J. COMBIN. MATH. COMBIN. COMPUT. 127b (2025) 4871--4881

Journal of Combinatorial Mathematics
and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

# A web-based multimedia English teaching model based on learning motivation theory

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ABSTRACT

To enhance the effectiveness of network-based multimedia English education, this study proposes a new teaching model integrating learning motivation theory and constructivism. The model's design is based on the analysis of statistical features from the parameters of network multimedia English teaching, utilizing learning motivation and constructivism as foundational theories. Additionally, the model incorporates deep learning techniques and intelligent datasets rooted in mathematical logic. By constructing both a network multimedia English teaching dataset and a multimedia teaching resource access dataset, the model applies structural similarity analysis to evaluate these datasets under the influence of learning motivation and constructivism. This paper further investigates the various constraints and objectives faced by students and courses in the context of network-based multimedia English education. The optimization of the teaching algorithm is realized within this framework, aiming to improve efficiency and learner engagement. Simulation results demonstrate that the proposed method offers robust resource matching capabilities with minimal deviation, contributing to enhanced student satisfaction. Moreover, it supports users in the excavation and strategic planning of network-based multimedia English education.

*Keywords:* learning motivation theory, Constructivism, Multimedia English teaching, Multi-objective hierarchical analysis with constraints

## 1. Introduction

With the advancement of global trends, the multipolarization of the world and economic globalization have emerged as unavoidable phenomena. The exchange and learning of economic, technological, and cultural aspects significantly contribute to social progress, with English serving as a crucial medium for communication [1]. In China, English as a foreign language education is highly valued. English is included as part of the mandatory curriculum in primary, secondary, and higher education, aiming to equip students with fundamental skills in listening, speaking, reading, and

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Received 20 February 2024; Revised 25 April 2024; Accepted 20 November 2024; Published Online 16 April 2025.
DOI: 10.61091/jcmcc127b-269

writing, while also imparting essential linguistic knowledge. Moreover, proficiency in English helps expand students' perspectives, enriches their life and academic experiences, and enhances their capacity to assimilate new information. It fosters cross-cultural awareness, nurtures innovation, promotes Chinese culture, and strengthens patriotic sentiments. Concerning the integration of learning motivation theory and network-based multimedia English teaching (ET) under constructivism, international research has been conducted earlier than in China, offering more comprehensive theoretical frameworks. Such research can be classified into two main categories: one based on expert analysis of historical student behavior data in multimedia ET, and the other emphasizing student interaction to gather preference information, which is then used to inform ET planning strategies under learning motivation theory and constructivism [2].

In recent years, the growth of online multimedia ET in China has been notable, with significant increases in the industry's revenue, fostering its healthy development. As the network multimedia English teaching (NMET) sector expands, numerous platforms and products have been introduced. To cater to the diverse needs of students, it is essential to integrate individual preferences with learning motivation theory and constructivist principles, thus establishing a planning model that aligns multimedia ET with students' unique behavioral traits. This approach is crucial for enhancing the targeted marketing of online multimedia ET products, advancing the intelligent information management of online multimedia ET, and improving overall student satisfaction.

This paper puts forward the learning motivation theory based on deep learning and the NMET algorithm based on constructivism. Firstly, the learning motivation theory and big data analysis model of NMET under constructivism are established. Then, the features of learning motivation theory and NMET big data under constructivism are extracted and matched. According to the matching results, the learning motivation theory and NMET design under constructivism are carried out.

## 2. Data Analysis Model and Feature Mining of NMET Based on Learning Motivation Theory and Constructivism

### *2.1. Learning motivation theory and constructivism under the NMET characteristics distribution big data model*

The UGC (User-Generated Content), equipment, and record data associated with network-based multimedia English teaching (ET) encompass vast amounts of student information, forming a foundation for comprehensive analysis. However, the research findings derived from such data exhibit strong regional characteristics, limited scalability, and lack of clear interpretability. In the context of big data, a distributed student information mining model is proposed. This model utilizes students' prior data to align learning motivation theory with key features identified in the NMET process under constructivist principles. By analyzing students' personalized preferences, relevant information is extracted to guide intelligent management and planning of multimedia ET routes.

