Abstract: At present, there is a poor connection between theory and practice in the driving mechanism of industry–teaching integration in colleges and universities. And with the increasing courses, the recommendation accuracy of the recommendation algorithm has also decreased. Therefore, the research built a teaching platform of the Internet of Things (IoT) based on the integration of industry and education and improved its internal online education course recommendation algorithm. Meanwhile, experiments verified its performance. The experimental results show that the response time of several important interfaces is maintained between 0 and 300 ms. In the verification experiment of the improved algorithm for building the rule engine, when the rules are 50, the traditional Rete algorithm takes the most time. In terms of total time consumption, the traditional Rete algorithm takes more time than the improved Rete algorithm. The mean absolute error of the User-Characteristics and Interest Clustering (CCIC) algorithm is 0.8116, the root mean square error is 0.9455, the accuracy is 0.3043, and the recall is 0.1475, which are better than the comparison algorithms. In the recommendation of actual agricultural courses, the overall satisfaction of the User-CCIC algorithm is more than 70%, with good prediction accuracy. In general, the IoT education platform based on the combination of industry and education established by this research has better application prospects, and the User-CCIC algorithm recommended by this research has a good practical effect in actual course recommendation.

Keywords: educational reform, course recommendation algorithm, dynamic mechanism of industry–education integration, collaborative filtering

1 Introduction

The development of computer information technology has led to the gradual informatization of education. The comprehensive application of modern information technology in education has also promoted the reform and development of education [1]. Educational reform is a product of the development of the times, and its purpose is to bring harmony and happiness to students [2]. With the rapid development of information technology,
more and more physical objects are connected to the Internet at an unprecedented speed. The Internet of Things (IoT) is a network that extends and expands the user end on the basis of the Internet, utilizing information sensing devices to achieve information exchange and communication between things according to agreed protocols. The integration of the IoT, cloud computing, big data, and other technologies can more accurately and quickly achieve the identification, positioning, tracking, monitoring, and management of physical objects, thereby promoting product and service innovation [3–5]. Therefore, the research on IoT-related technologies and the implementation of their typical applications has become an important direction for universities. To effectively improve the skills and learning awareness of teachers and students and enhance students’ learning interests, Ali et al. proposed a recommendation system to support online learning in the context of educational reform [6]. Marras et al. proposed a formal model on the basis of educational principles to ensure that online courses recommend equal learning opportunities for middle school students and ensure the development of online education platforms [7]. To realize personalized product recommendations for users, Iwendi et al. introduced a collaborative filtering (CF) algorithm based on the recommendation system of the project and proposed a machine-learning model [8]. However, the existing IoT teaching platforms lack practical teaching functions and the industry coverage of teaching content is low, which makes it difficult to connect theoretical teaching and practical teaching effectively. Students find it difficult to understand and master the complete industry application process, and innovation needs to be improved. Under this background, the research optimizes the rule engine algorithm of Rete, proposes a teaching platform of the IoT based on the integration of industry and education, optimizes its internal online learning course recommendation algorithm, and proposes a system filtering recommendation algorithm based on User Characteristics and Interest Clustering (User-CCIC). Its purpose is to address the lack of practical teaching functions and low industry coverage of teaching content in the implementation of industry education integration in universities under the current educational reform background. It aims to expand the application of IoT platforms in industry education integration while promoting the rapid development of efficient industry education integration driving mechanisms. In addition, the study has constructed a sick state of industry education integrated IoT teaching, which realizes the integration of theory and time, as well as multi-course autonomous learning. This has provided assistance for the development of course recommendation algorithms in the context of education reform and also laid a theoretical foundation for the application of the IoT in the education industry under multi-disciplinary conditions.

2 Related works

In the context of educational reform, the curriculum recommendation algorithm is widely used in the integration of industry and teaching in colleges and universities, and it also promotes the organic combination of college education theory and practice [9]. Among many course recommendation algorithms, the CF algorithm is widely used. It is to find similar (interested) and specific users in the group by analyzing their interests and comparing them with the information of a specific user to determine the preference for the information [10]. Based on this, a wide range of domestic and international scholars have conducted in-depth research on it. Jia et al. proposed a CF recommendation algorithm for online learning resources based on the knowledge association model, aiming at the information overload of online learning platforms, thus effectively realizing personalized recommendations of resources and prediction [11]. To solve the online product overload, Sharma et al. proposed a book recommendation system based on a CF algorithm and hybrid system, which effectively filtered content and improved the accuracy of recommendations [12]. To improve the satisfaction of course recommendations, Bergner et al. proposed a multi-dimensional project response theory machine learning method based on CF, which effectively improved the prediction accuracy of student performance and satisfaction [13]. To build corresponding systems according to different professional knowledge, Wang and Lv built corresponding personalized learning models based on the distributed computing method of the IoT, thus providing students with effective personalized learning methods [14]. To reduce the data information overload in online learning activities, Lin et al. proposed an intelligent recommendation system using a CF algorithm,
thus improving the accuracy of recommendation on the basis of overcoming the shortcomings of traditional recommendation systems [15].

