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Prediction of Student Performance in Massive Open Online Courses Using Deep Learning System Based on Learning Behaviors

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ABSTRACT: Massive open online courses (MOOCs) provide numerous open-access learning resources and allow for self-directed learning. The application of big data and artificial intelligence (AI) in MOOCs help comprehend raw educational data and enrich the learning process for students and instructors. Thus, we created two deep neural network models. The first model predicts learning outcomes on the basis of learning behaviors observed when students watch videos. The second is a novel exercise-based model that predicts if a student will correctly answer examination questions on relevant concepts. The study data were collected from two courses conducted on the National Tsing Hua University's MOOCs platform. The first model accurately evaluated student performance on the basis of their learning behaviors, and the second model efficiently predicted student performance according to how they answered the exercise questions. In conclusion, our AI system remedies the present-day inability of MOOCs to evaluate student performance. Instructors can use the systems to identify poor-performing students and offer them more assistance on a timely basis.

Keywords: Learning analytics, Educational big data, Massive open online courses, Artificial intelligence

1. Introduction

Massive open online courses (MOOCs), an open-access educational resource available to online learners worldwide, represent a new approach to learning. MOOCs provide not only various study materials and resources but also aid students in self-directed learning. With increasing enrollment in MOOCs, a large amount of learning data has become available for collection and analysis. By harnessing data science, analytics approaches to learning can leverage educational data and help students and instructors enrich their learning processes (Vieira, Parsons, & Byrd, 2018).

Many researchers have analyzed MOOCs data by incorporating big data and artificial intelligence (AI) in their research design. Big data and AI have gained prominence in various fields, including machine learning and data science. Machine learning algorithms are more effective when using larger datasets, and the combination of machine learning and big data has made impressive breakthroughs in data science (Ghahramani, 2015).

In recent times, deep neural networks, an important branch of machine learning, has been used successfully in many AI applications (Su, Chou, Chu, & Yang, 2019; Su, Ni, Li, Lee, & Lin, 2020; Su, Ding, & Chen, 2021). Several researchers have constructed multilayered models that capture more complex features, particularly how online learners learn (Hwang, Sung, Chang, & Huang, 2020; Kastrati, Imran, & Kurti, 2019; Li & Zhou, 2018; Su & Lai, 2021; Yang, Brinton, Joe-Wong, & Chiang, 2017). Boulay (2016), for instance, specified that AI techniques help practitioners better understand learning and pedagogical trends, and related systems help students acquire new skills and grasp new concepts. Therefore, the application of AI to MOOCs has drawn considerable attention in big data analytics. The NMC Horizon Report noted that AI will strengthen the online teaching model, which facilitates adaptive learning and research, and make student–teacher interactions more intuitive and frequent (Adams, Cummins, Davis, Freeman, Hall, & Ananthanarayanan, 2017). Fauvel et al. (2018) designed an AI tool to analyze students' learning effectiveness by collecting learning behavior data with the objective of helping MOOC learners better understand concepts and MOOC instructors deliver more effective courses and offer higher-quality educational tools. AI tools are mainly used to bridge the gap between online learning and physical classes and enable students to achieve their learning goals. Therefore, it is important to personalize MOOC services to students' learning adaptability, habits, and behaviors (Tekin, Braun, & Schaar, 2015).

MOOCs transcend spatial and temporal constraints and have popularized the concept of open education. There is a large quantity of structured and unstructured learning data that are based on learner behavior observations and diverse test questions. The data include personal information (e.g., gender, age, education level, and disciplinary background) and responses to test questions (e.g., number of candidates, number of graduates, number of test questions, responses to test questions, and evaluation goals). Many scholars have proposed that data analysis can be used to improve a teacher's course and make it more adaptable (Ndukwe & Daniel, 2020; Er, Gomez-Sanchez, Dimitriadis, Bote-Lorenzo, Asensio-Perez, & Alvarez-Alvare, 2019; Lee, 2019; Lu, Huang, Huang, & Yang, 2017; Ruipérez-Valiente, Munoz-Merino, Diaz, Ruiz, & Kloos, 2017). In MOOCs, learners are free to study the topic of their choice irrespective of time and place. In addition, they do not need to follow the instructor's intended course sequence (Matt, 2018). While the self-regulated learning structure of MOOCs offers considerable flexibility and a wealth of valuable resources, many learners do not complete the courses because of the pressure-free learning environment (Azevedo & Cromley, 2004; Bol & Garner, 2011; Peverly, Brobst, Graham, & Shaw, 2003). MOOCs use self-directed learning as their development model (Li, 2019), and thus, learners must set learning goals and use learning strategies commensurate with their aptitude and background knowledge to master the course content. Through videos, exercises, forums, and other interactive functions, learners must develop appropriate self-regulated learning (Lan, Hou, Qi, & Mattheos, 2019; Matt, 2018). Consequently, to help students achieve classroom success, many researchers have proposed assessment systems that can not only improve students' performance and self-regulation abilities (Lu, Huang, Huang, Lin, Ogata, & Yang, 2018) but also identify scope for improvement in course designs on the basis of students' learning behaviors.

There is growing literature on the application of big data in education. Processing large quantities of learning data can elucidate the relationship between learning behaviors and learning effectiveness, which can help educators forecast learning outcomes (Hwang, Chu, & Yin, 2017). The conceptual framework underlying learning analytics can be used to analyze course characteristics, assess student performance, and predict learning progress. According to Lu et al. (2018), learning analytics help educators save time, which can be used to refine their teaching expertise and identify at-risk students at an earlier stage. However, MOOCs have fundamental problems. The most well-known being the low completion rate and the lack of learning guidelines (Freitas, Morgan, & Gibson, 2015). There are varying factors attributable to low completion rates. However, studies have reported that most MOOC learners are unprepared for the extensive course content and isolated learning environment (Kim, Olfman, Ryan, & Eryilmaz, 2014).

