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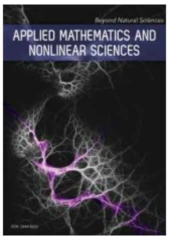

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Research on Practical Innovation of Elderly Education Service System in the Era of Artificial Intelligence

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Abstract

The trend of our country into an aging society is becoming more and more obvious, and the elderly education service has become the focus of social attention. The integration of artificial intelligence into elderly education is one of the inspiring ideas in which the personalized recommendation algorithm can recommend educational resources according to the characteristics of older people, and it has the prospect of application. In this paper, we first provide a CTransD-GAT recommendation model based on a knowledge graph, which improves traditional problems such as data sparsity by setting weight preference and feature aggregation. A dynamic preference-capturing method is proposed based on contextual interaction to capture the variable user learning interests more accurately and flexibly. This paper examines the practical utility of personalized recommendation methods for educational resources based on these two improved techniques. The post-test mean score of each knowledge module test of the experimental group is improved by 1.83 points compared with the pre-test, 11.46 points improve the score of teaching ability, and the scores of perceived usefulness, ease of use, and intention to use are 3.82, 3.89, and 3.97, respectively. It shows that the improved educational resource recommendation model has an excellent effect on improving knowledge structure and teaching ability, and it is characterized by simplicity and ease of use.

Keywords: Personalized recommendation algorithm; CTransD-GAT; Dynamic preference capture; Geriatric education.
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1 Introduction

Major scientific and technological innovations will promote the change of production relations and reshape the order of social governance and individual lifestyles. Artificial intelligence technology has a strong spillover driven by the “wild goose” effect, new theories and new technologies have had a broad and far-reaching impact on human society [1-3]. Despite the relative lag in the integration of education and artificial intelligence, education must buttress the new trend of scientific and technological progress and the sustained impact of artificial intelligence on education has been fully realized [4-5]. This includes but is not limited to innovating the talent training system, restructuring the knowledge structure of talent, reshaping the talent training program, improving the comprehensive ability of teachers, accelerating the pace of textbook innovation, building the teaching mode of industry-teaching integration, meeting the market demand for diversified talents, and so on [6-7].

With economic development and social progress, the country has entered an aging society. In the next 20 years, the situation of the country’s aging population will become even more serious. Elderly education is also an inevitable demand to cope with the aging society and meet the life of older people, as well as an educational supplement to build a learning society and enhance the value of the life of older adults [8-9]. With the rapid development of science and technology in recent years, the application of artificial intelligence technology has become more and more mature. The application of artificial intelligence technology in education is also an important part of the national strategy. Elderly education is an important part of lifelong education carried out by all people. It is particularly important to utilize intelligent technology to deeply integrate with elderly education [10-11]. Starting from the new era of intelligent background based on artificial intelligence technology, the innovation of the senior education service system is an inevitable trend to meet the educational needs of older people as well as diversified educational services [12-13].

As the country moves into an aging society, geriatric education plays an important role in meeting the needs of older people in their lives. Literature [14] argues that both older adults and individuals across the age spectrum are affected by negative ageism and proposes a Positive Education Model (PEACE) with a view to removing negative, inaccurate images of older adults and providing them with personalized, collaborative, positive contact experiences through geriatric education. Literature [15] studied 448 older adults over the age of 60 with the aim of understanding the differences in learning outcomes obtained from different positive aging activities, and the results suggest that diverse actions are needed to support each of the positive aging activities. Literature [16] designed a positive aging questionnaire on the topic of individuals’ perceptions of their role in the aging process and invited 20 college students and 23 older adults in Oklahoma to participate in the experiment. And found that college students’ perceptions of the study topic changed more than older adults and that education can change attitudes toward positive aging. Literature [17] used multivariate regression and structural equation modeling to analyze the differences between education and income affecting cognitive functioning in older adults and found that education had twice the effect on cognitive functioning as income and that it moderated the effect of income on cognitive functioning.

Intelligent education can break through the traditional elderly education dilemma, and literature [18] discusses an artificial education system for personalized learning in parallel intelligent education, which uses a k-nearest neighbor to assess the knowledge level of the learner and accurately provides differentiated guidance. Literature [19] designed a smart higher education platform using Internet of Things (IoT) technology to improve the intelligence of the teaching and learning environment and verified its performance through platform testing, which can effectively improve classroom utilization. Literature [20] aims to study the impact of AI on education and finds that it is widely used in different forms in educational platforms to improve the efficiency of teachers’ execution of different management functions and to meet the personalized needs of learners to improve the quality of teaching and learning efficiency.

