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Application of Deep Learning-Based Personalized Learning Path Prediction and Resource Recommendation for Inheriting Scientist Spirit in Graduate Education

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Abstract. This study explores the application of artificial intelligence (AI) and deep learning (DL) technologies in graduate education to promote the inheritance and development of the scientist spirit. This study employs a Long Short-Term Memory (LSTM) network to predict students' learning paths. Meanwhile, it constructs a DL-based personalized learning path and resource recommendation model by integrating a hybrid recommendation mechanism combining collaborative filtering and content-based filtering. The model inputs students' historical learning data and utilizes LSTM to capture long-term dependencies for predicting future learning activities. At the same time, it dynamically adjusts the learning rate through a reinforcement learning mechanism to optimize model performance. Additionally, this study introduces the Local Interpretable Model-Agnostic Explanations (LIME) algorithm to enhance the model's interpretability, ensuring that educators can understand the model's decision-making logic. Model training employs cross-validation techniques, and Principal Component Analysis (PCA) is used for dimensionality reduction and feature selection to improve data processing efficiency. Experimental results demonstrate that the DL model significantly outperforms traditional models in personalized learning path prediction, resource matching efficiency, and student performance prediction. Particularly, the DL model has an accuracy of 92.5%, an F1 score of 91.8%, an Area Under the Receiver Operating Characteristic Curve value of 0.95, a user satisfaction rate of 89.2%, and a prediction bias of only -0.75%. Furthermore, through user satisfaction surveys and expert reviews, this study qualitatively analyzes the impact of AI and DL technologies on educational practices. This confirms their value in enhancing education quality and fostering a scientist spirit. The study concludes that AI and DL technologies can effectively optimize graduate education models and promote the inheritance of the scientist spirit. Moreover, these technologies can cultivate innovative capabilities and provide theoretical support and practical guidance for intelligent educational reform.

Keywords: Artificial Intelligence, Deep Learning, Scientist Spirit, Graduate Education.

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1. Introduction

Against the backdrop of accelerating globalization and informatization, graduate education is undergoing profound transformations. It cultivates students' professional skills while shaping their research literacy and innovative capabilities. However, traditional graduate education models often emphasize systematic knowledge transmission while neglecting the cultivation of the scientist spirit. The scientist spirit encompasses not only a rigorous and truth-seeking research attitude but also a mindset of exploring the unknown, questioning authority, and daring to innovate [1-3]. Nevertheless, existing graduate training systems still exhibit shortcomings in fostering independent research capabilities, interdisciplinary integration, and the stimulation of innovative thinking. These lead to difficulties for some graduate students in initiating original research and independently solving complex problems [4, 5]. Hence, how to leverage modern technologies to optimize graduate education models and promote the effective inheritance of the scientist spirit has become a critical issue to address..

In recent years, the rise of artificial intelligence (AI) and deep learning (DL) technologies has provided new possibilities for personalized learning path recommendations, intelligent resource matching, and research capability assessment [6-8]. AI technologies can optimize the allocation of educational resources based on big data analysis, enabling tailored teaching; DL technologies demonstrate exceptional capabilities in pattern recognition, text understanding, and intelligent decision-making [9-12]. However, despite the initial applications of AI and DL in education, current research still exhibits some gaps. First, existing studies primarily focus on the application of AI in knowledge transmission and intelligent assessment, overlooking its role in fostering a scientist spirit. Second, the effectiveness of personalized learning path recommendations in graduate education lacks systematic validation. Additionally, the mechanisms underlying AI-driven research capability prediction and the cultivation of scientific literacy remain unclear.

This study proposes an intelligent education model based on AI and DL to address these research gaps. It aims to enhance graduate students' self-directed learning abilities and research literacy, accurately match high-quality learning and research resources, and optimize the efficiency of educational resource allocation. To achieve these objectives, this study trains and evaluates various DL models' performance based on a large-scale dataset of graduate student learning behaviors and validates the personalized path recommendations' effectiveness through experiments. Furthermore, by combining user satisfaction surveys and expert reviews, this study conducts quantitative and qualitative analyses of the impact of AI and DL technologies on educational practices. Experimental results demonstrate that, compared to traditional teaching models, the proposed AI-driven approach significantly outperforms baseline models in personalized learning path planning, resource matching efficiency optimization, and research capability prediction. Thus, it effectively enhances graduate students' research literacy and promotes the cultivation of a scientist spirit.

The contributions of this study are as follows:

- It proposes a personalized learning path prediction and resource recommendation method based on AI and DL to fill the research gap in cultivating a scientist spirit in graduate education.

- This study develops the prediction mechanism of scientific research ability and provides quantitative analysis tools for colleges and universities to optimize the talent training program.
- Through experimental verification and user feedback, this study systematically evaluates the application value of AI and DL technology in graduate education, providing theoretical support and practical guidance for intelligent education reform.