In the planning phase, feature depth mining methods [3] and fusion clustering techniques are employed to facilitate personalized route planning for NMET. Additionally, the method of mining historical preferences related to students' NMET paths is used to achieve regional integration in route planning under a heterogeneous distributed storage system. Among the prevailing theories of learning motivation and methods for NMET under constructivism, one approach involves designing algorithms that utilize UGC data, multimedia data, user behavior data, and other related inputs to recommend NMET plans. However, these systems often suffer from long processing times, high resource costs, limited interactivity, and difficulty in adjusting existing plans. Another method involves providing rich interactive features to assist users in planning their ideal NMET experience, making it more user-friendly but frequently lacking data-driven guidance.

Both of these approaches predominantly focus on students, leaving out data support and interactive analysis, which limits their ability to provide adequate ET planning services for developers of multimedia ET products. To address this gap, it is essential to build a big data model that maps students' personalized characteristic distributions [4] and derive a binary model for big data distribution as follows:

$$\begin{cases} x = \left(x_1, x_2, \ldots, x_n\right) \\ y = F(x) = \left(f_1(x), f_1(x), \ldots, f_m(x)\right)^T \end{cases} \tag{1}$$

where $x$ is the information characteristics of NMET under learning motivation theory and constructivism; $y$ represents the distribution node set of NMET lines and the storage space of students' information. According to the students' NMET information, the characteristic distribution set $P\left(n_i\right) = \left\{p_k \mid pr_{kj} = 1, k = 1, 2, \cdots, m\right\}$ of NMET under learning motivation theory and constructivism is obtained. By adopting the structural consistent learning algorithm, the spatial distribution set of NMET under learning motivation theory and constructivism is as follows:

$$RTT_s = (1-\alpha) \times RTT_s + \alpha \times RTT \tag{2}$$

According to the distribution of students' NMET history routes, the attribute classification scheduling is carried out, and the method of label information identification is adopted to establish the spatial clustering ambiguity function of personalized planning of NMET routes.

In this paper, various technologies such as topic classification, data dimensionality reduction, frequent subgraph mining, visualization, etc. are integrated. With the help of dynamic interaction such as association and filtering, users are allowed to freely choose the NMET collection in different data dimensions, and the subgraph mining algorithm is used to mine the frequent NMET features in the collection.

### *2.2. Language intelligence information and students' interest parameter information feature matching*

To explore NMET, a visual overview of NMET is developed, presenting a variety of data such as evaluations, interviews, and topic compositions. This visual representation aids users in quickly analyzing and comparing different aspects of NMET. The process of data mining, analysis, and interactive comparison is designed with high interpretability, enabling users to thoroughly understand the structure and characteristics of the data through exploration.

Using spatial information fusion techniques [5], a big data mining model for the distribution of NMET is created under the theoretical framework of learning motivation and constructivism. The resulting output from this model is as follows:

$$\begin{aligned} P\left(U \mid \alpha_U\right) &= \prod_{i=1}^{M} N\left(U_i \mid 0, \alpha_U^{-1} I\right) \\ P\left(V \mid \alpha_V\right) &= \prod_{j=1}^{N} N\left(V_j \mid 0, \alpha_V^{-1} I\right) \end{aligned} \tag{3}$$

Wherein, $U, V$ is the clustering feature vector, which extracts many kinds of information correlation dimension features that reflect the evaluation, interview, topic composition and other aspects of NMET. Fuzzy information perception technology [6] is used to manage the NMET line information, and the personalized evolution features of NMET line are obtained. The keyword-based emotional visual analysis method of multimedia teaching resources needs to be added to the planned long NMET to optimize the path. The algorithm converges quickly, and the NMET under learning motivation theory and constructivism has good real-time performance.

