Intelligent and Interactive Chatbot Based on the Recommendation Mechanism to Reach Personalized Learning

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ABSTRACT

With the impacts of Covid-19 epidemic, e-learning has become a popular research issue. Therefore, how to upgrade the interactivity of e-learning, and allow learners to quickly access personalized and popular learning information from huge digital materials, is very important. However, chatbots are mostly used in automation, as well as simple occasions of general standard question and answer. But to solve the different problems of e-learners in the learning process, chatbots are used to filter the blind spots of learners and to provide further relevant information, so that e-learning can improve in efficiency and interactivity. This study utilizes AI, two-stage Bayesian algorithm, and crawler technology to provide customized learning materials according to learner's current learning situation. The experimental results show that this research system can indeed correctly understand and judge the blind spots of digital learners, and effectively find the relevant e-learning and video information. The accuracy rate reaches nearly 90%.

KEYWORDS

Bayesian Algorithm, Blind Spots, Chatbot Tutor, Crawler Technology, E-Learning, Personalized Learning Mechanism, Sustainability of Education

INTRODUCTION

The Cross-domain learning has become an irresistible trend in recent years. The e-learning itself means that the learning materials and resources in other professional fields can be viewed at any time, and it is not limited to any time or place. The e-learning has developed into an important learning method and channel for cross-domain learning in other professional fields. However, how to create an excellent digital learning platform to allow e-learners to reduce their difficulties and barriers in different subjects or college majors will be the most important key factor affecting the effect of e-learning.

This research utilized courses in learning to cook as an example, with the concept of healthy eating gaining popularity during the Coronavirus disease (COVID-19) lockdowns. However, despite the various recipes and teaching videos on the Internet, it can be impossible to solve the various problems or exceptions encountered by the cook owing to one or more technical gaps, leading to the

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failure of the finished product. The proper use of an e-learning platform and artificial intelligence technologies (Ayodele et al., 2011; Wahyono, 2019) could immediately provide solutions to actual problems for users learning to cook. This could also provide more detailed teaching explanations and instructions when encountering such problems, thereby effectively addressing the key blind spots in cooking. That is, when learners watch online teaching videos (Carver et al., 1999; Salehi et al., 2013), they can ask for more detailed answers in time by entering keywords to the robot teaching assistant when they encounter problems (Chen et al., 2008; Chen, 2011). The finished dish will not only be more fulfilling but will also make the entire e-learning process more interesting. This research also used two-stage Bayesian algorithms and chatbots to interact with learners and created an intelligent e-learning platform to help them effectively and instantly solve the difficulties encountered in the learning process (Ramaswami & Rathinasab, 2012; Yao, 2017; Ogata & Yano, 2004). Simultaneously, this approach could bring the real-time puzzle function of a virtual teacher to e-learning (e.g., to solve the above problems) (Chen & Li, 2010), attract increased user attention to active learning, and enhance the effects of e-learning (Chu et al., 2004; Cormac & Siobhan, 2008).

Many people are interested in learning about various topics after they graduate or outside of their original majors, but they often do not have sufficient time to take these professional courses, owing to tremendous factors, such as work, school, and family. Therefore, the e-learning has become the gospel for students in online learning (Obasa et al., 2013). Still, the current popular research topics in e-learning mainly focus on the production and provision of digital teaching materials and how to automatically provide additional digital teaching materials to learners. As a result, learners are often faced with a huge amount of digital learning materials, but they do not know where they should start learning at present or where they really want to learn. Therefore, e-learning often lacks the proper digital textbooks to give students when they encounter problems and is unable to provide direct guidance (like a real person could) or find the crux of the problem. Moreover, e-learning cannot quickly understand the student's situation based on the student's current encountered problems. Because these problems in the learning process (learning blind spots) cannot be solved immediately, the learning process will either be stuck and cannot continue, or the students even give up learning.

Accordingly, e-learning often lacks interactivity and an understanding of the learners' actual learning and absorption status during the learning process (Chen, 2011). It is necessary, therefore, to rely on learners to select courses that meet their own learning progress from a large number of digital textbooks. But this requirement is difficult for most digital learners. The e-learners really need to get instant solutions and help in the process of distance learning.

Hence, this research aims to address the abovementioned shortcomings in the field of e-learning and mobile learning by proposing an intelligent and interactive "Chatbot for a Personalized Learning System"; this system can also be improved and upgraded (Kao, 2017; Wi, 2017). First, this system utilizes two-stage Bayesian algorithms combined with chat robots to personalize digital learning and enhance its interactivity. Moreover, to effectively grasp the actual learning situations of users in the e-learning process, the learning system of this research provides a smart recommendation mechanism for better understanding the blind spots (Fayyad et al., 1996; Roy & Mandal, 2015) during the learning process by letting users enter the instant learning questions (Han & Kamber, 2001; Shyu et al., 2005). The chatbot teaching assistant will perform semantic analysis on the questions input by the learners and, after extracting the keywords, use the Bayesian algorithm to filter out the closest learning materials and recommend them to the learners for reference (Xiao et al., 2018). It provides personalized real-time digital supplementary teaching materials to learners (Yi & Zhang, 2021; Catarinucci et al., 2015), saving them time otherwise spent searching for other suitable digital teaching materials by themselves (Hamet & Tremblay, 2017). The system is aimed at the different learning problems encountered by digital learners when watching the teaching videos and teaching materials and uses an analysis based on "natural language" and a "Bayesian algorithm" to analyze the logical relationships between the units of each course. Accordingly, it can recommend suitable learning programs, digital learning materials for different learners, and commentary materials for specific units as solutions.

In this paper, the intelligent learning and recommendation strategy with the virtual teacher chatbot (Joseph, 2014) provided not only the real-time learning materials according to the individual e-learner's learning situations, in addition, the effect of the recommending mechanism on upgrades to the learning interests, learning behaviors, active learning attitude, and the learning achievement of the e-learner. The research objectives are as follows:

1. To discuss the impact of virtual teachers collecting and providing real-time digital learning support for e-learning and the effect on e-learners.
2. To explore the cultivation of active learning and casual hobby attitudes in e-learning through the assisted learning of chatbot virtual teachers (Homsi et al., 2008).
3. To explore the effect of the recommending mechanism on continuously cultivating the learning interest and capabilities of e-learners.
4. To discuss the differences in the learning achievement with different recommending learning algorithms (Hogo, 2010).

