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PAPER

Optimizing Vocational Education Design with Big Data and Educational Technology

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ABSTRACT

Amidst the rapid advancements in big data and internet technologies, profound transformations have been witnessed in modern societal and economic structures. Vocational education, a pivotal component within the educational domain, faces challenges in course design and optimization. While the majority of existing research focuses on utilizing educational technology to optimize courses, most methodologies still rely on traditional data analysis and mining techniques, with little exploration of deep learning and big data technologies. This research proposes a novel strategy for course design and optimization. Initially, the course theme optimization is addressed through a short text clustering algorithm that utilizes a linear fusion of the biterm topic model (BTM) and global vectors for word representation (GloVe) similarity. Subsequently, course content is planned using a deep interest network (DIN) recommendation algorithm in conjunction with the gated recurrent unit (GRU) time series model. This study provides the vocational education sector with a new perspective on course design and optimization, which has important theoretical and practical implications.

KEYWORDS

big data, vocational education, course design, biterm topic model (BTM), global vectors for word representation (GloVe), deep interest network (DIN) recommendation algorithm, gated recurrent unit (GRU)

1 INTRODUCTION

The rapid development of big data and internet technologies has brought about significant changes in societal and economic structures, leading to new challenges and opportunities in the field of education [1–7]. Particularly in vocational education, traditional teaching methods and course content have become increasingly misaligned with the rapidly evolving demands of modern industry and society [8–11]. Thus, the optimization and design of vocational education courses, utilizing contemporary educational technology, have emerged as significant trajectories in current educational research.

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In the era of big data, every industry and field is inundated with a deluge of data, offering precious "raw materials" for educational research [12]. Employing this data, researchers can delve deeper into understanding students' learning habits, interests, and needs, thereby providing more precise and effective educational services [13, 14]. Moreover, the integration of educational technology with big data can further enhance the quality and efficiency of vocational education, providing students with a more enriching and diverse learning experience.

Presently, despite numerous studies dedicated to leveraging educational technology for course design and optimization, most methodologies continue to remain at the conventional level of data analysis and mining, with little exploration of deep learning and big data technologies [15, 16]. This implies that these methodologies have inherent limitations when dealing with large-scale, complex, and unstructured educational data [17–20]. Additionally, traditional recommendation algorithms often overlook the dynamic learning processes of students, resulting in recommended content that fails to promptly adapt to their changing needs.

The main research content of this study is divided into two segments. Initially, a short text clustering algorithm is introduced, which aims to optimize course themes grounded in educational technology. The algorithm is based on the linear fusion of biterm topic model (BTM) and global vectors for word representation (GloVe) similarity. This algorithm can effectively uncover students' learning needs and interests, thus delivering more targeted course content. Subsequently, a time-series model called gated recurrent unit (GRU) is introduced to optimize course content planning in the deep interest network (DIN) recommendation algorithm. This method considers not only the current demands of students but also their learning journey, ensuring that the recommended content is more precise and targeted. On the whole, this research provides a novel strategy for designing and optimizing courses in the vocational education field, which holds significant theoretical and practical value.

2 OPTIMIZATION OF COURSE THEMES BASED ON EDUCATIONAL TECHNOLOGY

The paramount objective of vocational education is to train students to acquire the specialized skills and knowledge necessary for real-world work environments. With the rapid changes in society, technology, and the economy, demands across various sectors are constantly evolving, resulting in a shift in the industry's expectations and requirements for its employees. Such dynamism signifies that the course content of vocational education requires timely adjustments to align with these changes. The optimization of vocational education course themes ensures that students acquire skills and knowledge that align with current market and industry demands upon graduation, thereby enhancing their competitive employability.

The short-text clustering algorithm, introduced herein, is based on the linear fusion of BTM and GloVe similarity. It can capture students' learning needs and interests with enhanced precision. The field of vocational education involves a vast amount of unstructured data, including student feedback, online discussion content, and instructional materials. Figure 1 illustrates the workflow of the clustering technique used in this study. The fusion of BTM and GloVe technologies demonstrates efficacy in managing short-text data, extracting valuable information, and providing data support for optimizing course themes. Concurrently, as time progresses, variations in students' needs, shifts in the industry, and technological updates may render course content obsolete. This algorithm is capable of real-time analysis of the most recent data, dynamically adjusting course themes, and ensuring that educational content continuously aligns with current demands. By employing this method, educators can offer more relevant and engaging course content to students, thereby enhancing their enthusiasm for learning.