In the context of NMET under the framework of learning motivation theory and constructivism, deep learning methods [7] are employed to match language intelligence features with students' interest parameters. The assumption is made that the attribute set for association rules, which are used in the information management of distributed NMET systems, is defined as follows. Furthermore, the distribution weights for the information features of NMET lines are calculated based on these parameters, as outlined below:

$$W_k(U) = g\left(\frac{1}{M}\sum_{i=1}^{M}\frac{\sum_{j\in Liem} r_{i,j,c_k}}{\sum_{j\in Liem} s\times\hat{r}_{i,j}+O}\right) \tag{4}$$

$$W_k(V) = g\left(\frac{1}{M}\sum_{i=1}^{N}\frac{\sum_{j\in UJ\sigma_i} r_{i,j,c_k}}{\sum_{j\in UJ\sigma_j} s\times\hat{r}_{i,j}+O}\right) \tag{5}$$

Wherein, $g$ is the development factor of NMET for network multimedia English teachers, $M$ is the free choice analysis parameter of NMET under the theory of learning motivation and constructivism, $s$ is the characteristic value of emotional image distribution of multimedia teaching resources, $r_{i,j,c_k}$ is the learning cost of NMET data under the theory of learning motivation and constructivism, and the information typing parameter of NMET line. According to the dynamic structure of NMET route information, the multidimensional feature reconstruction is carried out. The keyword-based emotional visual analysis method of multimedia teaching resources integrates guide layout and keyword visualization technology, establishes the identification information of students' NMET historical route, analyzes NMET projects, and carries out NMET route information fusion according to the joint distribution of students and projects, thus obtaining the information fusion set:

$$\max_{x_{a,b,d,p}}\sum_{a\in \mathrm{A}}\sum_{b\in \mathrm{B}}\sum_{d\in \mathrm{D}}\sum_{p\in \mathrm{P}} x_{a,b,d,p}V_p \tag{6}$$

$$s.t.\sum_{a\in \mathrm{A}}\sum_{d\in \mathrm{D}}\sum_{p\in \mathrm{P}} x_{a,b,d,p}R_p^{bw} \le K_b^{bw}(\mathrm{S}), b\in \mathrm{B} \tag{7}$$

Wherein, $x_{a,b,d,p}$ is attribute characteristic, $V_p$ is ET history route, according to the characteristic group of students' NMET history route, dynamically reconstructs distributed students' personalized preference characteristics, and carries out fuzzy clustering according to the attribute characteristics of data to obtain the information recognition probability of students' NMET history route characteristics. Deep learning method is adopted to mine the characteristics of students' NMET history route in the personalized planning process, and the output is as follows:

$$P(k) = P(1)[1-p(1)]^{k-1} \tag{8}$$

Wherein, $p(1)$ is the initial clustering center parameter. Using deep learning algorithm, the feature matching between language intelligence information and students' interest parameter information in the process of NMET under the theory of learning motivation and constructivism is carried out, and the fuzzy search mean function [8] is:

$$E(k) = \frac{1}{\left(1-\frac{1}{L}\right)^{m-1}} \tag{9}$$

Wherein, $L$ is the attribute parameter of NMET data, $m$ is the schedule of NMET with complete itinerary, and the average number of time slots of NMET under the theory of individualized learning motivation and constructivism is:

$$T_{l-ay} = E(k)L = \frac{L}{\left(1-\frac{1}{L}\right)^{m-1}} \tag{10}$$

Wherein, $E(k)$ represents the data parameter of mathematical logic intelligence, from which the information characteristic distribution set of NMET line is calculated, and the joint information entropy mining method is adopted to analyze students' personality and hobbies and match characteristics.

## 3. ET model optimization design

### *3.1. Analysis of structural similarity of NMET data set based on learning motivation theory and constructivism*

On the basis of the above-mentioned learning motivation theory and the big data model and feature matching of students' personalized characteristics distribution in NMET under constructivism, the learning motivation theory and NMET algorithm under constructivism are optimized. we put forward the learning motivation theory based on deep learning and NMET algorithm under constructivism. The personalized planning information of the NMET line information management system is identified by the tag identification method[9], and the characteristic quantity of the NMET line information state is output. The NMET line information collection and NMET method information sampling are carried out at more than twice the baud rate, and the statistical characteristic quantity of the NMET model parameters under the learning motivation theory and constructivism is extracted. Under the control of intelligent data sets of deep learning and mathematical logic, the statistical features obtained are as follows: individualized planning and feature matching are carried out on the collected information feature distribution set of NMET routes, a priori distribution model of students' NMET history routes is established, and joint feature mining[10] is carried out by using information fusion method. The random probability density distribution model of NMET under the theory of output learning motivation and constructivism is as follows:

$$P_{ij}(k) = \frac{\left(l_j(k)-l_i(k)\right)\eta_{ij}(k)}{\sum\limits_{j\in N_i(k)}\left(l_j(k)-l_i(k)\right)\eta_{ij}(k)} \tag{11}$$