RELATED RESEARCH AND TECHNOLOGIES

Mobile Learning

Mobile learning is often referred to as m-learning and represents a method of digital learning. The most significant difference from general e-learning is that m-learning focuses on the use of mobile devices (smartphones, tablets, etc.) so that users can learn anytime and anywhere, without being restricted to classrooms or fixed places and times. The advantages and disadvantages of mobile learning are listed in Table 1.-Some scholars have proposed a "Person-Centered Sustainable Model for Mobile Learning," indicating that the core role of mobile learning was as the teacher, that is, to directly interact with all of the people involved in the mobile learning role (Guo et al., 2006; Kuo et al., 2011; Kumar et al., 2015). When the students encounter problems, teachers and students must maintain a trustworthy and clear communication channel for mobile learning to proceed smoothly (Sakulwichitsintu et al., 2018; Panigrahi et al., 2018).

From the above viewpoints, it can be concluded that mobile learning should have four main aspects: use of mobile vehicles or wireless network technologies, meaningful learning activities for learners, active and contextual elements, and a ubiquitous learning environment. In traditional digital teaching, some students are often distracted or unable to keep up with the course, but teachers frequently cannot grasp such students' learning conditions (Roy & Mandal, 2015). Real-time recording, effective compilation, and uses for future follow-up counseling have led to obstacles in communication between teachers and students.

This research intends to use the information of students in learning, such as portions where there are more pauses when viewing a textbook, the technical terms of a query, the question of a chat robot, and the download statistics of an online textbook (Cohen et al., 2001; Lim & Cho, 2006; Liao et al., 2011). This information is transmitted to the system for storage in real time; for future tracking analysis, the teacher can clearly understand the students' problems when they are recommending other related textbooks to help students solve their difficulties immediately, and even when giving feedback to teachers for consultations to adjust online textbooks (Bell et al., 2021; Homsi et al., 2008).

Data Mining

Data mining can be separated into data mining and data exploration (Fayyad & Uthurusamy, 1996; Liu, 2009). It is knowledge discovery process for databases. It is a process of finding the trend

Table 1. Advantages and Disadvantages of Mobile Learning

Advantages	Disadvantages
1. Use mobile devices to learn anytime and anywhere	1. Lack of instant interaction, learners tend to feel isolated when they encounter problems
2. Adapt to individual differences, learners can learn according to their own level and progress	2. Badly designed teaching materials can easily make learners feel bored
3. Students can repeat until they understand the content of the course	3. Learners with poor autonomy tend to fail halfway according to the plan
4.The teaching activities are carried out with students as the main body, and the teacher becomes the role of the guide	4. Learners must spend a significant amount of time participating in course content activities, which will undoubtedly constitute a learning obstacle for learners who are not motivated to learn

characteristics and correlations hidden in data from a large database. To discover the meaningful patterns or rules in a large amount of data, it is necessary to explore and analyze the data in an automatic or semiautomatic manner (Brijesh & Baradwaj, 2011).

Data mining has become an important research issue in e-learning and m-learning, when information is readily available, and the amount of such information is massive. This study used an association rule, word segmentation technology, and a Bayesian algorithm as mechanisms for helping chatbots to answer questions.

Chatbot

A chatbot is a program that responds to a “natural language” input and attempts to simulate a human in its response. Chatbots are currently divided into two categories: open and closed. Closed-domain chatbots provide information on fixed and single-domain topics, such as news, weather, and e-commerce (Wang et al., 2021); they can respond according to preset function items. Although they cannot answer questions without the database, these chatbots can answer quickly and very specifically; thus, they are suitable for interactive common questions, such as those regarding support and service functions. The chatbot in this research uses this function to answer the question and answer (Q&A) the basic questions of digital learning materials (Gao et al., 2016).

Open-domain chatbots can accept topics in any field and use natural language understanding, natural language processing, and machine learning to perform while learning. The interactivity is higher and more personal than in the closed domain.

In addition, chatbots can be personalized according to the user’s personal data and past behavior records and learn their preferences over the time of the record to provide suggestions and even predict needs (Jagadeesan & Subbiah, 2020).

Bayesian Algorithm

The Bayesian algorithm is a machine learning method based on a probability type classification. It uses Bayes’ theorem to perform calculations and assumes that the events between the features are independent of the establishment of a simple and effective classification algorithm for a small number of training sets. Good classification accuracy is generally achieved.

The Bayesian algorithm uses the concept of tags to classify various data into each type of tag, finds the likelihood probability for each type of tag, and puts these values into the Bayesian formula to calculate the posterior probability and determine the relevance of the tag. This is used to judge whether each type of label adds weight to the probability of influencing the result (Guo et al., 2006; Lim & Cho, 2006). The advantages and disadvantages of the Bayesian algorithm are listed as follows (Table 2).

Table 2. Advantages and Disadvantages of Bayesian Algorithm

Advantage	Disadvantages
1. Low computational cost and efficiently process large data	1. In the data model, it is almost impossible to obtain completely independent predictors
2. Performs better on discrete response variable data	2. If there is no training tuple of a specific class, it will lead to zero posterior probability. In this case, the model cannot predict this problem; this is called the zero-frequency problem
3. Can be used for many prediction problems	3. Does not handle a large number of multiclass features or variables well
4. When the independence assumption is established, Bayesian classifier performs better than other models, such as logistic regression	

One of the disadvantages of naïve Bayes is that if there are no occurrences of a class label and a certain attribute value, then the frequency-based probability estimate will be zero. This will result in zero when all probabilities are multiplied. The zero probability problem is that when the data set is large enough and a certain item X in the data set is used for machine learning, if it does not appear in the training set, the probability result of the entire X item will be 0.

But in the machine learning processing of text classification, when a word does not appear in the training samples, the probability of the word appearing is 0. To solve this type of problem, Laplace smoothing can be used to assist in the correction.

Laplacian smoothing is a smoothing technique. Assuming that the dataset is large enough to add a piece of data to each category without affecting the estimated probability, the zero-frequency problem will be overcome. To solve the problem of zero probability, this study uses the Laplace smoothing method, which was proposed by the French mathematician Laplace. The premise of the method is that the original data set is large enough. Use the method of adding 1 to estimate the probability of items that have not appeared before, so that the data with extremely low probability will not become 0 and will not have any impact on the selected data set.

