Application of MOOC Data Based on Autonomous Intelligent Robot System in Students' Learning Behavior

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In the traditional teaching classroom, teachers' supervision has an important influence on students to a large extent. The MOOC (massive open online courses) platform requires learners to conduct self-supervision to improve their self-regulation ability. To increase the MOOC's learning impact, students must also actively engage in the course activities. In the autonomous intelligent intelligent robot system, the cognitive model is required to be able to classify and identify the perception information of the robot, realize action decision-making, and at the same time, it can feedback and control the robot to obtain the information of the students' MOOC learning progress, and can accept the students' MOOC learning behavior signals to amend the decision. This paper preliminarily analyzed the factors that affected the learning effect. Based on the preliminary analysis of the influencing factors of MOOC learning behavior, through the comparative analysis of the existing learning behavior analysis framework, an operational learning behavior analysis framework for MOOC courses has been designed. The types of MOOC learning behaviors and associated variables and indicators were identified. By constructing the MOOC learning behavior analysis framework, the learning behavior patterns of MOOC learners were mined. The system log data of the MOOC platform and the basic information of learners were collected. The indicators that need to be studied in the learning behavior analysis framework were screened out. Based on learner behavior data, MOOC learners' cumulative video viewing time distribution and video viewing number distribution were explored, and learner behavior features were extracted. Further, the learning behavior patterns were classified based on behavior preference and learning motivation, respectively. Differences between the learning characteristics of different types of learners were analyzed. Among them, 40 learners believed that the quality of the learning resources of the MOOC platform based on the autonomous intelligent robot system was very important in the process of autonomous learning, accounting for an average of about 32.6%. This paper helps to enhance pupils' independence in their education and stimulate their curiosity in learning.

Povzetek: Za pomoč študentom so analizirali uporabo podatkov MOOC na podlagi avtonomnega inteligentnega robotskega sistema. Razvita je analiza učnih vedenj, ki izpostavlja vzorce, povezane z motivacijo in preferencami učencev, ter izboljšuje njihovo samostojnost in zanimanje za učenje.

1 Introduction

Educational big data comes not only from the educational and teaching activities in the formal environment, but also from the learning activities in some informal educational environments. A large number of learning records are maintained in the MOOC platform, and the forums and discussion areas it provides. It is not only convenient for learners to consult at any time, but also easy to grasp the overall learning status of the course. As part of educational big data, this information reproduces the teaching and learning process with the aid of existing big data technologies. The purpose of discovering students' learning laws, predicting students' learning achievements, constructing students' learning models, and optimizing teaching models has been achieved, so as to achieve a win-win development of teaching and learning and educational progress. In MOOCs, course reviews, as collectible records of learning behavior, are of great significance for observing and measuring the teaching and learning rules of courses and students. Therefore, based on the course teaching background in the above MOOC environment, the discussion content of students in the course discussion area is collected as research data. It is feasible to apply learning analysis technology to data analysis represented by MOOC course reviews.

Research contents such as data mining and learning behavior analysis have attracted more and more researchers. It has become a research field that integrates educational teaching theory and computer application. Balogun S K investigated the influencing factors of exploratory learning behavior [1]. Using data from 31 variables, Maiti S measured multiple aspects of social learning and extracts its basic structure [2]. In order to study the effective automatic identification algorithm of distance education classroom, Fei X took the Internet + intelligent innovation and entrepreneurship education classroom as an example to analyze [3]. The purpose of Paananen S was to analyze differences in team learning behavior of national respondents during military staff exercises [4]. Wang L proposed the design of an operating system experiment course with a flat learning curve [5]. However, the learning behavior they propose just stays on the learner's behavioral hobby, which is not comprehensive enough. This paper cited an autonomous intelligent robot system to optimize it.

The autonomous intelligent robot system can greatly improve the operation efficiency of the operation platform. Umam F developed an intelligent trash can robot designed to solve the problem of garbage type selection and identification of its navigation process [6]. Patil R R introduced a cost-effective robot. It was able to recognize different faces and intelligently track humans with real-time obstacle avoidance [7]. Brito T described an innovative approach. This approach used collaborative robots to support intelligent inspection and corrective actions of quality control systems in the manufacturing process [8]. Danthamala K R studied the behavior of robots in private spaces [9]. Chaitanya P used python code to verify the properties of machine learning and train a robot with predefined images [10]. However, they did not explore too much the self-supervision properties of autonomous intelligent robotic systems.

MOOC has broken the limitations of students' age, participation scale, and knowledge exchange range in traditional offline courses. It allows learners of all ages and educational backgrounds from all over the world to participate in the course. The analysis of course learning behavior on this basis ensures the credibility and universality of the results. The MOOC platform not only contains text, pictures, audio, video and other types of course resources, but also can be used as a learning database to store all learning track records in the platform. From the perspective of data collection, the sources are more abundant, which ensures the scientificity and accuracy of the learning analysis results. Due to the large amount of learning data and the fast content update speed, there are certain difficulties in the manual large-scale information collection process. At the same time, traditional data processing methods and technologies are time-consuming and labor-intensive, which are far from being able to cope with the data volume of hundreds of millions and the processing speed of seconds. Therefore, the synthesis of existing computational tools and techniques can overcome these difficulties. In the framework of educational big data, the collection of massive learning records and the processing of course data have become effective and feasible. This makes the students' learning process and course participation progress traceable, which ensures the efficiency of the data analysis process. No online communication and interaction accounts for the largest proportion, accounting for 60% of the total number of people.

2 Methodology

2.1 Student learning behavior in the environment of autonomous intelligent robot system

2.1.1 Data gathering

In this section, we gather a dataset of 100 students who utilize learning resources from the MOOC platform focused on the autonomous intelligent robot system. The data are collected from the System log data, basic information of learners, MOOC Indicators of Learning Behaviour, Learning behaviour. Out of 100 collected data, about 32.6% emphasised the importance of high-quality learning materials on the MOOC platform.