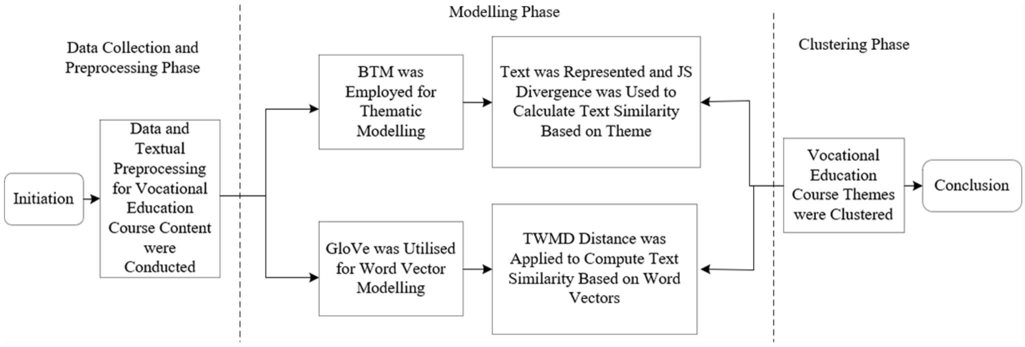

Fig. 1. Workflow of clustering technique employed in the study

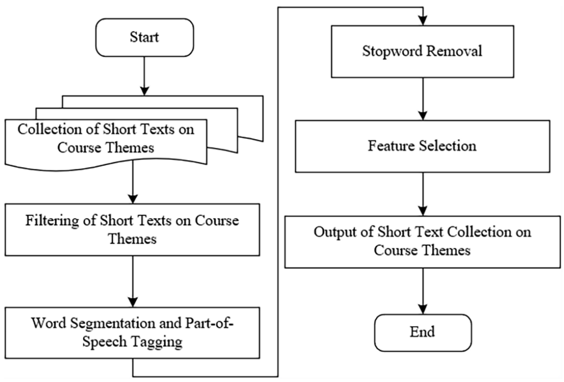

Fig. 2. Pre-processing workflow of course themes

Prior to conducting similarity linear fusion, the preprocessing of course themes is required. Figure 2 presents the workflow for course theme preprocessing. Perplexity is a commonly used metric for assessing the quality of topic models. Generally speaking, a lower perplexity signifies superior predictive performance for the model. Initially, a range of vocational education course themes are selected. Subsequently, for each selected number of vocational education course themes, topic modeling for vocational education courses is conducted using BTM. A subset of the dataset, such as a validation set, is utilized to calculate the perplexity of each model. Assuming the total number of word pairs is represented by $|R|$ and the joint probability of word pair n is denoted by $o(n)$, the formula for calculating perplexity is as follows:

$$PE = \exp\left\{-\frac{\sum \ln o(n)}{|N|}\right\} \tag{1}$$

It is postulated that the probability distribution of the vocational education course theme x is denoted by $o(x) = \phi_x$. The probability distribution of the feature word q_u given the course theme x is represented by $o(q_u|x) = \theta_{u|x}$, and a similar representation exists for the feature word q_k given the theme x. The formula for calculating joint probability is expressed as:

$$o(n) = \sum_x o(x)o(q_u \mid x)o(q_k \mid x) = \sum_x \varphi_x \theta_{u|x} \theta_{k|x} \tag{2}$$

Biterm topic model, which specializes in short text design, establishes thematic structures in short texts more transparently by modeling topics through word pairs instead of individual documents. Each document is represented by the output of BTM, which yields a topic distribution vector. Each dimension of the vector represents the weight of a specific topic. In this research, the top 6 feature words in $o(x|f)$ are selected as the document's feature words. At this point, the document vector is represented by the following posterior topic distribution vector:

$$f_{u\_NYL} = \left\{ o\left(x_1 \middle| f_u\right), o\left(x_2 \middle| f_u\right), \ldots, o\left(x_J \middle| f_u\right) \right\} \tag{3}$$

Moreover, two documents are selected and their topic distribution vectors are chosen. The divergence between the two documents is then calculated using the *JS* divergence formula. A smaller *JS* divergence indicates a higher similarity between two documents, while a larger *JS* divergence suggests a lower similarity. The similarity between f_u and f_K is translated into calculating the similarity between f_{u_NYL} and f_{j_NYL}, with the text similarity calculation formula expressed as:

$$\begin{aligned} DIS(f_{u\_NYL}, f_{k\_NYL}) &= DIS(f_u, f_k) = DIS_{KA}(f_u, f_k) \\ &= \frac{DIS_{JM}\left(f_u \middle\| \frac{f_u + f_k}{2}\right) + DIS_{JM}\left(f_k \middle\| \frac{f_u + f_k}{2}\right)}{2} \end{aligned} \tag{4}$$

Global vectors for word representation, a method for pre-training word vector representations on large text corpora, maps words to multi-dimensional spaces using global statistical information. This technique brings semantically similar words closer together in the vector space. The GloVe algorithm is used to train textual data, which generates a vector representation for each word. For each document, the internal word vectors are averaged or weighted averaged to obtain the document's vector representation.

Furthermore, the IWMD distance is employed to calculate text similarity. For two documents, A and B, their word vector representations are first obtained. The WMD distance between A and B, which is the minimum distance that words need to be moved from A to B, is calculated. The reciprocal is taken to obtain IWMD. A higher IWMD value indicates greater similarity between two documents, and vice versa. Assuming the H-order weight transition matrix is denoted by Y_{ay}, the weight of word a in f_u is transferred to word y in f_k represented by $Y_{uk} \geq 0$. The calculation formula is as follows:

$$DIS_{GV}(f_u, f_k) = DIS_{JM}(f_u, f_k) = \underset{Y \geq 0}{NIN} \sum_{a,y=1}^{H} Y_{ay} v(a, y) \tag{5}$$

Under constrained conditions, the minimum cumulative cost of transferring from f_u to f_k is obtained by $MIN_{Y\geq 0} \sum_{z,y}^{H} Y_{zy} v(a, y)$ linear programming. Assuming the word transition cost is represented by $v(a,y)$, the conditions that need to be met are as follows:

$$\sum_{y=1}^{H} Y_{ay} = q\_ov_a, \forall a \in \{1,...,H\} \tag{6}$$

$$\sum_{a=1}^{H} Y_{ay} = q\_ov_y, \forall y \in \{1,...,H\} \tag{7}$$

The IWMD similarity, based on GloVe, and the JS divergence similarity, based on BTM, are linearly fused to obtain a comprehensive similarity. This comprehensive similarity considers both the semantic and topic information of the text. Appropriate clustering algorithms, such as K-means or hierarchical clustering, are used to cluster short texts based on their overall similarity. Each cluster can be considered as a theme. Assuming the total number of texts in the dataset is denoted by b, the u-th document is denoted by f_u, the cluster center collection by V_r, and the number of clusters by J, the following formula provides the cluster center update formula for the means clustering algorithm:

$$v_r = \frac{1}{b} \sum_{f_u \in V_R} f_u, r = 1,2,...,J \tag{8}$$

The clustering criterion function corresponding to the fusion of two types of similarity distances is given by:

$$\begin{aligned} R &= \sum_{r=1}^{J} \sum_{f_u \in V_r} DIS(f_u, v_r)^2 \\ &= \sum_{r=1}^{J} \sum_{f_u \in V_r} \left[\eta \cdot DIS_{NYL}(f_u, v_r) \cdot DIS(f_u, v_r) \right]^2 \end{aligned} \tag{9}$$

Following the clustering results, the course themes of vocational education are optimized. Similar course content is grouped together under the same theme, ensuring that the content within each theme is highly related. At the same time, there are significant variations in content between different themes.