In order to address these issues, this study aimed to develop an AI-based system that helps teachers better understand their students' learning performance. The system has two functions. First, it analyzes students' learning behaviors to evaluate their learning performance at a given time. Second, it uses a novel exercise-based model to predict if students will correctly answer examination questions on relevant concepts. We first collected data on the video-watching behavior of participating MOOC students and the frequency at which students watched the videos. These data were subsequently analyzed and used to predict students' scores. The scores calculated using our formulated neural networks can be used to identify students with learning difficulties, the key practical implication of this feature. Previous studies have indicated the following challenges in developing intelligent tutoring systems: techniques that simulate the intelligence of human experts and the need for human tutors' knowledge and experience to make judgments and decisions using the best available evidence to help solve learners' problems and improve their learning ability (Hwang, Xie, Wah, & Gašević, 2020). Second, we collected students' answers to exercises and data on their answering process. Using the data, our system predicted whether a student would answer an examination question correctly.

The system is based on deep learning, a promising technology applied in the field of education. While there has been growing interest in AI-based education research since 2001, less than 5% of such studies focus on AIED. However, considering its rapid advancement, there is much potential in the application of deep learning in education (Chen, Xie, & Hwang, 2020). Therefore, our proposed system could exemplify the development of a deep learning system to predict student performance.

Finally, most software tools based on AI technologies used for educational purposes are designed to learn languages or mathematics (Chen, Xie, Zou, & Hwang, 2020). The data used for this study are collected from two MOOCs courses: *Introduction to IoT* (where IoT refers to the Internet of Things) and *Calculus I*. Both are introductory courses. The former is for computer science undergraduates from the National Tsing Hua University (NTHU) and covers related techniques. Therefore, in light of future research, the system proposed in this study can be used for programming learning purposes, an arguably important advance in artificial intelligence in education research.

The present AI-based system used NTHU's MOOCs platform as an experimental site. Its objective is to provide teachers with accurate evaluations to identify students with learning difficulties. Furthermore, the predicted results for students' examination answers could help teachers understand students' learning experience without the need to conduct additional exams. Consequently, teachers may be able to better guide their students and increase their motivation to learn. This study was based on the following research questions:

RQ1. In a MOOC learning environment, can video-watching data that reflect learning behaviors be used to evaluate learning outcomes in addition to online assessment scores (e.g., quiz or examination scores)?
RQ2. In addition to the proportion of correctly answered questions, can deep learning be applied to the aforementioned video-watching data to evaluate if a student has mastered the course content and understood related concepts?

2. Literature review

2.1 Data analysis and enhancement of learning effectiveness

AI refers to the simulation of human intelligence in machines such that their judgments and decisions exhibit the characteristics of a human mind (Akerkar, 2014; Su, Ding, & Chen, 2021; Su, Suen, & Hung, 2021). In recent years, research on artificial intelligence in education (AIED) has flourished with the increasing sophistication of data analytics (Kay & Kummerfeld, 2019; Schwendimann, 2017; Su & Lai, 2021; Su & Wu, 2021). The literature has also witnessed the development of new research methods and subfields, such as educational data mining and learning analytics, where scholars gather learner data from online platforms to analyze learning processes (Daghestani, Ibrahim, AI-Towirgi, & Salman, 2020; Alexandron, Ruipérez-Valiente, Chen, Muñoz-Merino, & Pritchard, 2017; Romero & Ventura, 2017).

The proliferation of data analytics, especially big data analysis, in education has paved the way for a new teaching approach, wherein student activities and progress are tracked to improve learning outcomes. In addition, students can track their learning progress for better self-directed learning (Alonso-Mencia et al., 2019; Kavitha & Raj, 2017). Hwang et al. (2020) developed a fuzzy expert system-based adaptive learning approach while accounting for both affective and cognitive factors. The experiment results indicated that the learning system could enhance students' learning achievements and reduce their learning anxiety.

Advances in learning data analytics have led to the creation of an accommodating online learning environment that helps students achieve their learning goals, especially in higher education distance teaching and teacher training courses. Using such technologies, teachers can track learning behaviors and evaluate students' learning effectiveness across several dimensions (Meier, Xu, Atan, & Schaar, 2016).

2.2. Evaluation of learning performance based on student behavior

Learning behaviors are learned actions commonly used to assess students' learning and performance. Examining students' learning behaviors not only gives teachers insight into students' learning situations, but also ensures the feasibility of teaching materials. Hsu et al. (2021) developed an instructional tool for AI education and used videos and screenshots to record learning behaviors. Their study revealed meaningful behavioral patterns when students learned the application of AI.

Students' learning behaviors on MOOCs are also an important factor in learning assessments. MOOCs, however, commonly report low completion and high dropout rates (Sun, Ni, Zhao, Shen, & Wang, 2019). Numerous studies have proposed methods to predict students' success or failure in courses (Er et al., 2019; Lu et al., 2018). One such method uses a logistic regression model for prediction. Lee (2018) applied this method to analyze the behavior of students engaged in uninterrupted video watching and examined data drawn from the students' learning logs. Students reported interrupted learning if they did not watch the course video for two consecutive days. The author estimated the frequency and duration of uninterrupted learning actions from the learning log data and inputted the data into the prediction model. Lee then defined three thresholds for continual learning (10, 30, and 60 minutes) and compared the effect of uninterrupted learning across the thresholds. The 60-minute threshold occupied the largest area under the precision-recall curve, indicating that the threshold was the most useful in predicting student success in obtaining a course certificate. In other words, students are more likely to obtain a course certificate if they participated in more learning activities and engaged in learning for a longer duration.