Table 1: Student interaction on the MOOC platform

Student ID	**1**	**2**	**3**
Timestamp	2024-02-01 8:00	2024-02-02 10:15	2024-02-03 13:45
Activity	Video viewing	Quiz Attempt	Discussion post
Duration (minutes)	30	20	15
Resource type	Video	Quiz	Discussion
Age	25	30	20
Gender	Male	female	Male
Educational Background	Bachelor's Degree	Master's Degree	High school Diploma
Learning Behaviour indicator 1	frequent access to the course materials	Spending a moderate amount of time on activities	Low interaction with the interactive elements
Learning Behaviour indicator 2	High interaction with the interactive elements	a moderate pace of content progression	Infrequent use of the course materials

2.1.2 Data pre-processing using Min-max Normalization

Min-max normalization is a widely used approach for data normalization, which involves changing the values of the feature under consideration to new, smaller values within a predetermined range, often [0–1]. It's recognized that min-max equation (1).

$$v' = \frac{v - min_A}{min_A - max_A}(new\_max_A - new\_min_A) + new\_min_A \quad (1)$$

Where v' represents the new normalized value and v represents the original value for the specified feature, max_A and min_A are the maximum and minimum values, respectively, for the given feature A, and new_max_A and new_min_A stand for values for the new range being considered, including maximum and minimum.

2.1.3 Cognitive analysis

The use of cognitive models to autonomous intelligent robot systems is a developing area in the rapidly expanding field of robotics research that has great potential. Inspired by human cognition, these cognitive models enable robots to observe, interpret, and react to their surroundings in a way that is similar to human intelligence. These robots can achieve increased autonomy and adaptability by using cognitive concepts in their design, which enable them to make well-informed decisions, adapt to varying conditions, and interact with people in a seamless manner. As this field of study develops, the incorporation of cognitive models into autonomous intelligent robot systems has the potential to transform robotics' potential and applications, bringing in a new era of collaboration and human-robot interaction.

3 Implementation of MOOC data in student learning behavior

The traditional classroom method of teaching, group teaching is carried out by means of fixed time and fixed place, which can play a stronger role in managing learners' engagement in the instructional process. During the teaching process, it is also possible to observe and supervise the learning status of the learners. After class, students can be urged to preview and review through various methods such as homework and tests. In MOOC classrooms, learners have complete autonomy. Currently, there is no way to detect whether a learner is doing unrelated things while watching an instructional video. There is no guarantee that the learner does not consult the data during the test. Therefore, the data obtained through the network may not be real and valid. The learning effect of learners also cannot be guaranteed. In the MOOC learning process, learners often learn alone. There is no mutual encouragement from study partners. The learning process is relatively boring. Their enthusiasm for learning decreases with the extension of learning time, it limits the learning effect's improvement [11-12].

The MOOC learning platform is an improvement on traditional online learning. Online learning uses the network to carry out learning activities and publish the learning content, including learning videos and related materials, to the corresponding platform. Learners can use the network to watch videos, download materials and other learning activities to complete the learning, which is a brand-new interactive way of teaching and learning. MOOC learning is based on network learning, with more control over learning behavior. For example, during the video viewing process, the pre-set topics are popped up. The learner only continues to play the video after completing the question, which ensures that the learner is learning to a certain extent, rather than performing unrelated behaviors while playing the video [13].

When learners learn online, especially in the process of MOOC learning, a large amount of data is generated, which is reflected in the following aspects:

(1) Diversity: Since the MOOC learning platform allows anyone to register for learning, learners can conduct learning activities as long as there is a network. Therefore, any one course is open to tens of thousands of students from different backgrounds. The types of courses offered on the MOOC platform are diverse. The learning behaviors of learners in the learning process are also diverse, including video learning, downloading learning materials, and Q&A in the discussion area.

(2) Real-time: During the learning process of MOOC learners, all learning behaviors of MOOC learners can be recorded by the platform in real time, including the time when the learner logs in to the platform, the time when each teaching video starts to be watched, the time to pause and the time to stop watching, etc.

(3) Large amount of data: With the continuous accumulation of time, the learning materials of the MOOC platform continue to increase, including videos and course materials. Similarly, the number of learners participating in MOOC learning is also increasing, this implies that the learning data produced by learners in the learning process is also accumulating and increasing [14,15].

For each example i, the class to which it should belong is computed:

$$c^{(i)} = \min_j \left| x^{(i)} - x^{(j)} \right|^2 \tag{2}$$

The student participation rate $T_{Participation}$ is calculated as follows:

$$T_{Participation} = \frac{\sum_{i=1}^{N} \frac{F_i}{R_i}}{N} \tag{3}$$

In the Formula, N is the number of courses included in the subject.

In the calculation of the review participation ratio, the review features involved include the total number of courses in a subject, the number of students participating in each course, the number of topics in each course, and the number of views of each course. In addition, considering the difference in the number of questions in different courses, the number of questions is used as a divisor in the calculation of the comment participation ratio to achieve the normalization of the course comment participation rate. The calculation methods of the number of comments per capita and the browsing ratio are [16]:

$$FPC = \frac{\sum_{i=1}^{N} \frac{CF_i}{CS_i \times N_i}}{N} \tag{4}$$

$$VR = \frac{\sum_{i=1}^{N} \frac{CF_i}{VN_i \times N_i}}{N} \quad (5)$$

Through the guidance of teachers and the communication and sharing of peers, students gradually construct new knowledge from the outside into their own knowledge system. Accordingly, the original cognitive structure is enriched in practice. Therefore, under the inspiration of constructivist learning theory (which maintains that the world exists objectively, and individuals' understanding of things is determined by themselves), aiming at the teaching and learning environment of MOOC, on the one hand, it is important to assist pupils to actively establish the significance of learning. On the other hand, a good interactive communication environment is created, so that students can get inspiration and innovative learning in the interaction with the outside world. While taking an online course, based on the learner's external environment and individual needs, the dual stimulation of the learner's extrinsic motivation and intrinsic motivation is triggered, resulting in learning activities, which are also individual behaviors. Therefore, it is necessary to have an in-depth understanding of students' learning needs before studying learning behaviors. It is convenient to guide and evaluate students' learning performance, which truly achieves teaching students in accordance with their aptitude. In the process of MOOC learning, students change from passive knowledge receivers to active information absorbers, so that their learning initiative increases. At the same time, under the effect of learning needs, the learning motivation is also enhanced accordingly, thus triggering students' active learning behavior. In the teaching process, it is crucial to correctly comprehend the key meaning of the theory of behavioural science. It is also necessary to master the different learning motivation levels of learners to create appropriate learning situations. By encouraging group collaboration and discussion, individualized learning and development of students is achieved [17-18]. With an emphasis on constant improvement and adaptation based on learner experiences and observations, Figure 1 illustrates the iterative instructional design process in a constructivist learning environment.

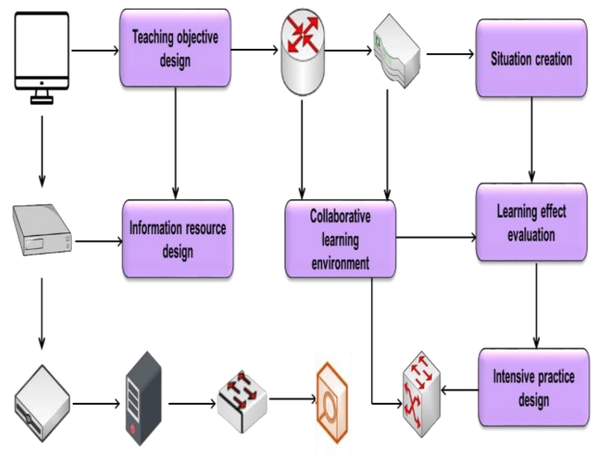

Figure1: Instructional design process in a constructivist learning environment

4 Implementation of learning behavior based on autonomous intelligent robot system

Fully autonomous intelligent robot has always been a hot research field that has attracted international attention and is interdisciplinary. It is an inevitable trend of social development and will greatly change the way of human life. The fully autonomous intelligent robot should have the characteristics of high mobility and environmental adaptability, so the fully autonomous intelligent robot adopts the embedded system for design and implementation, and the realization and optimization of various algorithms under the embedded system has become a research hotspots and difficulties.

Autonomous intelligent robotic systems play a vital role in many areas of human life. With the advancement of knowledge and technology, autonomous intelligent robot systems will gradually appear in more and more fields that we are familiar with and are closely related to us, promoting social progress and changing our way of life. In order to adapt to the uncertainty of the dynamic network of the MOOC learning platform and make the autonomous intelligent robot nodes autonomously perceive the network intelligent nodes distributed on the Internet, it is necessary to realize the autonomous perception of robot nodes and the plug-and-play of sensing intelligent nodes on the Internet. The distributed intelligent system based on network intelligence is based on the autonomous perception of intelligent nodes and the ability of "network plug and play". Autonomous intelligent robot nodes can autonomously and dynamically find and utilize sensing intelligent nodes in the MOOC learning platform network. The new sensor intelligent node can be called by the robot node immediately as long as it is registered on the network server, which realizes the dynamic real-time data collection of students' MOOC learning behavior. The "network plug and play" mode can make the distributed intelligent system have advantages in the network environment, this significantly increases the system's dynamic expansion capabilities. If the proportion of the i-th MOOC data samples in the student MOOC learning behavior data sample set D to the total samples is Pi (i=1, 2, n), the formula of the information entropy of the set D is [19]:

$$\mathrm{Ent}(D) = \sum_{i=1}^{n} p_i \tag{6}$$

The study time allocation ratio is calculated by calculating the ratio of the study time used by students in the course learning process to the number of courses participated in the review. Statistical features involved include the number of courses students participate in and the total length of online learning on the platform. Its calculation method is as follows:

$$\mathrm{TAR} = \frac{\sum_{i=1}^{N} \frac{SF_i}{SC_i}}{N} \tag{7}$$

If the transaction to be classified may be divided into multiple classifications, the information of learning behavior symbols is defined as [20]:

$$D(x_i) = \log_2 p(x_i) \tag{8}$$

In order to calculate entropy, it is necessary to calculate the expected value of student learning behavior information contained in all possible values of all categories. By the following formula, it can be obtained:

$$H = \sum_{i=1}^{n} \log_2 p(x_i) \tag{9}$$

The user's behavior, that is, the control commands issued by the user in the control process of the robot, usually reflects his intention, that is, the robot is expected to complete a specific task or perform a specific action. The control commands issued depend on the operator's intent. The formation of intention requires the operator's perception of various situations such as the remote robot and its environment. However, due to the uncertain delay of data transmission, the robot at the execution end cannot receive and execute control commands in time. The network user at the operating end cannot perceive the state change of the robot due to the realization of the control command in time. The discrepancy between what the user sees through video and other feedback information and the actual situation of the remote robot at that time destroys the coherence and consistency between user behavior and intention. Due to the inability to see the realization of the control intention in time and the misunderstanding of the current state of the robot, the user repeatedly sends control commands to strengthen the realization of his intention. At the far end, the robot receives unreasonably redundant commands. These commands lead to confusion in the behavior of the robot, thereby reducing the performance of task completion, and even jeopardizing the robot system. In teleoperated mobile robot control, the user sends commands and receives feedback through the network to remotely supervise the mobile robot to achieve tasks. Mobile robots also follow a series of control commands and actions from users through the network to achieve assigned tasks or adapt to situations and environments. At the same time, it also sends various kinds of information reflecting the remote status to the user [21-22].