In addition, to effectively improve students’ learning performance, Wankhede et al. used machine learning methods to build a prediction model of students’ behavior, thus effectively improving their abilities [16]. To achieve the effective recommendation of music education resources, Sakurai et al. implemented the classification of music acoustic features using deep reinforcement learning and CF algorithms on the basis of a knowledge map, thus improving the accuracy of recommendation [17]. To help users make fast decisions in learning, Yu et al. proposed a semantic recommendation algorithm by using reinforcement learning and weighted meta-path methods, thereby improving the accuracy of learning recommendations and improving user satisfaction [18]. To solve the sparsity and fuzziness in recommendation feedback, Lee proposed a new knowledge distillation model based on the CF algorithm, which effectively improved the accuracy of knowledge recommendations [19]. Raleiras et al. addressed the issue of neglecting learning differences in existing learning systems and comprehensively discussed the application of course recommendation algorithms in learning systems using a data-driven approach, thereby providing assistance for the course recommendation algorithms [20]. Zankadi et al. proposed a new course recommendation algorithm for online MOOCE learning by utilizing social media, thus providing assistance in enhancing the learning interest [21]. Lutfiani et al. proposed a course recommendation method for improving learning strategies in educational technology by utilizing big data technology, which effectively solved the problems in students’ learning [22]. Iwendi et al. proposed an improved CF algorithm based on machine learning models to address the related issues in personalized recommendation, thus effectively improving the accuracy of personalized recommendations [8]. Raj et al. comprehensively discussed content recommendation algorithms in adaptive and personalized learning environments to address related issues in personalized learning. This not only improved recommendation accuracy but also provided assistance in improving learner satisfaction [23]. da Silva et al. proposed a course recommendation method for distance education using virtual learning technology, effectively reducing the phenomenon of disqualification and dropout [24].

From the research of domestic and foreign scholars, although traditional recommendation algorithms based on content have a simple process, relying solely on partial preference information in real application scenarios may lead to misjudgment and low accuracy. There are still shortcomings in using CF algorithms for user recommendations, ignoring issues such as classification and changes in interest preferences of similar user groups, feature extraction of user feature items, and historical user behavior. Therefore, the research can effectively improve the accuracy of the recommendation by using the students’ interests and preferences to improve the CF algorithm, which is innovative. The research constructs an industry–teaching integrated IoT teaching platform that unifies online teaching and practical teaching, which can improve students’ learning interests in an all-round way. The specific comparison and analysis steps between existing and research methods are shown in Table 1 and Figure 1.

3 Analysis of the application of the curriculum recommendation algorithm in the driving mechanism of the integration of production and teaching in colleges and universities

3.1 Construction of the IoT teaching platform based on the driving mechanism of industry–education integration

In view of the current implementation of industry–teaching integration in colleges under the background of education reform, the research uses the rule engine optimization algorithm of Rete as the basis to build an industry–teaching integration IoT teaching platform with convenient equipment management and real-time data visualization. It uses the improved CF algorithm under the platform architecture to implement
The driving mechanism of the integration of industry and education is the main way for the development of college education at present. It combines industry and education organically on the basis of the synergy theory so as to realize the synergy of school education with industry and enterprises in educating people [25,26]. The so-called coordination theory is to regard the whole society as a system, in which various factors influence each other, thus affecting the whole society. The training goal of higher education should be that students have strong professional ability and solid theoretical knowledge, broad knowledge, strong practice ability and strong professional innovation ability. The implementation of coordination theory can better meet the training goals of higher education.