Guo, Kim, and Rubin (2014) proposed several features that educational video production should incorporate to increase engagement, which was measured by the duration of video watching and whether students attempted a post-video exercise. Using simple statistical tools, the authors found that shorter videos, in addition to other video production decisions, led to greater engagement. These findings can be useful for MOOC instructors.

Kim et al. (2014) revealed that video length was strongly and negatively correlated with engagement; that is, learners were less likely to finish watching a longer video. The authors also demonstrated that students were more likely to view the entire video when they watched it for the first time rather than when they did so more than once. Using binning and kernel-based smoothing, the authors then produced second-by-second plots of peaks in video interactions (defined by play, pause, and skip). The plots revealed students' learning behaviors when they watched a video. Each peak was manually classified into five categories to explain the underlying cause of the peak. Their results elucidated how students interact and learn, and practitioners can use these findings to improve video interfaces for learning.

Sun et al. (2019) proposed a gated recurrent unit-recurrent neural network (GRU-RNN) model to construct a dropout prediction model. The model is based on an RNN with a URL embedding layer. The authors used their model to compare student performance before and after course entry and to determine the number of days students did not spend on learning. They then analyzed different approaches to learning, such as answering exercise questions, interacting on forums, and taking examinations. Finally, the authors examined students' learning habits through their sequence of learning behaviors to predict learning performance.

2.3. Measurement of learner proficiency in MOOCs

Traditional learning assessments offer a judgment score or standard reference. However, students differ in their learning ability and speed. Difficult test questions poorly reflect the comprehension level of students with low learning ability. To address this issue, researchers formulated test response theory, which became increasingly popular in education research and practice. According to test response theory, students receive questions on the basis of their response to the previous ones, and thus, the difficulty level of the test is tailored to a student's ability. However, the theory does not address ways to dispel student misconceptions or to diagnose learning disabilities (Liu, Lin, & Tsai, 2009). There are several methods to conduct a diagnosis. Interviews are the most common qualitative method, and test response theory is the most frequently used quantitative method. With the growing application of AI technology, including neural networks, diagnostic testing is an emerging subfield in the testing industry. Chu (2020) envisioned cognitive diagnostic testing that is based on cognitive science theory as a crucial future trend. The author designed a cognitive diagnostic test and proposed a question-response model to verify if cognitive science theory yields valid evaluations for student ability (Chu, Li, & Yu, 2020). Their method helped improve learning data analytics, thus allowing MOOC teachers to better evaluate student performance and track learning behaviors across various learning dimensions.

The MOOC literature has widely investigated online assessments and learner participation. DeBoer, Ho, Stump, and Breslow (2014) analyzed the concept of participation and desirable metrics for learning success and participation quality. However, learners might sign up for a course and not complete the assessments. Admiraal, Huisman, and Van de Ven (2014) explored the assessment quality of MOOCs. MOOCs entail a dynamic learning process: learners engage in a series of actions comprising perception, learning, thinking, and problem-solving. Thus, final scores are an inadequate indicator of learner performance (Shepard, 2001). Teachers must observe students' learning behaviors during a course since learning is a process rather than an outcome. The aforementioned conclusions emphasize the need for alternative assessment methods in MOOCs.

2.4. Prediction of learning performance using exercises

Moreno-Marcos, Pong, Muñoz-Merino, and Delgado-Kloos (2020) presented a method to predict students' assignment, examination, and final grades on the basis of their learning status, performance in discussion forums, video-watching behaviors, answers to practice questions, and previous assignment scores. The authors found that previous assignment scores and average answer scores were highly predictive of the aforementioned three grades, whereas student performance in discussion forums was only slightly predictive. Because some courses provide videos without exercises, the authors used student behavioral data such as click counts as a model feature but noted no substantial change in performance.

Learning styles in MOOCs can be categorized by performance in course assessments (Alario-Hoyos, Pérez-Sanagustín, Delgado-Kloos, Parada, & Muñoz-Organero, 2014). Alario-Hoyos et al. (2014) used learner performance in a sequence of course activities (including videos and exercises) to cluster learners into three broad categories: lurkers, participants who did not complete a course, and participants who completed the course. Although the authors did not detail their clustering method, it appeared to be based on simple statistics.

Ashenafi, Riccardi, and Ronchetti (2015) proposed a method to predict the final examination results of students in two undergraduate programming courses (*Informatica Generale I* (IG1) and *Programmazione II* (PR2)) at the University of Trento, Italy. Throughout the courses, students participated in a set of peer-based online homework activities with three main tasks: ask a question, answer a question, and rate answers. A total of 14 types of data were captured before they were used as input features in a prediction model with logistic regression. The prediction model outperformed its counterparts by a root mean square error of 2.93 for one course and 3.44 for the other.

Huang, Chen, Tzeng, and Lee (2018) designed a concept assessment system with a knowledge map using deep learning. The authors presented each week's knowledge topology as a knowledge map. They collected data on the difficulty level of exercises and student behaviors when watching videos and used the data to predict students' comprehension of the content in a given week's course. The prediction model was based on a deep learning method.

Li, Xie, and Wang (2016) proposed a model to predict test scores. Drawing on several educational theories, the authors predicted quiz grades using 15 features such as student age, gender, education level, registration time, number of videos watched, number of exercises, and related actions. However, the features were not significantly associated with examination scores, and thus, could not be used in the prediction model.