Therefore, this study adds 1 to the column with the number of data 0 as Laplace smoothing, so that when the algorithm extracts the data item with the number of data 0, the probability of 0 does not occur, so as to be more in line with the actual condition of the mother. The main significance of Laplacian is to remove statistical extremes by smoothing coefficients, so that the sampled sample set is more in line with the actual distribution of the parent.

This research uses the Bayesian algorithm to analyze the types of problems that users encounter in learning, to find similar problems, and then to determine the possible causes of the problems. When users encounter problems, sometimes it may not be that a certain step cannot be understood or is difficult to implement. It may be that the steps in the first few steps are wrong, or that the basic knowledge is incorrectly understood or unclear. If there is something students do not understand, they must spend a considerable amount of time consulting various reference materials. Even if the information is found, it may not be the solution to the real cause of the problem; moreover, it may not be completely understood because the basics are not complete. For students who are just beginning, this may cause a confidence blow, and reduce their willingness to learn (Fazeli et al., 2016; Long, 2016). Therefore, through the Bayesian classifier, the points that will potentially cause problems among the entire learning data set are classified, labels and weights are set to determine the possible probabilities of the causes of the problems encountered by the students, and the probability and weight are used to determine the ultimate causes of the problems. Then, relevant teaching materials and videos can be provided, along with guidance to solve the difficulties encountered.

Scenario-Aware Learning

Behind people's learning behaviors, there is often various important learning information that remains hidden. Therefore, context-aware technology can obtain information regarding the user's environment through sensors to understand the user's behavioral motivations. Through context-aware technology, we allow the mobile learning system to use the relevant environmental information that otherwise is not easily noticed and to develop system functions more in line with the learning needs of the users (Verbert et al., 2012).

To effectively enhance the interactivity of mobile learning and increase the sustainability of active learning, this study uses scenario-aware learning to assist the system in improving learners' willingness and motivation to learn. Context-aware learning is based on the premise of a perfect network and communication equipment and uses context-aware technology and various sensors, the high mobility of mobile devices, and contextual learning theory to enable learners to simultaneously learn anytime and anywhere and to interact with real situations (Catarinucci et al., 2015). In addition, this system records the user's learning process through a "situational awareness module" (Luis et al., 2017) and provides personalized learning services. When users use the system, they learn about their learning status, learning problems, and preferred learning (Tsai, 2009). Projects and other tasks are recorded and relevant teaching materials are given according to preferences. Moreover, personal learning maps are generated to produce a more interactive learning experience.

FRAMEWORK OF INTELLIGENT MOBILE LEARNING INFORMATION SYSTEM

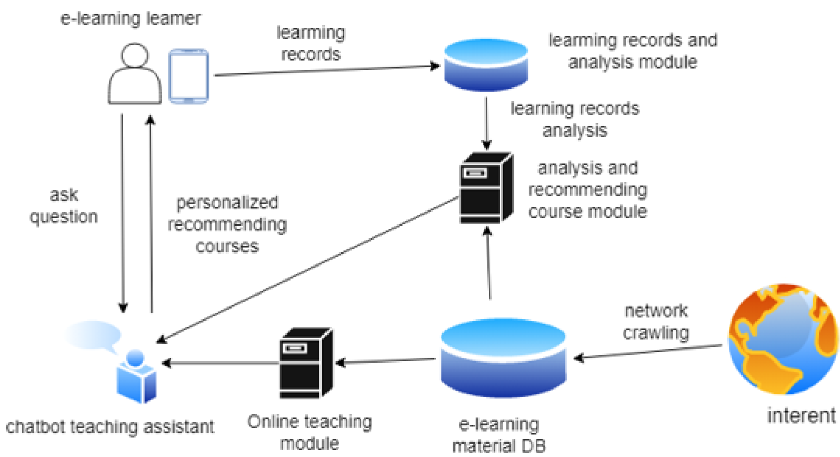
In the chapter 2.1. Mobile Learning, this research analyzed the advantages and disadvantages of mobile learning, aiming to increase the sustainability of e-learning. This chapter focuses on these shortcomings and deficiencies and explains in detail how to use the modules and functions of this research system to effectively improve and enhance the interactivity of traditional e-learning systems. The goal is to increase learners' mastery and understanding of actual learning and absorption in the learning process so as to enhance the learning quality of e-learning and m-learning, thereby effectively enhancing e-learners' active learning abilities and achieving the sustainable development of e-learning.

The recommended learning mechanism of the virtual chatbot based on the Bayesian algorithm in this study is also applicable to the content of general e-learning materials, that is, it can effectively find highly relevant e-learning materials according to the learners' problems and provide them to the learners. And the improved two-level Bayesian algorithm proposed in this study can further find "digital learning materials that are related to the keywords of the questions raised by learners". Therefore, the learning functions of this study are also applied in the e-learning materials for others professional fields, but this study chose the learning content of cooking courses as an example to illustrate. The main reason is that cooking courses are learning content with a high degree of practicality and are also a relatively difficult digital learning content. Therefore, in order to confirm the applicability of this research, the cooking course was chosen as the digital learning course of this research.

System Architecture

This system has five main modules: a user interface, learning record and analysis module, chatbot teaching assistant that is a virtual tutoring system (Motaung & Makombe, 2021), course analysis and recommendation module, and e-learning materials DB(Database), as shown below in Figure 1. A user can log in to the system and inform the chatbot of the content of the digital teaching materials they want to learn, and the chatbot will proceed to the "digital textbook database" to find the suitable digital teaching materials for the user according to the learning demands. Then, when the learner uses the digital textbook or watches video lectures, the robot can offer timely replies to all the questions. After the chatbot receives the content, it uses the "Question Analysis Module" to segment

Figure 1. System Architecture Diagram



the sentences and determine their semantic meanings, and then the analyzed semantics are used to determine the main meanings and intentions of the e-learners. Then, the system will enter the back-end analysis module, use the "Two-Level Bayes Analyzer" to search for the most relevant learning content and digital teaching information for the user, and, according to the level of relevance, sort the online teaching materials according to their relevance. The system will then judge the priority order and provide the materials to the user. When users encounter problems in online learning or do not understand a certain part of the online video teaching material, the "Line Bot Assistant" can act as a teacher to supplement knowledge and solve problems. This will help solve the past shortcomings of e-learning or m-learning (e.g., past learners becoming overwhelmed when they encounter problems), and will simultaneously increase the interactivity, so that e-learners can feel like learning partners.