2. Literature Review

2.1. Application Status of AI and DL in Graduate Education

In recent years, the application of AI and DL in higher education has attracted widespread attention. AI technologies have been utilized in the intelligent tutoring system (ITS), adaptive learning platforms, and academic behavior analysis, among other areas [13-15]. Among these, DL technology, due to its powerful data processing capabilities, demonstrates significant potential in personalized learning path recommendation, learning resource matching, and the assessment of students' research capabilities. Guettala et al. (2024) explored the application of generative AI in education and proposed an AI-based adaptive personalized learning system. Their research revealed that generative AI could optimize course design and learning paths in graduate education, enhancing the adaptability of teaching and the autonomy of learners [16]. Pratama et al. (2023) analyzed the role of AI in personalized learning, emphasizing AI-driven real-time learning analytics and intelligent feedback mechanisms. Their study showed that DL models could dynamically adjust teaching strategies, enhancing the individualized experience in graduate education and improving learning efficiency and outcomes [17]. Yılmaz (2024) investigated the application of AI in personalized learning for science education, reviewed current technological advancements, and outlined future trends. Their research indicated that AI-supported intelligent recommendation systems and adaptive assessments could optimize graduate education content, improve learning outcomes, and promote the development of intelligent education [18].

2.2. Research Status of Personalized Learning and Intelligent Resource Recommendation (IRR)

Personalized Learning Path Prediction (PLPP) aims to construct optimal learning paths based on students' learning behavior data to enhance learning efficiency and research capabilities. Traditional methods primarily rely on rule-based matching or collaborative filtering (CF) approaches. For example, Tang et al. (2020) proposed a CF-based personalized recommendation system that could predict optimal courses based on students' historical learning behaviors [19]. However, these methods exhibited limitations when handling high-dimensional and dynamically changing data. Over the years, DL methods have been widely applied in PLPP. Tapalova et al. (2022) studied the application of AI in personalized learning paths and proposed an intelligent recommendation system based on AI education (AIEd). Their research demonstrated that DL algorithms could dynamically adjust learning content, improve the accuracy of path prediction, and enhance learner experience and learning outcomes [20]. Essa et al. (2023) systematically reviewed machine learning-based personalized adaptive learning technologies, focusing on the analysis of different learning style recognition methods. Their study found that DL models could optimize learning path prediction, improve teaching adaptability, and effectively enhance learner engagement and outcomes [21]. Kanchon et al. (2024) explored AI-driven personalized learning models and proposed a DL-based learning style recognition and content adaptive optimization strategy. Their research demonstrated that AI could accurately identify learner needs and dynamically adjust learning paths, improving the intelligence and precision of personalized education [22].

IRR is a key technology for enhancing learning experiences and research efficiency, and numerous scholars have conducted related research. Gm et al. (2024) reviewed the development of personalized learning recommendation systems and discussed the application of AI in online education. Their research demonstrated that DL-driven resource recommendation systems could dynamically adjust learning materials based on learner behaviors and preferences, improving learning efficiency, adaptability, and personalized learning experiences [23]. Lokare et al. (2024) proposed an AI-based learning style prediction model that utilized DL to analyze learner characteristics and optimize intelligent learning resource recommendations. Their study showed that the model could effectively match individual learning needs, improve recommendation accuracy, and provide more intelligent support for personalized teaching [24].

2.3. Research Gaps and Innovations

In summary, although AI and DL technologies exhibit great potential in graduate education, current research still faces the following shortcomings. (1) Existing PLPP methods lack optimization for cultivating graduate students' research capabilities, making it difficult to effectively support the development of scientist spirit; (2) IRR systems lack sufficient personalization, hindering precise adaptation to different research backgrounds and resulting in low efficiency in learning resource matching; (3) Research capability prediction methods still face bottlenecks in cross-disciplinary adaptability and long-term predictive abilities, making it challenging to meet the individualized development needs of graduate students. To address these challenges, this study proposes an AI- and DL-based PLPP model to optimize graduate education models and enhance the cultivation of a scientist spirit.

3. Research model

3.1. Theoretical Analysis of DL Models

DL models have demonstrated significant advantages and potential in graduate education, particularly in personalized learning path prediction and intelligent resource recommendation systems [25-27]. This section provides a theoretical analysis of DL models, emphasizing their architecture, learning capabilities, and generalization potential. Figure 1 illustrates the architecture of a DL model.

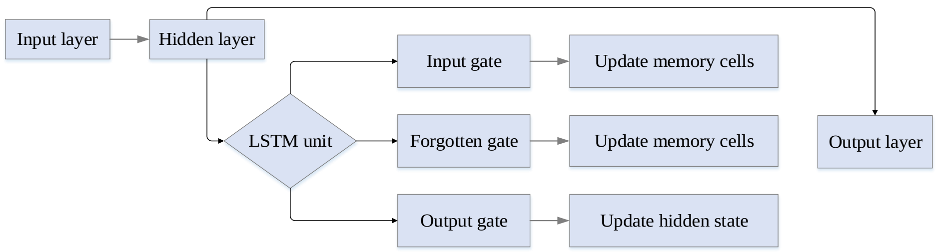

Fig. 1. Architecture of a DL model

1) Model Architecture: The core strength of DL models lies in their hierarchical architecture, which enables them to automatically learn complex feature representations from raw data. In the context of graduate education applications, the model typically comprises an input layer, multiple hidden layers, and an output layer [28]. The input layer processes various types of learning data from students, including course grades, study duration, and interaction records. The hidden layers perform sophisticated data transformations through the connections between neurons, extracting high-level abstract features. For example, in personalized learning path prediction, Long Short-Term Memory (LSTM) networks can capture temporal dependencies and understand the dynamic evolution of student learning behaviors. In intelligent recommendation systems, Convolutional Neural Networks (CNNs) can process image or text data to uncover intrinsic relationships within course materials [29-31].