3 COURSE CONTENT DESIGN AND PLANNING BASED ON OPTIMIZED DIN RECOMMENDATION ALGORITHM

In light of the rapid evolution of technology, seismic shifts have been witnessed across numerous industries. Vocational education has emerged as a crucial factor in equipping students with practical occupational skills, ensuring a smooth transition into the labor market after graduation, and enabling them to make significant contributions to the social and economic sectors. The essence of vocational education, without a doubt, lies in the design and planning of course content, which directly impacts the skills and knowledge acquired by students and its alignment with industry requirements. Alignment of course content with the tangible demands of the job market is paramount, as it enhances the likelihood of students securing relevant employment.

In the current era of big data, the needs and backgrounds of students, trainees, and vocational trainers are constantly changing. The proposition of this study relates to an optimized DIN recommendation algorithm, which is designed to effectively capture the dynamic learning interests and needs of trainees. This algorithm aims to tailor course content to each trainee's current situation. Contrastingly, traditional course design and planning typically adhere to a static paradigm, lacking the adaptive capacity to guarantee benefits for all trainees. The recommendation system proposed here seeks to overcome this limitation by providing personalized course recommendations that cater to the specific needs of each trainee. This will ultimately improve learning efficiency and training effectiveness.

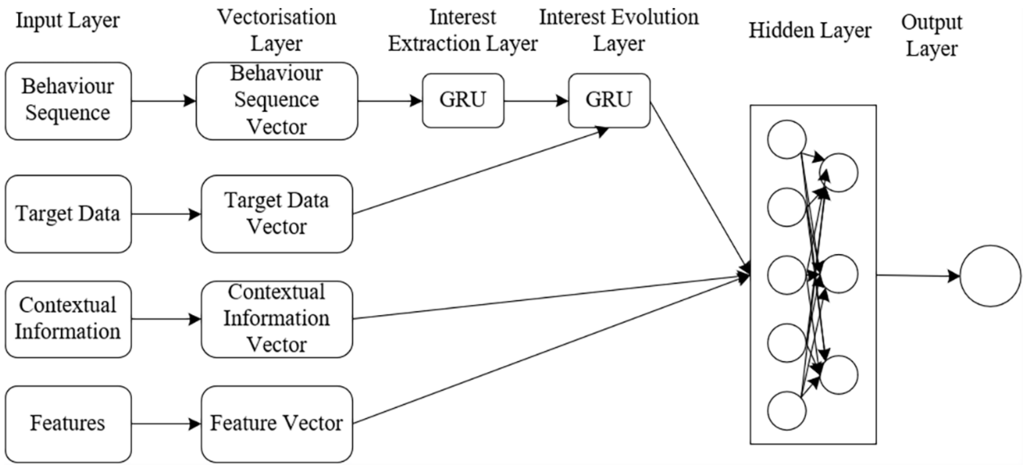

Fig. 3. Architecture of the optimized DIN recommendation model

The proposed optimized DIN recommendation algorithm consists of three main layers: an interest extraction layer, an interest evolution layer, and a hidden layer. Figure 3 illustrates the architecture of the optimized DIN recommendation model. A key objective of the interest extraction layer is to capture the interests and preferences demonstrated by trainees during their previous learning experiences. This data is then used to generate foundational information for subsequent course recommendations. The gated recurrent unit (GRU) is proficient at effectively capturing long-term dependencies within sequential data, making it particularly suitable for monitoring trainee learning trajectories and evolving interests. By utilizing the GRU structure, this layer is able to capture the temporal variations in trainee learning behaviors and interests. As a result, it can access not only the trainees' current interests but also comprehend how these interests evolve over time.

In deep learning models, challenges often arise in the form of training instability when model layers are added or when structures become complex. The interest extraction layer primarily utilizes the GRU structure. Although GRUs have partially addressed the problem of gradient vanishing, it may still occur in certain deep network architectures. Auxiliary loss functions, which serve as intermediate training objectives, can provide clearer gradient information during the initial stages of training. This facilitates more stable model learning and also offers more direct network feedback, helping to mitigate issues related to gradient vanishing. Assuming that the output of teacher u at time y in the GRU network is denoted by g_y^k, the teacher's actual behavior sequence is represented by r. The negative sample sequence obtained by negative sampling is denoted by $r^\wedge$, and the length of the teacher Embedding sequence is symbolized by B. The formula for calculating auxiliary loss function is provided below:

$$M_{AU} = -\frac{1}{B}\left(\sum_{u=1}^{B}\sum_{y=1}^{Y}\log\delta(g_y^u, r_n^u[y+1]) + \log(1-\delta(g_y^u, r_n^u[y+1]))\right) \tag{10}$$

The final formulation for the global loss function is depicted as follows:

$$M = M_{TA} + \beta * M_{AU} \tag{11}$$

The aim of the interest evolution layer is to elucidate the evolutionary trajectory of a trainee's learning interests over time and content progression. By integrating the attention model with the GRU structure, individual weights can be assigned to each past learning behavior, determining which behaviors are of crucial importance when suggesting new courses. In this context, the attention model assigns different levels of importance to various historical learning behaviors, while the GRU monitors the temporal dynamics of interests. The convergence of both ensures that the system gives proper consideration to both the trainee's recent and long-term learning interests (Figure 4).