Wherein, $l_j(k)$ is the dimensionality reduction result of NMET, and $\eta_{ij}(k)$ is the distance between NMET points. By using personalized information fusion method, the relevance of NMET under the theory of learning motivation and constructivism is detected, and the association rule scheduling model is established by using the method of joint fuzzy recognition. The big data fusion scheduling set of NMET line informatization planning is obtained as $s(t)$. The information entropy of planning information is extracted, and the sample set of students' personalized preferences is output as follows:

$$s(v) = \int_0^v \sin\left(\frac{\pi}{2}x^2\right)dx \tag{12}$$

$$y(t) = u(s(t-\tau))\exp\left(j\omega_C s(t-\tau)\right) \tag{13}$$

Wherein, $v$ represents the correlation directional characteristic quantity of NMET under the theory of learning motivation and constructivism, and $u(t)$ is the fuzzy characteristic matching set of NMET under the theory of learning motivation and constructivism. Combined with the high-order statistical characteristic analysis method, the distribution dimension of personalized planning of

NMET line is $n, N_1, \cdots, N_n$, in L time slices, The matching set of fuzzy correlation features between learning motivation theory and constructivism NMET is obtained. Based on the k - kernel filtering method, the standard quantitative set of learning motivation theory and constructivism NMET informatization planning is obtained as follows:

$$E_{Tx}(l,d) = E_{(Tx-elec)}(l) + E_{(Tx-amp)}(l,d) = lE_{elec} + l\varepsilon d^{\alpha} \\ = \begin{cases} lE_{elec} + l\varepsilon_{fs} d^2, & d < d_0 \\ lE_{eloc} + l\varepsilon_{mp} d^4, & d \geq d_0 \end{cases} \tag{14}$$

Wherein, $E_{(Tx-elec)}$ is the visual coding of the data selection view, $\varepsilon$ is the dynamic component of the distance between online multimedia ET points, and $d$ is the probability density parameter of each topic. Using the fuzzy self-adaptive scheduling method [11-12], this paper constructs the model of online multimedia ET data set and multimedia teaching resource access data set under the theory of learning motivation and constructivism, and combines the personalized planning algorithm to fuse big data information, so as to improve the ability of analyzing the structural similarity of online multimedia ET data sets under the theory of learning motivation and constructivism.

### *3.2. Learning motivation theory and constructivism under the NMET optimization*

Under the control of deep learning and intelligent data sets of mathematical logic, the model of NMET data sets and multimedia teaching resource access data sets under the theory of learning motivation and constructivism is constructed. By adopting the method of structural similarity analysis of NMET data sets under the theory of learning motivation and constructivism[13], the association rules ofNMET line informatization planning are obtained as follows:

$$c_k = \frac{1}{j_k}\left[\frac{d^k}{d\omega^k}\ln(\Phi(\omega))\right]_{\omega-0} \\ = (-j)^k\left[\frac{d^k}{d\omega^k}\Psi(\omega)\right]_{\omega=0} = (-j)^k\Psi^k(0) \tag{15}$$

Wherein, $\Phi(\omega)$ is the collection of interesting NMET lengths, $\Psi^k(0)$ is the initial collection of interesting NMET lengths, and $\Psi^k(0)$ is the result of NMET mining. According to the number of nodes, the collected personalized features in the NMET line information management system are scheduled for resource information [14-15], and the planned adaptive information fusion model is established by combining the beamforming algorithm. And construct the bottom database, the maximum distribution interval of data fusion clustering is $r_{\max} = \left(P\left(N_0\beta\right)^{-1}\right)^{1/\alpha}$, the sample space distribution of personalized planning of NMET line information management is $d \leq r_{\max}$, and the multi-information fusion results are as follows:

$$X_\alpha(m) = A_\alpha \cdot e^{(j/2)\cot a \cdot m^2 \Delta u^2} \tag{16}$$

Wherein, $A_\alpha$ is the statistical characteristic quantity extracted from the learning motivation theory and the information planning of NMET under constructivism, and the association rule set of learning motivation theory and NMET under constructivism is obtained. By using the fuzzy correlation detection technology, the lines in the process of learning motivation theory and NMET under constructivism are de-duplicated.