System Module Operations and Features

Virtual Teachers to Collect and Assist Learners' Learning Situation in Time

The "Line Bot Intelligent Tutor" module is a module for showing the user interface to the user, and the learner can implement actions through the operation interface (Escobar-Fandiño et al., 2020). Various learning management functions can be accessed, such as browsing digital teaching materials or video teaching and searching for past textbooks. The processes are shown below as steps (Ramaswami & Rathinasab, 2012) of Figure 2. On the other hand, the User Interface(UI) also receives the recommended courses sent back by virtual teachers, chatbots, and answers to questions from online learners. The processes are shown below as steps (Cormac & Siobhan, 2008) of Figure 2.

Establish Learners' Active Learning Attitudes and Habits

The "Semantic Aware" module and "Multimedia Teaching" module, together with the "Personalized Learning Database(DB)," can provide personalized services by analyzing students' learning profiles, referring to the correlations between courses, and providing the contents of the video teaching materials. That is, by analyzing the main semantics in the e-learner's question, after finding the blind spots, the course relevance analysis agent will use the most suitable keywords to perform a two-level Bayesian algorithm to find the most related learning materials from multimedia teaching material DB to the e-learner, as shown below in step (Ogata & Yano, 2004; Carver et al., 1999; Salehi et al., 2013) and step (Chen et al., 2008) of Figure 2. The relevant learning materials and information are provided to learners, which will help cultivate a continuous active learning attitude and self-management learning style in e-learners. Therefore, learners can easily consider autonomous learning plans and then, through active learning, achieve the main goal of the sustainability of their e-learning and education.

Through the Recommendation Mechanism, Continuous to Build Learners' Learning Interests and Capabilities

The "Learning Record" module can record the textbooks that the user has learned and link the recorded data to the "Analysis and Recommendation Module" so that it can analyze the user's possible learning through the "Bayesian Classifier" technology, for example, to identify problems encountered and possible causes of problems encountered in the past. After the analysis is complete, this module will use the "context-aware learning technology" to predict the textbooks or e-learning materials users may be interested in, and based on the above data, it will integrate and recommend suitable learning materials or learning routes for users to learn more efficiently, as shown in steps (Salehi et al., 2013) and (Chu et al., 2004) of Figure 2. When learners watch video teaching files from the multimedia teaching material DB which is the database and encounter unintelligible content, they can use the line bot to help them judge the learning blind spots the learners are currently encountering and provide other highly relevant digital learning materials through the recommendation mechanism, as shown in step (Cormac & Siobhan, 2008) of Figure 2. It can also reduce the time required to select learning materials and find solutions to problems, achieving a multiplier effect with half the effort.

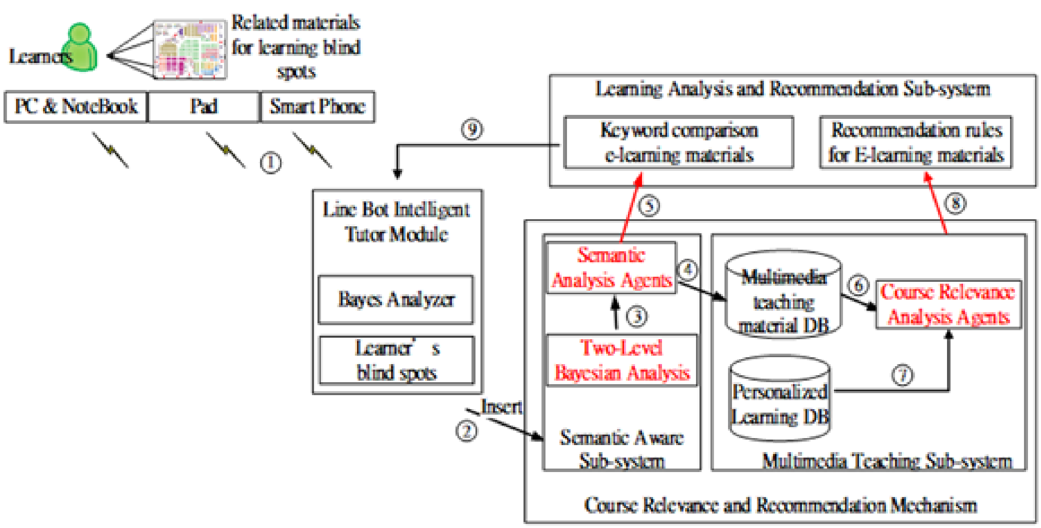
System Functions

User Management

- List of recipes and history records

First of all, the e-learners can obtain relevant audio-visual cooking teaching materials for e-learning through the personal computer(PC), notebook(NB), pad which is a general term for a tablet computer, or smart phone and other small, portable devices. Users can choose the cooking they want to learn through the cooking list and can classify the cooking according to the type of cooking,

Figure 2. System Architecture and Modules



difficulty, and time consumption. After determining the learning goal, this information is sent to the chatbot. This allows the chatbot to give learners the textbook videos, materials, and precautions they need for learning. In addition, the history record can record the cooking that the user has performed and classify the cooking style, difficulty, time, and other factors according to the record, viewing time, number of views of a certain clip or teaching material, etc. The data sent to the database allow the "Analysis and Recommendation Module" to recommend suitable learning objectives for the user, and it can also be linked to the "Learning Record" module to record the problems encountered by the user. Users can also review their cooking history based on this record to view their own learning status.

- Recipe collection and sharing

Recipe collection allows users to collect their favorite textbooks, and then to learn directly through this function in the future.

Recipe sharing allows users to write recipes or experiences that they want to share and upload them to the database so that other users can also learn via video teaching and communication. This system also adds a scoring system, uploads it to the database, and links to the "Recommendation and Analysis Module," so that recipes with high ratings can be more easily exposed to other users.

Learning Record and Analysis

This function records the number of times the user has watched a textbook, where in the textbook the user has been paused, and the length of the viewing time. At the same time, it records the problems encountered in learning, uploads learning materials to the database, and identifies when the user successfully solves the problem. It also records which data are used to solve the problem so that the user can review and give higher recommendations for the problem-solving data when other users encounter the same problem. This allows users to analyze where learners have blind spots that are not clear or understood.

Learning Material Database

This function is used to store a database of various teaching materials. In addition to storing various teaching material videos and related data, a network is also used to collect various teaching materials, videos, and data provided by the "User Sharing" function, so as to expand the database.

