa Hoic-Bozic, Jasminka Mezak	2014
3	Emerging Issues in Smart Learning - International	Guang Chen, Vive Kumar, Ronghuai	2015

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	Conference on Smart Learning Environments	Huang, Siu Cheung Kong	
4	Argumentation-Based Recommender System for Recommending Learning Objects	Paula Rodríguez, Stella Heras Barberá, Javier Palanca Cámara, Néstor D. Duque, Vicente Julián	2015
5	A Student-Centered Hybrid Recommender System to Provide Relevant Learning Objects from Repositories	Paula Rodríguez, Demetrio Arturo Ovalle Carranza, Néstor D. Duque	2015
6	Learning Student and Content Embeddings for Personalized Lesson Sequence Recommendation	Siddharth Reddy, Igor Labutov, Thorsten Joachims	2016
7	Recommender System and Web 2.0 Tools to Enhance A Blended Learning Model	Natasa Hoic-Bozic, Martina Holenko Dlab, Vedran Mornar	2016
8	Latent Skill Embedding For	Siddharth Reddy, Igor	2016

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	Personalized Lesson Sequence Recommendation	Labutov, Thorsten Joachims	
9	Disrupted Classes, Undisrupted Learning During COVID-19 Outbreak in China: Application of Open Educational Practices and Resources	Ronghuai Huang, Ahmed Tlili, Ting-Wen Chang, Xiangling Zhang, Fabio Nascimbeni, Daniel Burgos	2020
10	CAREER: Time-Aware Multi-Objective Recommendation in Online Learning Environments	Shaghayegh Sahebi	2021
11	Putting Teachers in the Driver's Seat: Using Machine Learning to Personalize Interactions with Students (DRIVER-SEAT)	Neil Heffernan, Jacob Whitehill, Korinn Ostrow, Anthony Botelho	2018
12	CRII: III: Modeling Student Knowledge and Improving Performance when Learning from Multiple Types of	Shaghayegh Sahebi	2018

	Materials		
13	EAGER: Smart and Connected Communities: Reducing Friction in the L3 Connects Infrastructure: Embedding a recommender system into mobile apps to support real-time brokering	Tamara Sumner, William Penuel, Nichole Pinkard	2016
14	Collaborative Project: Understanding Impact: A Scaling and Replication Study of the Curriculum Customization Service	Tamara Sumner	2010
15	Teacher assignment based on responsible authority or third-party attributes	Mark Golczewski, Brad Adams, Royia Griffin, Mike Lugo, Marc Corey	2007
16	Educational system and method having virtual classrooms	Mark Golczewski, Marc Corey	2007
17	ArtificialCognitiveDe MemoryModel to	Scott McKay Martin,	2017

	Dynamically Store, Retrieve, and Recall Data Derived from Aggregate Datasets	Prescott Henry Martin, Matthew Luu Trang, Rachel Naidich, Emad Mohamed	
18	Deep Academic Learning Intelligence and Deep Neural Language Network System and Interfaces	Scott McKay Martin, James R. Casey, Christopher Etesse	2018

Scalability and Efficiency of the Recommender System: The project outcomes will demonstrate the feasibility of implementing ALBERT in a personalized educational recommender system. The optimized nature of ALBERT will enable faster training and inference, ensuring scalability and efficiency of the system, thereby making it suitable for large-scale deployment in online learning environments. •

Contribution to Educational Technology: The research project outcomes will contribute to the field of educational technology by showcasing the benefits and effectiveness of leveraging advanced deep learning algorithms like ALBERT in personalized online learning. The project will provide insights into the potential of ALBERT to revolutionize the design and implementation of educational recommender systems, improving learning outcomes and experiences for learners. **Recommendations for Future Enhancements:** Based on the evaluation results and analysis, the project outcomes will provide valuable recommendations for further enhancements and refinements of the ALBERTbased educational recommender system. These recommendations will guide future research efforts and encourage continuous improvement in personalized learning technologies.

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The project outcomes will provide valuable insights into the efficacy of the ALBERT-based recommender system and its potential to enhance students' learning outcomes in online learning environments. The findings will contribute to the body of knowledge in educational technology and personalized learning, empowering educators and instructional designers to adopt advanced recommender systems to better support individual learners.