Table 1: Comparison results between existing methods and research methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>CF recommendation algorithm for online learning resources</td>
<td>Realized personalized recommendations for online learning resources</td>
</tr>
<tr>
<td>A book recommendation system</td>
<td>Filtered content and improved recommendation accuracy</td>
</tr>
<tr>
<td>Machine learning methods for multidimensional project response theory</td>
<td>Improved prediction accuracy of student performance</td>
</tr>
<tr>
<td>Corresponding personalized learning models</td>
<td>Provided effective personalized learning methods</td>
</tr>
<tr>
<td>Intelligent recommendation system</td>
<td>Improved accuracy of recommendations</td>
</tr>
<tr>
<td>A predictive model for student behavior</td>
<td>Improved students' abilities</td>
</tr>
<tr>
<td>Effective classification of music acoustic features has been achieved</td>
<td>Improved recommendation accuracy</td>
</tr>
<tr>
<td>Semantic recommendation algorithm</td>
<td>Improved the accuracy of learning recommendations</td>
</tr>
<tr>
<td>A new knowledge distillation model</td>
<td>Improved the accuracy of knowledge recommendation</td>
</tr>
<tr>
<td>Comprehensive discussion on course recommendation algorithms</td>
<td>Provided assistance for the development of course recommendation algorithms</td>
</tr>
<tr>
<td>Course recommendations based on social media</td>
<td>Increased learner interest in learning</td>
</tr>
<tr>
<td>Course recommendation based on big data technology</td>
<td>Effectively solved problems in students' learning</td>
</tr>
<tr>
<td>Improved CF algorithm based on machine learning</td>
<td>Improved the accuracy of personalized recommendations</td>
</tr>
<tr>
<td>Comprehensive discussion on content recommendation algorithms</td>
<td>Improved the learner satisfaction</td>
</tr>
<tr>
<td>Course recommendation based on virtual learning technology</td>
<td>Reduced the disqualification and dropout in distance education courses</td>
</tr>
<tr>
<td>Research method</td>
<td>Superiority</td>
</tr>
<tr>
<td>An IoT teaching platform that integrates industry and education</td>
<td>Solved the high misjudgment rate in traditional recommendation algorithms, improved the substantive recommendation effect, and considered the user feature extraction more comprehensively, effectively improving the accuracy of recommendations and comprehensively enhancing students' learning interest</td>
</tr>
</tbody>
</table>

Summary and Discussion of Existing Course Recommendation Methods

Analysis of the Application of Curriculum Recommendation Algorithm in the Motivation Mechanism of the Integration of Industry and Education in Universities

Construction of Internet of Things Teaching Platform Based on the Power Mechanism of Industry Education Integration

Research on Improved Collaborative Filtering Course Recommendation Algorithm in IoT Teaching Platform

Simulation Experiment Analysis of Course Recommendation Algorithm Application

Figure 1: Schematic diagram of research and analysis steps.

personalized recommendations for students to promote the enthusiasm of students and the effect of school-enterprise collaborative education. The driving mechanism of the integration of industry and education is the main way for the development of college education at present. It combines industry and education organically on the basis of the synergy theory so as to realize the synergy of school education with industry and enterprises in educating people [25,26]. The so-called coordination theory is to regard the whole society as a system, in which various factors influence each other, thus affecting the whole society. The training goal of higher
education is to let students apply the knowledge they have learned to the actual development of the industry. Therefore, in the actual industry–education integration model, the market demand and the development of the industry should be taken as the leading factors to establish an operating entity that organically integrates science, teaching, production, learning, and research so as to promote the cultivation and employment of talents.

At present, there are still some problems in the implementation of the integration of production and teaching in colleges and universities. First, the relevant policies and financial support are obviously insufficient. Second, the strength of industry-related organization guidance and supervision is obviously insufficient. Next, the enthusiasm of relevant enterprises to participate in collaborative education is not high. Finally, the training system and assessment system of university teachers are not perfect. Therefore, these problems can be solved by using synergy theory. To sum up, from the perspective of synergy theory, building a cooperation platform between university education and enterprises and implementing the dynamic mechanism of industry–education integration can not only promote the development of universities but also improve the comprehensive competitiveness of the region. Therefore, the research constructs the IoT teaching platform to achieve the smooth integration of production and teaching, and the rule engine is its core. The Rete algorithm is introduced to construct the rule engine. It is the most efficient rule-matching algorithm applied in the rule engine. Its internal terms mainly include facts, rules, and patterns \[27\]. The Rete algorithm organically matches facts and rules to achieve effective reasoning and judgment. If facts and a condition are completely matched, the relevant operation corresponding to the condition is directly executed. The expression of this process is given as follows:

\[
\text{if}(Q_1, Q_2, \cdots, Q_m), \text{then}(B_1, B_2, \cdots, B_n). \tag{1}
\]

In formula (1), \(Q_m\) represents the mode, that is, the condition in the rule. \(B_n\) represents an action sequence. In the actual application scenario of the IoT, the Rete algorithm has the problems of low data matching efficiency and cannot adapt to the mismatch of variables in the actual application scenario. Therefore, the research optimizes it from two aspects: node sharing and pre-sorting and translation lookaside buffer (TLB). Among them, the algorithm flow of Rete network construction under node sharing and pre-sort optimization is shown in Figure 2.