In order to solve the difficult problem that learners' learning interests change dynamically and are difficult to capture and recommend, this paper extracts the long and short-term dynamic preferences of elderly learning, respectively, uses the representation learning model to map the knowledge graph accurately in a low-dimensional vector space, and on the basis of which the joint graph attention network, according to the weight coefficients of the node's information propagation and aggregation operations, and obtains the recommendation results through the scoring prediction, which improves the personalized relevance and flexibility of recommendation. Capture the importance of elderly users to different relationships, and calculate the weight of the relationship to the user in the knowledge graph through the attention mechanism to judge the degree of influence of neighboring entity nodes on the current entity node. Using the inner product of the embedding vector of the elderly user and the embedding vector of the relationship to represent the importance of the relationship to the user, the feature information of the entity node is propagated to the neighboring nodes according to the weight coefficients along the connectivity between the nodes, and the feature information of the entity node and its neighboring nodes is embedded and aggregated using convolutional operations, which solves the problems of data sparsity and cold-start inherent in the existing recommendation algorithms.

2 Research on personalized recommendation algorithms for learning resources

2.1 Dynamic preference capture based on contextual interactions

2.1.1 Dynamic preference capture based on contextual interactions of older adults

Older adults' learning interests are dynamic and subject to temporal changes, suggesting that contextual information affects older adults' learning behaviors, so integrating contextual information in the process of recommending learning resources is crucial to capturing older adults' dynamic interests.

To distinguish the influence of different contexts on the current decision-making of older adults, the dynamic learning interests of older adults are captured in two steps. Figure 1 shows the first step to capture the dynamic interest of older adults, and Figure 2 shows the second step to capture the dynamic interest of older adults. In the first step, considering that older adults and contexts are different objects and have different characteristics, the static user potential vector e^s and the context potential vector e_{c_m} are mapped to the shared hidden space as shown in Equation (1):

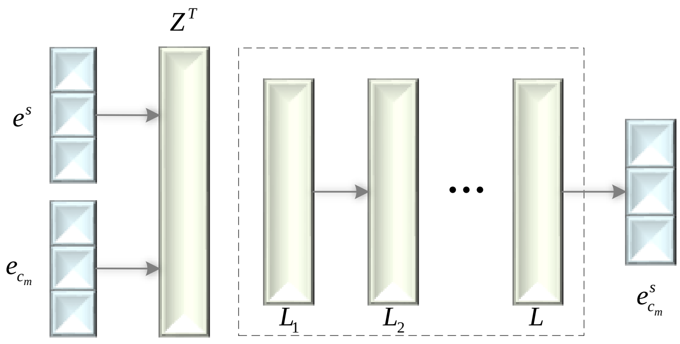

Figure 1. Obtaining elderlies' dynamic interest Step 1

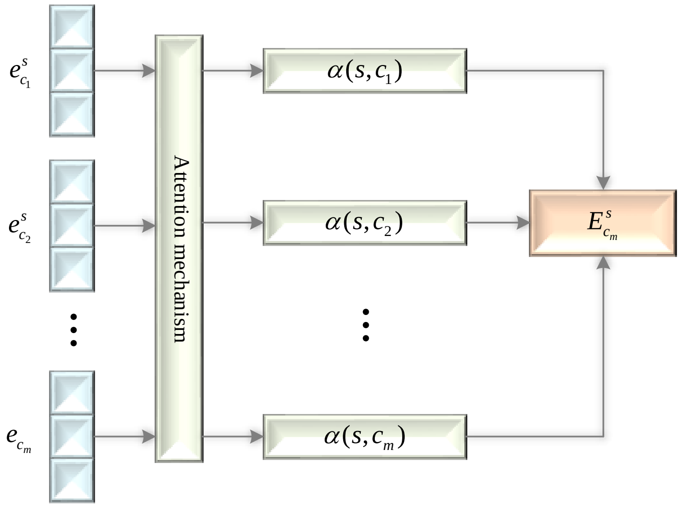

Figure 2. Obtaining elderlies' dynamic interest Step 2

$$Z^T = f\left(W_s^T e^s + W_c^T e_{c_m} + b_z^T\right) \tag{1}$$

Where W_s^T, W_c^T, b_z^T and $f(\cdot)$ represent the transformation matrix of the elderly potential vector, the context potential vector, the bias term, and the ReLu activation function, respectively [21]. Subsequently, the output of the bilinear layer is passed through the fully connected layer to output the interaction vector between older people and the context, as shown in Equation (2):

$$e^s_{cm} = f_L(W_L^T Z_{L-1}^T + b_L^T) \tag{2}$$

Where W_L^T, b_L^T and $f_L(\cdot)$ denote the weight matrix, bias vector, and ReLu activation function, respectively. In the second step, in order to distinguish the influence of different contexts on different older adults, the importance of interaction effects $e^s_{c_m}$ is distinguished through the attention mechanism. Given a potential vector $e^s_{c_m}$ and a static older adult potential vector e^s, the attention score $\alpha(u,c_m)$ is calculated as shown in Eq. (3), and the aggregation of the interaction effects is returned as a dynamic potential vector representation of older adults $E^s_{c_m}$:

$$\alpha(s,c_m)^* = W_1^\alpha f\left(W_2^\alpha e^s_{c_m} + W_3^\alpha e^s + b^\alpha\right) \tag{3}$$

