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A Study of the Impact of Online Course Construction in Higher Education on the Transformation of Students' Learning Styles

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Abstract With the advancement of digital transformation, online courses have a profound impact on higher education. This study explores the impact of online course construction in higher education on the transformation of students' learning styles, aims to analyze the current situation of online course construction and its value, proposes a course recommendation model based on knowledge graph, and explores its role in the transformation of students' learning styles. The study combed the development history and construction content of online courses through the literature analysis method, constructed a knowledge graph graph convolutional network recommendation model (KGCN-CNSH) integrating common neighbors and structural holes, and conducted learning situation analysis based on 149,561 valid questionnaire data from 32 colleges and universities in 15 provinces. The results show that the KGCN-CNSH model improves the two metrics of Recall and NDCG by 0.83% and 0.39%, respectively, compared to the previous best-performing SGL algorithm on the Last-FM dataset; 75% of college students participated in at least one online course and took an average of 4.107; and the recommendation of online courses is the main factor influencing students' gains in online learning one of them ($p<0.001$). The study conclusions show that online courses provide students with greater autonomy of choice while breaking through time and space constraints; the course recommendation model based on knowledge graph can effectively improve the level of learning personalization; and students' maintenance of concentration and persistence in the process of self-selecting courses is a key factor influencing the effectiveness of online learning.

Index Terms higher education, online courses, learning styles, course recommendation, knowledge graph, KGCN-CNSH model

I. Introduction

In the digital transformation of education, curriculum digital transformation is a key link. Specifically, curriculum digital transformation is to carry out digital upgrading and innovative application of curriculum with the help of digital transformation thinking and related technologies to fully explore the potential of curriculum data under the promotion of national education digitalization and the construction of high-quality education system [1]. As a representative of curriculum digital transformation, online courses play a key role in promoting the digitalization of teaching services, realizing personalized education services and innovative teaching modes, which not only provides students with more flexible learning options, but also puts forward new requirements for the traditional education model [2]-[4].

In recent years, worldwide online course construction and teaching form change marked by MIT open courseware program has gradually become a hotspot of concern in the field of teaching theory and practice, causing changes in the management decision-making mode and teaching form in the field of education, and becoming a powerful driving force to promote the development of teaching innovation [5]-[9]. After the epidemic, worldwide, online courses have become a hot topic of common concern for colleges and universities, media, enterprises and so on, bringing impact and reflection to the field of education worldwide, especially higher education. Online courses, as a typical practice of in-depth integration of education and technology, play a key role in deeply promoting the integration and innovative development of information technology and educational teaching practice, so that information technology is gradually transformed from an exogenous variable affecting the development of education to an endogenous variable triggering deep systemic changes in education [10]-[13].

With the rapid development of various online learning platforms, the demand for online courses continues to grow. The context in which learning occurs has become more diverse, and students can learn not only within the classroom, but also in libraries, reading rooms, and other places with an Internet connection, and these flexible learning modes break through the limitations of space and time, give students greater autonomy and choice, and promote students' self-efficacy and satisfaction [14]-[17]. The forms of learning support have also become increasingly diversified, expanding from traditional instructor guidance to a variety of support forms such as online tutoring, peer-to-peer support, intelligent learning assistants, etc. These diversified forms of support further enhance students' learning effectiveness by providing customized help and resources [18]-[21]. The needs of teaching and learning have also changed, with a growing demand for personalized and interactive online courses, shaping a new paradigm of how students learn.

In the digital transformation of education, curriculum digital transformation is a key link. Specifically, curriculum digital transformation is to carry out digital upgrading and innovative application of curriculum with the help of digital transformation thinking and relevant technologies to fully explore the potential of curriculum data under the promotion of national education digitalization and the construction of high-quality education system. Online courses, as a representative of the digital transformation of courses, play a key role in promoting the digitalization of teaching services, realizing personalized education services and innovating teaching modes, which not only provides students with more flexible learning options, but also puts forward new requirements for the traditional education model. In recent years, the online course construction and teaching pattern change marked by MIT open courseware program around the world has gradually become a hotspot of concern in the field of teaching theory and practice, causing changes in the management decision-making mode and teaching pattern in the field of education, and becoming a powerful driving force to promote the development of teaching innovation. After the epidemic, worldwide, online courses have become a hot topic of common concern for colleges and universities, media, enterprises and so on, bringing impact and reflection to the field of education worldwide, especially higher education. Online courses, as a typical practice of in-depth integration of education and technology, play a key role in deeply promoting the integration and innovative development of information technology and educational teaching practice, and in gradually transforming information technology from an exogenous variable that affects the development of education to an endogenous variable that triggers deep systematic changes in education. With the rapid development of various online learning platforms, the demand for online courses is increasing. The contexts in which learning takes place are more diversified, and students can learn not only in the classroom, but also in libraries, reading rooms, and other places with an Internet connection, and these flexible learning modes break through the limitations of space and time, give students greater autonomy and choice, and promote students' self-efficacy and satisfaction. The forms of learning support have also become increasingly diversified, expanding from traditional teacher guidance to a variety of support forms such as online tutoring, peer-to-peer support, and intelligent learning assistants, and these diversified forms of support further enhance students' learning effectiveness by providing customized help and resources. The needs of teaching and learning have also changed, with a growing demand for personalized and interactive online courses, shaping a new paradigm in the way students learn.

This study explores the impact mechanism of online course construction in higher education on the transformation of students' learning styles. First, we sort out the development history and content of online courses, analyze the current situation of online course construction from three dimensions: course elements, open behaviors and learning support services, reveal its value implication, and propose a model of online course design and development process. Secondly, the course recommendation model is constructed based on knowledge graph, and the KGCN-CNSH course recommendation model is proposed by establishing course ontology, integrating common neighbors and structural hole algorithm, and its effectiveness is verified through experiments. Again, based on the survey data of students in national colleges and universities, we analyze the online course learning situation, learning experience and influencing factors of students in different regions and different types of institutions, with special attention to the influence of course recommendation on learning effect. Finally, it summarizes the path and mechanism of the influence of online course construction on the change of students' learning styles, and provides suggestions for the construction of online courses in colleges and universities and students' independent learning. Through the above research, it can not only enrich the theory of online education in the context of digital transformation of education, but also provide practical guidance for the construction of online courses in colleges and universities, and promote the transformation of students' learning styles from passive acceptance to active exploration.