2) Learning Capabilities: DL models exhibit powerful learning capabilities, enabling them to process large-scale datasets and autonomously identify patterns and regularities within the data. This ability arises from the model's nonlinear transformations, which allow it to approximate complex function mappings and solve classification and regression problems in high-dimensional spaces. In graduate education, DL models can discern individual differences in students' learning histories, facilitating the customization of learning plans for each student. Additionally, these models can predict students' future academic performance, assisting educators with early intervention and the optimization of teaching strategies [32-35].

3) Generalization: The generalization ability of DL models refers to their capacity to maintain high performance on unseen data. To enhance generalization, it is essential

to avoid overfitting, where the model performs well on training data but struggles with new, unseen data. In the context of graduate education, generalization can be effectively improved through techniques such as regularization (such as L1/L2 regularization), Dropout, data augmentation, and thoughtful model architecture design. These methods ensure that the model can accurately predict the learning behaviors of new students or make appropriate recommendations for unfamiliar course resources [36-38].

3.2. Model Design

The LSTM network is employed to predict students' learning paths and facilitate the development of personalized learning plans. A DL-based recommendation engine is created, utilizing a hybrid approach that combines CF and content-based (CB) filtering to recommend the most suitable educational resources for students. The model is trained using cross-validation techniques, with hyperparameters optimized to enhance performance. Several evaluation metrics, including accuracy, recall, F1 score, and Mean Squared Error (MSE), are employed to assess the model's predictive capabilities and the precision of the recommendation system.

Feedback from both students and instructors is collected through surveys and user testing to continually refine and enhance the model and system. Figure 2 illustrates the detailed computational process of the DL model.

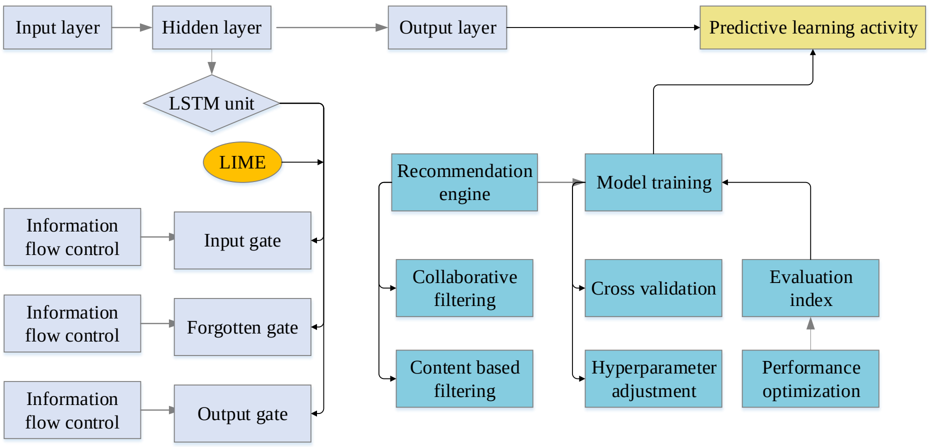

Fig. 2. Specific computational flow of the DL model

The specific computational process of the DL model is as follows:

Input Layer: Receives the student's learning history, encoded as time-series data [39].

Hidden Layer: The LSTM unit captures long-term dependencies. Each unit consists of an input gate, a forget gate, and an output gate, which regulate the flow of information [40].

Output Layer: Predicts the next course or learning activity that the student is most likely to select [41].

Let the learning behavior dataset be $X = \left[x_1, x_2, \cdots, x_t\right]$, where xi represents the feature vector of the ith student. The study uses Principal Component Analysis (PCA) for dimensionality reduction, which can be expressed as equation (1):

$$Z = XW \tag{1}$$

Z represents the dataset after dimensionality reduction through PCA, and W is the feature vector matrix. The top k eigenvectors corresponding to the largest eigenvalues are obtained using Singular Value Decomposition (SVD) to enhance data interpretability.

PLPP employs a dual-layer LSTM structure, where the first layer captures students' short-term learning preferences and the second layer models long-term trends.

h_i refers to the hidden state at time t; xi represents the input vector. The calculation of LSTM is as follows:

$$i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \tag{2}$$

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{3}$$

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{4}$$

$$c_t = f_t \odot c_{t-1} + i_t \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right) \tag{5}$$

$$h_t = o_t \odot \tanh\left(c_t\right) \tag{6}$$

i_t, f_t, o_t, c_t, and h_t represent the input gate, forget gate, output gate, cell state, and hidden state, respectively. σ means the sigmoid activation function; W and U are the weight matrices; b is the bias term; tanh refers to the hyperbolic tangent activation function; $\odot$ denotes the element multiplication (Hadamard product).