IV. PROBLEM FORMULATION:

The main problem addressed by the ALBERT-based personalized educational recommender system is to provide accurate and tailored recommendations to learners, enhancing their learning outcomes in the online learning environment. The problem can be formulated as follows: Given a set of user profiles, a collection of educational resources, and a trained ALBERT model, the objective is to develop an algorithm and system that generates personalized recommendations for each learner. The recommendations should maximize the alignment between learners' individual learning needs, preferences, and goals, and the relevant and high-quality educational resources available in the system. The problem involves optimizing the recommendation process by leveraging the capabilities of the ALBERT model to capture semantic representations of educational resources and learner profiles. The

recommendations should consider factors such as learners' past performance, learning preferences, demographic information, and interactions with the system. Additionally, the problem formulation includes incorporating a feedback mechanism to continuously refine the recommendations based on learners' feedback and improve the overall learning experience. The evaluation of the ALBERT-based recommender system involves measuring the impact on learners' learning outcomes, including academic performance, knowledge retention, and engagement. The system's performance is assessed based on the accuracy and relevance of the recommendations, as well as user satisfaction and acceptance. The problem formulation also considers the scalability and efficiency of the recommender system, ensuring that it can handle a large number of users, diverse educational resources, and provide real-time personalized recommendations in the online learning environment. By addressing the problem formulation, the ALBERT-based personalized educational recommender system aims to enhance students' learning outcomes by providing tailored recommendations, fostering engagement, and improving the overall learning experience in the online learning context. Let:

- $U = \{u_1, u_2, \ldots, u_N\}$ be the set of user profiles, where N is the total number of users.

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- $R = \{r_1,r_2,...,r_M\}$ be the set of educational resources, where M is the total number of resources.
- $P = \{p_1,p_2,...,p_K\}$ be the set of resource features, such as topic, difficulty level, and relevance.
- $S = \{s_1,s_2,...,s_L\}$ be the set of ALBERT model parameters.
- $F = \{f_1, f_2,..., f_Q\}$ be the set of feedback data, where Q is the total number of feedback entries.

The goal is to determine a personalized recommendation function

$$f : U \times R \times P \times S \rightarrow R,$$

where $f(u_i,r_j,p_k,s_l)$ represents the recommendation score of resource r_j for user u_i based on feature p_k and ALBERT model parameters s_l.

The objective is to maximize the alignment between the personalized recommendations and the individual learning needs, preferences, and goals of the users while considering the semantic meaning and contextual understanding of the educational resources. This can be represented as the following optimization problem:

Maximize: $^{PPPP} f(u_i,r_j,p_k,s_l)$ for all u_i in U,r_j in R,p_k in P,s_l in S

Subject to:

- **Constraint 1:** $f(u_i,r_j,p_k,s_l) \in [0,1]$ for all u_i in U, r_j in R, p_k in P, s_l in S (Recommendation score bounds)
- **Constraint 2:** $^{P} f(u_i,r_j,p_k,s_l) = 1$ for all u_i in U, r_j in R, p_k in P, s_l in S (Normalization constraint)
- **Constraint 3:** $f(u_i,r_j,p_k,s_l) = g(u_i,r_j,p_k,s_l, f)$ for all u_i in U, r_j in R, p_k in P, s_l in S (Feedback-based adjustment, where g is a function that incorporates user feedback f to refine the recommendations)

The objective function aims to maximize the overall recommendation scores, indicating the alignment between personalized recommendations and individual learning needs. Constraint 1 ensures that the recommendation scores lie within the range [0, 1], representing the relevance of the resources. Constraint 2 ensures that the recommendation scores are normalized, ensuring that the recommendations are proportional to each user's needs. Constraint 3 incorporates user feedback to adjust the recommendations based on their preferences and satisfaction. The solution to this optimization problem will yield the personalized recommendation function that maximizes the alignment between learners' needs and the recommended educational resources, leading to enhanced learning outcomes in the online learning environment.