II. Online course development building

II. A. Status of online course development

The construction of online courses in colleges and universities has made great development [22].

The development of online open courses has gone through four key stages, namely, the stage of fine courses, the stage of fine open courses, the stage of online open courses and the stage of first-class undergraduate courses.

The rise of catechism has changed the pattern of traditional teaching and effectively realized the sharing of knowledge, marking that higher education has entered a new era, leading the education system towards a more open, flexible and innovative direction. From the construction of online open courses to the construction and recognition of first-class undergraduate courses, the construction of online courses continues to make new breakthroughs after experiencing the rapid development of Mucous Classes from 2012 to 2019, the wide application of online teaching in 2020, and the new development of online courses after 2021.

In this process, colleges, universities, enterprises and other parties have actively participated in the construction of many online course platforms.In 2022, the launch of the National Intelligent Education Public Service Platform provides more comprehensive support for the development of online courses.

II. B.Content of online course construction

After years of development and evolution, the number of online courses has been increasing, the quality has been improving, and the construction of a more complete online course now includes three aspects of course elements, open behavior, and learning support services.

II. B. 1) Teaching content

Course elements mainly include teaching content, teaching activities and teaching evaluation.

Teaching content is an important carrier for transferring knowledge information, and the teaching content of online courses is usually presented in the form of short video media. Since some online courses are characterized by fragmentation of knowledge points, this leads to the systematic, complete, coherent and hierarchical nature of teaching content being affected. Therefore, the construction of online courses requires the re-planning and deployment of traditional teaching content to help students connect and integrate fragmented knowledge points to form a complete knowledge system.

Instructional activities are interactions that promote deeper cognitive understanding of the learning content, usually in the form of online interactions, such as online discussions, accompanying quizzes, and other activities. These activities are closely aligned with the content and promote effective online communication between students and teachers, as well as among students.

Instructional assessment is the evaluation of a student's cognitive state, usually combined with the results of assignments, online quizzes, and exams, which are computed online and presented in the form of scores or grades. Homework, test and exam questions are designed to support process and personalized assessment to evaluate learning outcomes holistically. To ensure fairness and transparency of assessment, examination methods and assessment criteria are announced before the course begins, which helps students to clarify learning objectives and requirements, enhance motivation, plan ahead and complete tasks as required.

II. B. 2) Open behavior

In order to promote course sharing, consistency in interpreting course data and conducting course evaluations can be achieved at all levels and in all types of educational institutions. At the same time, to simplify the process of selecting courses and recognizing credits in colleges and universities, the behavior of course opening needs to follow certain norms. Open courses have clear start and end dates and course schedules. The semester system is usually adopted, in which the time period between the start date and the end date is called a semester, and the one-time release of teaching resources and teaching activities is called a lecture. By standardizing the organization of teaching activities and regularly opening teaching resources, it not only helps students to complete their course learning in an orderly manner, but also facilitates universities to assess the intensity of course learning, scientifically plan students' study plans, and achieve the goals of mutual recognition of credits for cross-campus and cross-platform online courses. This orderly open mode helps to improve teaching effect and promote cross-campus cooperation and resource sharing.

II. B. 3) Learning support services

Learning support service is a distinctive feature that distinguishes online courses from traditional classroom teaching, including guided learning service, course assistance service and supervisory function. Guided learning services include course introduction, study guide, FAQs and course recommendations, which are important guides for students' learning. Course support services include real-time and non-real-time discussion, problem feedback, learning navigation and difficult questions, etc., which are the necessary means for the normal operation of the course and the necessary services to ensure that the course plays the function of educating people. Supervision function usually refers to the use of technical means to analyze students' learning data, provide necessary reminders and supervision to students with slow progress or the possibility of abandoning their studies, and provide students with timely and effective information feedback, which is an important means to ensure the smooth development of the learning process.

II. C.Value Implications of Online Courses

The online course developed from the network course is based on digital information technology as the key support and online learning theory as the important foundation. It is an important online learning resource that can be disseminated and shared with more attention to learning behaviors such as course interaction and more emphasis on the learner's subject position. This course mode, the learners and teachers of the digital capabilities have put forward higher requirements.

Online courses boost the process of digital development of education. The comprehensive and in-depth application of modern information technology in education teaching and education management and other educational fields is the key to the digital transformation of education, and has become a common trend in the change and development of education in today's world. Online courses as a product of information technology development, its generation and development has increased the whole element of education and teaching, the whole process, a full range of intelligent support, promote the deep integration of information technology and education and teaching, help educators to fragmented teaching resources for online integration and use, the use of big data information to carry out diagnosis and analysis of the learning situation, so that the learners can realize ubiquitous learning with the help of cell phones, tablets and other technological tools. The deep integration of information technology and education teaching has helped educators integrate and apply fragmented teaching resources online and use big data information to diagnose and analyze learning conditions, enabling learners to realize ubiquitous learning with the help of mobile phones, tablets and other technological tools, and accelerating the realization of education digital transformation.

Online courses promote the quality and balanced development of educational resources. The quality of educational resources is related to the realization of the goal of high-quality development of education, and the online courses and online course platforms emerging under the auspices of digital technology, based on the learning needs of learners, integrate more excellent teachers and high-quality courses and other educational resources, promote the structural reform of the supply side of educational resources, and realize the continuous improvement of the quality of educational resources. In addition, the openness and shared nature of online courses have made it possible to share and apply more high-quality educational resources on a wider scale in society, prompting “substantial equivalence” between weak schools and high-quality schools, and improving the level of equalization of public services in education among regions, urban and rural areas, and between schools.

Online courses help education and teaching realize deep changes. When the teaching concept, teaching content and talent evaluation methods are subverted and innovated, education and teaching will naturally realize in-depth changes. Online courses, as an important endogenous force in the process of change, enable learners to break through the restrictions of the traditional classroom field at the same time, improve their independent choice of curriculum resources, and enable them to personalized learning in accordance with their own pace and ability level. At the same time, online courses have changed the traditional teaching content is limited to the textbook of the long-term educational challenges, teachers can rely on digital technology will be the cutting edge of the discipline and hot topics such as dynamic reconstruction of curriculum resources. In addition, with the support of digital technology, online courses have shifted the traditional formative talent evaluation methods, such as paper-based tests, to the process evaluation of learning behaviors and learning outcomes based on data.