The biggest difference between the teleoperated network mobile robot system and the mobile robot system that works independently is that the former requires the combination of man and machine. The human role in the latter is simply to maintain and get the robot to start or end its work. In the process of teleoperation, excessive interaction is affected by the delay of Internet communication, which is prone to unacceptable robot behavior. The lack of interaction results in low transparency of robot control and a narrow scope of task execution. Therefore, inappropriate human-computer interaction greatly reduces the work efficiency of the robot and the entire system. Internet-based teleoperation needs to maintain appropriate human-computer interaction to deal with delay problems and realize control tasks. It is not enough to rely on the autonomous intelligence of robots that are fixed and rigid in the usual sense. This single interaction method is also difficult to meet the control needs. In this way, it is urgent to find a suitable human-computer interaction mechanism to ensure that the network robot system can meet and adapt to every possible situation when faced with an uncertain time-delay environment. The interaction patterns between users and bots should be able to dynamically adjust to changing network conditions. This makes the interaction and communication between humans and machines fit the current network transmission conditions as much as possible, so as to best realize human-machine collaboration and complete tasks [23].

The learning process consists of items of learning behavior. The learning effect is more objectively demonstrated and explained by the learning achievement. Whether the quality of the learning effect is directly proportional to the efficacy of the learning activity. Therefore, there is an obvious causal relationship between the two. However, different learning behaviors have different effects on learning effects. Even for the same type of learning behavior, the number of behaviors has different effects on its learning effect. No matter what people do, they have a starting point, and so is learning. The starting point always affects the behavior, and so does the learning process. For example, before starting to participate in learning, whether the learner wants to have a preliminary understanding of a certain aspect of knowledge or want to conduct in-depth research always affect the learning process. The former is a general understanding. It may only focus on basic video explanations and understand basic concepts and principles. This does not take the initiative to participate in the discussion forum Q&A. The latter watches the video carefully and repeatedly, and consults the information in multiple ways. Learners also actively participate in the question and answer in the discussion area. If there is any knowledge they do not understand, they would also actively ask questions to find answers. Of course, the purpose of some people participating in learning is just to obtain a certificate, not to enrich themselves with knowledge. Therefore, their learning purpose is stronger. Learners who hope to learn in depth have more active learning behaviors, and the types of learning behaviors are more diverse. Therefore, different learners have different learning purposes, which affects their learning behaviors, such as the length of time they watch videos, the number of times they browse related materials, and the number of times they participate in the question and answer in the discussion area [24]. Different learning behaviors directly affect the learning effect. Figure 2 presents a thorough framework for explicit behaviour analysis in the context of student learning behaviours. This framework offers an organised method for comprehending and improving educational outcomes.

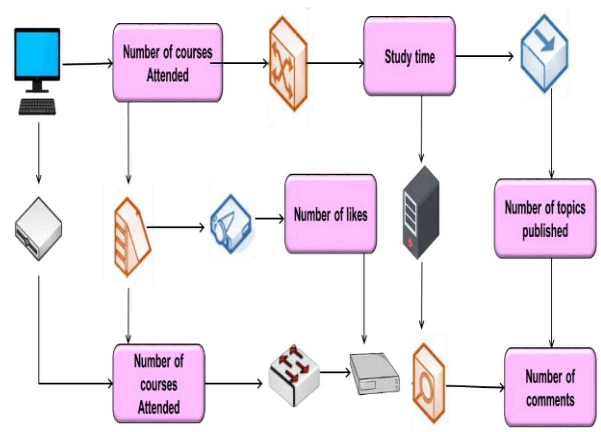

Figure 2: Explicit behavior analysis framework for student learning

The length of time spent logging on to online learning each week is a good indicator of how long learners are participating in the learning process. It can reflect Whether students have an adequate study strategy and whether they can stick to their studies. With an expansion of the course time, the weekly online time of learners shows a significant downward trend. The learner's enthusiasm for learning decreases significantly. Only some students can continue to study every week. Therefore, the online time reflects the learning time of learners to a certain extent. If the learning time is too short, the learning effect cannot be guaranteed. Excessive study time does not mean that the utilization of study time is high. The proportion of students' course reviews is used to reflect the degree of students' attachment to the course. It does this by calculating the proportion of course enrollment to student evaluations they have participated in. Statistical features involved include the number of courses students participated in and the total number of comments. Its calculation method is as follows:

$$\mathrm{SFR} = \sum_{i=1}^{N} \frac{\mathrm{SFN_i}}{\mathrm{SCN_i}} \tag{10}$$

The architecture of autonomous intelligent intelligent robot system is a logical computation structure that defines the relationship between the system parts and the function allocation, determines the information flow relationship and computes the system logically. Autonomous intelligence If intelligent robot systems want to complete complex tasks autonomously in unstructured and unknown working environment, the establishment of appropriate architecture is the first problem. The existing architecture classification is divided according to the relationship among students' learning behavior perception, planning and execution, which can be roughly divided into three major paradigms: deliberative, inclusive and mixed. By matching the student's username, the total number of comments of the student is obtained, and then the proportion of student comments is calculated. The expression for the distribution of course-review per capita is as follows:

$$SR = \sum_{i=0}^{M} \frac{NF_i}{FT}, i \in M \tag{11}$$

M is the set of per capita comment proportions in MOOC learning topics, and i is the per capita comment proportion.
Learning analysis analyzes the learning data in the education system and the MOOC education platform based on the autonomous intelligent robot system, to identify the learning requirements for each student and forecast their academic progress. The key technologies involved include social network analysis, visual data analysis, and content analysis (which is the analysis of the content of mass communication information such as books, magazines, movies, radio and television). In the whole process of learning analysis, it goes through four processes: data collection, data processing and analysis, data prediction, personalization or adaptation. According to the different data sources, the data collection process can be divided into two types. One is the learner's external data, that is, the learning status published in social software and the learning record data saved by the autonomous intelligent robot learning management system. This type of data can be obtained and used intuitively. The other is intelligent data, that is, learning data that cannot directly represent students' learning content. This type of data needs to be further processed by semantic analysis or other related techniques before it can be used [25].