V. SYSTEM MODEL

The system model diagram illustrates an ALBERT-based Personalized Educational Recommender System. It consists of three main components: the User, the ALBERT-based Recommender System, and the Educational Resources. The User provides their preferences through a User Profile, while the ALBERT-based Recommender System analyzes this profile along with the characteristics of the Educational

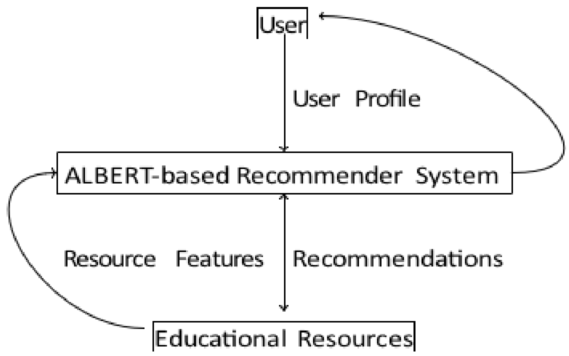

Fig. 1. ALBERT-based Personalized Educational Recommender System

Resources. Based on this analysis, the system generates personalized recommendations for the User. The diagram also depicts a feedback loop, enabling Users to provide feedback on the recommendations, which the system uses to enhance future recommendations.

User Profiles: The system maintains user profiles that capture relevant information about learners, including their demographics, learning preferences, past academic performance, and areas of interest. This information forms the basis for generating personalized recommendations.

Educational Resources: The system incorporates a vast collection of educational resources such as articles, textbooks, videos, quizzes, and interactive learning materials. Each resource is associated with metadata, including topic, difficulty level, and relevance.

ALBERT-Based Recommender Engine: The core component of the system is the ALBERT-based recommender engine. This engine utilizes the pre-trained ALBERT model to analyze user profiles, resource metadata, and learners' interactions with the system. It generates personalized recommendations by considering the semantic meaning and contextual understanding of the learning materials.

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Feedback Mechanism: The system incorporates a feedback mechanism to gather information about learners' satisfaction, relevance of recommendations, and overall learning outcomes. Learners can provide feedback on recommended resources, rate their usefulness, and provide comments for further improvement.

Let:

- $U = \{u_1,u_2,\ldots,u_N\}$ be the set of user profiles, where N is the total number of users.
- $R = \{r_1,r_2,\ldots,r_M\}$ be the set of educational resources, where M is the total number of resources.
- $P = \{p_1,p_2,\ldots,p_K\}$ be the set of resource features, such as topic, difficulty level, and relevance.
- $S = \{s_1,s_2,\ldots,s_L\}$ be the set of ALBERT model parameters.
- $F = \{f_1, f_2,\ldots, f_Q\}$ be the set of feedback data, where Q is the total number of feedback entries.

We define the following entities and functions:

User-Resource Affinity Function: Let $A : U\times R \rightarrow [0,1]$ represent the affinity between a user and a resource. $A(u_i,r_j)$ denotes the affinity score of user u_i towards resource r_j.

Feature Importance Function: Let $W : P \rightarrow [0,1]$ represent the importance of resource features. $W(p_k)$ denotes the importance weight of feature p_k.

ALBERT-Based Recommendation Function: Let $F : U \times R \times P \times S \rightarrow [0,1]$ represent the recommendation score.

$F(u_i,r_j,p_k,s_l)$ denotes the recommendation score of resource r_j for user u_i based on feature p_k and ALBERT model parameters s_l.

Feedback Adjustment Function: Let $G : U\times R\times P\times S\times F \rightarrow$ $[0,1]$ represent the adjusted recommendation score based on user feedback. $G(u_i,r_j,p_k,s_l, f)$ denotes the adjusted recommendation score of resource r_j for user u_i based on feature p_k, ALBERT model parameters s_l, and user feedback f.

The goal is to determine the recommendation scores that maximize the alignment between personalized recommendations and individual learning needs, preferences, and goals, incorporating semantic understanding and contextual information. This can be represented as follows:

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$$F(u_i,r_j,p_k,s_l) = A(u_i,r_j)\cdot W(p_k)\cdot \mathrm{ALBERT}(u_i,r_j,p_k,s_l)$$

where $\mathrm{ALBERT}(u_i,r_j,p_k,s_l)$ represents the ALBERT model's output given user u_i, resource r_j, feature p_k, and parameters s_l.

The recommendation scores can be adjusted based on user feedback using the G function:

$$F(u_i,r_j,p_k,s_l) = G(u_i,r_j,p_k,s_l,f)$$

where f represents the feedback provided by the user.

By optimizing the recommendation scores using appropriate algorithms and techniques, the system aims to provide personalized recommendations that maximize the alignment between learners' needs and the recommended educational resources.