Subsequently, the final hidden state h_T is used as input to predict the next learning activity. A fully connected layer and an activation function (softmax) are then applied to generate a probability distribution for predicting the next learning activity. This process enables the model to learn patterns in student learning behavior, facilitating personalized learning path recommendations.

To optimize the training process of the model, a reinforcement learning (RL) mechanism is introduced, and the learning rate is adjusted through the policy gradient method. If the parameters of the policy network are θ and the policy function is $\pi_\theta\left(a_t \mid s_t\right)$, then the goal is to maximize the expected return $J\left(\theta\right)$, which can be written as equation (7):

$$J\left(\theta\right) = E_{\pi_\theta}\left[\sum_{t=1}^{T} R_t\right] \tag{7}$$

R_t refers to the reward of time step t. Gradient updating follows the policy gradient theorem, as shown in equation (8):

$$\nabla_\theta J(\theta) = E\left[\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(a_t \mid s_t) R_t\right] \tag{8}$$

By continuously adjusting the learning rate, RL strategies can dynamically optimize the learning rate based on the training state, improving the model's convergence speed and performance.

In terms of enhancing model interpretability, the Local Interpretable Model-Agnostic Explanations (LIME) algorithm is used to improve the transparency of the DL model. LIME explains model prediction by performing linear approximation within local neighborhoods, and its optimization objective Q is as follows:

$$Q = \arg\min_{g \in G} L(f, g, \pi_x) + \Omega(g) \tag{9}$$

f refers to the original model; g means the local explanatory model; G represents the space of all possible linear models; L denotes the model fitting loss function; π_x is the local neighborhood weight; $\Omega(g)$ indicates the model complexity regularization term.

Through LIME, educators can understand the decision-making logic of the model and increase trust in personalized learning path recommendations. Additionally, regularization techniques and cross-validation are integrated into the model design. Regularization methods are applied during the training process to prevent overfitting and enhance the model's generalization ability on unseen data. Cross-validation and hyperparameter optimization techniques are further utilized to ensure stable model performance across diverse datasets. This approach builds educators' trust in the model's recommendations, which is crucial for achieving personalized learning and improving educational quality.

Furthermore, recognizing the impact of different disciplines and educational levels on the model's effectiveness—particularly given that some fields may prioritize quantitative analysis while others may emphasize qualitative approaches—the model is designed to be modular and configurable. This design provides flexibility, allowing educators to adjust and optimize the model according to the specific needs of their disciplines. A set of pluggable feature extraction and processing components is developed, enabling educators to select or create components that align with their teaching objectives and subject characteristics. Moreover, the model's hyperparameters and algorithm configurations can be tailored based on disciplinary characteristics to achieve optimal personalized learning path recommendations. This adaptability ensures that the model can meet the analytical needs of various disciplines, adjusting to diverse learning objectives and motivations across different educational levels, thus providing effective personalized learning support in varied educational environments.

In the practical application of the model, consider a graduate student named Tom, whose objective is to enhance his research capabilities in the field of machine learning. The model will create a personalized learning path for Tom, leveraging multi-source data that includes his historical learning behaviors, course grades, participation in research projects, forum post content, and conference attendance records. Initially, Tom's learning data undergoes cleaning and standardization, including the removal of erroneous or inconsistent records, addressing missing values, and converting textual data into Term Frequency-Inverse Document Frequency (TF-IDF) representations. To mitigate class imbalance issues, diversity enhancement techniques are applied, ensuring that the model effectively learns the features of all categories. The input layer then processes Tom's historical learning behavior data, which includes previously enrolled courses, completed assignments, and discussions participated in. The LSTM layer captures the temporal characteristics of this data to predict the next learning activities Tom is likely to engage in. For example, if Tom has recently interacted with papers and courses related to deep learning, the model may predict that his next area of interest will be reinforcement learning. After predicting Tom's potential learning path, the hybrid recommendation engine combines CF and CB filtering methods to suggest the most relevant educational resources. The CF component considers resources chosen by students with similar learning behaviors, while the CB filtering component selects materials from the resource repository based on Tom's learning interests and goals. Ultimately, the model generates a personalized learning plan for Tom, comprising a range of resources, including courses, research papers, and projects.

4. Experimental Design and Performance Evaluation

4.1. Dataset Collection

This study meticulously constructs a comprehensive and multi-dimensional graduate education dataset to support the training and validation of DL models. The dataset's collection and preprocessing are critical initial steps that directly influence the reliability and validity of subsequent experiments. The data in this study are primarily sourced from the following three channels during the period from September 2023 to July 2024:

1) Online learning platform records: These include students' login times, course viewing frequencies, assignment submission records, forum interactions, and quiz scores. These data reflect students' learning behaviors and engagement levels.