II. D.Modeling the online course design and development process

The ADDIE model is a generic online course design and development model usually adopted by researchers and practitioners. This study combines the ADDIE model and proposes a process model for the design and development of online courses based on the above conceptual model as well as the research and practical experience of online course design and development.

The process model of online course design and development is shown in Figure 1. The model includes three phases: pre-master planning, mid-term system design, and post-development and iteration. Each phase has specific design tasks and workflows.

The pre-masterplanning is crucial to the mid-term system design and determines whether the online course design can realize innovation. The mid-term system design should closely follow the course objectives and content system and design concepts determined in the early stage, and carry out systematic learning design for each element of the course. In order to achieve learner-centeredness, the preliminary planning should carry out in-depth user research, the mid-term design should fully consider the characteristics of the users, and the later development should focus on user participation and feedback to realize agile development and iteration with user participation.

(1) Preliminary summary planning

This stage includes four tasks: curriculum design team formation, topic selection and user analysis, goal and content system design and design concept selection. Whether the course design can be innovative often depends on the completion of the work in this phase.

(2) Mid-term system design

The overall planning in the early stage determines the system design in the middle stage. The selection (design) of platforms and tools is the basis of medium-term system design. Designers should first focus on completing the design of learning resources, learning activities and learning evaluation, and then design supporting learning guidance, learning support and visual dynamic effects, and finally all elements of the design should be committed to achieving the learning objectives and creating a good learning experience.

(3) Post-development and Iteration

This phase is mainly to promote the design program in the early stage to the ground, release and run the course, collect user feedback, form iterative update program, improve and develop the course. This phase includes seven tasks such as prototyping, sample development, system development, release trial, operation, user feedback and iterative update. Prototyping, which is a concrete form of design expression and essentially a form of development, is also categorized in phase three. At the same time, the development of prototypes first, and then the development of samples is conducive to the flexible adjustment and optimization of the overall design of the course according to the needs of the overall design of the course, to enhance the development efficiency and quality. In this stage designers should pay attention to collecting user feedback.

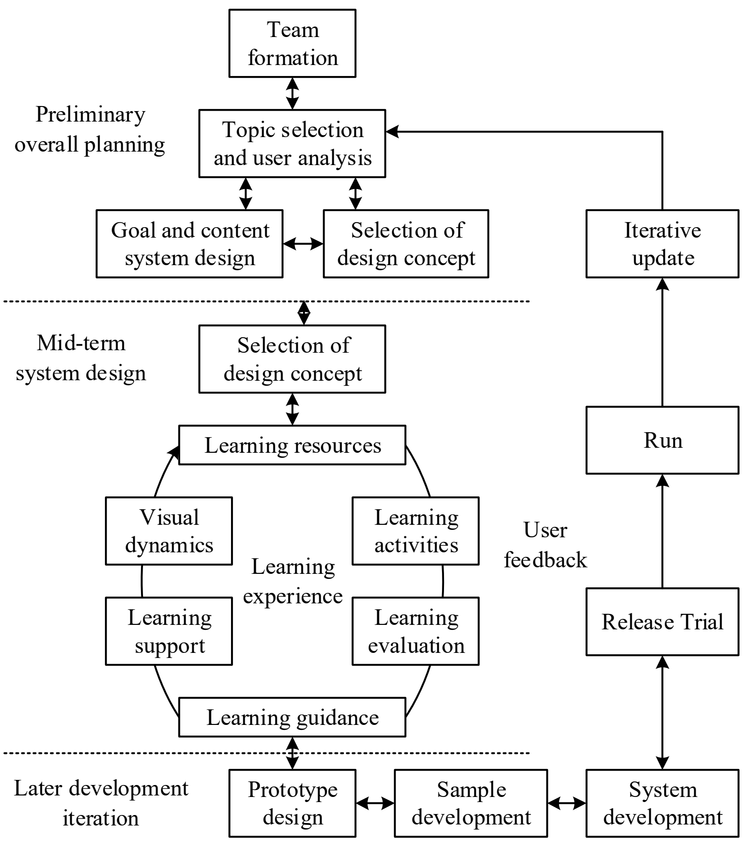


Figure 1: Process model of online Course design and development

III. Recommended learning styles for online course resources

The core idea of classroom teaching to change students' learning styles under the perspective of deep learning is to realize the change of students' learning styles, i.e., the change of learning styles from “learning” to “knowing how to learn” and then to “independent learning”. The core idea is to realize the transformation of students' learning styles from “learning” to “learning” and then to “independent learning”. The key to the in-depth development of classroom learning lies in the deep participation of students. By proposing a recommendation model for online course resources, we can give students the most needed teaching resources, so that they can learn to learn independently.

III. A. Construction of course knowledge map based on online course resources

The schema layer of the knowledge graph serves as the conceptual model of the knowledge graph, which prescribes and constrains the representation of various concepts in the data layer by providing an explicit and normalized description of the domain knowledge [23].

1) Objectives and process of course ontology construction

The core goal of the construction of course ontology is to carefully and comprehensively sort and classify all kinds of course-related information in MOOC resources, to form a set of common standardized and structured course resource management system, so as to enhance the effective use of MOOC resources and user experience. The specific objectives are as follows:

(1) Through the analysis of the current mainstream MOOC platforms at home and abroad, divide and categorize various information elements, such as course themes, teaching content, teaching resources, etc., to form a clear knowledge framework.

(2) Establishing the structure of course ontology, defining the knowledge concept descriptions and relationships of MOOC resources, and setting the description attribute categories and relationship types.

(3) Express the course ontology through the knowledge representation language so that the course knowledge can be understood and processed by computers.

2) Analysis of course resources on MOOC platforms

Curriculum content in the field of education is extremely rich, and can be divided into basic education, vocational education, higher education and so on according to different levels. With the rise of online education, there are a large number of MOOC platforms on the Internet, and according to different groups and learning objectives, the focus of each platform's course resources is also different. The research on domestic and foreign MOOC learning platforms are mainly as follows:

(1) China University MOOC
(2) Xuedang Online
(3) Netease Cloud Classroom
(4) IMOOC (Mucun.com)
(5) edX
(6) Udemy

Analyzing the information of course resources of each MOOC platform, they can be roughly divided into three categories:

The first category is the basic course information, including the name of the course, introduction, subject theme classification, course duration, course difficulty, course rating, course price, etc.

The second category is course content information, including teaching objectives, detailed description of the course, syllabus, course chapters, prerequisite knowledge reserves, study materials, and so on.