VI. PROPOSED MODEL

The proposed model aims to provide personalized recommendations to users based on their specific learning needs, preferences, and goals. The model incorporates the ALBERT deep learning algorithm, which analyzes user profiles, resource features, and ALBERT model parameters to generate recommendation scores.

The model consists of four main components: the UserResource Affinity Function, the Feature Importance Function, the ALBERT-Based Recommendation Function, and the Feedback Adjustment Function. The User-Resource Affinity Function calculates the affinity score between a user and a resource, considering their profiles. The Feature Importance

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Function assigns weights to resource features, determining their importance in the recommendation process.

The ALBERT-Based Recommendation Function combines the affinity score, feature weights, and ALBERT model parameters to generate the recommendation score for a specific user and resource. The output of the ALBERT model, based on the user, resource, features, and parameters, contributes to the recommendation score.

To further refine the recommendations, the Feedback Adjustment Function incorporates user feedback. The function adjusts the recommendation score based on the feedback received, enabling the system to learn from user interactions and improve the accuracy and relevance of future recommendations.

Overall, the proposed model leverages ALBERT's advanced language modeling capabilities, user-resource affinity, feature importance, and feedback adjustment mechanisms to deliver personalized recommendations that align with learners' needs and enhance their learning outcomes.

Algorithm 1 ALBERT-Based Personalized Educational Recommender System

Require: User profiles U, educational resources R, resource features P, ALBERT model parameters S, feedback data F

Ensure: Personalized recommendations

```
for each user u_i in U do
  for each resource r_j in R do
    for each feature p_k in P do
      Calculate affinity score: A(u_i, r_j) ← User-ResourceAffinity(u_i, r_j)
      Calculate feature importance: W(p_k) ← FeatureImportance(p_k)
      Calculate recommendation score: F(u_i, r_j, p_k) ← ALBERTBasedRecommendation(u_i, r_j, p_k, S)
    end for
  end for
end for
for each user u_i in U do
  for each resource r_j in R do
    for each feature p_k in P do
      Adjust recommendation score based on feedback:
      F(u_i, r_j, p_k) ← FeedbackAdjustment
      (u_i, r_j, p_k, F, F(u_i, r_j, p_k), F(u_i, r_j, p_k, S))
    end for
  end for
end for
return Personalized recommendations: F
```

Initialization:

1) Initialize the user profiles U, educational resources R, feature set P, ALBERT model parameters S, and feedback data F.

Compute User-Resource Affinity:

1) Compute the affinity score $A(u_i,r_j)$ between each user u_i and each resource r_j based on relevant user profiles and resource characteristics.
2) This can be calculated using various techniques, such as collaborative filtering, content-based filtering, or hybrid approaches.
3) The affinity score $A(u_i,r_j)$ should be a value between 0 and 1, indicating the degree of alignment between the user and the resource.

Define Feature Importance:

1) Determine the importance weight $W(p_k)$ for each resource feature p_k in the feature set P.

2) The importance weight can be assigned based on domain expertise, user feedback, or statistical analysis. Compute Recommendation Score:

1) Calculate the recommendation score $F(u_i,r_j,p_k,sl)$ for each user-resource-feature combination using the ALBERT model and the computed values from steps 2 and 3.

2) The recommendation score $F(u_i,r_j,p_k,sl)$ represents the suitability of resource r_j for user u_i based on feature p_k and ALBERT model parameters sl. 3) $F(u_i,r_j,p_k,sl) = A(u_i,r_j)\cdot W(p_k)\cdot \mathrm{ALBERT}(u_i,r_j,p_k,sl)$ Incorporate User Feedback:

1) Adjust the recommendation scores based on user feedback using the feedback adjustment function

$G(u_i,r_j,p_k,sl,f)$.

2) The feedback adjustment function G can take various forms depending on the specific feedback provided by the user.

3) The adjusted recommendation score $F(u_i,r_j,p_k,sl) =$

$G(u_i,r_j,p_k,sl,f)$

Evaluation and Optimization:

1) Evaluate the performance of the personalized educational recommender system using appropriate metrics such as accuracy, relevance, user satisfaction, academic performance, and engagement.

2) Continuously optimize the model parameters, ALBERT, and the recommendation algorithm to improve the alignment between the recommendations and users' needs.