2) Academic performance records: These encompass graduate students' publication histories, participation in research projects, and conference attendance records. These records provide a basis for assessing students' research capabilities and academic achievements.

3) Personal background information: These involve students' basic demographic information, academic backgrounds, and research interest areas. These data are used to build student profiles, serving as the foundation for personalized learning path recommendations.

By collecting the above-structured and unstructured data, the dataset is enriched. Structured data, such as grades, login times, and the number of publications, are easily quantifiable and convenient for model processing. Unstructured data include text data from student forum posts, course reviews, and paper abstracts, as well as multimedia data such as conference presentation videos and course recordings. These unstructured data require additional preprocessing to convert them into formats suitable for model processing. The implementation process of data preprocessing is detailed in Table 1:

Table 1. The implementation process of data preprocessing

Data preprocessing phase	Specific activity	Objectives
Data cleaning	Removing or correcting inconsistent or erroneous records	Ensuring the accuracy and consistency of data
	Handling missing values	Avoiding the impact of missing values on model training
Data balancing	Applying oversampling and undersampling techniques	Addressing the issue of class imbalance and improving the model's generalization ability
Data augmentation	Adding noise or applying transformations to generate new data points	Simulating learning modes under different student backgrounds and educational environments
Feature engineering	Converting text data to TF-IDF representation	Converting text data into a numerical format suitable for model processing
	Converting time series data to sliding window format	Making time series data suitable for model processing such as LSTM
Tag encoding	Converting categorical data into numerical codes	Making classification data suitable for model processing
Data standardization	Using Z-score standardization or minimum maximum scaling	Ensuring that all features are on the same scale to avoid feature bias
Feature selection	Selecting the most relevant features for learning path prediction	Reducing noise and irrelevant features to improve model performance
Feature dimensionality reduction	Using PCA and other methods to reduce feature dimensionality	Reducing computational complexity and improving model training efficiency
Outlier handling	Identify and handle outliers	Preventing the impact of outliers on model training and prediction results

Finally, the dataset is partitioned into training, validation, and testing sets, with 70%, 15%, and 15% of the data allocated to each, respectively. This partitioning ensures proper training and performance evaluation of the model. In terms of data privacy and ethics, anonymization processing, obtaining consent for data use, and implementing data security measures should be strictly observed to protect student privacy and ensure research compliance.

4.2. Experimental Environment and Parameters Setting

To ensure the reproducibility of the experiments and the validity of the results, this section provides a comprehensive overview of the experimental setup, including hardware configuration and key parameter settings. The aim is to offer a clear and transparent reference framework for future research. The experiments were developed using Python 3.8, primarily leveraging TensorFlow 2.5 and the Keras library. The LSTM units included 128 hidden units, with a dropout rate of 0.2 to mitigate the risk of overfitting. During model training, the Adam optimizer was employed with an initial learning rate of 0.001.

Table 2 shows the hardware configuration.

Table 2. Hardware configuration

Configuration Name	Description
Central Processing Unit (CPU)	Intel Xeon E5-2690 v4 @ 2.60GHz x 24, providing robust computational power to accelerate data processing and model training.
Graphics Processing Unit (GPU)	NVIDIA Tesla V100-SXM2-16GB, equipped with high-bandwidth memory and numerous CUDA cores, enabling efficient parallel computations for DL algorithms.
Memory (RAM)	128GB DDR4 ECC, ensuring rapid read and write operations and efficient caching for large datasets.
Storage	2TB NVMe SSD, offering high-speed data access for storing raw datasets and intermediate processing results.

Table 3 displays the parameter settings.

Table 3. Parameter settings

Parameter	Description
Model Architecture Parameters	The LSTM layer comprises 128 units, with a dropout rate of 0.2 to reduce overfitting.
Optimizer Parameters	The Adam optimizer is utilized with a learning rate of 0.001. Beta values are set to $\beta_1 = 0.9$, $\beta_2 = 0.999$, and epsilon = 1e-08.
Training Parameters	The batch size is set to 32, with a maximum of 100 epochs. Early stopping is applied based on validation set loss, halting training after 10 consecutive epochs with no improvement.
Regularization Parameters	The L2 regularization coefficient is set to 0.0001 to penalize weight matrix size and prevent excessive model complexity.

4.3. Performance Evaluation

A) Model Performance Evaluation.

The performance of the constructed model is evaluated using multiple metrics. Figure 3 illustrates the results.

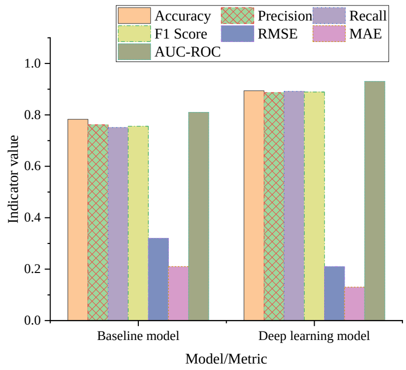

Fig. 3. Model performance evaluation

The evaluation demonstrates that the DL model consistently outperforms the baseline model across nearly all metrics, including accuracy, F1 score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). These findings highlight the clear superiority of the DL model in predicting personalized learning paths and providing intelligent resource recommendations for graduate education.