Where W_1^α, W_2^α, W_3^α, b^α and $f(\cdot)$ are the model parameters and the activation function ReLu respectively. The attention scores are normalized by the SoftMax function as shown in equation (4) [22]:

$$\alpha(s,c_m) = \frac{\exp(\alpha(s,c_m)^*)}{\Sigma \exp(\alpha(s,c_m)^*)} \tag{4}$$

After obtaining the attention scores for each older adult contextual interaction, the dynamic older adult representation of older adult s is computed $E^s_{c_m}$ as shown in Equation (5):

$$E^s_{c_m} = \sum_i^M \alpha(s,c_m) e^s_{c_m} \tag{5}$$

2.1.2 Modeling Long- and Short-Term Dynamic Preferences of Older Adults

In the modeling part of short-term dynamic preferences, the global temporal dependence is captured by the Long Short-Term Memory (LSTM) network through a given embedding sequence of short-term preferences $S^s = \{e^s_{id1,}e^s_{id2,...,}e^s_{idt}\}$ as follows [23]:

$$f^s_t = \sigma\left(W^1_f e^s_{id_t} + W^2_f h^s_{t-1} + b_f\right) \tag{6}$$

$$i^s_t = \sigma\left(W^1_i e^s_{id_t} + W^2_i h^s_{t-1} + b_i\right) \tag{7}$$

$$o^s_t = \sigma\left(W^1_o e^s_{id_t} + W^2_o h^s_{t-1} + b_o\right) \tag{8}$$

$$\tilde{C}^s_t = \tanh\left(W^1_c e^s_{id_t} + W^2_c h^s_{t-1} + b_c\right) \tag{9}$$

$$c^s_t = f^s_t c^s_{t-1} + i^s_t \tilde{C}^s_t \tag{10}$$

$$h^s_t = o^s_t \tanh(c^s_t) \tag{11}$$

Where f^s_t, i^s_t, and o^s_t denote forgetting gates, input gates, and output gates, respectively. LSTM outputs sequential preference representations by modeling short-term sequences of behaviors as hidden state vectors h^s_t at time t while passing information from the past to the present via cell states c^s_t. Since older adults may be interested in various aspects of a learning resource, a single attentional network is not sufficient for capturing representations of multiple aspects. Therefore, the use of a multi-headed self-attention network is considered to capture the preferences of older adults from different aspects. Self-attention networks are a special case of attention mechanisms that use the sequence itself as a d -dimensional query, key, and value vector and use the output $H^s = \left\{h^s_{1,}h^s_{2,...,} \quad h^s_t\right\}$ of the LSTM as the input to the self-attention network, aggregating the output vectors after the self-attention network. The multi-head self-attention network is capable of attending to information from different representational subspaces at different locations and can capture older adult preferences in terms of multiple interests, and the output matrix is shown in Equation (12):

$$H^s = \text{Multihead}(H^s) = W^h(\text{haed}^s_1 \,\|\, ... \,\|\, \text{haed}^s_h) \tag{12}$$

Where W^h represents the weights, h represents the number of heads of attention, and each haed^s_c represents a potential preference, $head^s_c = Attention(W^Q_c H^s, W^K_c H^s, W^V_c H^s)$.

Where W^Q_c, W^K_c, W^V_c represents the linearly transformed weight matrices for query, key, and value, respectively. $Q^s_c = W^Q_c H^s, K^s_c = W^K_c H^s, V^s_c = W^V_c H^s$ The attention score matrix is calculated as shown in Eq. (13) and Eq. (14):

$$f(Q^s_c, K^s_c) = Q^{sT}_c K^s_c \tag{13}$$

$$A^s_c = \text{softmax}(f(Q^s_c, K^s_c)) \tag{14}$$

Next, perform weighting and pooling:

$$head_c^s = V_c^s A_c^{sT} \tag{15}$$

In order to mine more fine-grained personalized information about older adults, a user attention mechanism is added to the short-term dynamic preference and long-term dynamic preference modeling sections. The dynamic user representation $E_{c_m}^s$ is used as a query vector for $input^c$. Next, the short-term preference representation $S^{s'}$ is computed as shown in Eq. (16):

$$\theta_c^* = f\left(W_1^\theta \text{input}^c + W_2^\theta E_{c_m}^s + b^\theta\right) \tag{16}$$