2.5. Lack of evaluation mechanisms in MOOCs

Student performance has been traditionally evaluated using standardized tests, and thus, there is a need for learning tools that evaluate learning investments in hybrid, remote, or virtual learning environments. MOOCs have altered global learning trends, although they face many challenges in terms of their long-term development and learning models, including low completion rates (5-10% on average) and high learning loss rates (Sun, Ni, Zhao, Shen, & Wang, 2019). Evaluating learner performance in MOOCs is inherently difficult because students cannot be monitored in real-time, limiting MOOCs' ability to be impartial or provide reliable proof of coursework (Bady, 2013). Moreover, MOOCs have numerous learners, and teachers cannot interact with every student. In such cases, students must rely on active interactions with other online learners to obtain learning feedback and practice. Importantly, students must be self-directed learners (Crosslin, 2018). Previous evaluation methods for online learners can serve as a guide for educators; however, MOOC educators are seeking to develop online metrics for large-scale data collection for students of different levels and ages. Table 1 summarizes missing components in MOOC assessments, factors contributing to these gaps, and how these gaps can be bridged with our deep learning system.

Table 1. Lack of assessment in MOOCs: Reasons and proposed solutions

Learning problem	Reason	Solution
Assessment is potentially unfair.	Students cannot be monitored in real-time, and there is scope to cheat on tests.	Our system performs a big data analysis to provide MOOC educators with an evaluation system that supplements examinations.
Examinations do not provide clear and objective evaluations.	MOOC learners are diverse, and some may have inadequate background knowledge for a course.	Our system uses neural networks to estimate objective and credible evaluation scores using large datasets on learning behaviors and judgments.
Effective learning feedback is lacking.	Different learners absorb different content.	Our system draws on learning behaviors to predict the proportion of questions students will answer correctly. These predictions will help teachers understand if students have grasped related concepts.

3. Methods

This section describes the use of data on video-watching behaviors and answers in exercises to predict students' learning performance in MOOCs.

3.1. Course information and collection of data on learning behaviors

Students from two MOOCs courses participated in this study. Table 2 details the two courses. Students must obtain a minimum score of 60 to complete either course.

The introductory course for IoT is for computer science undergraduates at NTHU and covers techniques used in IoT. Students are expected to spend three hours per week watching online videos and to participate in offline laboratory sessions during which they can conduct experiments. Students can complete exercises as practice and discuss the course content with their peers on the online platform.

The 12-week comprehensive introduction to calculus is a prerequisite for all first-year students and must be completed during the summer vacation. Students are expected to spend three hours per week watching videos and to complete relevant exercises.

Table 2. Course information

	Introduction to IoT	Calculus I
Duration	March 2–June 29, 2020	May 1–August 31, 2020
Number of students	255	1,062
Number of videos	87	144
Number of weeks	5	12
Average video time	525	792
Number of exercises	71	143
Number of quizzes	1	3
Number of questions per quiz	50	20
Quizzes interval time (in weeks)	5	4
Course qualification	No	High school students only
Fee	Free	Paid

Videos constitute the primary teaching method in most MOOCs. For this study, we collected data on video playback actions, such as play, pause, search, and adjust playback speed, on the YouTube application programming interface (API) and then stored the data on the MongoDB database (Table 3). In addition, we collected data on each user's answers for all exercises (Table 4). If students navigated to the exercise page but did not answer the exercise questions, we coded student responses to the exercise as "no." The "timeCost" feature is the duration students took to answer a question. For example, if a student spent 20 seconds answering a question, the timeCost value for the question was 20.

Table 3. Student video activity schema

	Description	Example
userId	Student ID	2,556
courseId	Course ID	10900MATH0001
chapterId	Chapter ID	10900MATH0001ch79
videoId	Video ID	-RHQ75vrT3Q
Action	Student action when recording	Playing
currentTime	Video time when recording	29.57483
playRate	Video play rate when recording	1.25
Volume	Video volume when recording	100
update_at	Recording time	2020-05-20T15:48:03

Table 4. Student exercise activity schema

	Description	Example
userId	Student ID	2,556
courseId	Course ID	10900MATH0001
chapterId	Chapter ID	10900MATH0001ch79
exerId	Exercise ID	10900MATH0001ch79e1
score	Exercise answer score	0.6
timeCost	Time cost on exercise	15
userAns	User answer	[1, 3]
correctAns	Correct answer	[1, 2, 3]
update_at	Recording time	2020-05-15T09:33:35

3.2. Learning variables: Video-watching frequency and duration

This subsection presents the definition of the variables used in this study: frequency and duration of video watching (Table 5). The variables are associated with a given day: on such a day, students primarily learned by watching videos. The average duration of a video is 10–15 minutes. We considered students to have engaged in learning if they watched a video for more than 5 minutes. Figure 1 is an example of a student's video-watching log.