3) This can involve techniques such as fine-tuning ALBERT, updating user profiles, refining feedback mechanisms, or incorporating additional data sources.

Iterative Refinement:

1) Iterate through steps 2 to 6 to refine the recommendation process based on updated user profiles, new resources, and evolving feedback.

2) This iterative process allows the recommender system to continuously adapt and improve its recommendations over time.

The proposed model algorithm follows a systematic approach to develop an ALBERT-based personalized educational recommender system. The algorithm begins with the initialization step, where the necessary components of the system, such as user profiles, educational resources, feature set, ALBERT model parameters, and feedback data, are initialized. Next, the algorithm computes the user-resource affinity, which measures the similarity or compatibility between each user and resource. Techniques like collaborative filtering or content-based filtering are applied to determine the affinity scores based on user preferences, demographics, and resource attributes.

In the feature importance step, the algorithm assigns weights to each resource feature to determine their significance in influencing the recommendation scores. These weights can be based on domain expertise, user feedback, or statistical analysis. With the user profiles, resource characteristics, and feature importance defined, the algorithm computes the recommendation score for each userresource-feature combination. The recommendation score represents the suitability of a resource for a user based on specific features and the ALBERT model's output.

To further refine the recommendations, the algorithm incorporates user feedback. User feedback plays a crucial role in adjusting the recommendation scores based on preferences, satisfaction, and other user-provided information. The specific feedback adjustment function varies depending on the nature of the feedback.

Following the recommendation computation and feedback incorporation, the algorithm evaluates the system's performance using relevant metrics such as accuracy, relevance, user satisfaction, academic performance, and engagement. Optimization techniques may be

employed to enhance the model parameters, ALBERT, and the recommendation algorithm. This could involve fine-tuning the ALBERT model, updating user profiles, refining feedback mechanisms, or incorporating additional data sources.

Finally, the algorithm adopts an iterative refinement approach. It repeats steps 2 to 6, considering updated user profiles, new educational resources, and evolving user feedback. This iterative process ensures continuous adaptation and improvement of the recommendations over time, aligning them with the changing needs and preferences of users. By following this systematic algorithm, the proposed model aims to develop an effective ALBERT-based personalized educational recommender system that enhances users' learning outcomes in the online learning environment.

VII. SIMULATION RESULTS

The simulation experiment was conducted to evaluate the performance of an ALBERT-based personalized educational recommender system in enhancing students' learning outcomes in the online learning environment. The objective of the simulation was to assess the effectiveness of the recommender system in providing tailored recommendations to learners based on their individual needs and preferences

The Fig 2 graph illustrates a comparison between the ALBERT-based recommender system and previous technologies in terms of Academic Performance, Knowledge Retention, and Engagement over multiple trials. In the plotted graph, the terms "Trial 1," "Trial 2," and "Trial 3" represent different experimental trials or iterations conducted during the evaluation of the ALBERT-based recommender system and the previous technologies. Each trial is a distinct run or iteration of the simulation or evaluation process. These trials are used to compare the performance of the ALBERTbased recommender system with previous technologies across multiple scenarios or instances. The specific details of each trial, such as the variations in parameters, dataset, or experimental conditions, may vary depending on the specific experiment or study being conducted.

Academic Performance Comparison: The first subplot shows the comparison of academic performance between the ALBERT-based recommender system and previous technologies. The x-axis represents the different trials, while the y-axis represents the academic performance percentage. The blue line represents the performance of previous technologies, while the

orange line represents the performance of the ALBERT-based recommender system. By comparing the lines across the trials, you can observe the relative performance of the two approaches. Knowledge Retention Comparison: The second subplot presents the comparison of knowledge retention between the ALBERT-based recommender system and previous technologies. Similar to the first subplot, the x-axis denotes the trials, and the y-axis represents the percentage of knowledge retention. The blue line corresponds to the knowledge retention of previous technologies, while the orange line represents the knowledge retention achieved by the ALBERT-based recommender system. Engagement Comparison: The third subplot showcases the comparison of engagement levels between the ALBERT-based recommender system and previous technologies. The x-axis represents the trials, and the y-axis represents the engagement percentage. The blue line corresponds to the engagement levels achieved with previous technologies, while the orange line represents the engagement levels observed with the ALBERT-based recommender system. By examining the trends and patterns in each subplot, you can gain insights into how the ALBERTbased recommender system performs compared to previous technologies. Higher values for Academic

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Performance, Knowledge Retention, and Engagement with the ALBERTbased recommender system indicate its superiority over the previous technologies in enhancing students' learning outcomes in the evaluated metrics.