Line Bot

- Question and Answer learning set

When learners encounter difficulties or unclear points while watching digital teaching videos or e-learning materials, they can get immediate help by asking the virtual tutor (Saric & Seric, 2018), line bot that is called chatbot, directly. When the line bot receives the problem, it turns into a problem module, analyzes the student's problem using the "word segmentation technology" and find the related other learning materials through the "Bayesian algorithm", and provides solutions or suggestions from the database to the learner. This is shown in Figure 3.

After the solution is given by chatbot, it is simultaneously recorded so that the user can solve the same problem more quickly in the future. As many technologies contain many different basic knowledge sets, the data recorded by this module can also be used as a piece of data for judging parameters when more advanced problems are encountered. The actual operation interface of the intelligent chatbot tutor is used in this research, as shown in Figure 4.

Figure 3. The Logic Analysis and Judgment Process of the Line Bot Instant Answer Module to Assist the Recommended Learning Flowchart of e-learners

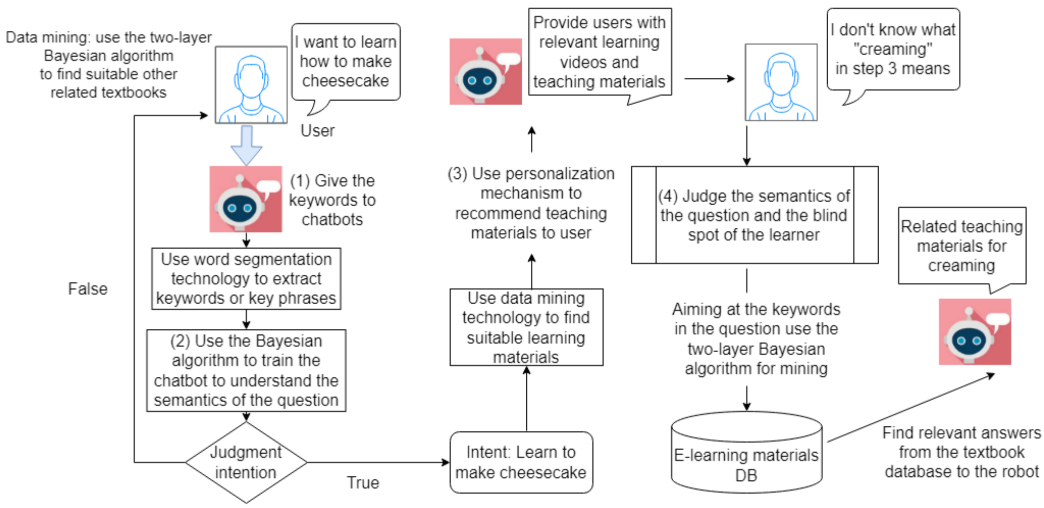
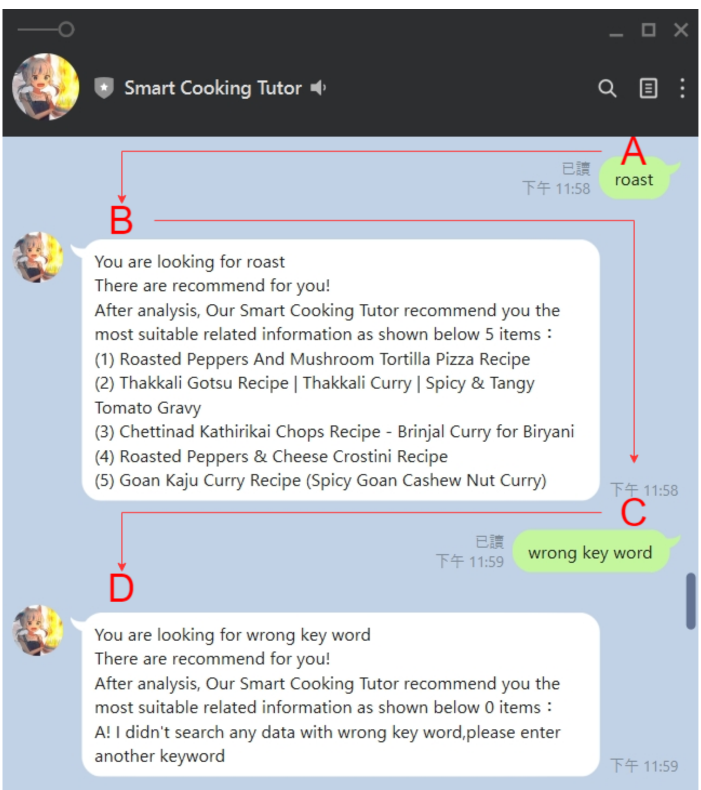


Figure 4. Line Bot Response Test Chart



Intelligent Recommendation Learning Mechanism of Two-Level Bayes Algorithm

To solve the problem that teachers and students cannot communicate in time, resulting in poor learning performance in e-learning, this research developed the virtual tutoring system, which uses recommended learning algorithms to recommend suitable learning materials for students. Specifically, chat robots are used to increase the interactivity of e-learning, along with the "Intelligent Tutor Recommending Learning Algorithm" (ITRL), and related instructions, as follows.

The following is a detailed description of the main three parts of the above ITRL algorithm, as shown Table 3.

- User analysis

The "User Analysis" can be used to analyze the historical records of students learning. The "Situation Awareness Learning System" can be used to identify the relationships between the learning units that users are interested in to determine the user's preferences and degrees and to summarize such data to the users. When a user finishes the implementation, he/she can review the problems encountered in the implementation and provide additional information regarding his/her unskilled areas.

In the recipe example, this experiment records the user's learning and dietary preferences and divides the data set in the database into "diet," "cuisine," and "category," to classify the data. Then it uses the "Bayesian algorithm" to analyze the record, compare it with the user's preferences, and recommend relevant types of learning materials to the user.

Table 3. Intelligent Tutor Recommending Learning Algorithm

```
Phase 1: User's digital textbook feedback and questioning module( )
    (1) Line bot software robot interaction, and collection problems ( )
    (2) IF (Line bot search course Q & A DB) & (judge question related
            library)
            Automatic reply
        else
            Sort answer groups by relevance( )
            Answer the closest answer( )
        recommended video learning sets ( )
Phase 2: Recommended video learning set ( )
        Pre-processing of learner's problems ( )
        for (set keywords in range (e-learning courses))
            Calculate the value of the relativity of the keywords and
              learnings video materials
            Algorithm of intelligent recommended teaching materials ( )
            Determine the category of the problem attribute
Phase 3: Algorithm of intelligent recommended teaching materials ( )
        IF (Bay-style intelligent problem search algorithm)
            for (Related video teaching in textbook learning library)
                if (Relevance to user question > threshold)
                    Recommending collection of related digital textbooks
                Recommended the sorted suitable video teaching materials
```

This study uses the number of user votes to select the favored dishes based on the relevant technology the user has learned for classification (e.g., according to the high or moderate and low degrees of relevance). Additionally, the data are used to recommend information to users so that they can extend their own learning map, for example, based on the other relevant learning materials recommended by previous users from various courses.