The third category is course source information, which mainly includes the situation of the offering organization and the instructor's profile.

3) Course ontology design

According to the analysis of the course resource information of MOOC platform in the previous section, the core entity types are defined. First of all, “course” and “subject”, which are common to many MOOC platforms, are selected as the basic entities, and “organization” and “instructor” are selected as the course source entities. The “course provider” and “instructor” are selected as the course source entities. Providers include universities, educational institutions and individuals. For the resources related to the course, “course section”, “video resource” and “exercise resource” are defined as resource entities.

In order to reflect the content and pedagogical objectives of the curriculum, the entity “knowledge point” is defined. Knowledge points are the core elements of a course, the key concepts of the course content, and the smallest unit of the course's pedagogical objectives. After defining the entity types of the course, a series of attributes of these entities, including data attributes and object attributes, need to be identified.

Summarizing the data attribute information of each entity, it is found that the ontology data attributes can be classified into three categories: the first category is the basic information, such as the name, introduction or slogan of the course entity, which is summarized into three data attributes, namely, name, introduction and English name. The second category is instructor information, including name and title, which is used to briefly introduce the instructor. The third category is resource information, such as the title and duration of the video resource entity, the title of the chapter, and the title and answer of the exercise resource.

After the definition of the attributes of each entity is completed according to the curriculum resources, the relationship between the entities needs to be analyzed. This paper constructs the object attributes of the entities according to their relationships, which are divided into three categories: the first category is the relationship related to the course. The second category is character-related relationships, i.e., the tenure relationship between the lecturer and the offering institution. The third category is resource-related relationships, i.e., inclusion relationships between chapters and video resources, and between chapters and exercise resources.

4) Protégé-based course ontology realization

Protégé is an ontology construction tool developed based on the Java language. The tool can be used to create entity concepts, entity hierarchies, entity data attributes and entity relationship attributes.Protégé has good scalability, supports XML, OWL, PDF and other file formats for modification and preservation, has a clear and easy-to-operate interface, and also provides visualization plug-ins to achieve the display of the knowledge graph. In this paper, Protégé development tool is chosen to complete the realization of the course domain ontology model.

III. B. Constructing the KGCN-CNSH course recommendation model

In the practical application of knowledge graph-related recommendation algorithms, there is also a lack of processing of logical relationships of knowledge. Although knowledge graphs can express the logical relationships between courses, existing knowledge graph-based recommendation algorithms tend to focus only on the direct associations between courses, while ignoring the indirect associations and logical order between courses. This may lead to problems such as stagnant difficulty and disorder in the recommended courses, making it difficult to help users plan their learning paths according to the internal logic between courses.

This chapter proposes a knowledge graph graph convolutional network recommendation model (KGCN-CNSH) that incorporates common neighbors and structural holes. The model firstly takes the nodes with common neighbors in the graph as candidate neighbors, and uses the structural hole theory to rank the importance of the candidate neighbor nodes and select the most influential neighbor nodes. Then the nodes obtained from sampling are input into KGCN and combined with its aggregation idea to make recommendation, which improves the logical relationship and interpretability between users and courses.

The KGCN-CNSN model is a course recommendation method that combines knowledge graph and deep learning. The overall structure of the model can be divided into the following main parts: knowledge graph embedding layer, sampling layer, graph convolutional layer, feature aggregation layer and prediction layer.

1) Graph Convolutional Network

Graph Convolutional Neural Network is a kind of network that learns the data after representing it in the form of graph data structure. It extracts both topology and vertex attributes of the data, and continues to learn information about the target vertex in the global space, which is a direct-push type of learning [24].

A graph is usually represented by $G(V,E)$, where V denotes the set of nodes and E denotes the set of edges. Under this definition, nodes are usually represented by pixels in an image, and adjacent nodes have connectivity between them, then the adjacency matrix A used to illustrate the relationship between a node and its neighboring nodes is denoted as:

$$A_{ij}=\begin{cases}1 & \text{if } \{u_i,u_j\}\in E and i\neq j\\ 0 & \text{otherwise}\end{cases} \tag{1}$$

The value between two nodes is 1 when there is an edge relationship between nodes u_i and u_j, and 0 otherwise. The Laplace matrix L of the graph is computed after determining A:

$$L_{ij}=\begin{cases}d(u_i) & \text{if } i=j\\ -1 & \text{if } \{u_i,u_j\}\in E and i\neq j\\ 0 & \text{otherwise}\end{cases} \tag{2}$$

where $d(u_i)$ is the number of edges associated with a node.

It is known that L represents the Laplace matrix of the graph and A represents the adjacency matrix of the node. D is a diagonal matrix, and D_i represents the degree of the i th node, then:

$$D_{ii}=\sum_{j=1}^{n}A_{i,j} \tag{3}$$

Graph Convolutional Neural Networks are defined as follows:

$$\tilde{A}=A+I \tag{4}$$

$$\tilde{D}_{i,i} = \sum_{j} \tilde{A}_{i,j} \tag{5}$$

$$H^{(l=1)} = \sigma\left(\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}\right) \tag{6}$$

where $H^{(l)}$ and $W^{(l)}$ denote the output and trainable parameters of layer 1, and $\tilde{D}^{-\frac{1}{2}}\tilde{A}\tilde{D}^{-\frac{1}{2}}$ is a symmetric normalized form of L. Preventing gradient explosion or vanishing as the depth of the graph convolutional neural network increases during training. $\sigma(\cdot)$ is an activation function expression.

2) Neighborhood Sampling Algorithm Fusing Common Neighbors and Structural Holes

This paper proposes an importance ranking sampling method based on common neighbors and structural holes. By combining common neighbors and structural holes for sampling, the relationship between users and items in a recommender system can be explicitly considered to further improve the accuracy of recommendations.