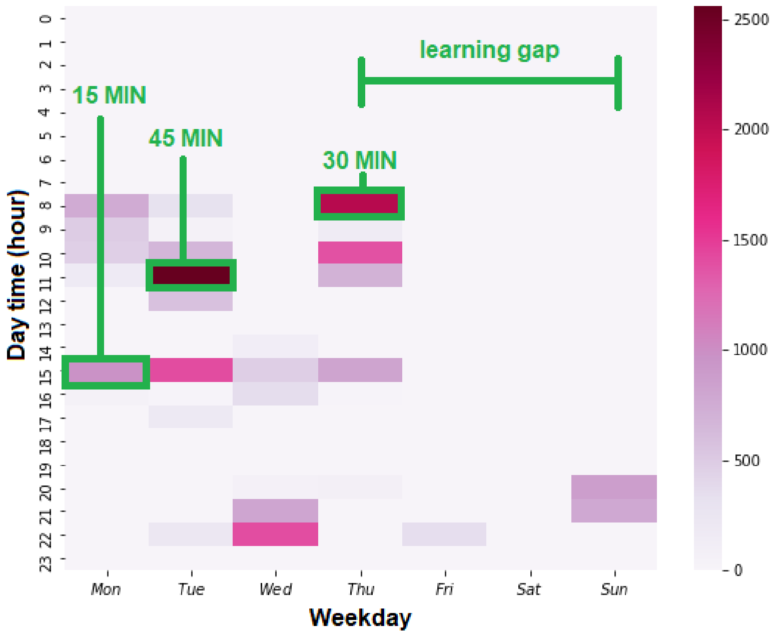

Figure 1. Student video-watching log

Table 5. Video-watching features

Features	Description
videoFinishRate	Proportion of videos finished
videoSpendTime	Time spent watching videos/total time of all videos
Play	Mean of playing in watching videos per week
gapMean	Mean of days not spent on learning per week
gapStd	Standard deviation of *gapMean*
regDay	Number of days per week spent on learning
weekBlockNumMean	Mean number of learning blocks per week
weekBlockNumStd	Standard deviation of *weekBlockNumMean*
weekBlockTimeMean	Mean time of learning blocks per week
dayBlockNumMean	Mean number of learning blocks per learning day
dayBlockNumStd	Standard deviation of *dayBlockNumMean*
dayBlockTimeMean	Mean time of learning blocks per learning day
15Min	Mean number of learning blocks >15 minutes/week
30Min	Mean number of learning blocks >30 minutes/week
45Min	Mean number of learning blocks >45 minutes/week
weekNum	Weeks since course started

3.2.1. Video-watching behavior

In addition, we defined variables for each student that captured their behaviors when watching a video. The variables were the proportion of course videos a student finished watching and that of total video playback time. The second variable was calculated as $1 - (a / b)$, where a is the total playback time for parts of all videos a student did not watch and b is total playback time for all course videos.

3.2.2. Learning gap

A learning gap refers to the number of days a student did not spend on learning and was used to indicate a student's learning pace.

3.2.3. Uninterrupted learning

A learning block constitutes uninterrupted periods of learning. We estimated the number of learning blocks for each student and the duration of the learning blocks per day or week. We set three time thresholds as per the length of the videos.

3.2.4. Learning regularity

We determined whether a student was learning regularly. To denote such regularity, we first recorded if a student had a dedicated learning day per week throughout the semester. We then aggregated the total number of such days. However, we also found some students dedicating learning days closer to the examination rather than throughout the semester. In other words, they "crammed" their learning, and such students were given the lowest regularity value (−1).

3.3. Learning variable: Answers to exercise questions

We recorded and analyzed each student's answer to all exercise questions and extracted eight features (Table 6).

Table 6. Exercise features

Features	Description	Example
Exercise type	Exercise type (single, multiple, fill in the blanks)	Multiple
Correct rate	Percentage of questions answered correctly	0.1
Answer count	Number of attempts before student answers correctly	3
Time cost	Time taken to complete exercise	60
Pre-answer review	Whether student watched a related video before answering correctly the first time	False
Post-answer review	Whether student watched a related video after answering correctly the first time	True
Answering process	Type of question-processing style (type 1–6)	5
Correct count	Number of questions answered correctly	0

3.3.1. Rate of correctly answered questions

The rate of correctly answered questions indicated the difficulty level of an exercise. We use this indicator because the difficulty levels of exercises are not always defined by the test creator, and not all students have similar learning abilities. A higher number of correctly answered questions denotes greater student proficiency.

3.3.2. Number of attempts before correctly answering a question the first time

The number of attempts before correctly answering a question for the first time indicates the difficultly level of an exercise, where a greater number indicates a higher difficulty level. However, this feature may be directly affected by the difficulty level of an exercise.

3.3.3. Watching related videos before or after correctly answering the first time

If students watched videos related to a question within 10 minutes of answering correctly the first time, we defined them as having an impression of relevant concepts when attempting the exercise. By contrast, if students watched related videos within 10 minutes of finishing the exercise, we defined them as being unfamiliar with the concepts and indicated that they gained familiarity only after watching the videos.

3.3.4. *Student approach to questions before answering correctly the first time*

We collected data on student behaviors before correctly answering a question the first time. Students were divided into six types depending on how they processed the answers (Table 7).

Table 7. Types of students based on answering process

Answering Process	Attempt Count Before Answering Correctly First Time	Incorrect Answer Count Before Answering Correctly First Time	Final Result (Correct or Incorrect)	Example
1	1	0	True	[C]
2	2	1	True	[W, C]
3	>2	>1	True	[W, W, C]
4	>1	0	True	[no, no, C]
5	>0	>0	False	[W, no, W]
6	≥0	0	False	[no, no, no]

Note. C = correct answer, W = wrong answer, no = skipped question.

3.3.5. *Number of correct answers*

Except for the number of correctly answered questions, all the aforementioned features are related to student behaviors when correctly answering a question for the first time. These represent a student's proficiency in corresponding knowledge nodes, as formulated by Muñoz-Merino, Ruipérez-Valiente, Alario-Hoyos, Pérez-Sanagustín, and Kloos (2015), who also mentioned that the repeated practice of exercise questions improves student learning and achievement. While exercises on NTHU's MOOC platform are not in parametric form (and thus, such repeated practice is less effective), we believe the number of correct answers represents a student's perception of how much information an exercise contains.