B) User Satisfaction Analysis for Personalized Learning Path Recommendations

User satisfaction with the personalized learning path recommendations is also analyzed, with results depicted in Figure 4.

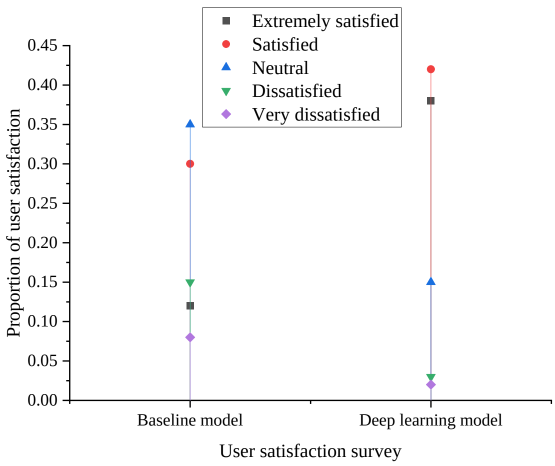

Fig. 4. User satisfaction analysis for personalized learning path recommendations

The analysis reveals that the baseline model exhibits relatively low user satisfaction, as indicated by a substantial proportion of users reporting "neutral" or lower satisfaction levels. This suggests that the baseline model may not effectively address user needs. Conversely, the DL model demonstrates a significant enhancement in user satisfaction, with the majority of users indicating they are "very satisfied" or "satisfied." This improvement reflects the model's ability to deliver a higher level of personalization in its recommendations, ultimately leading to a more positive user experience.

C) Comparison of Model Predictions with Actual Student Performance

A comparison between the model's predictions and students' actual performance is presented in Figure 5.

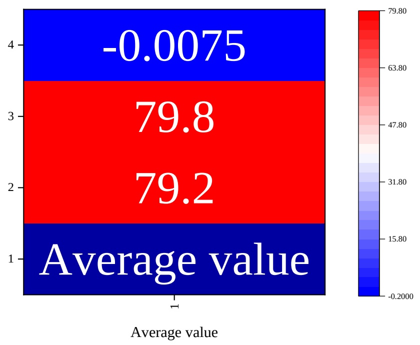

Fig. 5. Comparison of model predictions with actual student performance

The results indicate that the average predicted score generated by the model is 79.2, while the average actual score is 79.8. This suggests that the model slightly underestimates students' actual performance, with an average percentage difference of -0.75%. Although the model demonstrates a minor negative bias, the small magnitude of the discrepancy highlights its high accuracy in predicting student performance.

D) Performance Metrics of the DL Model Across Different Disciplines

The performance metrics of the proposed DL model across various academic disciplines are depicted in Figure 6.

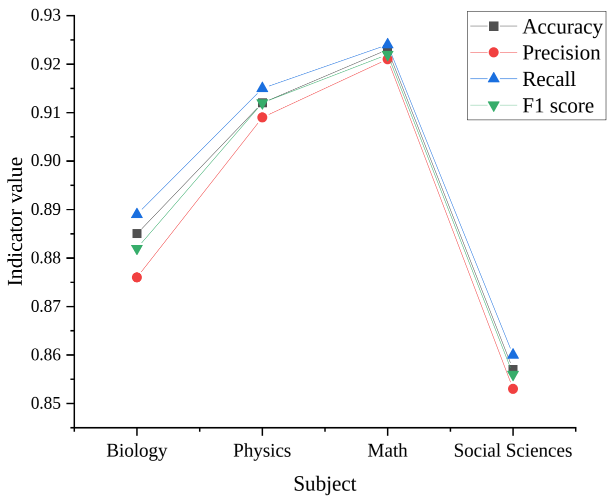

Fig. 6. Performance metrics of the DL model across different disciplines

The analysis reveals that the model achieves its best performance in mathematics, likely due to the well-structured and less ambiguous nature of mathematical data, which facilitates the model's learning process. In contrast, the model's performance in social sciences is slightly lower, potentially reflecting the inherent complexity and variability of data in this field. The performance in biology and physics is similar but slightly lower than in mathematics, possibly due to the intricate concepts and data uncertainties characteristic of these disciplines. For all disciplines, the F1 score is closely aligned with accuracy and recall, indicating a balanced performance in classification tasks.

E) Trend of Model Prediction Accuracy Over Time

The trend of prediction accuracy for the proposed DL model over time is illustrated in Figure 7.

The results in Figure 7 reveal a consistent improvement in the accuracy of the DL model over successive time periods, while the baseline model demonstrates a slower rate of progress. This trend underscores the advantages of the DL model in leveraging additional data and feedback for continuous optimization. The percentage increase in performance for the DL model grows progressively each semester, which can be attributed to its ability to capture and learn from long-term trends and patterns in student performance. This gradual enhancement reflects the model's capacity to adapt and improve as more data becomes available, further validating its robustness and scalability.