In this paper, we calculate the combined score of the central entity in the knowledge graph with all its neighboring entities $score(i,j)$, the more important neighboring entities have higher scores, and the process of its calculation is shown in Equation (7):

$$Score(i,j) = E(i,j) * W(j) \tag{7}$$

where, $E(i,j)$ denotes the similarity between two entity nodes i.e. common neighbor calculation index to identify the neighboring nodes of these starting nodes. And from them, common neighbor nodes adjacent to multiple starting nodes are selected as sampling targets, which are calculated as shown in Equation (8):

$$E(i,j) = \frac{|N(i) \cap N(j)| + 1}{|N(i)| + |N(j)|}, j \in N(i) \tag{8}$$

where $|N(i) \cap N(j)|$ denotes the size of the intersection of sets $N(i)$ and $N(j)$, i.e., the number of common neighbors of node i and node j, and the numerator plus one can make it possible to give a meaningful score even in the absence of common neighbors. $N(i)$ and $N(j)$ then denote the number of neighbors of node i and node j, respectively. $W(j)$ denotes the weight of the entity node, and in this paper, we use structural hole metrics to calculate the node weights, which are calculated as shown in Equation (9):

$$W(j) = 1 / C(j) \tag{9}$$

where $C(j)$ is the evaluation index of structural hole theory, which is a new member of the interpersonal network theory family, developed from the concept of "structural hole".

In this paper, we use the constraint coefficient to calculate the structural holes in complex networks, and its calculation method is shown in equations (10) and (11):

$$C(j) = \sum_{k \in N(j)} (p_{jk} + \sum_{q \neq j,k} p_{jq} * p_{qk})^2 \tag{10}$$

$$p_{jk} = a_{jk} / \sum_{k \in N(j)} a_{jk} \tag{11}$$

where node q is an indirect connection point between node j and node k, p_{jk} represents the connection weight between node j and node k, p_{jq} and p_{qk} represent the connections between node j and node q, and node q and node k, respectively, and a_{jk} is an element of the corresponding adjacency matrix. The smaller the value of the constraint coefficient, the less restricted the ability of node j to utilize structural holes in the network, i.e., the freer node j can utilize structural holes to obtain information or resources. On the contrary, the larger the constraints on node j are, indicating that its ability to utilize structural holes in the network is relatively weak.

3) The process of graph convolution on the knowledge graph

First assume that the set of users is L and the user vector is denoted as l, the set of courses is C and the vector of courses is denoted as c. To compute the prediction of users' ratings on courses, it is most commonly done by using Eq. (12):

$$\hat{y}_{lc} = f(l,c) \tag{12}$$

where $f(\cdot)$ sums the inner product function. The value of the function is used to predict the degree of user preference for a course. When recommending courses, each user may have a different preference for the same course because of their individualized differences.

Users may have different preferences for the same course, some focus on the classification to which the course belongs, some focus on the number of learners in the course, and some may prefer the instructor, so $f_l(r_i)$ is used here to represent the importance of the relationship learning r_i to user L, as shown in Equation (13):

$$f_l(r_i) = g(l,r_i) \tag{13}$$

where $g(\cdot)$ denotes the inner product function and r_i is the relation vector connecting the i rd neighbor.

Then the neighborhood structure of course c is calculated by Eq. (14):

$$c^l_{S(c)} = \sum_{e\in S(c)} \tilde{f}_l(r_i)\cdot c_i \tag{14}$$

where, $\tilde{f}_l(r_i)$ is obtained by softmax function as shown in equation (15) and c_i is the feature vector of the corresponding i rd neighbor. As shown in equation (15):

$$\tilde{f}_l(r_i) = softmax(f_l(r_i)) \tag{15}$$

After obtaining the neighborhood structure of the course it is possible to obtain the feature representation of the course by using equation (16):

$$c = \sigma(W\cdot agg(c^l_{S(c)},c)+b) \tag{16}$$

where w is the linear transformation matrix, b is the bias term, and $agg(\cdot)$ denotes the summation aggregation method, which involves adding the elements corresponding to vector v and vector e as shown in Eq. (17):

$$agg_{sum}(v,e) = v+e \tag{17}$$

Processing course features through graph convolutional networks allows the construction of a complex relationship model between users and courses, and accordingly accurately predicts the degree of user preference for a particular course.

IV. The role of online course recommendation models and their learning styles

IV. A. Online course recommendation model analysis

The main purpose here is to validate that the KGCN-CNSH proposed in this paper improves its working performance compared to the current mainstream knowledge graph based recommendation algorithms.

In order to ensure the reliability of the experimental results, three datasets commonly used for various knowledge graph-based baselines were used, namely Amazon-book, Yelp-2018, Last-FM, and the dataset details are shown in Table 1. The dataset is divided into three parts: training set, experimental set, and test set according to the ratio of 8:1:1 during the experiment. Every time the algorithm completes in the training process, the current result is used as a parameter to carry out a verification of the experimental evaluation index. And then the parameter with the best performance of the evaluation index is taken to be tested on the test set, and the result is taken as the final index of the algorithm performance.

Table 1: Data set details

		Amazon-book	Yelp-2018	Last-FM
User-Item Interaction	# Number of users	51213	32015	22546
	#Quantity of project	91054	35447	49213
	# Interaction record	3002164	1589542	3061500
Knowledge Graph	# Number of users	63085	570038	57246
	#Quantity of project	40	52	10
	# Interaction record	2015359	302445	456451

To evaluate the performance of the model, Recall and Normalized Discounted Cumulative Gain (NDCG), which are commonly used in the field of recommendation algorithms, were used. K=10 was set to represent the training results of the model using the average metric results of all users in the test set.

The effect of the number of knowledge graph propagation layers on the experimental results was first investigated. During the experiment, the number of propagation layers was selected from {1, 2, 3, 4, 5}. The experimental results with the number of layers are shown in Table 2.

From the experimental results, it can be seen that within a certain range, the recommendation efficiency of KGCN-CNSH will be improved with the increase of the number of knowledge graph propagation layers. However, when the number of knowledge graph propagation layers exceeds a certain threshold, the recommendation efficiency of the algorithm will show a decreasing trend. On the sparser Amazon-Book and Yelp-2018 datasets, when the number of propagation layers is 4, the performance is optimal on the two performance evaluation indexes of Recall and NDCG. And on the Last-FM dataset, the best results are achieved when the number of propagation layers is 3.