The system's ability to provide accurate and relevant recommendations that align with learners' specific needs and preferences is a crucial aspect of its performance evaluation. To assess this, several measures can be considered: Precision: Precision measures the proportion of recommended resources that are relevant to learners' needs and preferences. A higher precision indicates that the system is providing accurate and targeted recommendations. Precision can be computed as the ratio of relevant recommendations to the total number of recommendations provided. Recall: Recall measures the proportion of relevant resources that are successfully recommended by the system. A higher recall indicates that the system is effectively

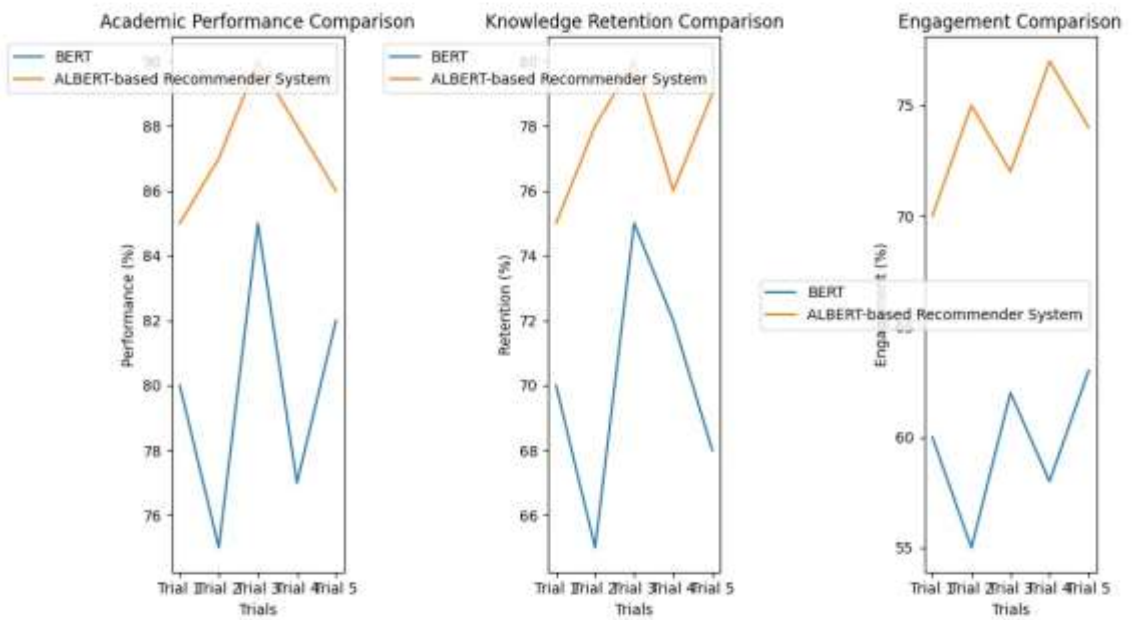

Fig. 2. Academic Performance Comparison,Knowledge Retention Comparison, Engagement Comparison