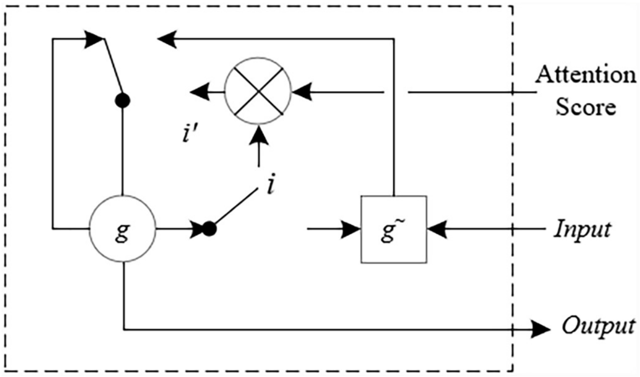

Fig. 4. Architecture of the interest evolution layer

Integrating the popularity of vocational education course content as a factor influencing model attention into the attention model yields the following formula:

$$s_y = \frac{\exp(g_y Qr_\beta + \alpha J'_{GH})}{\sum_{k=1}^{T} \exp(g_y Qr_\beta + \alpha J'_{GH})} \tag{12}$$

Assuming that the hidden layer state is denoted by $\tilde{g}'_y$ and the attention score by s_y, this study employs attention scores to substitute the update gates in the GRU network:

$$g'_y = (1 - s_y) * g'_{y\text{-}1} + s_y * \tilde{g}'_y \tag{13}$$

The update gate, which incorporates attention scores, is represented by $\tilde{i}'$, hidden layer state by $\tilde{g}'_y$, and characteristics of the optimized network model can be described using the following formula:

$$\tilde{i}' = s_y * i'_y \tag{14}$$

$$g'_y = (1 - \tilde{o}') \circ g'_{y-1} + \tilde{i}' * \tilde{g}'_y \tag{15}$$

The hidden layer primarily orchestrates the further amalgamation and processing of outputs from the preceding two layers to create a comprehensive representation, which will be used for the final course recommendation. The objective of the fully connected neural network is to decipher the complex relationship between features extracted from a trainee's historical learning behaviors and interest evolution and provide a final course recommendation.

Within deep neural networks, conventional activation functions have been known to cause gradient vanishing, which can affect the effectiveness of model training. The Dice activation function effectively alleviates this issue by adaptively adjusting input characteristics, ensuring a more stable gradient flow. Moreover, the Dice activation function, which is capable of autonomously adjusting its activation threshold according to the data, provides the model with improved non-linear fitting capability. This becomes crucial, particularly for complex recommendation tasks, such as personalized course recommendations in vocational education.

In order to dynamically adjust the segmentation point of the Dice activation function, expectations and variances need to be computed. Assuming data expectations and variances are denoted by $R[\cdot]$ and $VA[\cdot]$, respectively, and those calculated through the momentum method are represented by $R[\cdot]$ and $VA[\cdot]$, the computational formulas are as follows:

$$R[t_u]'_{y+1} = R[t_u]'_y + \beta R[t_u]_{y+1} \tag{16}$$

$$VA[t_u]'_{y+1} = VA[t_u]'_y + \beta VA[t_u]_{y+1} \tag{17}$$

In addition to data expectations and variances, o_u, a measure of data deviation, needs to be introduced, along with its computational formula:

$$t_u = s_u(1 - o_u)t_u + o_u t_u \tag{18}$$

$$o_u = \frac{1}{1 + e^{-\frac{t_u - R[t_u]}{\sqrt{VA[t_i u] + r}}}} \tag{19}$$

Given that the course content recommendation model constructed in this study falls under the category of recommendation prediction model, the negative log-likelihood function is chosen as the loss function for the hidden layer to supervise the training process of the model. The computational formula is as follows:

$$M(t \cdot d(z)) = \log(1 + e^{-td(z)}) \tag{20}$$

The sigmoid function, utilized for probability representation, has the specific computational formula:

$$h(d(z)) = O(t = 1 \mid z) = \frac{1}{1 + e^{-d(z)}} = \frac{1}{1 + e^{-\log ITA_{uk}}} \tag{21}$$

The final loss function of the model can be computed as follows:

$$M_{TA} = -\frac{1}{B} \sum_{(z,t) \in F}^{B} (t \log o(z) + (1 - t)\log(1 - o(z))) \tag{22}$$

Assuming that the model input vector set, which is formed by concatenating teacher information, teacher behavior sequence, data information, and context information, is represented by z, the training set size is represented by F. The variable t characterizes whether the teacher is interested in the data, taking values of 0 or 1. The final output of the model is represented by $o(z)$. The formula for the loss function of logistic regression is given as follows:

$$K(q) = -\frac{1}{b}\left(\sum_{u=1}^{b}(t_u \ln o(z_u) + (1-t_u)\ln(1-o(z_u)))\right) \tag{23}$$

With the model output-based course content recommendations, an analysis of student satisfaction and requirements for the current course is conducted. This analysis identifies course contents that are welcomed by the participants and the ones that requires optimization. Through the amalgamation of industry reports, expert interviews, and other methods, future trends in the vocational education market are forecasted, enabling proactive course planning.

Furthermore, the existing course content is updated and optimized based on student requirements and market trends. New courses, designed and launched according to market trends and student needs, aim to meet the demands of today's students. Simultaneously, ensuring the integration of course content with real-world work scenarios and the inclusion of practical projects and case studies enhances the practical abilities of participants. In course content planning, ensuring logical and coherent course content is essential for participants to systematically master knowledge and skills. Attention is needed to provide various learning paths and difficulty levels in order to satisfy the diverse learning needs of students. Concurrently, it is crucial to allocate teaching staff, teaching materials, and teaching equipment resources rationally, based on the importance of course content and the needs of participants.