The adaptive learning method [16-17] is adopted to optimize the distribution in the planning process, and the multi-constraint and multi-objective hierarchical analysis of students and teaching courses is carried out to realize the optimization of NMET algorithm under the theory of learning motivation and constructivism. The distribution function of the optimized planning is as follows:

$$H_i(x) = \sum_{k=1}^{K} p_k \ln \frac{1}{p_k} = -\sum_{k=1}^{K} p_k \ln p_k \tag{17}$$

Wherein, $p_k$ is the spatial state characteristic quantity of the NMET line. To sum up, the learning motivation theory based on deep learning and the improvement of the NMET algorithm under constructivism are realized.

## 4. Simulation and result analysis

The cloud database of NMET under the theory of learning motivation and constructivism is Pearson Database, and the length of the test sample of information characteristics of NMET under the theory of learning motivation and constructivism is 1024. The training set size is 500, and the results of NMET mining are grouped and counted according to the number of nodes. In order to allow users to view the quantity difference and distribution of frequent NMET of different lengths, and to facilitate selection and interaction, column charts are used to show the grouping statistics results, as shown in Figure 1. Users can select the interesting NMET length set and view the overview of each NMET.

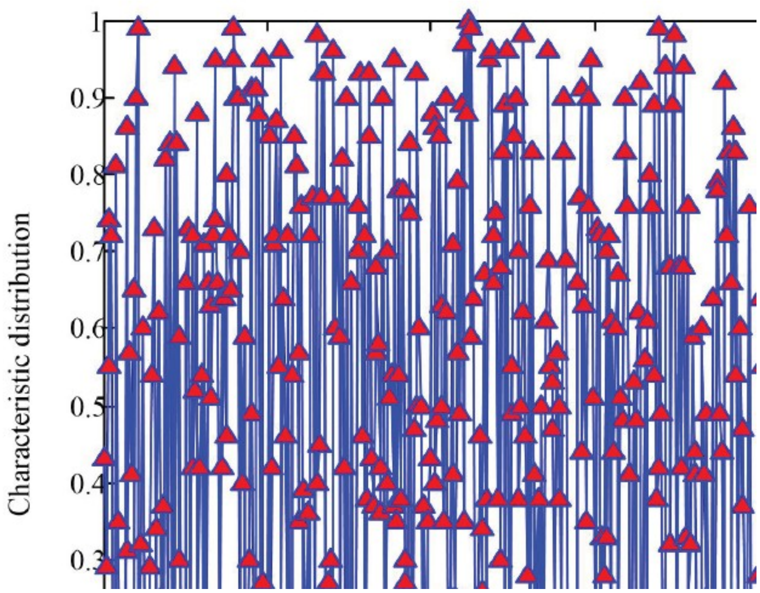


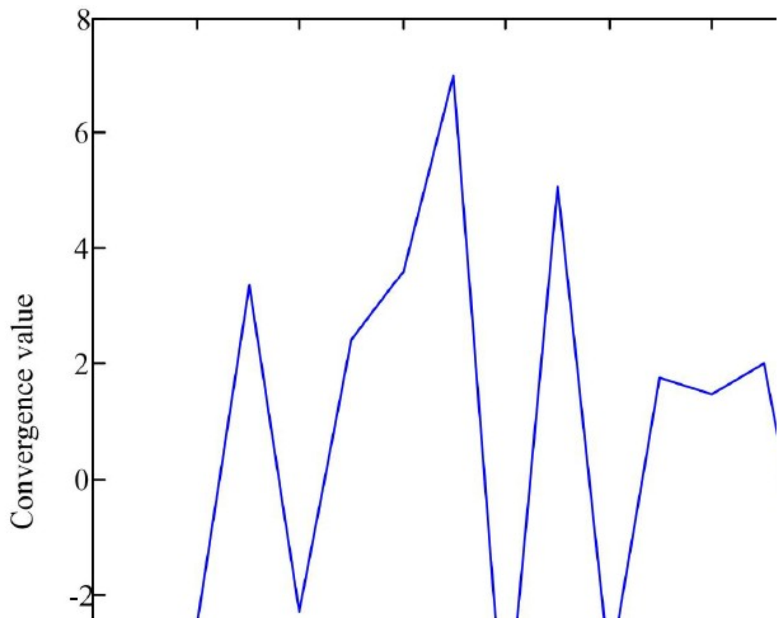

**Fig. 1.** NMET Collection View

For the frequent NMET, the path optimization method based on epipolar scanning genetic algorithm is used to optimize the order of teaching courses, and then the visual analysis method of hierarchical NMET plan is used to visually analyze the planned NMET. The sampling and distribution interval of NMET information under learning motivation theory and constructivism is 80KBps. The results of variance analysis of real-time test scores of each