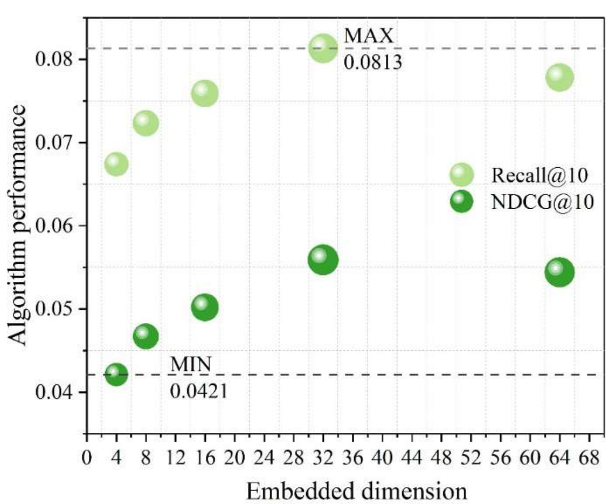
Table 2: The results vary with the number of layers

Layer number	Amazon-book		Yelp-2018		Last-FM	
	Recall@10	NDCG@10	Recall@10	NDCG@10	Recall@10	NDCG@10
GCN-1	0.0375	0.0387	0.0622	0.0378	0.0787	0.0524
GCN-2	0.0421	0.0412	0.0645	0.0412	0.0824	0.0596
GCN-3	0.0455	0.0456	0.0683	0.0433	0.0899	0.0727
GCN-4	0.0528	0.0513	0.0721	0.0520	0.0873	0.0601
GCN-5	0.0423	0.0465	0.0695	0.0461	0.0824	0.0593

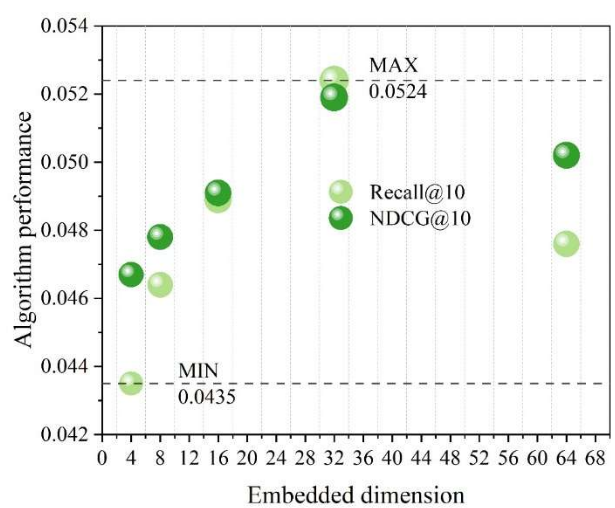
KGCN-CNSH model, the embedding vectors of relations and entities in the knowledge graph use the same size dimension, and the larger embedding dimension represents more parameters in the knowledge graph. In order to analyze the effect of embedding dimension on the algorithm, experiments were conducted on the experimental setup with embedding dimensions of {4,8,16,32,64}, respectively, and the experimental results of the effect of different embedding dimension sizes on the algorithm's effectiveness are shown in Fig. 2. Figures (a), (b), and (c) show the effect of embedding dimension on the performance of the KGCN-CNS algorithm on the Yelp-2018, Amazon-book, and Last-FM datasets, respectively.

For the datasets Yelp-2018 and Amazon-book, the recommendation performance of KGCN-CNS algorithm is optimal when the embedding dimension is set to 32 while the number of propagation layers and the neighbor sampling size are all constant.

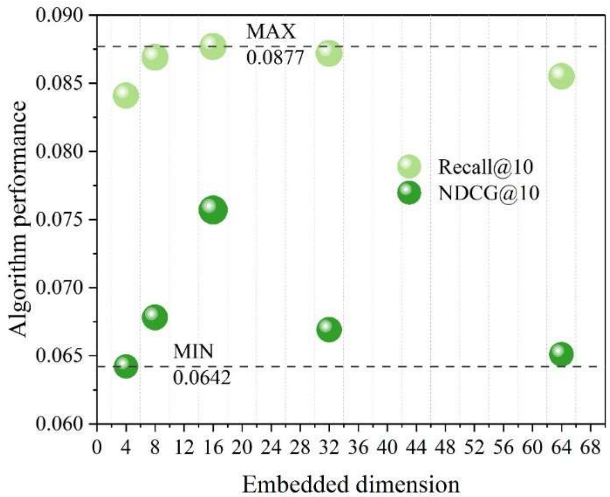
And on the dataset Last-FM, the KGCN-CNS algorithm works best when other parameters are unchanged and the embedding dimension is 16.



(a) Yelp-2018



(b) Amazon-book



(c) Last-FM

Figure 2: The effect of different embedding dimensions on algorithm effect

In order to highlight the effectiveness of the KGCN-CNS proposed in this paper, five cutting-edge collaborative recommendation algorithms of the same category are selected as the reference for side-by-side comparison experiments. In the experimental process, three experiments are conducted on three benchmark datasets respectively, and the average of the experimental results is taken as the final result of the experiment, in order to exclude the interference brought by randomness to the experimental results.

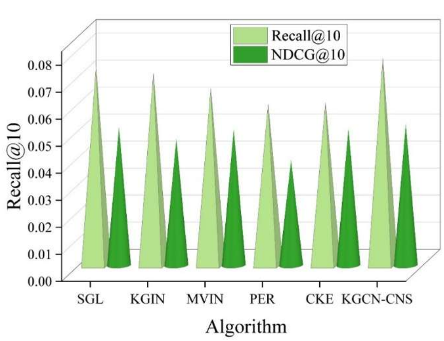
The comparison experiments of KGCN-CNS with five models are shown in Fig. 3. Figures (a), (b), and (c) show the recommendation performance of different algorithms on Yelp-2018, Amazon-book, and Last-FM datasets, respectively.

The experimental results show that the performance of the knowledge graph graph convolutional network recommendation model proposed in this paper, i.e., the KGCN-CNS model, is improved to varying degrees compared to the other five knowledge graph-based recommendation algorithms in the side-by-side comparison experiments.

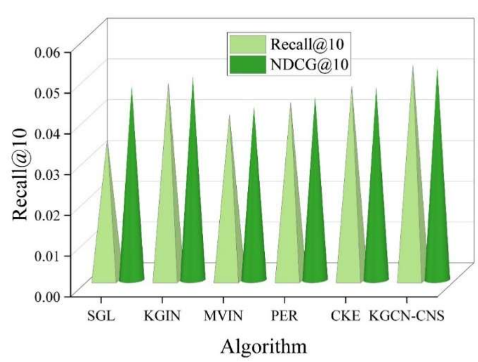
On the dataset Yelp-2018, the KGCN-CNS algorithm proposed in this paper has an improvement of 0.33% and 0.12% in the two metrics Recall and NDCG, respectively, compared to the previous best performing SGL algorithm.