Where and W_1^θ、W_2^θ、b^θ and $f(\cdot)$ are the model parameters and the ReLu activation function. The attention score θ_c^* is normalized by the Softmax layer as shown in Equation (17):

$$\theta_c = \frac{\exp(\theta_c^*)}{\Sigma \exp(\theta_c^*)} \tag{17}$$

The weight of each learning resource is now obtained, which reflects the importance of each learning resource. Subsequently, the short-term dynamic preferences of the older adults are calculated by the weight of each $input^c$ and its corresponding attention score, as shown in Equation (18):

$$S^{s'} = \sum_{c=1,\ldots,t} \theta_c \text{input}^c \tag{18}$$

In the long-term dynamic preference modeling section, there are two main reasons for considering modeling multiple feature scales: on the one hand, older adults usually focus not only on the learning resource itself but also on the features of the learning resource, such as the type of the learning resource (video-type or text-type), the length of the learning resource (length), and the instructor who teaches the lesson, etc., and older adults may be interested in only a few features of the learning resource Therefore, coding only the item ID features cannot capture the real learning preferences of older adults. On the other hand, older adults may interact with multiple learning resources belonging to the same feature, such as topics they do not know or subjects they are interested in. Modeling each feature scale L_f^s separately is used to describe the older person's preferences from different perspectives. For older person s, the learning resources c he has interacted with and each feature scale f_i describing the learning resources can be embedded from the pre-trained in-vectors into e_{id} and e_{f1}^s.

Long-term preference vector representations $L_f^{s'}$ of learning resource features f_i can be computed in a similar manner using different parameters. And encoded as fine-grained long-term dynamic preference representations $L^{s'}$ by the MLP network, computed as shown in Equation (19):

$$L^{s'} = f\left(W_{f_1}^\theta L_{f_1}^{s'} + \cdots + W_{f_F}^\theta L_{f_2}^{s'} + b_f\right) \tag{19}$$

2.1.3 Long- and short-term dynamic preference aggregation among older adults

In order to efficiently fuse the long and short-term dynamic preferences of older people and return the final elderly interest representation $e_s^{'}$, the vector λ_t^s is used to determine the contribution of the long and short-term preferences as shown in Equation (20):

$$\lambda_t^s = \text{sigmoid}\left(W_1^\lambda L^{s'} + W_2^\lambda S^{s'} + b^\lambda\right) \tag{20}$$

Where W_1^λ, W_2^λ and b^λ represent the model parameters, and the interest representation of older adults $e_s^{'}$ is calculated by Equation (21).

$$e_s^{'} = (1-\lambda_t^s) \odot L^{s'} + \lambda_t^s \odot S^{s'} \tag{21}$$

Where $\odot$ is the element multiplication.

In this way, it is possible to capture the global dynamic learning preferences of older people, better explore their complex and changing learning interests, and subsequently personalize the recommendations according to the specific environment and the specific situation older people are currently in.

2.2 CTransD-GAT recommendation model design

2.2.1 User Weighting Preference Layer

The weights in the knowledge graph are represented by edges connected by head and tail nodes, and the weight coefficients are shown in equation (22):

$$s_u^r = e_u^T e_r \tag{22}$$

Where e_u - Embedding vector of user *u*.

e_r - Embedding vector of relation *r*.

The knowledge graph is an unweighted graph that cannot show the weight magnitude, and the unweighted graph is transformed into a weighted graph by means of a user weight preference layer. In order to better assign the weights, it is necessary to perform a normalization operation on the weight coefficients through the Softmax function. The normalized weight coefficients are shown in equation (23):

$$\alpha_u^r = \text{softmax}(s_u^r) = \frac{\exp(e_u^T e_r)}{\sum_{e \in N(v)} \exp(e_u^T e_r)} \tag{23}$$

Eq:

α_u^r - the normalized weight coefficient, the

s_u^r - weight coefficients.

$N(v)$ - set of neighboring nodes of node *v*.

2.2.2 Feature Propagation and Embedding Aggregation

Feature information propagation is to propagate the feature information of entity nodes to neighboring nodes along the connection relationship between nodes according to the weight coefficients, and information embedding aggregation is to use convolution operation to embed the feature information of entity nodes with their neighboring nodes for aggregation, and to export the aggregated feature information as a new node representation. The process of propagating feature information is shown in Fig. 3.

Propagation is carried out for neighboring nodes of all relationship types, and the neighboring node feature information is weighted and summed to obtain the feature vector of the entity's neighborhood. The neighborhood feature vector $e^u_{N(v)}$ is shown in equation (24):

$$e^u_{N(v)} = \sum_{a \in N(v)} \alpha^r_u e_a \tag{24}$$

Where $N(v)$ - set of neighboring nodes of node *v*.

α^r_u - normalized weight coefficients.

e_a - neighbor nodes.