**Figure 2:** Pre-order Rete network construction algorithm based on rule frequency.
From Figure 2, the optimized algorithm utilizes rule frequency. It pre-orders the nodes according to the usage frequency of rules and preferentially selects the mode with higher usage frequency, thus increasing the sharing rate of nodes and reducing the memory consumption of the inference network. In the construction of the Rete inference network, the HashMap algorithm is used to count and locate quickly, and the access times of type nodes are recorded so as to pre-order them. On the rule node, the node-sharing method can be used, which not only saves the storage space but also increases the efficiency of rule matching. In addition, because the rules of the IoT application system have different data intervals and fewer preset rules, the change of the actual environment data perceived by the sensor is slow and linear. Therefore, in a short time, the change of data will not lead to a change of the rule of matching success, which is similar to the local principle. To solve this problem, the improvement of the Rete algorithm by using TLB is studied. The improved algorithm is shown in Figure 3.

From Figure 3, the research uses TLB to save the history of the rules that have been successfully matched before. When the next time it is used, it first matches the last rule. If it is successful, it only needs to be repeated several times to trigger the rule, which can greatly improve the matching speed of the rule. To improve the efficiency of access, the idea of HashMap and Least Recently Used is introduced to redesign the fast table. After two optimizations, the whole optimization of the Rete algorithm is completed. Therefore, with the support of the improved Rete algorithm and the optimized rule engine algorithm, the architecture of the industry–teaching integrated IoT teaching platform is shown in Figure 4.

From Figure 4, the industry–education integrated teaching platform of IoT is mainly composed of equipment, database layer, access layer, persistence layer, business service layer, gateway service layer, and UI interaction layer. In general, the functional module of the industry–teaching integrated teaching platform includes three independent sub-service modules, namely the user management module, theoretical teaching module, and practical teaching module. In the practical teaching module, a new rule engine function is built to support it. In the theoretical teaching module, the CF algorithm is used to realize personalized recommendations for teaching.
3.2 Improved CF course recommendation algorithm in the IoT teaching platform

In the theoretical teaching of the teaching platform of the IoT, to meet the actual needs of online education users, the User-CCIC algorithm is proposed based on the CF algorithm and the user’s own characteristics and interests. The traditional course recommendation algorithm will ignore the influence of user feature attributes on the actual recommendation results, which will affect the actual recommendation accuracy. Generally speaking, users with the same attribute characteristics will be interested in the same course. The characteristic attributes of users usually include age, gender, occupation, specialty, etc. These different attributes will always affect the judgment of user preferences [28]. Among them, the calculation expression of the degree of interest of a user with a certain characteristic attribute in a certain course is shown as follows:

$$f(O_i, L_i) = [U(O_i) \cap U(L_i)].$$  \(2\)

In formula (2), \(n\) represents the \(i\)th feature of the course set. \(L_i\) represents the \(i\)th user characteristic of the statistical characteristic. \(U(O_i)\) indicates the user set \(O_i\) selected for the course. \(U(L_i)\) represents a collection \(L_i\) of all users of statistical characteristics. The expression of \(L\) and \(O\) is shown in the following formula:

\[
O = \{O_1, O_2, \ldots, O_n\}, \\
L = \{L_1, L_2, \ldots, L_n\}.  \(3\)
\]

In formula (3), \(n\) represents the serial number of user characteristics. Overall, the degree of interest of users in the course is expressed by the number of users. But in the actual teaching process, if the time of a course is too short or the teacher’s attitude is too good, everyone will choose this course, which makes it very popular. Therefore, each user will give a very high value, and the most popular courses will be recommended to more people. Therefore, the attenuation coefficient is introduced to reduce the weight of popular subjects, which can reduce the impact on recommendation results. At this time, the calculation expression of the degree of interest is shown in the following equation:

$$f(O_i, L_i) = \frac{[U(O_i) \cap U(L_i)]}{\log(1 + [U(O_i)])}. $$  \(4\)

In formula (4), \(\log(1 + [U(O_i)])\) represents the attenuation coefficient. On the basis of formula (4), the degree of interest of the feature is weighted and summed to get the user’s course scoring results. The calculation is shown in the following equation:
In formula (5), \( u \) represents the user, \( L \) represents the collection of user characteristic attributes. \( \omega_i \) indicates the weight of user attribute characteristics. \( L_{f(u, O, L)} \) indicates the predicted score of the course set. Among them, the relevant expression of \( \omega_i \) is shown in the following equation:

\[
\sum_{i=1}^{|L|} \omega_i = 1.
\]