- Questions and teaching materials association

The main function of the portion "Question and Teaching Material Association" in the system is for the chatbot to first understand the correct semantics of the question, and then find out to which professional type the question belongs. Then, the chatbot is to use the two-level Bayesian algorithm with appropriate different keywords to link the video teaching and e-learning materials in order to identify the connection(s) between the user's problem data recorded in the system and the teaching material(s). According to the data of the "User Analysis Module," the "Bayesian Algorithm" can be used to analyze, for example, the watching time or the viewing times of a certain clip or textbook to determine the correlation(s) between the problem and the textbook and/or to address the user's inadequate or insufficient understandings and unskilled areas. Accordingly, the chatbot can give immediate suggestions for the problem or guidance and suggest how users should strengthen such areas.

- Recommended learning materials

"Teaching material recommendation learning" refers to the data recorded in the previous two modules and user-customized courses recommended based on "Situational Aware Learning," so that users can strengthen their unskilled areas or consider new interests and courses.

The intelligent recommending mechanism of this system mainly allows learners to have the same experience as real-person teaching in mobile learning so that they can learn smoothly. For example, even if they encounter problem bottlenecks, they can find solutions in real time and are proactive. Learning videos or suggestions can be recommended so that users can understand the problem as soon as possible, thereby increasing the interactivity that mobile learning often lacks. Therefore, this research developed a set of intelligent chatbot systems to help e-learners and provide effective and immediate answers to the learners' questions during their learning processes.

EXPERIMENTAL DESIGN AND RESULT ANALYSIS

This research combines machine learning technology and Bayesian algorithms to carry out e-learning and m-learning of remote cooking courses on the virtual tutor robot of this research, mainly to help students get timely answers to blind spots encountered in learning. The chatbot analyzes the blind spots of e-learners and can find other relevant recipe videos and e-learning materials through a two-level Bayesian algorithm so that students can gradually improve their self-learning ability in order to participate actively in e-learning, thus enabling sustainability of education. The original data of the experiment in this study are called the recipe box, which has a total of 10,421 data items used in this experiment. The recipe box is an open data which comes from a website that provides many public data and various applications of data science, and the name of the website is eight parts.

The learning materials of this recipe box are quite complete and rich, including the teaching materials of the main dishes from all over the world and various countries. To meet the algorithm requirements for data analysis, the original e-learning materials needed to be preprocessed first when some records of the relevant learning data set of the e-learning materials database had missing or inconsistent data. This process was mainly divided into the following two main stages: (A) data preprocessing, which consists of three main steps, and (B) data analysis. And the analysis and discussion are as follows.

Data Preprocessing

Check for Missing Values

The sample data sometimes have missing or incomplete parts, potentially leading to insufficient samples and/or reduced accuracy in prediction. This study used the isnull() function to check whether there were missing values in the data set. The missing data were deleted when there was an omission. If the output result was false, it meant the data were complete, as shown in the figure below Figure 5.

Eigenvalues

The type of the collected data set is not necessarily a quantized value, so this research used a label encoder to convert the type to a value so that the Bayes classifier could understand the data and make predictions. The left side of Figure 6 is the text before classification and the right side is the labeled data.

Feature Selection

In machine learning, problems of overfitting and dimensional disasters are often encountered. When the number of features increases, the classification effect usually increases; however, when the number of features exceeds a certain value, the classification effect decreases (Figure 7). Therefore, this study provided classification according to the frequency of proper technical nouns. After removing the extreme values, a technology with a higher frequency of occurrence was selected for classification.

Figure 5. Check for Missing Values

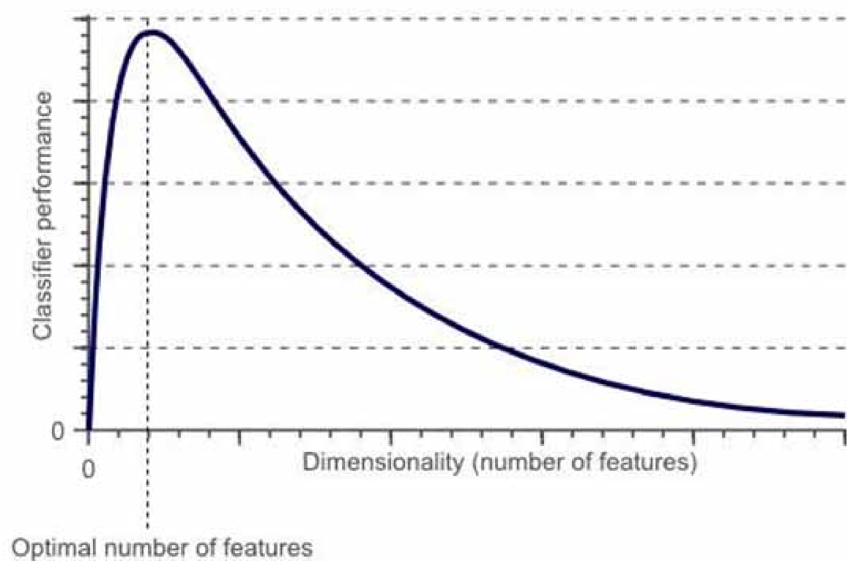
```
Any missing sample data: False
recipe_title     0
url              0
record_health    0
vote_count       0
rating           0
description      0
cuisine          0
course           0
diet             0
prep_time        0
cook_time        0
ingredients      0
```

Figure 6. Labeled Data

```
0                      Vegetarian
1                      Vegetarian
2                      Vegetarian
3        High Protein Vegetarian
4        High Protein Vegetarian
                   ...
8004                   Vegetarian
8005     High Protein Vegetarian
8006     High Protein Vegetarian
8007                   Vegetarian
8008                   Vegetarian
Name: diet, Length: 8009, dtype: object
```

```
[8009 rows x 19 columns]
      diet  category
664      9        71
2147     9        79
6556     5        79
3951     3        12
4062     4        80
...    ...       ...
2447     9        80
3876     9        37
3616     4        89
475      9        84
2211     9        79
```

Figure 7. Dimensional Disasters



Data Analysis

Bernoulli Naive Bayes versus Multinomial Naive Bayes

Bernoulli naive Bayes is suitable for use in data with binary values (Bernoulli, Bollinger); that is, it is used when the data have fewer eigenvalues, but when there are multiple data with such features, this Bayesian algorithm is not suitable.