3.4. Prediction of learning performance based on video-watching behaviors

Every student has a unique learning mode and behavior, and we hypothesized that these affect their learning performance. To verify this hypothesis, we fed data on learning blocks, gaps, and regularity into a deep neural network (DNN) model. The model used ReLU as the activation function to predict student performance. Note that when creating predictions in MOOCs, it is necessary to avoid inaccuracies caused by sparse data (Yang et al., 2017). To resolve this problem, we only incorporated learning data for students who took the quiz in our system. Figure 2 illustrates the architecture of our performance prediction model, including the features we used and the number of nodes in each DNN layer. The mean absolute error (MAE) was applied to denote the model's performance. In brief, we used 10-fold cross-validation and shuffling to obtain test data. The data were then used to calculate the MAE as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |(fi - yi)|,$$

where f_i and yi are the predicted and actual scores of student i, and N is the number of students. MAE is the difference between the predicted and actual scores, with a lower MAE indicating better predictive performance. The number of hidden layers was determined using trial and error and cross-validation in performance tests for DNN (Table 8). Figure 3 shows training and validation loss during the training of the predication model on the basis of video-watching behaviors.

Table 8. Number of hidden layers vs. mean absolute error

	6 layers	7 layers	8 layers
MAE	8.5	7.7	6.8

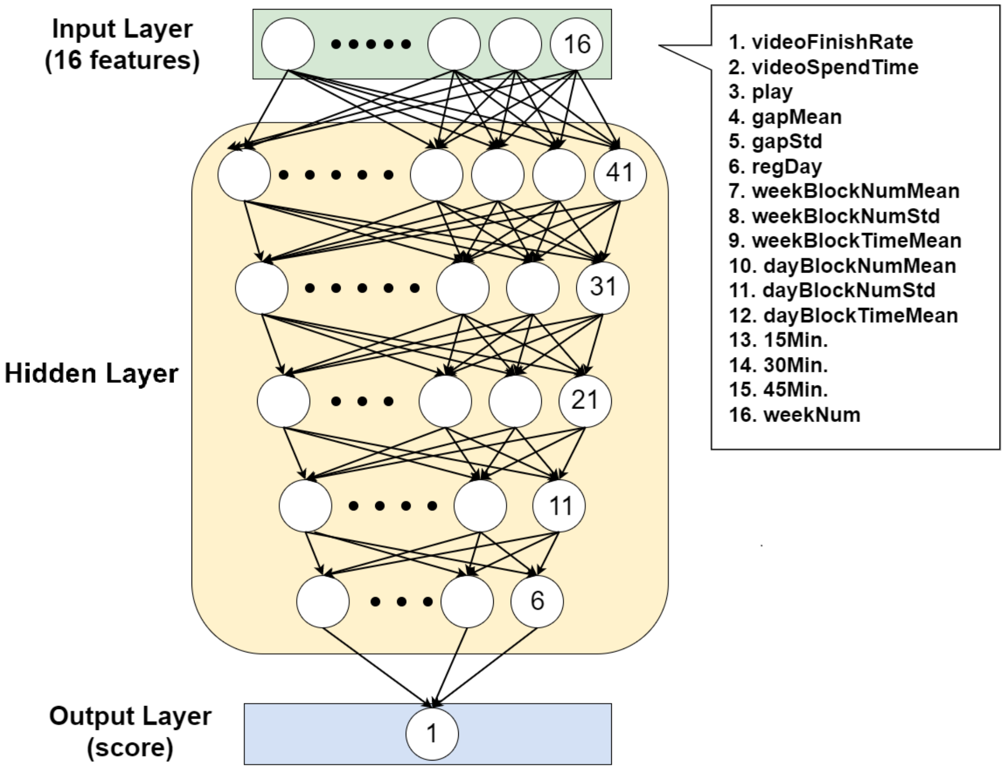

Figure 2. Architecture of score prediction model based on video-watching behaviors

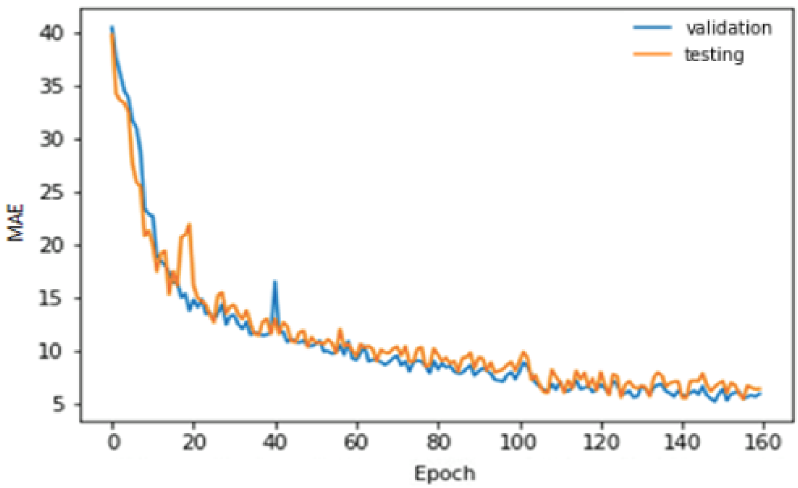

Figure 3. Learning curve for prediction model based on video-watching behaviors

3.5. Prediction of familiarity with concepts based on answers to exercises

Exercises potentially indicate if a student is familiar with a course's content. Thus, in this study, we input the aforementioned variables on students' exercise-answering behavior in a five-layered DNN model (Figure 4) to predict learning performance. Table 9 shows the number of hidden layers determined using trial and error and cross-validation. We defined a large number of such variables (e.g., number of attempts, videos watched before answering correctly, and rate of correctly answered questions) to obtain better predictions. We then used the sigmoid function as the activation function to determine the probability of a correct answer. We set the threshold to 0.5, and if the probability of a correctly answered question is greater than or equal to 0.5, then the answer can be judged as correct (and vice versa). Figure 5 shows training and validation loss during the training of the prediction model on the basis of exercise-answering behaviors.