4 RESULTS AND ANALYSIS

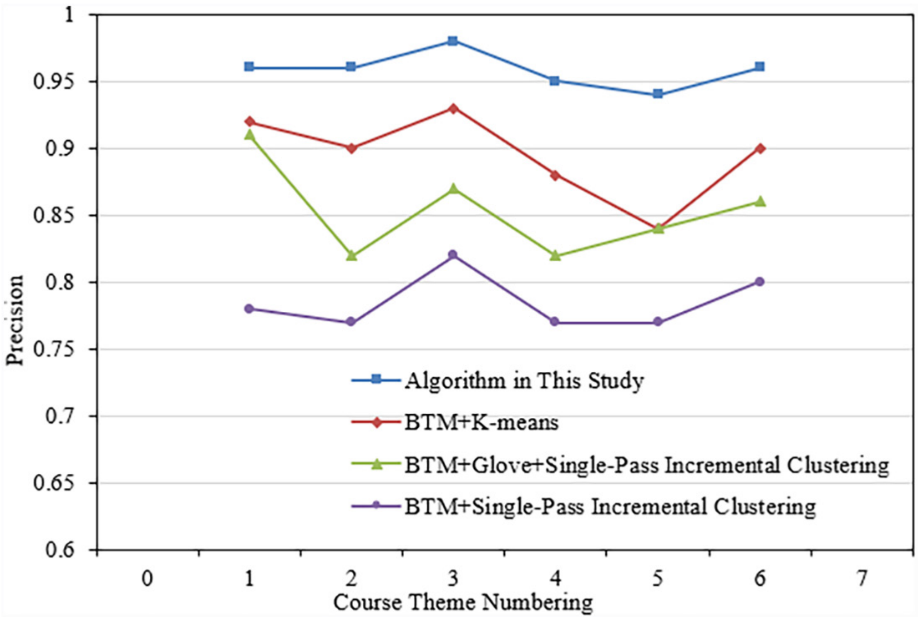

Fig. 5. Precision comparison among different topics

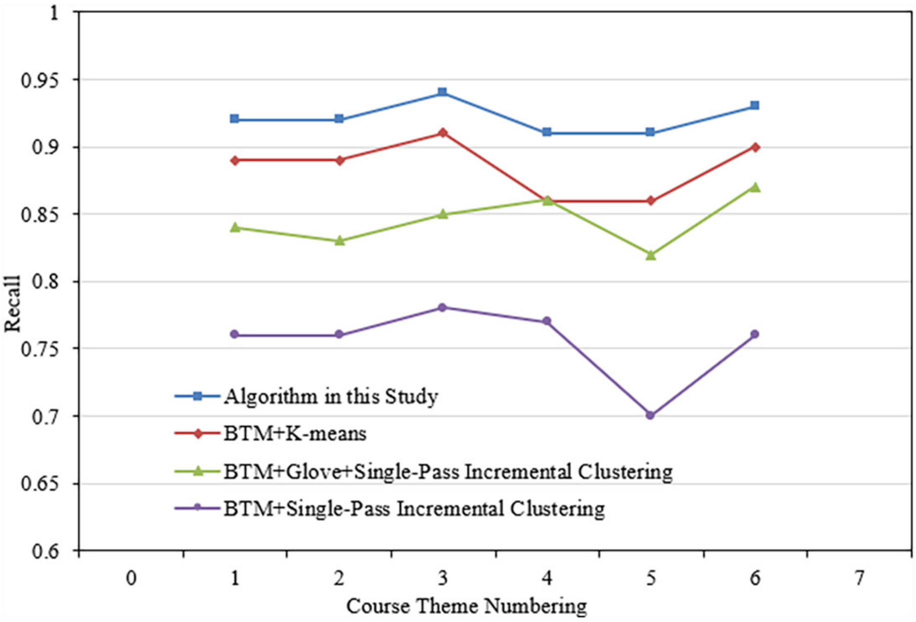

Fig. 6. Recall comparison among different topics

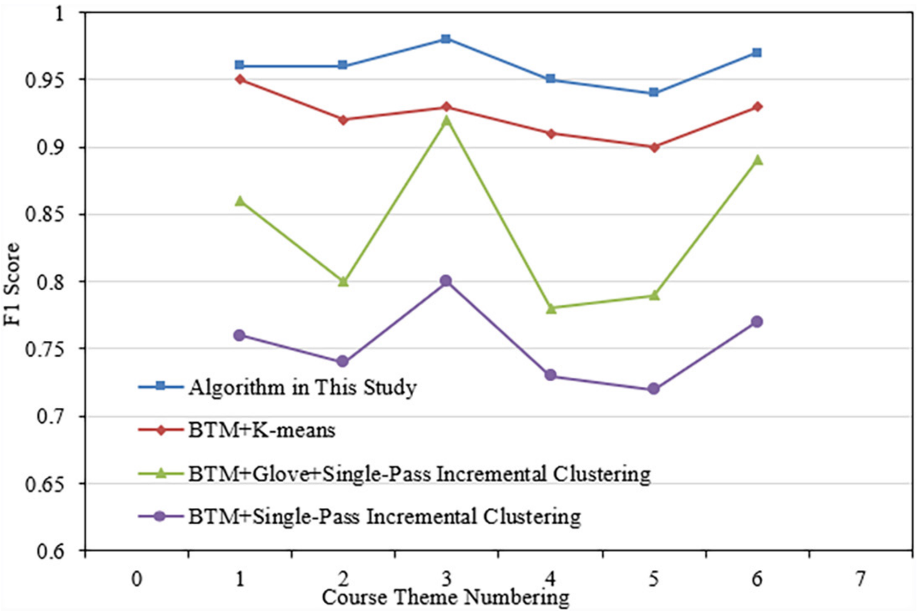

Fig. 7. F1 score comparison among different topics

An algorithm was designed to optimize vocational education course themes based on educational technology. The algorithm utilizes the linear fusion of BTM and GloVe similarity for short text clustering. Insight into the precision, recall, and F1 score for various vocational education course themes can be obtained from Figures 5 through 7. It can be discerned from Figure 5 that the proposed algorithm achieves the highest precision scores across all course themes, significantly outperforming three alternative methods. Notably, for course theme 2, the proposed algorithm achieved a precision as high as 0.98. This indicates an improved ability to accurately categorize short texts into the correct themes. Figure 6 reveals that the recall rate of the proposed algorithm surpasses that of other methods. Even though the difference is not significant for certain themes (such as course themes 3 and 4) when compared to BTM+K-means, the algorithm used in this study still maintains a dominant position. The F1 score, which represents the harmonic mean of precision and recall and is often used to evaluate the overall effectiveness of an algorithm, is shown in Figure 7 to be highest for the proposed algorithm across all themes. This indicates a well-balanced combination of precision and recall. Throughout the three figures, BTM + Single-Pass incremental clustering consistently exhibits the lowest effectiveness, while BTM + GloVe + Single-Pass incremental clustering occasionally outperforms BTM + K-means in certain scenarios, highlighting the role of GloVe in text data processing. However, the algorithm proposed in this study still demonstrates superior performance. In a general sense, the notable improvement in the classification results of vocational education course themes by the proposed algorithm has significant implications for advancing educational technology and meeting the personalized learning needs of students.