5 Student learning behavior outcomes

The average percentage of students not enrolled in MOOC courses is about 33%. Those who registered but never studied averaged is about 18%. From the statistics it can be seen that the proportion of students who did not register to study is the largest. The proportion of students who have completed the course from beginning to end and obtained the certificate is the smallest, and the gap is obvious. That is to say, although the total number of college students is large, there are very few students who choose MOOC courses for autonomous learning. However, in the open-ended test questions, some students said that most of them did not know much about the MOOC platform. It is hoped to increase the publicity of the MOOC platform and let more students share the high-quality resources of the MOOC platform. The statistical analysis of student's involvement in MOOC courses shown in Figure 3, providing information about their participation and interaction levels.

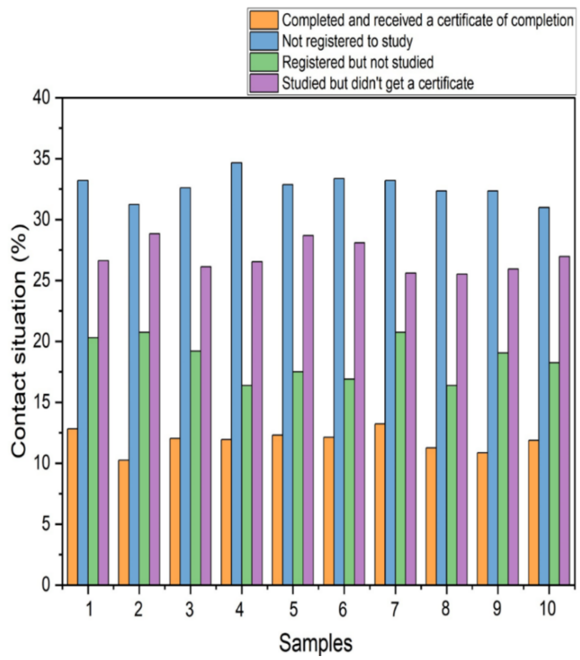

Figure 3: Statistics of students' exposure to MOOC courses

College students' MOOC autonomous learning is a process in Students themselves, as the fundamental source of learning, choose MOOC courses with purpose and plan under the premise of teachers' guidance. Therefore, this component is primarily separated into two parts: personal variables and external forces. It mainly involves the learning plan, learning motivation, learning communication and feedback, learning effect evaluation, and external factors such as schools, teachers and MOOC platforms in the MOOC learning process of college students. The total number of MOOC learners is smaller. However, some teachers have realized the resource sharing and high quality of MOOC platform courses. During the survey, some college students reported that some teachers would designate a MOOC course related to the course for students to learn, and set learning requirements. This part of the student's regards learning MOOC courses as a kind of task. Twenty-four students cite completing learning tasks as one of the motivations for taking MOOC courses. In general, the study life of college students is not as boring as high school, but has become colorful. Especially after the third year of college, the number of general courses and specialized courses basically decreases, and students' spare time increases. In addition to participating in various club activities, some highly motivated college students choose to study online courses to enrich their spare time. It not only enriches the extracurricular life but also expands the knowledge. In addition, the wide coverage of courses launched by MOOC has a certain correlation with the professional courses of college students, which has a strong use value. There have also been major changes in teaching concepts and teaching modes. The MOOC platform also offers courses that are of interest to learners, including songwriting and introductory guitar. Since some platforms do not provide certificates, some learners are not very motivated to obtain certificates. The learning motivation of MOOC learners is shown in Table 2.

There are many ways for the autonomous intelligent robot system to perceive the external environment, such as using the camera as its own eyes, collecting external visual information through the camera (students MOOC learning), as the main visual acquisition device; using the microphone as its own ear, placed in different positions the multiple microphones can locate the students' MOOC learning situation by one or several sound sources; the gyroscope can be used to imitate the function of the human brain, which can be used to adjust the robot's posture, coordinate the movements, etc., which is convenient for students' MOOC learning. With the development of science and technology, more and more sensing devices are applied to the fully autonomous intelligent robot, so that the fully autonomous intelligent robot can become more and more intelligent, and adapting to one's surroundings is also stronger and stronger.

Table 2: MOOC learners' learning motivation

Motivation to learn	N	Proportion (%)
complete learning tasks	24	24
Enrich your spare time	26	26
Obtain the certificate	20	20
pursue development	20	20
satisfy interests and hobbies	10	10

The communication and Interaction in the process of autonomous learning is also a significant aspect affecting the learning effect. One of the reasons why the MOOC platform is accepted by many learners is that it is different from the personalized design of traditional online courses and high-quality courses. Under the guidance of navigation, learners can discuss with learners and teachers who are studying the course at the same time, or interact through QQ groups, Weibo, etc. The effective investigation and interaction survey of learners in the process of MOOC self-learning is shown in Table 3. By sorting out the questionnaires, it is found that there are 15 students in the effective questionnaires of learners' autonomous learning who often communicate and interact with their classmates who are studying the same course. 25 students occasionally interact online. The largest proportion is that they have not conducted online communication and interaction, corresponding to 60% of all individuals. After screening the learners who have obtained the certificate through the screening function of EXCEL, it is found that 10 of the 15 learners who often participate in online exchanges have obtained the MOOC certificate. It can be seen that there is a great correlation between the acquisition of the certificate and the frequent communication and interaction.