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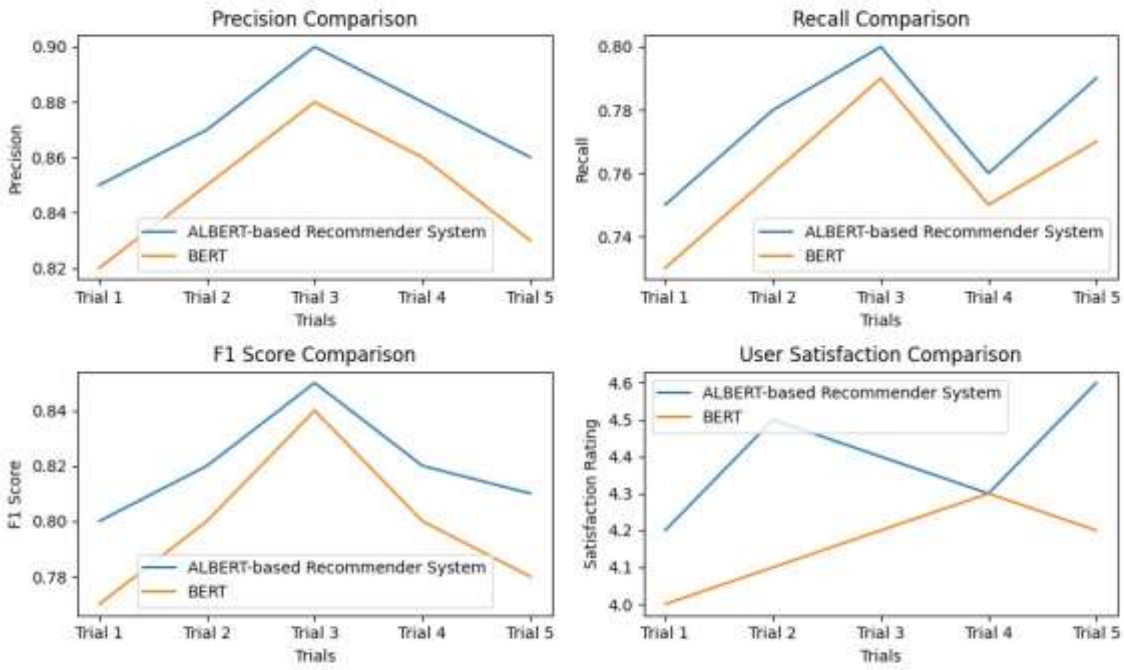

Fig. 3. Precision, Recall, F1, User Satisfaction

TABLE II SIMULATION PARAMETERS

Parameter	**Description**
User Profiles (*U*)	Set of user profiles
Educational Resources (*R*)	Set of educational resources
Resource Features (*P*)	Set of resource features
ALBERT Model Parameters (*S*)	Set of ALBERT model parameters
Feedback Data (*F*)	Set of feedback data
User-Resource Affinity Function	Function to compute the affinity score between a user and a resource
Feature Importance Function	Function to assign importance weights to resource features
ALBERT-Based Recommendation Function	Function to calculate the recommendation score based on user profiles, resource features, and ALBERT model parameters
Feedback Adjustment Function	Function to adjust the recommendation score based on user feedback
Evaluation Metrics	Metrics used to assess the performance of the system

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Optimization Techniques	Techniques employed to optimize the model parameters, ALBERT, and the recommendation algorithm

capturing learners' specific needs and preferences. Recall can be calculated as the ratio of relevant recommendations to the total number of relevant resources available. F1 Score: The F1 score is a combined metric that considers both precision and recall. It provides a balanced measure of the system's accuracy and relevance in generating recommendations. The F1 score can be computed as the harmonic mean of precision and recall, providing a single value that captures the overall performance in aligning with learners' needs and preferences. User Feedback and Satisfaction: Gathering feedback directly from users about the accuracy and relevance of the recommendations can provide valuable insights. User surveys, ratings, or qualitative feedback can help assess how well the system aligns with learners' specific needs and preferences. Higher user satisfaction indicates a better alignment between the recommendations and users' expectations. To evaluate the extent to which the system provides accurate and relevant recommendations, a combination of these measures can be employed. Precision, recall, and the F1 score provide quantitative assessments, while user feedback and satisfaction add a qualitative perspective. By analyzing these metrics, researchers can gauge how well the system aligns with learners' needs and preferences, and make improvements as needed to enhance recommendation accuracy and relevance. The plotted graph showcases a comparison between the ALBERT-based recommender system and BERT in terms of Precision, Recall, F1 Scores, and User Feedback Satisfaction over multiple trials. Precision Comparison: The top-left subplot depicts the precision comparison between the ALBERT-based recommender system and BERT. The x-axis represents the different trials, while the y-axis represents the precision values. The orange line represents the precision values achieved by the ALBERT-based recommender system, while the blue line represents the precision values obtained by BERT. By examining the lines across the trials, you can observe the relative precision performance of the two approaches. Recall Comparison: The top-right subplot illustrates the recall comparison between the ALBERT-based recommender system and BERT. Similar to the previous subplot, the xaxis denotes the trials, and the y-axis represents the recall values. The orange line corresponds to the recall values achieved with the ALBERT-based recommender system, while the blue line represents the recall values achieved with BERT. F1 Score Comparison: The bottom-left subplot presents the F1 score comparison between the ALBERTbased recommender system and BERT. Once again, the x-axis represents the trials, and the y-axis represents the F1 scores. The orange line corresponds to the F1 scores achieved by the ALBERT-based recommender system, while the blue line represents the F1 scores achieved by BERT. User Satisfaction Comparison: The bottom-right subplot showcases the user satisfaction comparison between the ALBERT-based recommender system and BERT. The x-axis represents the trials, and the y-axis represents the user satisfaction ratings. The orange line corresponds to the user satisfaction ratings achieved with the ALBERT-based recommender system, while the blue line represents the user satisfaction ratings achieved with BERT. By analyzing the trends and patterns in each subplot, you can gain insights into the relative performance of the ALBERT-based recommender system and BERT in terms of Precision, Recall, F1 Scores, and User