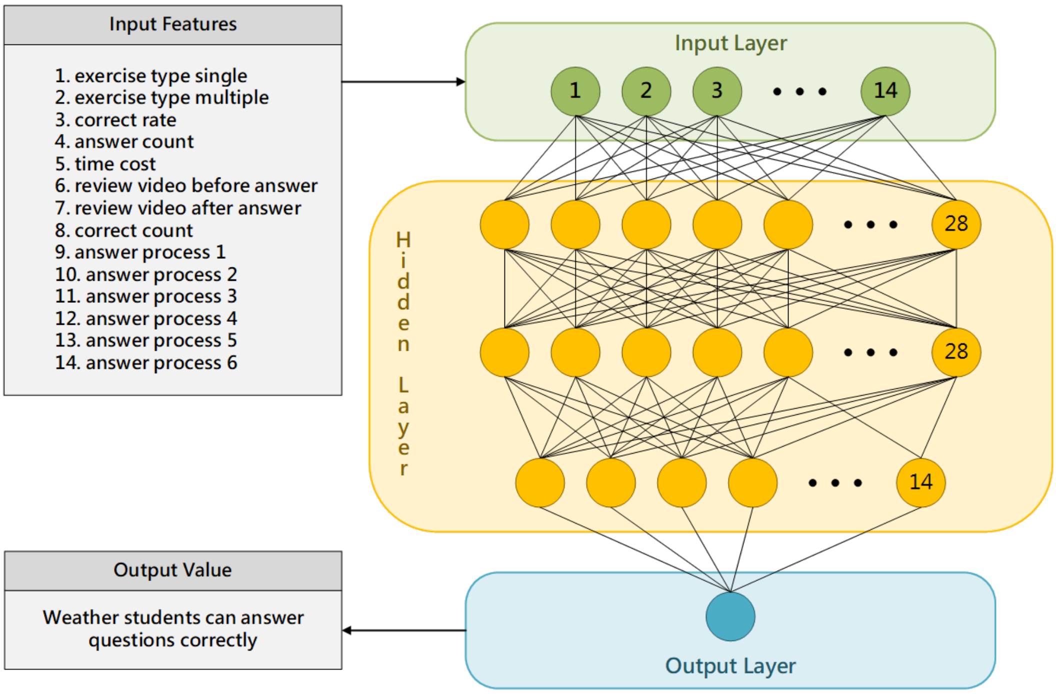

Figure 4. Architecture of prediction model based on exercise-answering behaviors

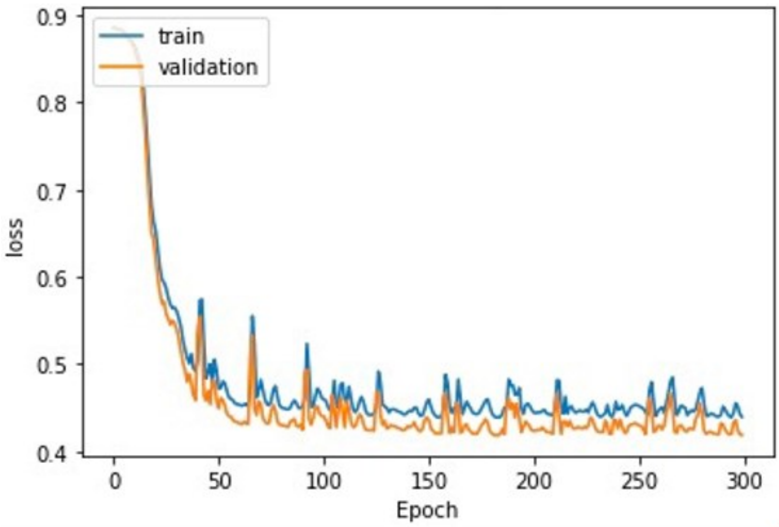

Figure 5. Learning curve of prediction model based on exercise-answering behaviors

Table 9. Number of hidden layers vs. accuracy

	4 layers	5 layers	6 layers
Accuracy	0.733	0.975	0.883

4. Results

4.1. Use of learning behaviors to evaluate learning performance

The introductory course on IoT conducts a final exam to evaluate student performance, whereas the calculus course administers a quiz every four weeks (a total of three quizzes). We built temporal performance prediction models on a weekly basis to measure the accuracy of the prediction approaches. We ran our models at the end of each week. "Week1" represents all collected log data from the beginning of the course to the end of the first week, and "Week2" denotes data collected from the start of the course to the end of the second. We construct similar variables for the remaining weeks of the two courses.We then verified the effectiveness of our prediction model on the basis of MAE using data for the two courses. Since the introductory IoT course conducted one final exam to evaluate students' performance, every predicted result is validated by the same actual data (students' final exam score). Therefore, Table 10 contains only one MAE. On the other hand, the calculus course had three tests, and thus, Table 11 comprises three MAEs. “Quiz1-MAE” is the comparison between our predicted scores and the actual scores of the first quiz. “Quiz2-MAE” is a comparison of our predicted scores with the actual scores of the second quiz, and “Quiz3-MAE” is a comparison of our predicted scores and actual scores of the third quiz.

Table 10. Predictive performance (MAE) for IoT introduction course

	MAE
Week1	18.2
Week2	13.6
Week3	10.1
Week4	7.9
Week5	6.9

Table 11. Predictive performance (MAE) for calculus-I course

	Quiz1-MAE	Quiz2-MAE	Quiz3-MAE
Week1	17.9	22.93	23.7
Week2	15.6	22.3	23.1
Week3	10.56	21.4	22.6
Week4	6.9	19.3	21.7
Week5	X	15.9	17.4
Week6	X	12.0	12.2
Week7	X	8.4	8.9
Week8	X	7.0	8.0
Week9	X	X	7.19
Week10	X	X	6.9
Week11	X	X	6.8
Week12	X	X	6.8

Table 10 shows a significant gap between students’ predicted scores at the beginning of the IoT introductory course and the actual final scores. However, our model’s performance improved in the following weeks. MAE based on Week5 (students’ whole learning behavior) was only 6.9 points, indicating that our model had acceptable accuracy.