On the Amazon-book dataset, the KGCN-CNS has a performance improvement of 0.45% and 0.26% in both metrics compared to the previous best performing KGIN algorithm.

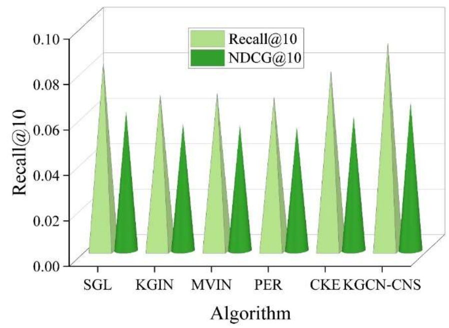
KGCN-CNS also has 0.83% and 0.39% performance improvement compared to SGL on the Last-FM dataset. The above experimental results can fully demonstrate the superiority of the performance of KGCN-CNS proposed in this chapter.



(a) Yelp-2018



(b) Amazon-book



(c) Last-FM

Figure 3: The comparison experiment of KGCN-CNS and five models

IV. B. Analysis of college students' online course learning situation under the normalization of online education

The data used in this paper comes from the "Online Course Learning" module of the September-December 2024 "Tracking Study of College Students' Learning and Development" survey. The survey covered 32 colleges and universities in 15 provinces, including 15 "double first-class" colleges and universities, 13 other undergraduate colleges and universities, and 4 higher vocational colleges and universities. 200,000 questionnaires were distributed and 167,054 were collected, with a recovery rate of 83.527%, among which 149,561 questionnaires were validly filled in, with an overall validity rate of 89.53%.

(1) Basic situation of college students taking online courses in the context of "normalization" of online education

The number, forms and platforms of online courses 75% of the college students who participated in the survey participated in at least one online course, which is higher than the participation rate of 49% in the similar survey in the United States.

The teaching and learning situation of online courses in different types of institutions in different regions is shown in Table 3.

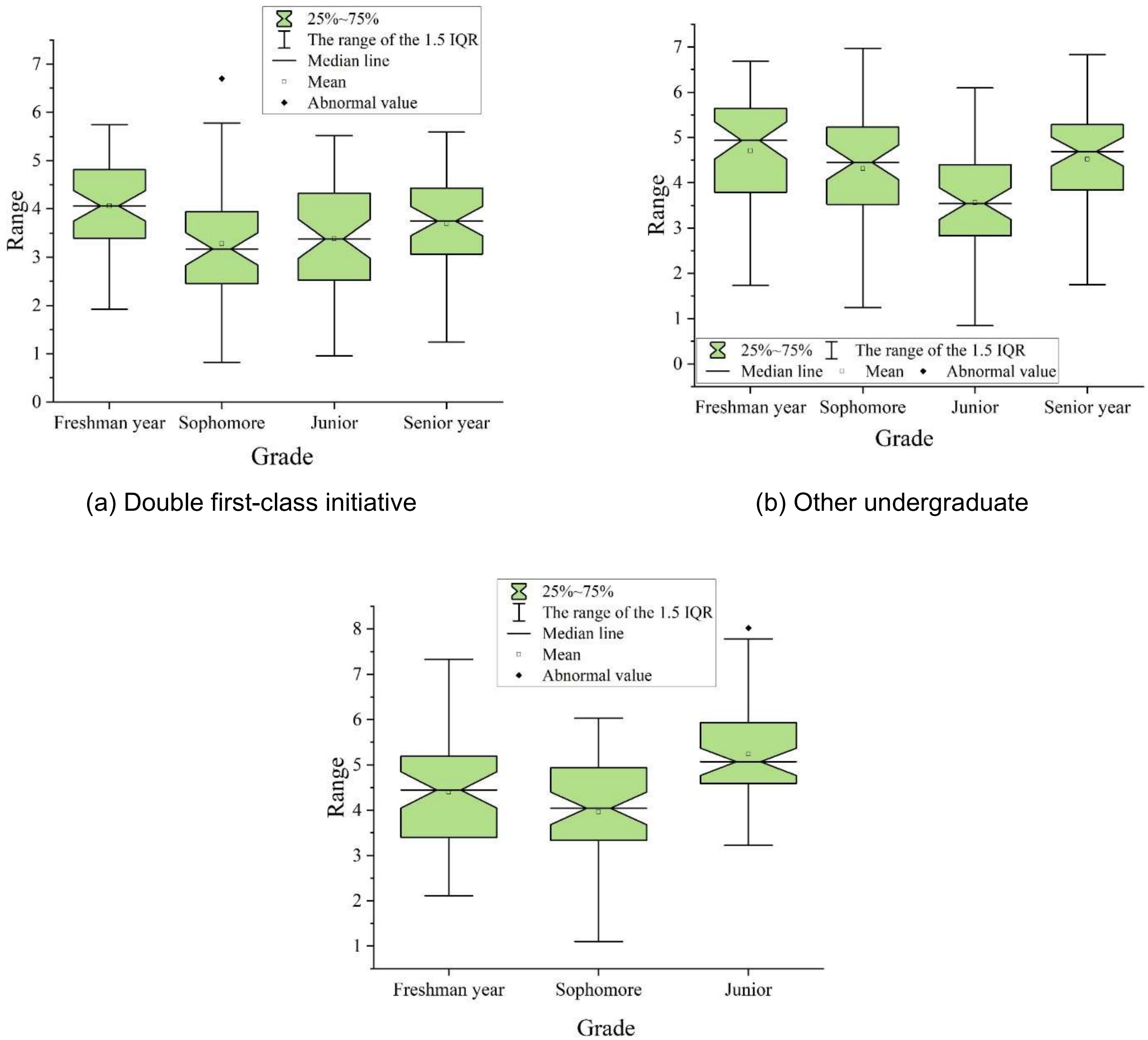
Table 3: The online course teaching and learning of different schools in different regions

		Double class	Other undergraduate	Higher vocational college
The number of doors for the online course	East	3.62	4.24	4.58
	Midwest	3.87	4.38	N/A
	T value	0.05	1.54	N/A
Recommended frequency of online courses	East	75.59	74.12	N/A
	Midwest	78.60	77.35	N/A
	T value	41.7***	80.36***	N/A

The number of students' participation in online courses at different levels in different types of institutions is shown in Figure 4. Figures (a), (b), and (c) show the number of students' participation in online courses in double-tier colleges and universities, other undergraduate colleges and universities, and senior colleges and universities, respectively.