Table 3: The survey of learners' interaction in the process of MOOC self-learning

Effective investigation	Frequency(student)	Proportion (%)
participate often	15	15
participate occasionally	25	25
never attended	60	60

The effect of autonomous learning is not only affected by personal factors such as learning motivation, learning plan, learning purpose, and learning foundation, but also by various external factors, such as the guidance of teachers, the quality of teaching resources, and the design of autonomous learning systems. Therefore, learners are also closely related to these factors in the process of MOOC autonomous learning based on autonomous intelligent robot system. In the survey, when asked about the most important external factors, 40 learners believe that the quality of the learning resources of the MOOC platform based on the autonomous intelligent robot system is very important in the process of autonomous learning, accounting for an average of about 32.6%. The significant metrics that clarify the learning effects influence are shown in figure 4, which offers an apparent indication of the effects significance in relevance to the research.

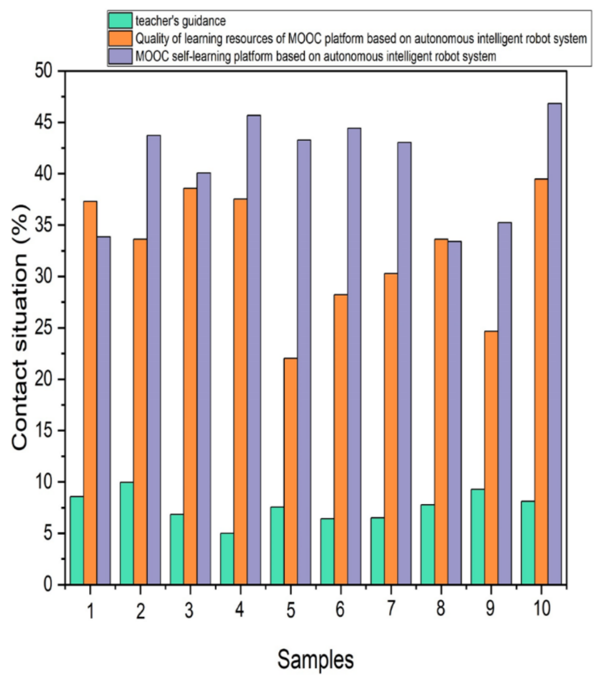

Figure 4: Importance statistics of learning effect impact

On the whole, the MOOC platform based on autonomous intelligent robot system is a new type of online learning platform, which is still unfamiliar to college students. Many college students learn about MOOC platforms through recommendations from classmates and friends, or through their own discoveries while browsing online education web pages. Fewer students learn about MOOC platforms through teacher or school channels. During the learning process, the respondents report that even if the teachers know that the students are studying MOOC courses, they would not take the initiative to guide them. When communicating with some teachers in a certain school, it is found that many teachers do not know the existence of MOOC, a new learning model. A considerable number of students learn MOOC courses through the introduction of friends or classmates. In the investigation and interview, some learners also reflect that as a college student, they have become accustomed to the way of learning under the supervision of schools, teachers and parents. There is still a big gap from the real and complete autonomous learning, which is also challenging for the college students. During the survey, some college students report that teachers do not provide effective guidance when students are studying MOOC courses. They also make it clear that learners are motivated if MOOC courses are combined with classroom instruction and appropriate teacher guidance. Figure 5 despite students engaging in tutoring sessions while pursuing independent learning, demonstrate the dynamic interaction between guided help and self-directed study among students.

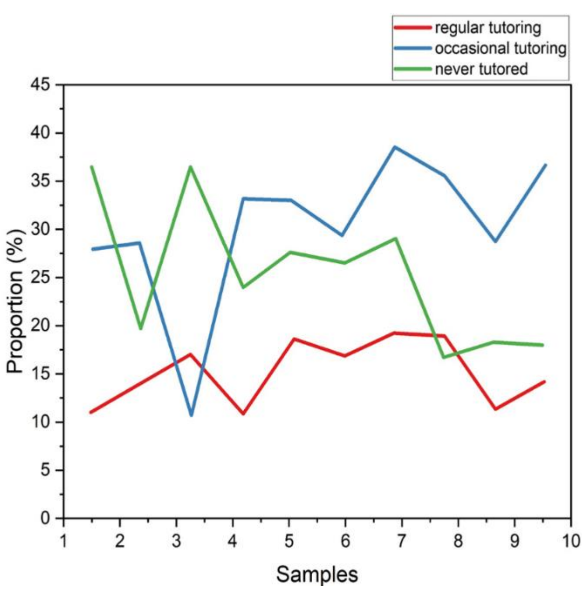

Figure 5: The situation of students receiving tutoring in the process of independent learning

The five courses with the most logging of learning behavior is selected to see how the course learning activities changed over time. The total log records for these five courses are all around 3,000. Course A has about 1000 log records. Course B has about 2000 log records. Course C has about 2500 log records. Course D has about 3000 log records. Course E has about 5000 log records. In general, the fewer learning journal records a student leaves behind, the higher their risk of dropping out. As the course progresses, the phenomenon of students dropping out of school becomes more and more obvious. Especially in the two weeks after the end of the course, the number of people studying online has a significant downward trend. This reminds teachers and platform designers that students' learning engagement does not always maintain a high level. Therefore, in order to prevent the occurrence of dropout, it is necessary to pay attention to the learning status of students in time. Furthermore, when necessary, interventions are required. Students need to select their preferred course by browsing courses. Students would only continue their studies if they find a suitable course. Therefore, the record of learning activities in the first week of the course is relatively high, and the second week decrease. At the same time, because the content of the course is relatively simple at the beginning, as the difficulty increases, the record of learning activities increases. By analyzing and comparing the distribution of learner types, it can be found that learners want to become active learners when they start learning on the MOOC platform. However, through the classification of learner types by learning behavior, it is found that most MOOC platform learners are less likely to participate in course learning. It is far from the expected learner type, which also leads to the high dropout rate of MOOCs. Therefore, by analyzing and studying the learning behavior of the MOOC platform based on the autonomous intelligent robot system, it is found that the learning behavior of the learners has changed during the learning process. It can monitor the learning behavior of learners in the process of learning in real time, so as to provide decision support for guiding the learning behavior of learners in the learning process.