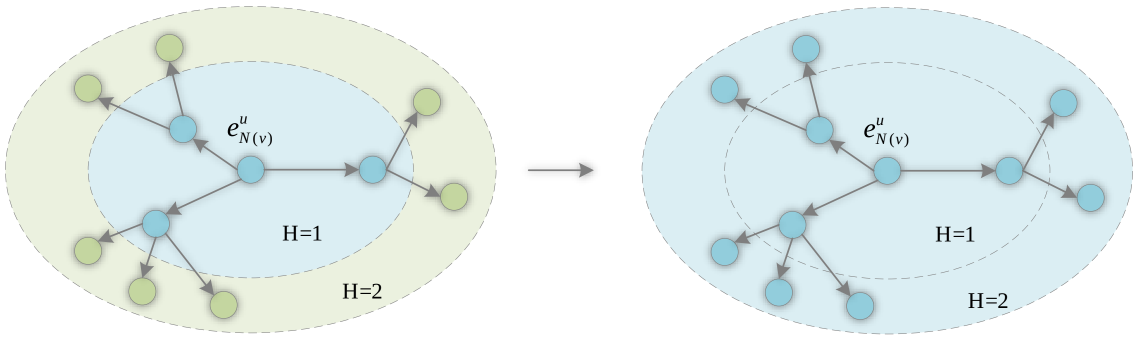

Figure 3. Feature information dissemination process

In order to fuse more semantic association information of neighboring nodes, the model explores the impact of using three different aggregation functions to aggregate the entity feature vector *v e* with its neighboring feature vector $e^u_{N(v)}$ to get the final feature vector e_k. In this paper, three types of aggregation functions are set up.

1) Sum aggregation function, which sums the entity feature vectors and their neighborhood feature vectors and then performs a nonlinear transformation. As shown in equation (25):

$$e_k = agg_{sum} = \sigma(W(e_v + e^u_{N(v)}) + b) \tag{25}$$

Where W - the matrix of weights, $W \in R^{d\times d}$.

b - deviation of weights, $b \in R^d$.

σ - ReLU activation function.

2) GraphSage aggregation function, which connects the entity feature vectors with their neighborhood feature vectors and then performs a nonlinear transformation [24]. As shown in equation (26):

$$e_k = agg_{GraphSage} = \sigma(W(e_v \| e^u_{N(v)}) + b) \tag{26}$$

Where $\|$ - vector connection operation.

3) BI-Interaction aggregation function, which first sums and nonlinearly transforms the entity feature vectors and their neighborhood feature vectors, then dot-multiplies the entity feature vectors and their neighborhood feature vectors to perform the nonlinear transformation, and finally performs the summing operation. As shown in equation (27):

$$e_k = agg_{BI} = \sigma\left(W_1\left(e_v + e^u_{N(v)}\right) + b_1\right) + \sigma\left(W_2\left(e_v \odot e^u_{N(v)}\right) + b_2\right) \tag{27}$$

Where W_1, W_2 - matrix of weights, $W_1, W_2 \in R^{d \times d}$.

b_1, b_2 - deviation of weights, $b_1, b_2 \in R^d$.

$\odot$ - dot product.

At this point, the design of the CTransD-GAT recommendation model is complete. The model is improved for the existing recommendation algorithms with the problems of data sparsity, cold start, and difficulty in capturing the preference degree of different aged learners and learning contents so as to provide more accurate personalized recommendation services for learning resources.

2.3 Constructing a Service System for Elderly Education

The use of personalized recommendation algorithms for learning resources is crucial in the rational allocation of resources for senior education and the improvement of the quality of geriatric education services. Based on the potential role of personalized algorithms in geriatric education, this paper proposes several aspects that a senior education service system should have.
The current contradiction between supply and demand in geriatric education is a major issue, and the consensus in practice is to expand the supply of resources, with a high standard of education being particularly crucial. Expanding the supply needs to condense the temperature and improve the precision of geriatric education, i.e., to adhere to the essence of “educating people” and the function of “service” of geriatric education with high standards.

Secondly, in view of the “marginalization” of geriatric education in the national education system, it is suggested that the barriers between school and out-of-school education should be broken down by a highly integrated education mechanism so as to promote the effective integration of educational resources at all levels and in all categories.

The problem of insufficient and unbalanced development of education for older people should be solved by utilizing a highly balanced allocation of resources. It is necessary to give full play to the technological advantages of “digitization”, use integrated learning platforms to break the temporal, spatial, and geographic limitations of resource allocation, and raise the participation rate of older people’s education in rural areas and underdeveloped regions through publicity channels, so as to realize lifelong learning for all.

Moreover, efficient and effective education is essential for building an education system for older people, and it is also an important indicator for evaluating the effectiveness of education for older people. The senior education service system should improve the quality of education and teaching standards, meet the needs of lifelong learning of older people, improve the quality of life and living of older people, help the elderly to realize the ideals of having a sense of worthiness, being active and enjoying themselves, and truly and effectively promote the development of the senior society, and promote the ideal of the society practicing the positive view of aging. At the same time, by constructing a geriatric education service system with high efficiency and effectiveness as the yardstick, the goal of promoting the social participation of older people, perfecting the national education system, and serving the healthy and sound development of the future pension cause can be realized.