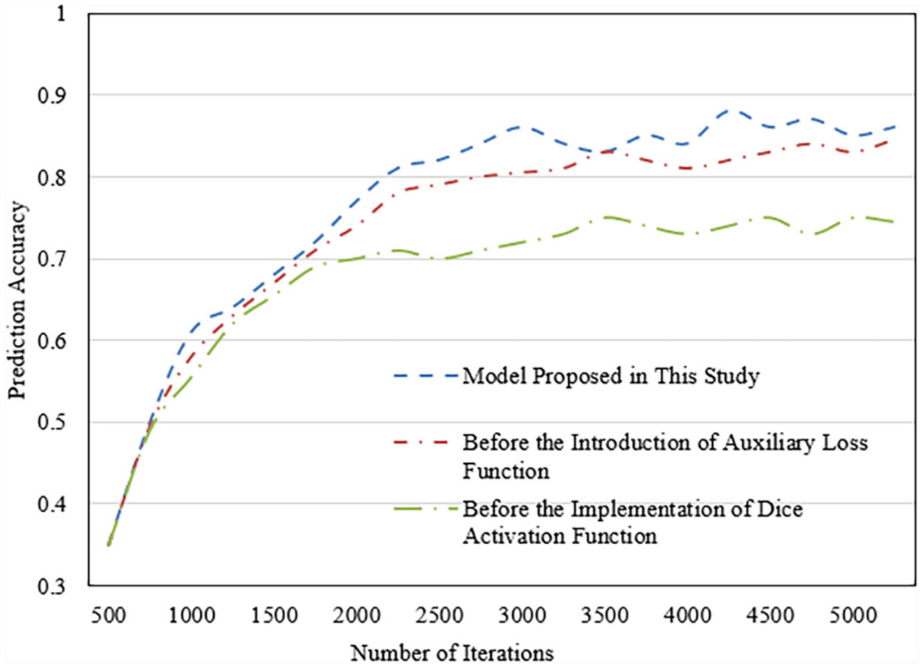

Fig. 8. Variations in prediction accuracy during the training process of the course content recommendation model

An integration of the GRU time-series model into the DIN recommendation algorithm has been introduced. This integration aims to implement vocational education course content recommendations and further optimize course content planning. Figure 8 demonstrates the prediction accuracies of the proposed model, the model prior to the introduction of the auxiliary loss function, and the model before the Dice activation function was employed, across different iteration counts. It can be observed that the proposed model consistently maintains superior prediction accuracy compared to the other two models. Particularly after a certain number of iterations, the prediction accuracy of the algorithm constructed in this study remains relatively stable, substantiating its efficacy and robustness. The model, prior to incorporating the auxiliary loss function, shows an increase in accuracy with additional iterations, although it is still lower overall compared to the proposed model. This indicates the performance-enhancing role of the auxiliary loss function. The prediction accuracy of the model prior to the introduction of the Dice activation function remained the lowest throughout the entire iterative process. This further validates the performance improvement imparted by the Dice activation function. In general, the algorithm developed in this study not only improves prediction accuracy but also shows consistent performance during the iterative process. This algorithm has significant practical value in recommending and planning vocational education course content.

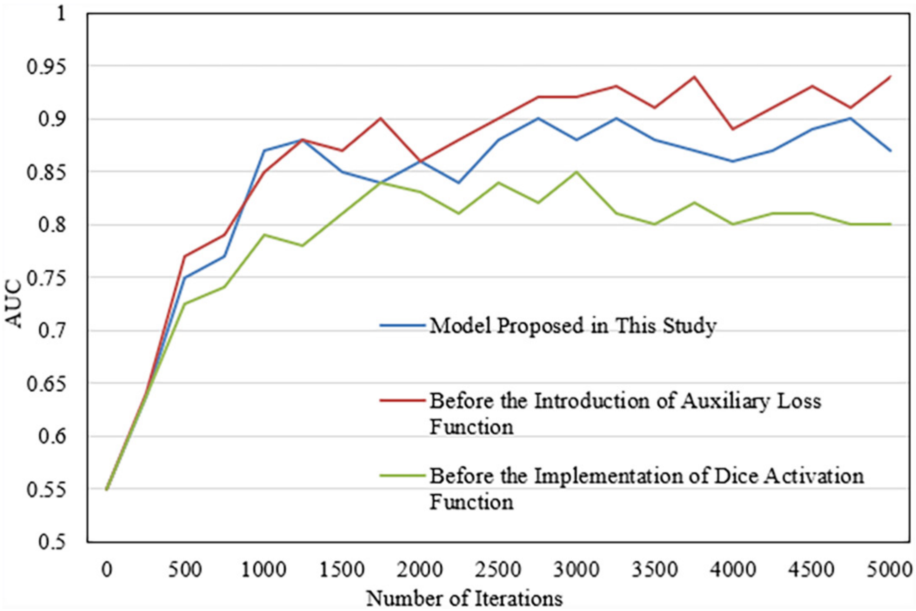

Fig. 9. Variation graph of the AUC of the course content recommendation model

An analysis of Figure 9 reveals that the AUC values of the model under discussion surpass those of the model prior to the incorporation of the Dice activation function throughout the entire iteration process. However, they do fall below certain iteration points compared to the model before the inclusion of the auxiliary loss function. This implies a commendable overall performance of the model in this study, despite a noticeable gap with the auxiliary loss function. A model prior to the implementation of the auxiliary loss function exhibits the highest AUC values for the majority of iteration points, highlighting the crucial role of the auxiliary loss function in improving model performance. Prior to the implementation of the Dice activation function, the model consistently demonstrated the lowest AUC among the three, reaffirming the positive impact of the Dice activation function on model performance. Consequently, it can be concluded that the inclusion of an auxiliary loss function significantly improves model performance in terms of AUC. This suggests that incorporating an auxiliary loss could lead to better recommendation results when optimizing course content. The introduction of the Dice activation function contributes to an increase in the AUC value of the model, further emphasizing its significance within the model.