For learners, they can always grasp their own learning situation, which is convenient to analyze the neglected links in the learning process as determined by the examination of learning effects. They can improve their learning methods as quickly as possible. At the same time, they can also find friends with the same learning style as their own, which can improve the fun of learning. For teachers, by mastering the use of educational resources by learners, they can continuously optimize the development of courses. This can help them develop curriculum resources that are more in line with learners' MOOC learning, thereby improving students' learning efficiency. Understanding the various learning styles allows instructors to better guide their students' learning processes and encourage more participation from them in all facets of their education. For the mastery of the students' learning situation in each link, rather than just relying on the final exam results, it is possible to evaluate the learners' learning situation more objectively. The data gathered from the learning process is comprehensively visualised in the learning behaviour log record, as shown in Figure 6.

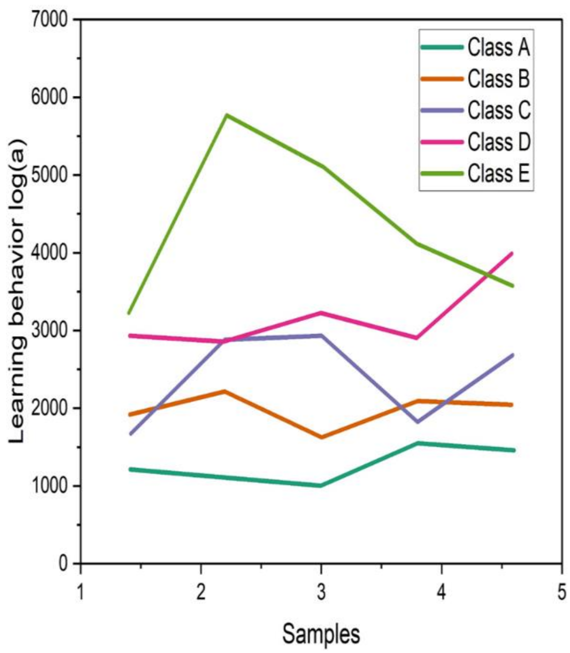

Figure 6: Learning behavior logging

In the traditional teaching classroom, the teacher's supervision has an important influence on the students to a large extent. The MOOC platform based on the autonomous intelligent robot system requires learners to conduct self-supervision and improve their self-regulation ability. It is also necessary to actively participate in the course activities to enhance the MOOC learning impact via the use of an autonomous intelligent robot system. Self-supervision is an unsupervised mode from another perspective.

Because for learners with poor self-regulation ability, self-supervision loses its meaning. At this time, it is necessary to take certain measures to strengthen the external monitoring of learners, so as to improve the learning effect of learners. By analyzing the differences of learners' learning behavior and predicting their academic performance, the behaviors that directly affect the learners' academic performance can be found, which are monitored. When learners have bad behaviors, they should immediately record and warn the learners, so as to prevent the learners from repeating bad behaviors during the learning process.

In the course selection time of the MOOC platform based on the autonomous intelligent robot system, the course offering is set according to the semester. Before opening the course, the teachers arrange the required class hours according to the course content. They also set the start time and end time of the course. The unit test time is also set by the teacher's deadline. When a learner chooses the course affects the time span of the learner. If the course selection time is too late, the learning span is short. Moreover, the completion and mutual evaluation of some assignments and tests are missed, which is difficult to guarantee a good learning effect. The release time of this course is 2017-07-12. The class starts on 2017-08-12. The end time is 2017-12-12. The total number of electives is 8488. In the first month of the course, that is, as of 2017-9-12, the total number of students enrolled in the course was 3,100, which is less than half of the total number of students enrolled in the course. As of 2017-11-12, the total number of enrolled students has reached 8,000. There are still 488 people who registered for the course within one month before the end of the course, which is too short for the study time. Figure 7, presents statistical data on the current and cumulative number of students enrolled across certain courses, presents a thorough examination of enrolment variation and patterns.

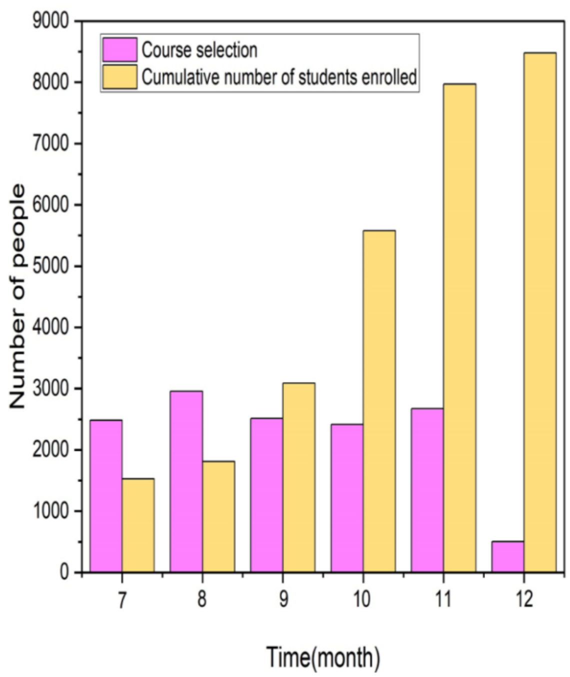

Figure 7: Statistics on the number of enrolled students and the cumulative number of enrolled students in selected courses

Behavioral data analysis can help users quickly and easily discover the resources they are interested in and better understand their needs. The attribute data of learners' expected study time per week is aggregated through the course questionnaire. The questionnaire has four time periods of 1-2h, 2-4h, 4-6h, and 6-8h. The learner's ten-week expected study time attribute statistics are cleaned. The last valid data has 55384 pieces. In the first four weeks, the MOOC platform is used for learning, and the enthusiasm of the students gradually declines. In the fifth week, the MOOC scheme based on the autonomous intelligent robot system is used for learning, and the enthusiasm of the students gradually increases. In general, the learners choose to study less on the MOOC platform based on the autonomous intelligent robot system every week, which shows that the learners use the short time to study in the MOOC platform. This provides an important suggestion for course designers of MOOC platforms. Each course should be controlled in a brief amount of time, so that learners can arrange their learning time reasonably and increase the effectiveness of their learning.