test group in the figure show that the main effect of independent variable of fine processing mode is significant ($p < 0.005$), and the partial Eta square is 0.128, reaching a meaningful middle level. The real-time test scores of the short text processing experiment are better than those of the sentence context processing experiment. The main effect of independent variables of multimedia design elements is significant ($p<0.001$), and the partial Eta square is 0.138, reaching a significant high level. The real-time test result of forward design experiment is better than that of reverse design experiment. The interaction between the two independent variables is far from significant. The adjusted R-square value shows that the two independent variables in the experimental model explain 21.3% of the total variation of the instant test scores. According to the distribution of NMET routes, the historical route preferences and route characteristics of students' NMET are shown in Table 1.

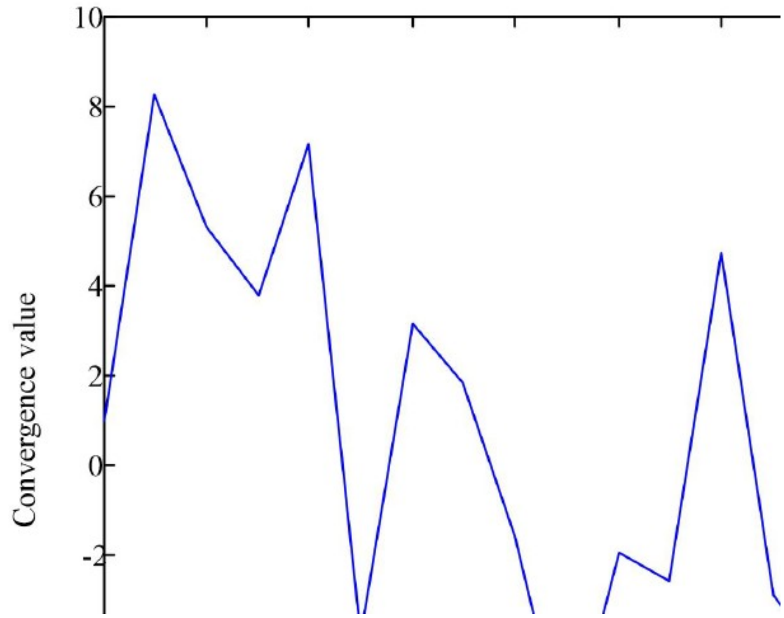
**Table 1.** Data distribution of students' NMET characteristics

| Data set | Fitted value | | Statistical value | |
|---|---|---|---|---|
| | Test set | Training set | Test set | Training set |
| Student autonomy | 580 | 982 | 943 | 8 |
| Teacher guidance | 341 | 326 | 789 | 717 |
| Students' independent processing | 138 | 188 | 325 | 979 |
| Teacher-guided processing | 348 | 271 | 817 | 328 |
| Essay context | 435 | 317 | 355 | 347 |
| Fine processing level | 849 | 484 | 487 | 925 |

According to the above simulation environment and parameter settings, the intelligent planning of NMET route is carried out. By using the learning motivation theory and the structural similarity analysis method of NMET data set under constructivism, the multi-constraint and multi-objective hierarchical analysis of students and teaching courses in the process of NMET under constructivism is carried out, and the route planning results are shown in Figure 2.