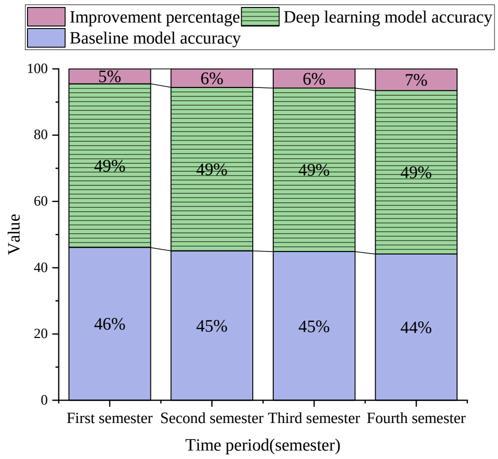

Fig. 7. Trend of model prediction Accuracy over time

4.4. Discussion

The experimental findings underscore the transformative potential of DL technology in graduate education while fostering a critical examination of current educational theories and practices. Through a comparative analysis of the DL model's performance with traditional approaches documented in prior research, several important insights have emerged:

1) Effectiveness of Personalized Learning Pathways:

The DL model's high accuracy and user satisfaction in predicting personalized learning pathways highlight its ability to effectively identify students' learning needs and preferences, enabling more precise educational resource recommendations. This result aligns with the work of Ginja et al. (2020) in educational psychology, which emphasizes the importance of differentiated instruction tailored to the unique characteristics of each student [42]. However, the proposed method in this study demonstrates a superior capacity for capturing individual differences and specific learning requirements, thereby surpassing conventional techniques.

2) Insights into Disciplinary Variations:

The analysis of model performance across various disciplines revealed that the DL model performs best in mathematics, with relatively lower performance in social sciences. This observation resonates with the findings of English (2022), who explored the intrinsic characteristics of academic disciplines [43]. Quantitative fields like mathematics, characterized by well-structured and organized data, are inherently more conducive to model learning. Conversely, qualitative disciplines such as social sciences present challenges due to their inherent complexity and subjectivity.

3) Improvements in Time Series Analysis:

The gradual enhancement in the model's predictive accuracy over time underscores the advantages of DL techniques in analyzing time series data. This observation is consistent with the trends discussed by Okewu et al. (2021) in the context of educational data mining, which highlight the capability of DL models to improve predictions through iterative learning and optimization [44]. Compared to traditional approaches, the method proposed in this study demonstrates superior efficiency in filtering and recommending educational resources tailored to students' evolving needs.

Thus, the primary distinction between the algorithm proposed in this study and other state-of-the-art algorithms lies in its integration of the dual advantages of DL and RL. Meanwhile, the LIME algorithm is introduced to achieve higher precision, adaptability, and interpretability in PLPP and resource recommendation. Compared to traditional CF or rule-based methods, the proposed algorithm captures long-term dependencies in students' learning behaviors through an LSTM network. This algorithm enables a more accurate prediction of students' learning paths with an accuracy of 92.5%, significantly outperforming existing methods. Furthermore, traditional educational models struggle to precisely match students' learning needs with research resources, leading to low learning efficiency. In contrast, this study captures long-term dependencies in students' learning behaviors through an LSTM network and combines it with a hybrid recommendation mechanism of CF and CB filtering. This remarkably improves the precision of resource matching, with a resource recommendation accuracy of 93.4%, addressing the issue of uneven resource allocation. Compared to algorithms relying solely on DL, this study dynamically adjusts the learning rate through RL, optimizing the model's convergence speed and prediction performance, with a prediction bias of -0.75%, outperforming other algorithms. More importantly, this study enhances the model's interpretability through the LIME algorithm. This enables educators to understand the model's decision-making logic and address the trust issues associated with traditional "black-box" models in educational applications. Consequently, the proposed algorithm outperforms existing methods in performance. Also, it exhibits significant advantages in cross-disciplinary adaptability, long-term prediction capabilities, and interpretability, offering a more intelligent and transparent solution for graduate education.

The potential long-term impacts of the proposed model's algorithm on students' career development and research skills highlight its capacity to align learning experiences with individual academic and career objectives. By providing personalized learning pathways and resource recommendations, the DL model enables students to acquire skills more effectively, improving both learning efficiency and satisfaction. This tailored educational approach offers students clearer career guidance by identifying their interests and strengths at an early stage. Additionally, the model's accurate predictions of academic performance provide educators with actionable insights, facilitating timely interventions to address academic challenges. Such support enhances students' research capabilities and problem-solving skills. Over time, this data-driven, personalized education methodology may significantly influence students' career trajectories, bolster their innovation capabilities, and increase their competitiveness in research fields. These findings offer empirical evidence supporting personalized education and valuable guidance for educators and policymakers seeking to leverage DL technologies to promote holistic student development.