3 Analysis of the application effect of the improved personalized recommendation algorithm

In order to detect the application effect of the improved learning resource recommendation algorithm, this paper selected all the elderly people (n=50) in one of the units of a community as the research object through random sampling and further verified the important facilitating role played by the personalized recommendation of learning resources based on the knowledge graph in elderly education through the knowledge structure detection and teaching ability detection.

3.1 Analysis of health and wellness knowledge

3.1.1 Analysis of performance on permaculture knowledge structure

In this paper, the subjects were randomly divided into an experimental group and a control group of 25 individuals each. The pre-tests of older people in the two groups were conducted separately, and it was found that the mean score of the various knowledge module tests in the control group was 6.2, and that of the experimental group was 6.14. Through statistical tests, it was found that there was no significant difference between the scores of the two groups on permaculture, thus allowing for an experimental comparison. In this experiment, the knowledge related to permaculture was used as the educational material, in which the experimental group used the resources recommended by the personalized recommendation system based on the knowledge graph as the learning material, while the control group followed the traditional teaching and mode of learning. After 8 weeks of learning, the learners' performance improved. By testing the older people in the experimental group and the control group, the average scores of the learners in the experimental group and the control group in each module of the pre-test and post-test were calculated respectively and compared and analyzed.

Figure 4 shows the comparison of the pre-and post-tests for the knowledge modules of learners in the control group. It can be found that the scores of most of the knowledge modules of the control group members have improved, and the overall average has increased from 6.2 to 6.76, indicating that the traditional teaching method also has some effect. However, the improvement of "health checkup results" is not obvious, only 0.2 points, "stress management" and "exercise habits" are unchanged, and "diet structure" is even improved in the pre-test. Dietary structure" even slipped from 6.7 to 6.3 points in the pre-test. This shows that the traditional teaching mode cannot achieve satisfactory results in the field of geriatric education.

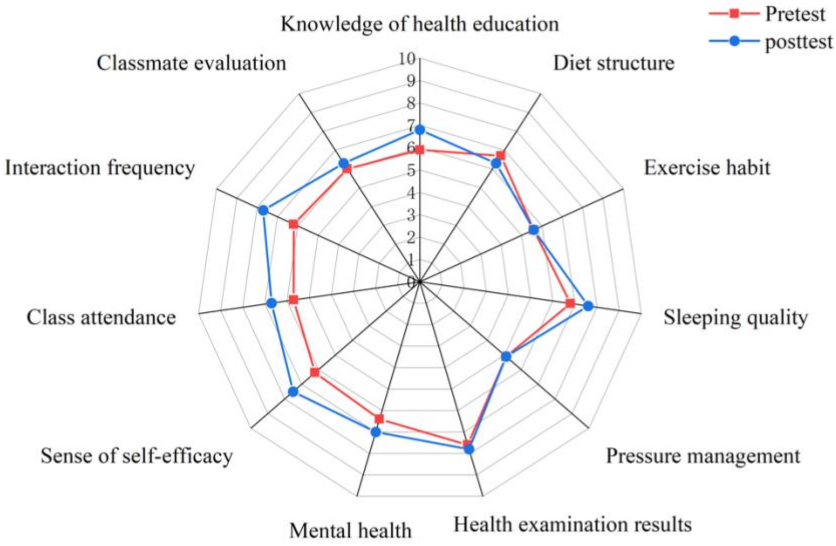

Figure 4. The comparison of knowledge model scores of the control group

The pre-and post-test comparisons of the experimental group learners' knowledge modules are shown in Figure 5. After applying the personalized learning resources recommendation, the experimental group's scores in each knowledge module were improved, leading to an overall average score increase of 1.83 points to 7.98 points. Self-efficacy was the most significant improvement, rising from 6.1 to 9.3, with a 52.4% increase. In this paper, a Z-test was conducted on the mean scores of the posttest scores of the two groups, and it was found that Z=3.12, which was greater than 1.96, indicating that there was indeed a significant difference between the posttest scores of the two groups. The personalized recommendation technology for learning resources based on knowledge graph technology has a positive impact on senior education.