(a) Student financial aid




(b)Teacher guidance

**Fig. 2.** Learning motivation theory and the results of NMET under constructivism

According to the analysis of Figure 2, the planning of NMET route by this method has good statistical analysis and prediction ability for students' NMET history route. The analysis results show that the main effect of the independent variable of fine processing mode is significant ($p < 0.001$), and the partial Eta square is 0.141, reaching a significant high level. The real-time test scores of teachers' guided processing experiments are better than those of students' independent processing experiments. The main effect of independent variables of multimedia design elements is significant ($p <0.01$), and the partial Eta square is 0.074, reaching the middle level. The real-time test result of forward design experiment is better than that of reverse design experiment. The interaction between the two independent variables has not reached a significant level. The adjusted R-square value shows that the two independent variables in the experimental model explain 17.1% of the total variation of the delayed test scores. Therefore, the optimal coverage of the NMET line is realized, the accuracy of the planning is improved, and the accuracy and time cost of the planning are tested. The results are shown in Figure 3. By analyzing Figure 3, it is known that with the increase of iterative steps, the accuracy of NMET under the theory of learning motivation and constructivism is improved, and the time cost is short.

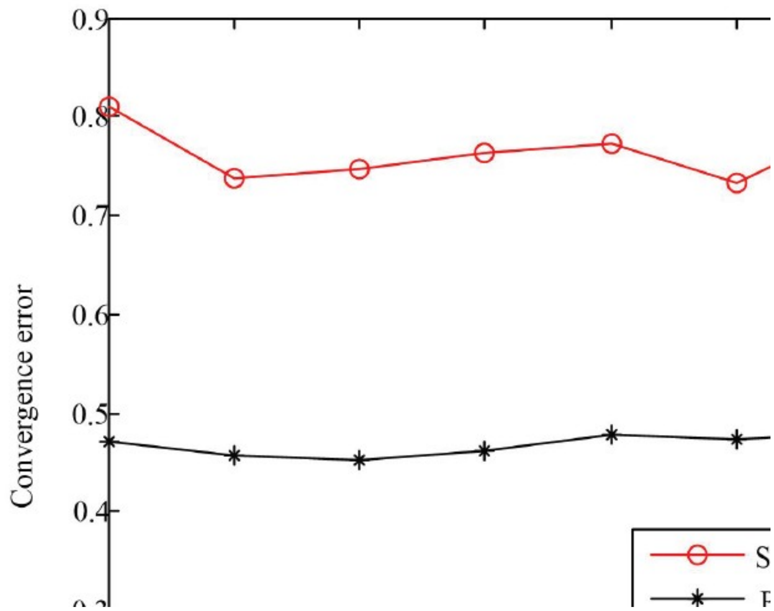



**Fig. 3.** Performance comparison

## 5. Conclusions

With the rapid growth of mobile Internet in recent years, an increasing number of students are utilizing online platforms, such as itinerary planning tools, multimedia English teaching (ET) reviews, and online maps, to customize their itineraries, share feedback, and search for multimedia teaching resources. As a result, these platforms have accumulated vast amounts of data related to online multimedia ET. This data, characterized by self-generation, large scale, and diverse types, offers a comprehensive and authentic reflection of online multimedia ET and multimedia teaching resources within the framework oflearning motivation theory and constructivism.

However, current online multimedia ET products face significant issues of homogeneity, exacerbating problems such as overcrowded learning content, poor student experience, and decreasing appeal to learners over time. Providers of NMET (Network Multimedia ET) are compelled to invest substantial resources in research to develop new products, with long planning timelines and tedious processes. Leveraging the aforementioned data, it is possible to identify high-quality teaching courses. This allows for the efficient analysis and planning of NMET and multimedia teaching resources, enabling the swift creation of comprehensive NMET plans in a short time. The research and evaluation processes based on this approach can significantly reduce the cost ofdeveloping new NMET products and foster continuous innovation within the sector. To meet students' individualized needs, it is crucial to integrate students' personal preferences with learning motivation theory and NMET under constructivism. This leads to the development of a planning model that aligns students' behavior characteristics with learning motivation theory and NMET. This paper proposes a deep learning-based learning motivation theory and an NMET algorithm based on constructivism. By applying feature depth mining and fusion clustering methods, personalized NMET route planning is carried out, with alignment of non-hub routes. Furthermore, spatial information fusion techniques are employed to construct a big data mining model for NMET distribution under the theory of learning motivation and constructivism. This model dynamically reconstructs distributed students' personalized preferences, enabling the optimization of NMET under this theoretical framework.

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