According to formulas (5) and (6), it can realize personalized recommendations of courses for new users in the absence of scoring data. In addition, when users learn, they usually select courses by entering keywords. For example, when a student majoring in agriculture (forestry) is browsing the course, when he sees the keyword for agricultural products, he will click in to browse and select the course. Therefore, keywords can be used to explore user preferences. The matrix expression of the user-course scoring data of the experimental data set is shown in the following equation:

\[
Z_{rxt} = \begin{bmatrix}
z_{t1} & z_{t2} & \cdots & z_{tt} \\
z_{t21} & z_{t22} & \cdots & z_{t2t} \\
\vdots & \vdots & \ddots & \vdots \\
z_{t1} & z_{t2} & \cdots & z_{rt}
\end{bmatrix}
\]

In formula (7), \( Z_{rxt} \) represents the user-course scoring matrix. \( r \) indicates the number of user sets. \( t \) indicates the number of course collections. Generally, a course can be described by multiple keywords. For example, the keywords “Agriculture (Forestry) Enterprise Management” include agriculture (forestry), enterprise, and management. Therefore, the corresponding attributes of multiple keywords of the course are shown in the following equation:

\[
K = \{k_1, k_2, \cdots, k_z\}.
\]

In formula (8), \( z \) represents the total number of course keywords in the experiment. Therefore, the expression method of the course keyword matrix is shown in the following equation:

\[
K_{t'xz} = \begin{bmatrix}
1 & 0 & \cdots & 1 \\
0 & 1 & \cdots & 1 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & 1
\end{bmatrix}
\]

In formula (9), \( K_{t'xz} \) represents the curriculum keyword matrix. \( t' \) indicates the total number of courses in the experiment. Based on formulas (7) and (9), the user-interest preference scoring matrix can be obtained, and its expression is shown in the following equation:

\[
P_{rz} = Z_{rxt} \cdot K_{t'xz} = \begin{bmatrix}
Z_1 \\
Z_2 \\
\vdots \\
Z_t
\end{bmatrix} \cdot \begin{bmatrix}
k_1 & k_2 & \cdots & k_z \\
k_1 & k_2 & \cdots & k_z \\
\vdots & \vdots & \ddots & \vdots \\
k_1 & k_2 & \cdots & k_z
\end{bmatrix} = \begin{bmatrix}
Z_1k_1 & Z_1k_2 & \cdots & Z_1k_z \\
Z_2k_1 & Z_2k_2 & \cdots & Z_2k_z \\
\vdots & \vdots & \ddots & \vdots \\
Z_tk_1 & Z_tk_2 & \cdots & Z_tk_z
\end{bmatrix}
\]

In formula (10), \( P_{rz} \) represents the user-interest preference matrix. Then, it is necessary to express the user’s score of course keywords in the form of the matrix, and the specific calculation expression is shown in the following equation:

\[
P_{rz} = \begin{bmatrix}
a_{11} & a_{12} & \cdots & a_{1z} \\
a_{21} & a_{22} & \cdots & a_{2z} \\
\vdots & \vdots & \ddots & \vdots \\
a_{t1} & a_{t2} & \cdots & a_{tz}
\end{bmatrix}
\]

In formula (11), \( a \) indicates the score of each keyword. It is worth noting that the use of keywords in practical applications cannot achieve the best recommendation effect. Therefore, the study introduces similar
preferences among user groups to improve it. For the clustering problem in the User-CCIC algorithm, a fast approximation algorithm (Canopy) is introduced and mixed with K-means clustering algorithm (K-means). The equality expression of the two thresholds in the Canopy algorithm is shown in the following equation:

$$ T_1 = 2 \times T_2. $$

In formula (12), $T$ represents the threshold value in the Canopy algorithm. The calculation of $T_2$ is shown in the following equation:

$$ T_2 = \frac{\sum_{i=1}^{n'} \sum_{j=1}^{n'} y_i \cdot y_j}{n'^2}. $$

In formula (13), $y_i$ and $y_j$ represent the point vectors of user clustering. $n'$ indicates the specific number of user clustering point vectors. Therefore, for target users, the similarity calculation formula can be used to predict the actual course score. The calculation of the predicted score is shown in the following equation:

$$ L_f(u, O) = \overline{r}_u + \frac{\sum_{O_i \in \text{user}} \text{sim}(u, v)(r_{i, O_i} - \overline{r}_u)}{\sum_{O_i \in \text{user}} \text{sim}(u, v)}. $$