Table 1. Comparative experimental results of course content recommendation across different models

Algorithm	Precision	Recall	F1
Before the Implementation of Dice Activation	73.25%	75.44%	74.59%
Before the Introduction of Auxiliary Loss Function	73.69%	73.25%	73.12%
Model Proposed in This Study	76.17%	77.33%	77.63%

From Table 1, it is evident that the model in this study has a precision rate of 76.17%, which is significantly higher than the precision rates of the other two models. The model, prior to the integration of the Dice activation function, exhibits a precision rate of 73.25%, which is slightly lower than the model before the inclusion of the auxiliary loss function. The latter presents a precision rate of 73.69%. The model in this study achieved the highest recall rate, recording 77.33%. The recall rate for the model before introducing the Dice activation function is 75.44%, which surpasses the recall rate of 73.25% for the model prior to the introduction of the auxiliary loss function. The F1 score, which serves as a composite evaluation metric of precision and recall, reaches its peak at 77.63% for the model in this study. The F1 score for the model before integrating the Dice activation function is 74.59%, which is higher than the F1 score of the model before including the auxiliary loss function, which was 73.12%.

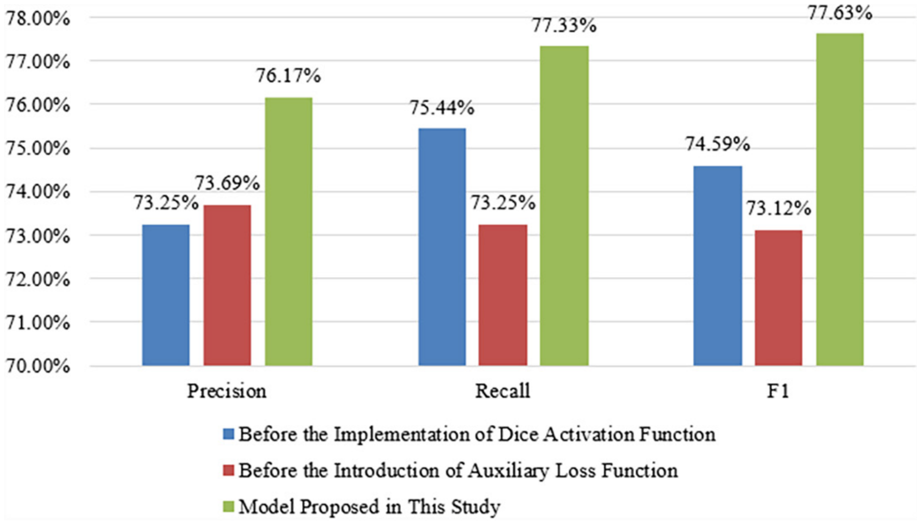

Fig. 10. Comparative experimental results of different course content recommendation models

Figure 10 provides a more intuitive perspective, showing that the model in this study significantly outperforms the models "before the introduction of the Dice activation function" and "before the inclusion of the auxiliary loss function" in terms of precision, recall, and F1 score. Compared to the model before the introduction of the Dice activation function, the model in this study demonstrates enhancements across all three evaluative metrics. This indicates that the Dice activation function within the hidden layer can more effectively capture data features, thereby enhancing the model's recommendation outcomes. In comparison to the model before incorporating the auxiliary loss function, this study's model shows increases across all three evaluation metrics. This implies that introducing the auxiliary loss function at the interest extraction layer facilitates more accurate capture of user interests, thereby enhancing recommendation precision. In summary, the algorithm developed in this study demonstrates exemplary performance in recommending vocational education course content. It effectively provides more precise and targeted course recommendations, thereby contributing to the optimization of vocational education course content planning.

5 CONCLUSION

Initially, this research introduced a short-text clustering algorithm based on a linear fusion of BTM and GloVe similarity. This amalgamation method adeptly captures information within short texts, thereby achieving a more accurate categorization and optimization of vocational education course themes. Furthermore, the GRU time-series model integrated the DIN recommendation algorithm, which analyzed students' learning behavior and interest variations from a temporal perspective. This integration allows for more targeted course content planning. Not only did this method effectively extract themes from short texts during the clustering phase, but it also took into account the students' temporal behavior during the course content recommendation phase, offering an overall comprehensive strategy for the design and optimization of vocational education courses.

From the experimental results, it can be discerned that the short-text clustering algorithm, based on BTM and GloVe, demonstrates commendable precision, recall, and F1 scores across various vocational education course themes. Compared to alternative methods, the effectiveness of this algorithm proves to be more pronounced. With the integration of the DIN recommendation algorithm from the GRU time-series model, improvements were observed in metrics such as accuracy and AUC for course content recommendations. When compared to models that do not include the Dice activation function and auxiliary loss function, the model proposed in this study demonstrated a significant advantage across multiple evaluation metrics.

A successful fusion of short-text clustering and the time-series recommendation algorithm was achieved in this study, presenting a novel strategy for course design and optimization in vocational education. Whether in theme categorization or course content recommendation, this strategy exhibited performance that surpassed alternative methods. This not only validates the effectiveness of the short-text clustering algorithm, which combines the BTM and GloVe similarity techniques, but also confirms that integrating the DIN recommendation algorithm with the GRU time-series model can result in more precise and tailored course content for vocational education. This research introduces a new perspective and application pathway in the field of vocational education, which holds significant theoretical and practical value.