Multinomial naive Bayes is suitable for naive Bayes data sets whose data satisfy the multinomial distribution. This classifier only considers whether words appear or not, so it is suitable for text classification with a greater number of feature values (this usually means that the data are the number of words, rather than their frequency).

The recipe digital textbook in this study had many different feature values, so it was not suitable to use the Bernoulli naive Bayes classifier to classify the techniques used in the recipes. Therefore, multinomial naive Bayes was used to classify the types of foods and types of recipes (e.g., as divided by type of cuisine), and we used the technology combined with these materials to infer the technology used in some recipes or to reverse-engineer this information.

Data Application Process

This research used classified data to infer the relevance of the technologies used in different recipes. When certain technical keywords appeared in the recipes, it was inferred that users could be interested in them.

First, we found the representative or frequently occurring technical terms in the data set and labeled the data after the nouns were counted. Next, when the user was learning a certain learning material, if he/she encountered an unclear or unfamiliar technology, the system could provide recommendations to the user. This technology was more detailed or useful than other learning materials for this technology (according to the technology label); thus, the user could save the time required to find a solution and learn directly according to the recommended learning materials and video teachings.

Accuracy Statistics

This research used a Bayesian algorithm to infer the correlations between recipes and focused on solving technical problems encountered by users. This research also used the recipes and steps in the data set as the main parameters for predicting recipes. The techniques, types of recipes, and suitable ethnic groups were also used.

Based on the experimental data, analysis was performed from the two aspects, namely, technical difficulties and frequency of use (Zughoul, 2021). The frequency of certain special cooking techniques that are relatively uncommon, as shown in Figure 8, is less than that of basic cooking techniques. This result will lead to overfitting phenomenon. The accuracy of the data predicted by the Bayesian classifier is relatively high. The analysis results show that when the number of samples is less than approximately 500, the accuracy of the Bayesian classifier is more than 95%, as shown in Figure 9. This is because of the data sample. When the number is too small, overfitting will occur. This situation accounts for about 5% of all data mainly because of some special cooking techniques that appear only in specific types of recipes or some techniques that are unique to certain regions. This study regards this situation as statistically extreme valued, as shown in Figure 9.

Ability to Refine the Recommendations of e-Learning Courses

Aiming at the blind spots of e-learners' or mobile learners' learning of recipe technologies, more complete and more relevant video recommended learning materials could be provided. Therefore, in addition to determining the relationship between cooking technologies and recipes based on recipe practices and materials, secondary parameters were also considered. The function of providing a refined recommendation of e-learning and mobile learning courses could be strengthened because most users usually first decide whether to refer to this learning material based on a rough description when learning. Therefore, this study used a rough description in the recipe to make a guess regarding the use

Figure 8. Frequency of Technology Used in the Recipe

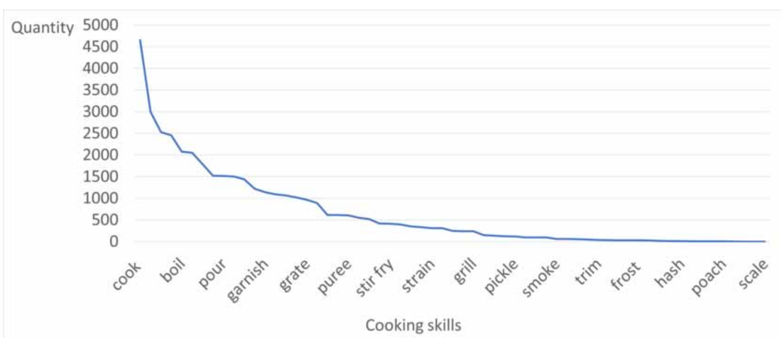


Figure 9. Predict Score of Main Parameters

of a technology, and then used it as a secondary parameter to recommend to users as a reference for learning materials (Figure 10). In general, the number of times a key technology is mentioned in the recipe description is much less than the number of steps, but the most critical and unique technology will be mentioned in a specific recipe, so the accuracy of the Bayesian classifier is very high. This is because the overfitting phenomenon is caused by the small number of data samples. This situation accounts for no more than 10% of the description data set. This study regards it as an extreme value and does not discuss it further (Figure 11).

This experiment conducted a double criticality search under the main parameters and the secondary parameters, and the obtained values for the recommended courses were nearly 90%, that is, sufficient to correctly find the relevant mobile learning materials. Therefore, in this study, the two-level Bayesian algorithm was used as the recommendation mechanism for e-learning and mobile learning, and other neural algorithms were no longer used as the methods for course recommendation because the recommendation mechanism of the two-level Bayes algorithm was very effective.

In addition, to allow users to expand the learning map, this study utilized the techniques used and types of recipes to infer suitable ethnic groups so that users can use automatic recommendations to effectively enhance the interest of e-learners and achieve active learning. When the Bayesian classifier uses unique technologies and recipe types to classify suitable ethnic groups, it shows very high accuracy. To improve the recommendation system, this study uses the types of dishes and appropriate ethnic groups, that is, groups of different cultures, in the learning materials to compare the data. When the information in the description and the instructions related to cooking technology are reversed, the accuracy is more than 70%, as shown in Figures 12 and 13, which also explains