In formula (14), $\text{sim}(u, v)$ indicates the similarity between users $u$ and $v$. $\overline{r}_u$ indicates the average score of user $u$. $r_{i, O_i}$ indicates the user $v$’s rating of the $i$th course. According to the similarity results, the relevant scores of users on the course collection can be predicted. Finally, the User-CCIC algorithm proposed by the research is obtained after the fusion of feature attributes and similar preferences. The specific scoring prediction method of the User-CCIC algorithm is shown in the following equation:

$$ L_f(u, O) = L_f(u, O_i) + aL_f(u, O_i). $$

In formula (15), $L_f(u, O_i)$ represents the scoring result of user characteristic calculation. $L_f(u, O_i)$ indicates the scoring result of clustering calculation based on user preferences. $a$ represents a constant, which is usually between (0, 1). Therefore, the specific process of the User-CCIC algorithm course recommendation is shown in Figure 5.

**Figure 5:** Specific process recommended by the user-CCIC algorithm course.

From Figure 5, the User-CCIC algorithm course recommendation is first to build a dataset of user-features, user-course scores, and course-keywords. The second is to normalize the score of user courses. The user preferences are calculated for course keywords. Then, the preference is clustered, and the improved user similarity is calculated to generate the nearest neighbor so as to obtain two prediction scores. Finally, the best recommendation result is obtained.
4 Course recommendation algorithm application simulation experiment analysis

4.1 Simulation experiment of the IoT teaching platform based on the driving mechanism of the integration of production and education in universities

To verify the effectiveness of the IoT teaching platform and the internal online course recommendation algorithm, the research conducted simulation experiments on both. First of all, due to various resource constraints, the research only tested the response speed of the platform, including the database index comparison test, cache comparison test, and the overall result test. The results are shown in Figure 6.

![Figure 6: Experimental results of response speed of IoT teaching platform. (a) Database index comparison test, (b) Cache comparison test, and (c) overall results test.](image)

From Figure 6, the query time with or without index under multiple interfaces is maintained within 0–350 ms, and the query time with index is lower than that without index on the whole. In the cache comparison experiment, the query time with cache is lower than that without cache in multiple interfaces. In the overall result experiment, the response time of several important interfaces is maintained between 0 and 300 ms, which is in a normal and reasonable range. In general, the interactive IoT teaching platform will increase the efficiency of the query with index and cache. The overall response performance is good, and the response speed is fast, meeting the actual non-functional requirements. These results are basically consistent with the results of previous studies [3–5]. On this basis, the improved Rete algorithm for building the important rule engine of the platform is experimentally verified. First of all, the memory consumption and time consumption are compared with the traditional Rete algorithm during construction, and the results are shown in Figure 7.

![Figure 7: Comparison results of memory consumption and time consumption of the two algorithms during construction. (a) Comparison of construction memory consumption, and (b) construction time consumption comparison.](image)
From Figure 7, with the increase of the rules, the memory consumption of these two algorithms has increased. When the rules are 300, the memory consumption of the traditional Rete algorithm is close to 8,000 kb, which is much higher than the improved Rete algorithm. In addition, the construction time of the improved Rete algorithm is slightly higher than that of the traditional algorithm. When the rules are 300, the construction time of the improved Rete algorithm exceeds 9,000 ms. In summary, the improved Rete algorithm greatly reduces the consumption due to the addition of pre-sorting, but the construction time is increased. However, compared with the time consumption of rule matching, the increased time is acceptable. Based on this, the research analyzes the time consumption and total time consumption of rule matching, and the results are shown in Figure 8.

![Figure 8: Comparison results of rule matching time consumption and total time consumption of the two algorithms. (a) Comparison of rule matching time consumption, and (b) total time consumption comparison.](image)

From Figure 8, in terms of rule matching time consumption, with the increase of the rules and facts, the time consumption of both algorithms has increased. When the rules are 50, the traditional Rete algorithm takes the most time. In terms of total time consumption, the traditional Rete algorithm takes more time than the improved algorithm. When the real events are 10,000, the total time consumption of the traditional Rete algorithm exceeds 3,500 ms, which is much higher than the improved Rete algorithm. When the number of facts is small, the proportion of network construction time is high, while when the number of facts is large, the proportion of the matching network is high. Therefore, in the actual teaching environment of the IoT, the improved Rete algorithm performs better. The algorithm proposed in the study can effectively store historical information, thus effectively improving the matching efficiency of the perceived data of the IoT and laying a good foundation for the internal course recommendation algorithm.