The number of students' participation in online courses in different grades in double first-class schools is 3.67, 3.42, 3.55, 3.91, the number of students' participation in online courses in other undergraduate colleges and universities is 4.62, 4.31, 3.87, 4.21, and the number of students' participation in online courses in higher vocational colleges and universities is 4.41, 4.09, and 5.12, respectively.

The average number of online courses taken was 4.107. Freshmen and seniors took the highest number of online courses ($p<0.01$). The demand for online courses was higher at Midwestern colleges and universities ($p<0.001$).



(a) Double first-class initiative

(b) Other undergraduate

(c) Higher vocational college

Figure 4: Different grades of students are involved in the number of online courses

(2) Online Learning Experience of Students in Different Regions and Types of Institutions

The online learning experience of students from different regions and types of institutions is shown in Table 4. The F-value of course recommendation in online course learning strategy is 31.20***, forming a significant correlation.

Multi-category ANOVA found that the regional differences in the online learning experience of students in “double first-class” institutions are relatively small, while the regional differences in non-“double first-class” institutions are larger, with the eastern part of the country being significantly higher than the central and western parts of the country.

Table 4: Different types of university students' online learning experience

		East			Midwest		F
Online learning	Online learning	Double first-class initiative	Other school	Higher vocational college	Double first-class initiative	Other undergraduate	
Strategies for online learning	Integrated learning resources	61.52	64.69	61.87	62.12	58.59	62.55***
	Plan and execute	63.97	68.15	66.78	65.58	64.96	32.11***

	Focus on learning is not disturbed	62.15	66.54	63.12	63.04	61.81	29.54***
	Online course recommendation	66.79	69.75	65.42	63.42	65.65	31.20***
Dynamic intensity of online learning	School course related	62.15	62.11	60.29	60.14	64.84	67.04***
	Actual demand correlation	50.34	52.43	51.24	48.27	53.45	89.54***
	Personal interest	52.17	52.63	50.45	47.09	52.13	55.21***
The technical ability of online learning	Accurate search of course information	72.43	75.58	71.63	72.51	72.64	72.15***
	Integrate into the online learning community	68.24	70.21	39.54	67.24	68.15	40.22***
	Easy use of tools	75.41	76.45	73.21	74.32	72.68	111.67***

(3) Analysis of Influencing Factors of College Students' Online Learning Gains

The analysis of the influencing factors of college students' online learning gains is shown in Table 5.

In order to further explore the mechanisms affecting students' online learning gains, the multiple linear regression model was analyzed for the subsamples from different regions and types of institutions, and it was found that the model could explain the variance at about 50%, which has a strong explanatory power.

In terms of online learning strategies, "focusing on learning without being disturbed" and "online course recommendation" are the main factors affecting the online learning gains of students from various types of colleges and universities in different regions. It can be seen that, entering the stage of normalization of online education, whether students can ensure sufficient concentration and persistence in online course learning based on self-selection of online courses and course recommendation model will be an important factor affecting the learning gains and learning effects of online courses.

In terms of online learning motivation, although the sources of motivation are different, they all have a significant effect on online learning gains ($p<0.001$). Whether motivated by intrinsic motivation (personal interest in knowledge) or extrinsic motivation (school programs), students who actively participate in online courses always have higher online learning gains.

Table 5: Analysis of influence factors of college students' online learning

		East			Midwest	
		Double first-class initiative	Other school	Higher vocational college	Double first-class initiative	Other undergraduate schools
Strategies for online learning	Integrated learning resources	0.06***	0.09***	0.03**	0.03	0.07***
	Plan and execute	0.07***	0.08**	0.09***	0.08***	0.08***
	Focus on learning is not disturbed	0.24***	0.21***	0.18***	0.23***	0.25***
	Online course recommendation	0.26***	0.27**	0.27***	0.19***	0.05***
Dynamic intensity of online learning	School course related	0.02	0.03***	0.02	0.04**	-0.01*
	Actual demand correlation	0.04***	0.02**	0.06***	0.03***	0.02***
	Personal interest	0.03***	0.06***	0.04*	0.05***	0.06***
The technical ability of online learning	Accurate search of course information	0.21***	0.22***	0.18***	0.18***	0.16***
	Integrate into the online learning community	0.24***	0.22***	0.27***	0.24***	0.27****
	Easy use of tools	0.02	0.05*	0.07***	0.04**	0.06***
R^2-adj	-	0.52	0.52	0.56	0.47	0.69
F	-	3125.87	1578.46	486.96	35712	3565.97

V. Conclusion

This study explores the impact of online course construction in higher education on the transformation of students' learning styles, and obtains the following main conclusions:

Online course construction has become an important trend in the development of higher education, and it has been deepened in the course of development from fine courses to first-class undergraduate courses. The construction of a perfect online course includes three aspects: course elements, open behavior and learning support services, in which learning support services are the distinguishing feature that distinguishes online courses from traditional classroom teaching. Online courses demonstrate their unique value by promoting the digital development of education, optimizing the distribution of educational resources and deepening teaching changes.

The KGCN-CNSH course recommendation model proposed in this study effectively improves the recommendation system performance. The experimental results show that on the Amazon-book dataset, the model improves 0.45% and 0.26% on the two metrics of Recall and NDCG, respectively, compared to the previous best-performing KGIN algorithm; and on the Yelp-2018 dataset, it improves 0.33% and 0.12%, respectively, compared to the SGL algorithm. This validates the effectiveness of the knowledge graph recommendation algorithm that incorporates common neighbors and structural holes.

The academic survey found that 75% of the participating college students participated in at least one online course, which is higher than the 49% participation rate of similar surveys in the United States. There are significant differences in the online learning experiences of students in different regions and types of institutions, among which the regional differences in the online learning experiences of students in “double first-class” institutions are relatively small, and the regional differences in non-“double first-class” institutions are larger. Multiple linear regression analysis shows that “focusing on learning without interruption” and “online course recommendation” are the main factors affecting students' online learning gains in various types of colleges and universities in different regions, and the variance explained by the regression model is about 50%.

In summary, online course construction plays an important role in promoting the transformation of students' learning styles. The course recommendation system based on knowledge graph can improve recommendation accuracy and provide students with personalized learning paths. In the context of normalized online education, whether students can maintain concentration and persistence in the process of self-selecting courses is a key factor affecting the learning effect of online courses.

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