Figure 10. Frequency of Technology Used in Recipe Description

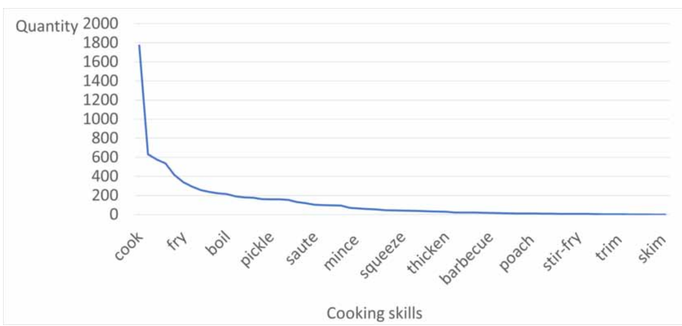
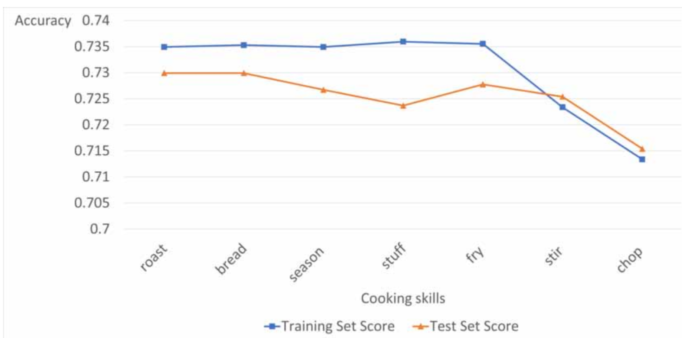


Figure 11. Predict Score of Secondary Parameters

Figure 12. Predict Suitable Group Score of Main Parameters

Figure 13. Predict Suitable Group Score of Second Parameters



some specific types of recipes. In this study, there is a very high probability that it will appear at the same time as the specific technology.

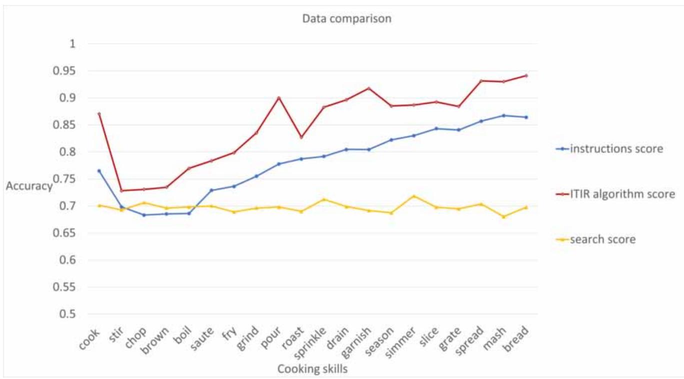
To verify whether the use of two parameters is better than one in the recommended learning materials, this study compares the results of the unprocessed data, the use of one parameter, and the pure use of the keyword search.

1. **Comparison before and after data processing:** When the data have not undergone the preprocessing of the compound keyword group proposed in this study, the performance accuracy rate in the Bayesian classifier is only approximately 40%–50%. When the keywords used in the data are labeled and classified after processing, the achieved accuracy rate significantly improved to more than 80%. Therefore, it can be proved that in the Bayesian classifier, the performance is unsatisfactory if the data have not been preprocessed as mentioned earlier and cannot be easily divided into two parts. This is because each piece of data will be interpreted as a completely different classification. Too many classifications will cause scattered data to be interpreted as unrelated to each other, reducing the accuracy, as shown in Table 4.
2. **Comparison using different numbers of parameters:** To effectively improve the accuracy of related technology searches so that the robot can sufficiently search for keywords, this experiment compares the number of different parameters: using only the keywords in the cooking instructions (the blue line in Figure 14) and using only the keywords in the cooking description (the orange line in Figure 14), compare with both used as compound parameters to infer the effect of the association

Table 4. Average Search Accuracy Comparison Using Compound Keyword Group Technology and a Different Technology in Data Preprocessing

	Accuracy before data processing	Accuracy after data processing
Training set score	0.449161613	0.826055417
Test set score	0.439450687	0.819669857

Figure 14. Comparison of the Accuracy of the ITRL Algorithm and Other Search Algorithms



and classification between the learning materials (the red line in Figure 14). Among using different numbers of keywords, the performance when using only the instructions as a single parameter are better than when using the description as a single parameter. This is because the instructions have more information about cooking techniques and food processing methods used than descriptions, so that the classifier can classify more accurately. If both are used for classification, the accuracy when using only the instructions can be increased from 70% to 80% or even 90%. In this recommended learning information system, the information can be recommended more accurately.

3. **Using only keywords to search and compare:** The results obtained from only searching keywords without classification was compared to those obtained with the Bayesian classifier. The Bayesian classifier is used to classify the learning materials that have not been classified. The data show that the performance with using only the search keyword and the Bayesian classifier using only one parameter is about 70%. The Bayesian algorithm alone is used in searching for information about related technologies. It uses only keywords to search and has the ability to search for related technologies. For instance, there is a lack of using keywords to infer the relevance of various teaching materials in the data for searching for keywords. This study yields significantly better search results than other methods, as shown in Figure 14. Through the ITRL algorithm proposed in this study, the Bayesian search algorithm that uses multiple keywords for the classified search can more effectively find the correlation between different technologies. From the data point of view, we use the Bayesian search algorithm. Compared to other search algorithms, the classifier can more effectively apply the correlation between various teaching materials to improve the search accuracy of related technologies and achieve an accuracy improvement of about 10% to 20%.

CONCLUSION

This research uses an application of chat robots in the field of e-learning to identify the different learning blind spots and learning difficulties of the learners at different levels for e-learning and mobile learners, so as to provide a personalized learning method to determine the appropriate correlations in a timely manner. These can be used as a supplement to improve learners' understanding of digital video teaching materials, thereby enhancing the sustainability of the active learning emphasized by digital learning and of education. The conclusions of this research and future work are as follows:

- First of all, the mobile networks and technology are developing rapidly, and both artificial intelligence and the Internet of Things have provided new opportunities for mobile learning, for example, to promote mobile learning in the future. One future goal is to increase the content for e-learning and make it more diversified so that students who want to learn different things can learn what they want anytime and anywhere, and so that mobile learning can also be as interactive as real-person teaching.
- Secondly, to overcome the shortcomings of e-learning and m-learning, chatbots can be used directly to solve or clarify the different problems encountered in the learning process, students can directly reflect the problems they encounter, and the chatbot can also provide real-time relevant solution information to help learners overcome difficulties in learning content in real time. And it will reduce the burdens on teachers who produce online teaching materials, thereby making action learning more effective and efficient.
- Finally, this research brings e-learning or m-learning closer to real-person learning so that the chatbot can understand students' difficulties like real-person teachers and can guide students to solve problems smoothly. Therefore, the recommendation mechanism of the intelligent chatbot in this study can effectively improve the learning interest and learning efficiency of the e-learners.

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