### 4.2 Performance analysis of improved CF algorithm

On the basis of verifying the performance of the platform, four indicators including mean absolute error (MAE), root mean square error (RMSE), accuracy, and recall are introduced to evaluate the User-CCIC algorithm. In the experiment, the User-based CF Recommendation Algorithm (UBCF), User Characteristics and Trust (User-CT), CF Algorithm for User Interest Preference Clustering (UICCF), and User-CCIC algorithm are compared. Among them, the comparison results of MAE and RMSE values of different algorithms under different numbers of close neighbor users are shown in Figure 9.

From Figure 9, MAE and RMSE change smoothly when approaching 70 adjacent points, and the User-CT algorithm is close to the algorithm in this article. At this time, the MAE value of the UBCF algorithm is 0.8453, UICCF is 0.8382, and User-CT is 0.8256. The User-CCIC algorithm is 0.8116, lower than the other three
comparison algorithms. In addition, when the number of nearest neighbors is 70, the RMSE value of the UBCF algorithm is 0.9528, UICCF is 0.9504, and User-CT is 0.9487. The User-CCIC algorithm is only 0.9455, which is also lower than the other three algorithms. Overall, the User-CCIC algorithm performs better. The comparison results of accuracy and recall values under different numbers of close neighbor users are shown in Figure 10.

In Figure 10, UICCF, User-CT, and User-CCIC algorithms are studied and compared. From Figure 9, the number of nearest neighbors is 60, which is a node of the three algorithms. At this time, the accuracy value of the UICCF algorithm is 0.2004, and User-CT is 0.2384. The user-CCIC algorithm is 0.3043, which is much higher than the comparison algorithms. In addition, the recall value of UICCF is 0.0924, and User-CT is 0.1163. User-CCIC is 0.1475, which is higher than the comparison algorithms. Overall, the accuracy and recall rate of the User-CCIC algorithm are better than the comparison algorithms, with better performance and the best recommendation effect. Therefore, to verify the actual recommendation effect of the algorithm, the research takes agricultural curriculum recommendation as an example to verify the recommendation effect and user satisfaction of the algorithm, and the results are shown in Figure 11.

In Figure 11, the study analyzed three courses with high similarity, namely, agribusiness management, agricultural economics, and agricultural technology economics, which are represented by A–C, respectively. Also, the courses were evaluated with a full score of 6. The satisfaction rating scores of the three courses maintained between 3 and 5, mostly 4 to 5, in the course evaluations of the six student users. In addition, the satisfaction rates of the three courses were in the range of 70 to 100%. Taken together, the User-CCIC algorithm course
recommendations were more effective, with higher user satisfaction, higher than 70% overall, and higher recommendation accuracy. It shows that the actual recommendation effect of the User-CCIC algorithm is better.

To further verify the robustness of the User-CCIC algorithm, a comparison was conducted between the content recommendation algorithm (a), the algorithm using big dataset technology (b), the recommendation method using CF algorithm (c), and the recommendation method using deep learning (d). Five different courses were selected for recommendation, and the results are shown in Table 2.

![Graph showing accuracy and user satisfaction of the User-CCIC algorithm in agricultural course recommendation.](image)

**Figure 11:** Accuracy and user satisfaction of the User-CCIC algorithm in agricultural course recommendation. (a) Satisfaction rating of different users for different courses, and (b) satisfaction rate of different users for different courses.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>1(%)</th>
<th>2(%)</th>
<th>3(%)</th>
<th>4(%)</th>
<th>5(%)</th>
</tr>
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<tbody>
<tr>
<td>a</td>
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<td>80.1</td>
<td>71.2</td>
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</tr>
<tr>
<td>b</td>
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<td>73.2</td>
<td>70.1</td>
</tr>
<tr>
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<td>80.0</td>
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<td>83.4</td>
</tr>
<tr>
<td>d</td>
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<td>77.2</td>
<td>74.3</td>
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</tr>
<tr>
<td>User-CCIC</td>
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<td>96.8</td>
<td>98.1</td>
<td>97.2</td>
<td>96.3</td>
</tr>
</tbody>
</table>

From Table 2, the User-CCIC algorithm maintains a recommendation of over 965% for all five courses. Due to the comparison of algorithms, this result indicates that the User-CCIC algorithm has high performance and robustness.