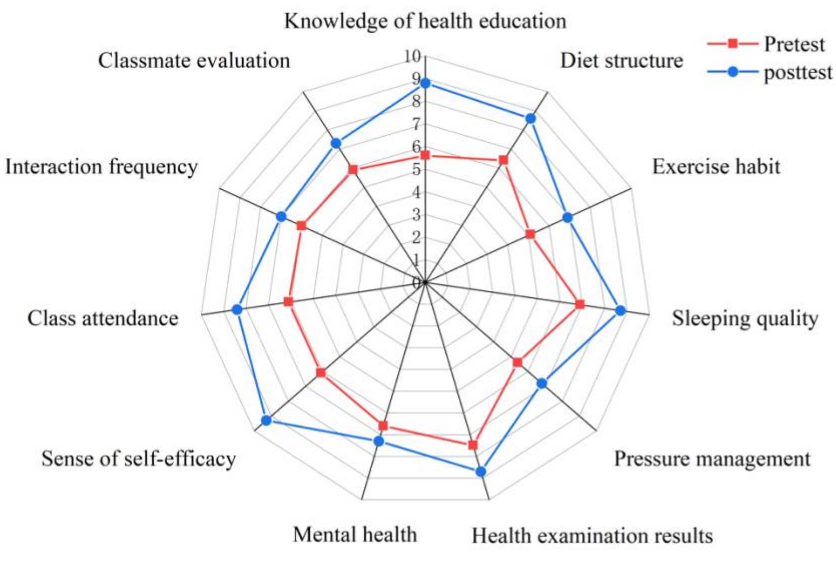

Figure 5. The comparison of knowledge model scores of the experimental group

3.1.2 Health and Wellness Teaching Competency Test

Teaching competence is a lateral manifestation of the learner's knowledge absorption, and it is more capable of exercising older adults' social interaction skills, increasing self-efficacy, and improving re-socialization. For this reason, this paper also includes a test of teaching competence to explore the role of personalized learning resource recommendation technology in this regard. Four tests were conducted to examine the healthcare teaching ability of learners in the experimental group and learners in the control group, and the results of the post-test of the teaching ability of experimental learners are shown in Table 1.

The permaculture teaching competence of both experimental group learners and control group learners has been increasing. Among them, both experimental group learners and control group learners' permaculture teaching ability showed an increasing trend in the first and second tests, and the mean score of the experimental group increased from 72.46 to 74.32, while the control group also increased by 2.18 points, but the Z-value of the two tests was less than 1.96, and the scores were not significantly different. The mean score of the experimental group's performance as measured in the fourth experiment has reached 83.92, which is an increase of 9.6 points over the second test, while the control group only increased by 2.49 points over the second test. The results of the two Z-tests are 2.611 and 3.042, respectively, which are greater than 1.96, indicating that there is a significant difference between the learners of the experimental group and the learners of the control group in the permaculture teaching ability in the third and fourth tests, to begin with, and in particular, the level of permaculture teaching ability of learners of the experimental group in the fourth test is significantly higher than that of the control group. It indicates that personalized learning resource recommendations based on knowledge graphs have a great influence on the improvement of learners' teaching ability, which is conducive to improving the teaching ability of elderly learners.

Table 1. The experimental results of the experimental students' teaching ability

First round test					
Test categories	Group	Number of people	Mean	Standard deviation	Z-test result
Experimental result	Experimental group	25	72.46	11.48	Z=0.586
	Control group	25	72.94	12.04	
Second round test					
Experimental result	Experimental group	25	74.32	12.76	Z=1.512
	Control group	25	75.12	12.37	
Third round test					
Experimental result	Experimental group	25	80.62	6.54	Z=2.611
	Control group	25	76.31	7.37	
Fourth round test					
Experimental result	Experimental group	25	83.92	4.87	Z=3.042
	Control group	25	77.61	5.69	

3.2 Personalized Recommendation Satisfaction Analysis

A questionnaire was distributed to all experimental subjects, which consisted of 13 questions covering three dimensions, namely perceived usefulness (questions 1-8), perceived ease of use (questions 9-11), and intention to use (questions 12-13). The five attitudes, according to the Likert scale, were assigned scores of 1, 2, 3, 4, and 5 from low to high. The stacked histogram depicted in Figure 6 displays the percentage of satisfaction for the three dimensions.

Overall, the mean score for the Perceived Usefulness Dimension questions was about 3.82. All eight questions of the Perceived Usefulness Dimension had an agreement rate above 60%, with the maximum being 82%. The lowest agreement rate was 62% for question 8, and 18% of the learners chose the option of uncertainty, with a disagreement rate of 20%. The question was, "Personalized learning resource recommendation helps me to find out the weak points in the learning process", which indicates that there is still room for improvement in the recommendation model's judgment of the knowledge structure deficiencies of older people. The survey data of the perceived usefulness dimension of the questionnaire shows that the respondents basically agree with several questions of the perceived usefulness dimension of the questionnaire, which can be judged that this personalized learning resources recommendation basically meets the learning needs of the elderly learners, but there is also room for improvement.