Based on the results of behavioral clustering analysis (which refers to the analysis process of grouping the learning behavior sample data set of physical or abstract objects into multiple classes composed of similar objects), learners can control the learning progress in time and improve their strategies. When combined with artificial intelligence theory and big data technologies, an analysis of the online learning platform's user behaviour is conducted, which can help platform users increase both the effectiveness and quality of online learning. The results of online learning behavior cluster analysis can provide guidance and intervention for learners to conduct effective learning. When learners continue to study for a period of time, they can evaluate which learning category they are in by analyzing the results. If in the non-value or general user category, the course learning progress should be enhanced and the learning style should be improved. If in the important development or important retention user category, the learner is in good learning state and can predict the possible future learning results. Based on the results of the correlation analysis between online learning behavior and learning effect, learners can know which factors can affect good academic performance and study purposefully. For example, when learners tend to watch course videos for a long time, but do not pay attention to interacting with learning peers and teachers, they may miss the reminder of course learning points and learning reflection and discussion, thus affecting the learning effect of online courses. Using the results of online learning behavior correlation analysis, the learning plan and process can be adjusted reasonably according to their own needs, so as to strengthen the progress of effective behavior. Figure 8 depicts the weekly distribution of learners' predicted learning time, presenting insight into the variability in their study commitments.

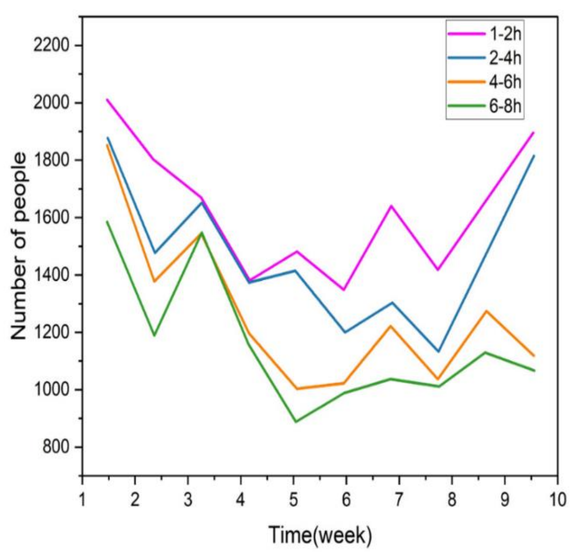

Figure 8: Data distribution of learners' expected learning time attribute data per week

6 Practical implication

The implications of the study's results are significant for educators and intelligent system developers simultaneously. Educational tactics to improve student autonomy, engagement, and learning outcomes might be influenced by educators' knowledge of the cognitive processes that underlie learners' interactions with MOOC platforms integrated with intelligent robot systems. Learning behavior patterns might be analyzed to get insights that can be used to develop personalized learning experiences that are suitable for the requirements and preferences of specific learners. Moreover, teachers might take use of these intelligent systems' feedback and control capabilities to provide prompt interventions and assistance, resulting in a more productive and flexible learning environment. The article highlights the significance of incorporating cognitive models into robotic platforms for intelligent system developers in order to facilitate more complex and human-like user interactions. Through the utilisation of cognitive concepts, developers can design intelligent robots that are autonomous and capable of perceiving, reasoning, and responding in a way that is consistent with human cognitive processes. This will improve the systems' usability, efficiency, and acceptance in a range of real-world applications, from industry and education to healthcare and beyond.

7 Conclusion

The research of autonomous intelligent robot system with cognitive ability is a relatively new topic in the field of robotics research. The traditional behavior Learning strategies were not able to satisfy the needs of robot intelligence. The field of intelligent robots urgently needs some new ideas and methods to break through the bottleneck of student learning behavior monitoring methods. By analyzing the online learning log data, this paper explored the behavior rules of learners. It has verified the characteristics of "high dropout rate, low participation" found in previous MOOC studies and the linear learning characteristics of learners in the process of knowledge acquisition. Not only the traditional clustering method was used to classify learners based on their behavioral preferences, but also a new statistically significant parameter classification method was proposed based on learners' learning motivation. The classification results showed that the learner's learning motivation determined its learning behavior pattern to a certain extent. This paper has predicted and mined the learning performance of MOOC course learners based on the autonomous intelligent robot system. A model was established to analyze the influence of different learning behaviors on the learning effect of MOOCs based on autonomous intelligent robot systems. The amount of data used in this experiment was small, which could not fully reflect the learning behavior characteristics of all MOOC learners based on autonomous intelligent robot systems. Therefore, for the experimental results, there may be some shortcomings. The data analysis of the learning behavior that affected the learning effect at the beginning of the study was based on the usual life experience. Because the learning behavior data contains too much content, only the learning behaviors that may have an impact can be listed based on experience. With further research, behavioral characteristics not listed in this paper may be found. Future study might concentrate on creating adaptive learning algorithms that use the discovered behavioural patterns to further personalize the MOOC experience, thereby improving student engagement and effectiveness.

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Study on the integration of the great spirit of the founding of the CPC into the ideological and political education practice of continuing education students in Jiangsu Universities, The Philosophy & Social Science Research Project in Colleges and Universities of Jiangsu Province Subject No.: 2023SJSZ0364

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