While the study primarily focuses on student outcomes, it also underscores the essential role educators play in the educational process. The insights generated by the model enable educators to better understand students' learning behaviors and needs, allowing for more targeted and effective instructional decisions. The predictive and analytical capabilities of the model assist in monitoring student progress, identifying those who may require additional support, and enhancing the overall efficiency of instruction. Furthermore, these tools facilitate the optimized allocation of resources to meet diverse learning needs. As educators become more familiar with and trust DL models, they can utilize these technologies to refine their instructional strategies in a data-driven manner, thereby improving educational quality. This study not only transforms the learning experience for students but also provides educators with a platform to integrate advanced educational technologies into their teaching practices. By offering new perspectives and tools for professional development, the study emphasizes the dual impact of DL models: enhancing student learning outcomes and advancing educators' instructional methods and professional growth.

Although this study focuses on the student experience, it acknowledges the vital role of educators in the educational process. Educators can utilize the insights provided by the model to gain a deeper understanding of students' learning behaviors and needs, facilitating more targeted instructional decisions. Furthermore, the model's predictive and analytical tools support educators in tracking student progress and promptly identifying those requiring additional assistance. This enhancement improves instructional efficiency and enables more effective allocation of resources to meet students' specific learning needs. As educators become increasingly familiar with and confident in the use of DL models, these tools can be employed to optimize instructional strategies in a data-driven manner, ultimately elevating educational quality. This study provides educators with a platform to integrate advanced educational technologies, offering new perspectives and tools for professional development and teaching practices. Consequently, DL models not only transform the learning experiences of students but also positively influence educators' teaching methods and professional growth.

When integrating AI technologies into education, several critical considerations must be addressed to ensure their effective and ethical application. First, regarding the potential dependency of students on the system, it is crucial to position educational technology as a complementary tool that enhances, rather than replaces, students' active learning and independent thinking. To mitigate the risk of over-reliance, educators should design curricula and activities that encourage students to critically evaluate and thoughtfully apply the model's recommendations. Educators should also guide students in understanding the limitations of AI-driven tools, fostering the ability to discern when and how to effectively utilize these suggestions within their learning contexts. Second, the current DL model evaluates student performance primarily based on academic data. Future iterations should expand to include additional data types, such as student engagement metrics, feedback, and self-assessments, to develop a more comprehensive learning profile. Incorporating these elements will better address students' personalized needs and provide a holistic understanding of their learning journeys. Concurrently, educators must acknowledge the importance of these non-academic factors and proactively provide interventions and support to facilitate students' overall development. Third, achieving a balance between quantitative and qualitative indicators is essential. An excessive focus on quantitative metrics risks overlooking critical qualitative dimensions of learning, such as creativity, emotional intelligence, and interpersonal skills, which are fundamental to students' holistic development yet challenging to quantify. Future evaluations of learning outcomes should adopt a multidimensional approach, combining quantitative indicators with qualitative measures, including student self-reports, peer evaluations, and educator observations. Such an approach will provide richer insights into students' personal and social competencies, enabling a more nuanced understanding of their growth and achievements. By adopting this comprehensive assessment framework, educational practices can better support the multifaceted development of students, fostering their academic success, personal growth, and social adaptability in an increasingly complex and interconnected world.

Graduate education typically prioritizes the development of independent research and innovation skills, while undergraduate education focuses on building foundational knowledge and exploring academic interests. Despite the distinct learning and research objectives at these two educational levels, the findings of this study offer valuable insights for enhancing undergraduate education. The application of DL models in designing personalized learning pathways and resource recommendations has significant potential to boost undergraduate students' motivation, support them in identifying and exploring their academic interests, and establish a solid foundation for their future academic and career trajectories. Adapting the model to the specific characteristics of undergraduate education is essential to achieve these outcomes. Methodologies and insights from this study can effectively support the modernization and personalization of undergraduate education through targeted customization and further investigation. Future research will focus on tailoring the proposed framework and tools to align with the learning needs and objectives of undergraduate students. Additionally, the effectiveness of these adaptations will be evaluated with respect to various learning motivations and educational goals, ensuring that the approach provides meaningful and impactful support for undergraduate learners.

5. Conclusion

5.1. Research Contribution

This study highlights the innovative application of DL technology in graduate education, demonstrating its significant effectiveness in personalized teaching, student performance prediction, and intelligent resource recommendation. By integrating advanced DL techniques, particularly LSTM networks and CNNs, the accuracy of personalized learning path predictions is notably enhanced, and the quality of educational resource recommendations is significantly improved. More importantly, this approach not only optimizes students' learning efficiency but also fosters the development of their innovative abilities. As such, the study provides new perspectives and tools for the modernization of graduate education, offering tangible benefits for both educators and students.

5.2. Future Works and Research Limitations

Looking ahead, further exploration of the potential of DL technology in interdisciplinary education is recommended, with a focus on evaluating its impact on the long-term career development of graduate students. Additionally, addressing data ethics and privacy protection concerns is crucial to ensure that technological advancements align with educational fairness and respect for student rights. Despite its contributions, this study acknowledges several limitations, including data bias, the "black box" nature of certain models, and the high computational costs involved. Future research should aim to improve model transparency, resource efficiency, and data representativeness, with the goal of fostering a more equitable, efficient, and responsible educational technology ecosystem.

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