6 ACKNOWLEDGEMENT

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7 REFERENCES

[1] K. Tota-Maharaj, "A critical perspective of an online hands-on laboratory framework for environmental engineering courses," *International Journal of Engineering Pedagogy*, vol. 2, no. 3, pp. 58–62, 2012. https://doi.org/10.3991/ijep.v2i3.2104

[2] B. K. Prahani, I. R. Dawana, B. Jatmiko, and T. Amelia, "Research trend of big data in education during the last 10 years," *International Journal of Emerging Technologies in Learning*, vol. 18, no. 10, pp. 39–64, 2023. https://doi.org/10.3991/ijet.v18i10.38453

[3] A. Y. Al-Zoubi, M. Dmour, and R. Aldmour, "Blockchain as a learning management system for laboratories 4.0," *International Journal of Online and Biomedical Engineering*, vol. 18, no. 12, pp. 16–34, 2022. https://doi.org/10.3991/ijoe.v18i12.33515

[4] P. Nasa-Ngium, W. S. Nuankaew, and P. Nuankaew, "Analyzing and tracking student educational program interests on social media with chatbots platform and text analytics," *International Journal of Interactive Mobile Technologies*, vol. 17, no. 5, pp. 4–21, 2023. https://doi.org/10.3991/ijim.v17i05.31593

[5] W. Nuankaew and P. Nuankaew, "Educational engineering for models of academic success in Thai universities during the COVID-19 pandemic: Learning strategies for lifelong learning," *International Journal of Engineering Pedagogy*, vol. 11, no. 4, pp. 96–114, 2021. https://doi.org/10.3991/ijep.v11i4.20691
[6] Z. Shi, Z. Wu, Z. Zhang, Y. Chen, and X. Liu, "Learning path planning algorithm based on career goals and artificial intelligence," *International Journal of Emerging Technologies in Learning*, vol. 17, no. 10, pp. 256–272, 2022. https://doi.org/10.3991/ijet.v17i10.28455
[7] R. M. Tawafak, I. Y. Alyoussef, and W. M. Al-Rahmi, "Essential factors to improve student performance using an E-learning model: Review study," *International Journal of Interactive Mobile Technologies*, vol. 17, no. 3, pp. 160–176, 2023. https://doi.org/10.3991/ijim.v17i03.35727
[8] Q. Meng, "Higher vocational English online course system based on the test paper formation algorithm of the distance education system," in *2021 International Conference on Aviation Safety and Information Technology, Changsha China*, 2021, pp. 419–424. https://doi.org/10.1145/3510858.3510980
[9] Z. Li, "The construction of university English translation teaching model based on fuzzy comprehensive assessment," *Mathematical Problems in Engineering*, vol. 2022, no. 7755508, 2022. https://doi.org/10.1155/2022/7755508
[10] L. Zhang, P. Wei, Y. Zhang, and N. Wang, "Artificial intelligence and edge computing technology promote the design and optimization of flipped classroom teaching models for higher vocational, ideological, and political courses," *Mobile Information Systems*, vol. 2022, no. 5385386, 2022. https://doi.org/10.1155/2022/5385386
[11] M. Ba, Y. Hu, C. Xu, and Y. Zhong, "A course scheduling algorithm in secondary vocational school based on genetic algorithm," in *2019 6th International Conference on Systems and Informatics (ICSAI)*, Shanghai, China, 2019, pp. 1543–1547. https://doi.org/10.1109/ICSAI48974.2019.9010352
[12] Y. Ning, S. Zhang, Q. Han, J. Song, and C. Pei, "Teaching reform of rural vocational education based on modern educational technology," in *2010 International Conference on Educational and Information Technology*, Chongqing, China, vol. 3, 2010. pp. V3–435. https://doi.org/10.1109/ICEIT.2010.5608334
[13] H. Zeng, "Advantages of using computer multimedia to assist public English teaching in higher vocational colleges," *Journal of Physics: Conference Series*, vol. 1992, no. 4, p. 042013, 2021. https://doi.org/10.1088/1742-6596/1992/4/042013
[14] Y. Han, "The construction of Chinese online resource database and teaching implementation in higher vocational education," in *The Sixth International Conference on Information Management and Technology*, Jakarta, Indonesia, 2021, pp. 1–5. https://doi.org/10.1145/3465631.3465996
[15] X. Yang and Z. Cheng, "Discussion on the course of cultural creative catering space design in higher vocational colleges based on VR technology," *Journal of Physics: Conference Series*, vol. 1533, no. 2, p. 022114, 2020. https://doi.org/10.1088/1742-6596/1533/2/022114
[16] N. A. Savotina, E. I. Khachikyan, V. Bondarenko, and A. Ilyukhina, "Digital technology in modern education: Risks and resources," *Journal of Physics: Conference Series*, vol. 1691, no. 1, p. 012095, 2020. https://doi.org/10.1088/1742-6596/1691/1/012095
[17] P. Li, "Research on the reform of governance system of higher vocational colleges under the background of modern information technology," in *International Conference on 5G for Future Wireless Networks, Huizhou*, China, 2021, pp. 617–624. https://doi.org/10.1007/978-3-031-04245-4_54
[18] P. Yang and H. Xue, "Design idea of professional talent evaluation system based on mobile internet," in *Data Processing Techniques and Applications for Cyber-Physical Systems (DPTA 2019)*, Singapore, 2020, pp. 943–951. https://doi.org/10.1007/978-981-15-1468-5_109

[19] Y. Sun, F. Li, and Z. Zhang, "Promotion of information technology teaching ability of food specialty teachers," in *Application of Intelligent Systems in Multi-Modal Information Analytics*, 2019, pp. 1397–1402. https://doi.org/10.1007/978-3-030-15740-1_176

[20] S. Guo, J. Jiang, and H. Zhang, "Research on the teaching organization model of Russian distance education based on online platform," *Boletin Tecnico/Technical Bulletin*, vol. 55, no. 20, pp. 408–413, 2017.

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