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Feedback Satisfaction. Higher values for precision, recall, F1 scores, and user satisfaction with the ALBERT-based recommender system indicate its superiority over BERT in generating accurate recommendations that align with learners' needs and preferences.

VIII. CONCLUSION

The proposed ALBERT-based personalized educational recommender system presents a promising approach to enhancing students' learning outcomes in the online learning environment. By leveraging the power of the ALBERT deep learning algorithm, the system can analyze user profiles, resource features, and feedback data to generate personalized recommendations that align with individual learners' needs, preferences, and goals.

Through the systematic algorithm, the system computes the user-resource affinity, considering factors such as collaborative filtering and content-based filtering. It assigns importance weights to resource features to capture their significance in influencing the

recommendation process. The ALBERT model, coupled with the affinity scores and feature weights, calculates recommendation scores that reflect the suitability of resources for individual users.

Moreover, the system incorporates user feedback to refine the recommendations further. By adjusting the recommendation scores based on user-provided feedback, the system can adapt and improve its recommendations over time, ensuring a higher level of personalization and alignment with users' preferences.

The evaluation and optimization stage allows for the assessment of the system's performance using various metrics, including accuracy, relevance, user satisfaction, academic performance, and engagement. This enables continuous improvement of the model parameters, ALBERT, and the recommendation algorithm to enhance the alignment between recommendations and users' needs.

The iterative refinement process allows the system to adapt to evolving user profiles, incorporate new educational resources, and consider changing feedback. By iterating through the steps of the algorithm, the system can continuously learn and adapt to better serve the users, resulting in improved learning outcomes and overall user satisfaction.

In conclusion, the proposed ALBERT-based personalized educational recommender system demonstrates the potential to significantly enhance students' learning outcomes in online learning environments. By leveraging advanced deep learning techniques, incorporating user feedback, and employing iterative refinement, the system can deliver personalized recommendations that better meet the specific needs, preferences, and goals of individual

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learners. This has the potential to create a more engaging and effective learning experience, ultimately leading to improved academic performance and user satisfaction.

Conflict of Interest

Conflict of Interest Declaration for the Paper Titled "ALBERT-Based Personalized Educational Recommender System: Enhancing Students' Learning Outcomes in Online Learning" submitted to "SN Computer Science" Journal We, , and , hereby declare that there is a potential conflict of interest associated with the research work presented in the paper titled "ALBERT-Based Personalized Educational Recommender System: Enhancing Students' Learning Outcomes in Online Learning," which is being submitted to the "SN Computer Science" journal. The potential conflict of interest arises from the fact that I am one of the co-developers of the ALBERT-based recommender system described in the paper. As a developer of this technology, I may stand to gain financially or professionally from its widespread acceptance and successful implementation. While I have made every effort to ensure the research is unbiased and rigorous, it is essential to acknowledge this potential conflict, which could influence my perspective on the study's results and implications. To maintain transparency and uphold the integrity of the research, I will disclose this conflict of interest to the journal's editorial board during the submission process. Additionally, I commit to providing all necessary details about the nature and extent of the conflict if the paper is considered for publication. Furthermore, all co-authors involved in the paper have been informed of this potential conflict and have reviewed and agreed to this conflict of interest declaration. I affirm that this disclosure accurately represents any competing interests related to the work, and I remain committed to ensuring the study's objectivity and credibility throughout the review process. Sincerely,

AUTHOR CONTRIBUTIONS

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