As can be seen in Figure 6, the mean score of the Perceived Ease of Use dimension questions is about 3.97, and there is not much difference in the scores of the questions, indicating that the respondents basically agree with the three questions of the Perceived Ease of Use dimension. In addition, the agreement rate for all three questions regarding the perceived ease of use dimension is 76%. The disagreement rate was 4% and 6% for the remaining two questions, except for question 11, which was 14%, or 7 people, indicating that only 5 of the 50 older adults chose to disagree or strongly disagree with the other two questions except for question 11 and that these were only a minority for the total number of cases. It can be seen that the vast majority of the respondents were able to operate the system proficiently during the use of this recommendation algorithm and use the various functions of the system to satisfy their own needs for use, so it can be assumed that this personalized recommendation system is simple and convenient and that the design of the functions basically meets the requirements of elderly learners.

The mean value of the scores of the Intention to Use dimension questions is 3.89, and the difference in the scores of each question is extremely small, indicating that the respondents basically agree with the evaluation of the Intention to Use dimension. In addition, question item 13 has an agreement rate of 80% and a disagreement rate of only 8%, while although question item 12 has an agreement rate of 62%, only 8% of the respondents chose to disagree or strongly disagree, in addition to 17.4% who were unsure. This shows that most of the learners who have used this personalized recommendation algorithm have the intention to continue to use it and recommend it to others, indicating that learners are satisfied with the use of this recommendation model.

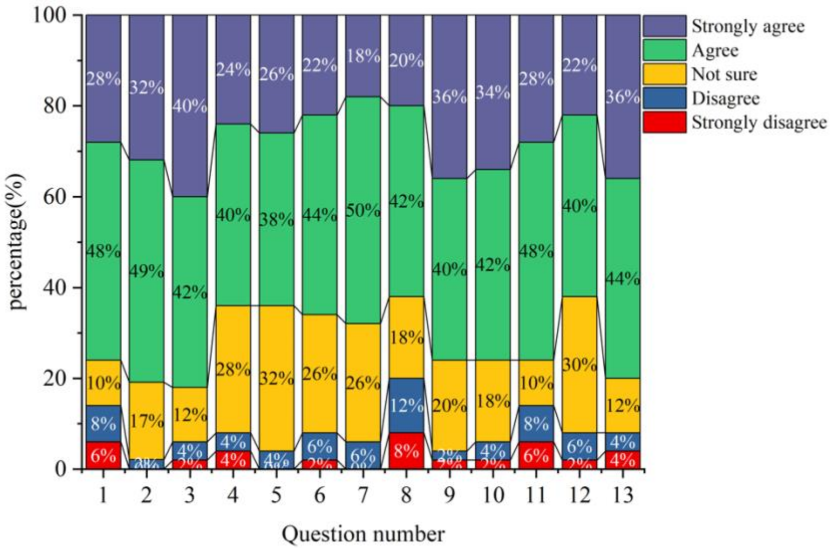

Figure 6. The percentage of satisfaction of the three dimensions

4 Conclusion

To verify the improvement effect of the CTransD-GAT recommendation model and dynamic preference capture based on contextual interaction on personalized recommendations, this paper designed experiments to test them. The results of the experiment on the knowledge structure of health and wellness show that the control group scored 6.2 on the pre-test and 6.75 on the post-test of each knowledge module, but the scores of the modules of “Stress Management” and “Exercise Habits” remained unchanged, and the score of “Diet Structure” even went from 6.2 to 6.75, while the scores of the module of “Diet Structure” even went from 6 to 6.75. However, the scores of the “Stress Management” and “Exercise Habits” modules did not change, while the score of “Diet Structure” even dropped from 6.7 to 6.3. In contrast, the experimental group achieved 6.14 on the pre-test and 7.98 on the post-test, representing an increase of 1.83 points, and each module saw improvement. The experiments on the teaching ability of older people also found that the teaching ability score of older people in the experimental group who received personalized recommendations of learning resources improved by 11.46 points cumulatively in the four rounds of testing, while the control group improved only 4.67 points, indicating that the new model has a positive effect on the teaching ability and expression ability of older people.

The personalized recommendation algorithm’s satisfaction analysis reveals a mean score of about 3.82 for the perceived usefulness question item, indicating a high level of satisfaction. Both cases have a 76% agreement rate and a 3.97 average ease of use score. The mean value of the intention to use score is 3.89, and the average agreement rate is 71%, indicating that the respondents generally agree with the evaluation of the intention to use dimension. Upon analyzing the questionnaire’s results, we discovered that in the three areas of perceived usefulness, perceived ease of use, and intention to use, the majority of respondents opted for agreement or strong agreement. This suggests that elderly individuals who have experienced the system’s application are more content with it. This suggests that the learning resource recommendation model is user-friendly, the function design is sound, and the resource recommendations largely satisfy the learners’ requirements. The results of resource recommendations are generally in line with learners’ psychological expectations and actual needs.

In summary, the new, improved knowledge graph-based personalized learning resource recommendation has had a positive effect on elderly education services.

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