### 5 Discussion

With the continuous innovation of technology, online education is booming, and more and more course resources are being placed on online education platforms. The number of online learning users and course resources is constantly increasing, causing information overload on online education platforms. The course recommendation system can effectively solve the online course information explosion. Highly reliable course recommendation algorithms need to be developed to quickly and accurately obtain the course information users need and provide perfect recommendation results, which has become a research focus. Course recommendation systems mine and analyze user-related information to achieve recommendation functions that meet user needs and interests. Therefore, the research has built an IoT teaching platform that integrates industry and education. Based on CF algorithms, a User-CCIC course recommendation algorithm is proposed for its internal online education.
The experimental results indicate that in the overall experiment, the response time of multiple important interfaces is maintained between 0 and 300 ms, which is within a normal and reasonable range. This result is basically consistent with Panda et al. [29]. When the number of real events is 10,000, the total time consumption of the traditional Rete algorithm exceeds 3,500 ms, which is much higher than the improved Rete algorithm. This result is better than the result of Williams et al. [30]. In addition, when approaching 70 adjacent points, the changes in MAE and RMSE are relatively stable, and the User-CT algorithm is relatively close to the algorithm in this article. At this point, the MAE value of the UBCF algorithm is 0.8453, the UICC is 0.8382, and the User-CT is 0.8256. The User-CCIC algorithm has a value of 0.9116, which is lower than the other three comparative algorithms, and this result is superior to the results of Amane et al. [31] and Ruiyuan [26]. A nearest neighbor number of 60 is one node of the three algorithms. At this point, the accuracy value of the UICC algorithm is 0.2004, the User-CT is 0.2384, and the User-CCIC algorithm is 0.3043, which is much higher than the comparison algorithms and the results of Tahir et al. [32].

Overall, the research on building an integrated industry education IoT teaching platform has achieved good results, and its internal online course recommendation algorithm performs well. The research on building an integrated industry education IoT teaching platform unifies online teaching and practical teaching, which can comprehensively enhance students’ learning interests.

6 Conclusion

To address the current issue of integrating industry and education in universities under the background of education reform, an IoT teaching platform integrating industry and education has been studied and constructed. The User-CCIC course recommendation algorithm has been proposed, and its effectiveness has been verified through experiments. The experimental results show that the response speed of the industry–teaching integrated teaching platform of the IoT is maintained within 0–350 ms when there is an index. The overall response speed meets the actual needs, and the platform performance is good. In the verification experiment of the improved Rete algorithm of its rule engine, when the number of rules is 300, the memory consumption of the traditional Rete algorithm is close to 8,000 kb. When the number of facts is 10,000, the total time consumption of the traditional Rete algorithm exceeds 3,500 ms, which is higher than that of the improved Rete algorithm. Finally, in the User-CCIC algorithm validation experiment recommended by the online education course within the platform, when the nearest neighbor number is 70, the MAE value of the User-CCIC algorithm is 0.8116, and the RMSE value is 0.9455, both lower than the comparison algorithm. The accuracy value is 0.3043, and the recall value is 0.1475, which are higher than the comparison algorithms. Finally, in the actual agricultural online course recommendation, the satisfaction of the User-CCIC algorithm is higher than 70%, showing high accuracy. In general, the constructed industry–teaching integrated teaching platform of the IoT has a good effect, and its internal online course recommendation algorithm has a better performance. However, the improved Rete algorithm proposed in the study does not optimize the construction of the Beta network during the network construction process due to the short-term invariance of rules. After the rules become more complex, it can be considered to solve the empty connection problem through pruning or dynamic linking and increase the index of Beta to ensure access speed. Although the research and design platform has the ability to distribute deployment and disaster recovery switching, sufficient clusters have not been constructed due to the limitations of the laboratory environment. In the comprehensive implementation of the platform, efforts should be made to build large clusters and solve the problems that arise during the process, making the platform a stable and reliable high-efficiency teaching platform.

Funding information: The research was supported by the Jiangsu Higher Education Association Evaluation Committee project: Research and practice on teaching quality evaluation and feedback mechanism of offline and online mixed courses from the perspective of social psychology (No.: 2021-Y12); the special project of “Research on the Digital Transformation of Intelligent Education and Teaching” in Jiangsu Universities in 2022: Research and practice on the whole-ecology collaborative development mode of talents training integrating
industry and education in industrial colleges (2022ZHSZ52); The practice path of “three dimensional and multiple” labor education in agriculture and forestry colleges under the background of ecological civilization. Excellent Practice Project of Labor Education in colleges and Universities of Jiangsu Province in 2022 (No. 2022JSLP1-078); Research on the practical path of constructing the “grand aesthetic education” system from the perspective of “Five-education integration” in agriculture and forestry colleges. Nanjing Forestry University 2022 Higher Education research project (No. 2022B15).

Author contributions: Yu Shen proposed a concept. Xiaojiang Yang analysed the data. Yu Shen and Xiaojiang Yang conducted the experiments and analysed the results. All authors discussed the results and wrote the manuscript.

Conflict of interest: The authors declare that they have no conflicts of interest to report regarding the present study.

Data availability statement: Data may be obtained from the corresponding author upon reasonable request.

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