Table 11 shows that Quiz1-MAE based on Week4, Quiz2-MAE based on Week8, and Quiz3-MAE based on Week12 are all less than seven points, indicating that the completeness of the collected data affected our model’s accuracy. That is, for a given test administered in WeekN of a course, our model’s prediction would have the least errors if its input was WeekN.

For **RQ1**, since all the above-mentioned MAEs are less than seven points, it is reasonable to conclude that our model can accurately predict student performance in a given course on the basis of their learning behavior. Accordingly, running our model on a weekly basis could give teachers reliable information on student performance at the end of each week.

The conclusion also supports that our system is an alternative approach that teachers can adopt to track student performance without repeatedly administering tests. Teachers can use the model to identify students who may need more teaching assistance and accordingly, provide such aid on a timely basis. Finally, this model could enable students who have failed courses to identify changes they need to make to their learning patterns.

4.2. Use of exercise data to predict learning performance

Using the features mentioned in Table 6, the exercise-based model could predict students’ familiarity with concepts when answering exercise questions. In other words, this model could predict if a student would correctly answer a question on relevant concepts by collecting and analyzing students’ answer records. Table 12 lists the number of times two Calculus I students (students C and D) answered the quiz questions correctly and incorrectly, along with the predicted result. Finally, we applied a confusion matrix (Table 13) to the model to estimate the model’s accuracy, recall, precision, and F1 score. All the aforementioned values were acceptable, indicating that the exercise-based model had acceptable predictive power.

Table 12. Comparison of predicted and actual results for two calculus-I students

	Student C		Student D	
	Real	Predict	Real	Predict
Question 1	Correct	Correct	Correct	Correct
Question 2	Correct	Correct	Correct	Correct
Question 3	Correct	Correct	Correct	Wrong
Question 4	Wrong	Wrong	Correct	Correct
Question 5	Correct	Correct	Wrong	Wrong
Question 6	Wrong	Wrong	Wrong	Wrong
Question 7	Correct	Correct	Wrong	Wrong

Table 13. Confusion matrix of predicted results for calculus-I students by exercise-based model

	Predicted wrong	Predicted correct
Actual Wrong	6,386	0
Actual Correct	173	418
Accuracy	0.975	
Precision	1	
Recall	0.707	
F1-Score	0.828	

Regarding **RQ2**, the confusion matrix results indicated that our system with the exercise-answering feature could provide high-quality predictions. MOOC instructors who use online exercises can feed answering data into our system to better understand how students learn.

4.3. Comparisons with other models

4.3.1 Use of learning behaviors to evaluate learning performance

We compared our research with another model by building a baseline model and using the same data as input. We referenced Python's scikit-learn (sklearn) library to build the SVR baseline model, and set the kernel parameter as "rbf." Table 14 lists the most critical MAEs in this baseline model.

Table 14. Support vector regression predictive performance

Calculus I	MAE
Week4: Quiz 1	15.6
Week8: Quiz 2	15.2
Week12: Quiz 3	15.6
IoT Introduction	MAE
Week5: Quiz	20.3

4.3.2. Use of exercise data to predict learning performance

Similarly, we deployed a decision tree model with the same data as input to predict if the students would correctly answer questions using relevant knowledge. We referenced Python's sklearn library to build the decision tree baseline model. We set the criterion parameter to "gini." Table 15 presents the predicted results for the decision tree model.

Table 15. Predicted results for calculus-I students by decision tree model

Accuracy	0.812
Precision	0.801
Recall	0.603
F1-Score	0.695

5. Conclusions

In this study, we designed a system with two functions to help teachers better understand students' learning performance. The first function evaluated student performance on the basis of their learning behaviors. We tested our system using student data from two courses conducted on NTHU's MOOCs platform. The data included students' video-watching behaviors and answering exercise questions. We formulated a deep learning model, which processed the data and estimated a predicted grade for each student. The study indicated that the model needed a complete overview of students' learning behavior to obtain the most accurate outcome. The second function used an exercise-based DNN model to effectively evaluate a student's performance on the basis of how they answered exercise questions.

(1) Recent research highlighted the problems of high dropout and low completion rates for MOOCs (Sun, Ni, Zhao, Shen, & Wang, 2019). Since MOOCs are a public online course platform, some students may cheat on an exam, and thus, it is difficult to ensure that students consistently follow the honor code. Therefore, MOOCs may not be a fair learning environment. Moreover, questions have been raised about the authenticity of course credits and certificates (Bady, 2013).

(2) Therefore, this study aimed to propose an objective and accurate AI-based method to examine students' learning effectiveness without interference in MOOCs.

(3) In addition, the proposed model could give teachers more accurate information on whether students have mastered a concept. Our system used the scores for video-watching behaviors and accuracy scores for assigned quizzes and final exams to reflect students' learning outcomes.

In conclusion, our AI system could remedy the present-day inability of MOOCs to evaluate student performance on the basis of learning behaviors, which is a major contribution of our study, particularly to the creation of precision education platforms. Importantly, the experimental results of our model were significantly better than those of the baseline models. The results sufficiently demonstrated the feasibility of using DNN. Instructors can use our systems to identify low-performing students and provide them with additional support. By doing so, our system may create a learning–teaching environment that benefits both students and lecturers.
Despite the valuable findings, our study is subject to certain limitations because of the constraints in time and testing frequency. We focused on two MOOC courses, and these courses did not administer quizzes every week. In addition, we only used student behaviors to evaluate their performance.

Therefore, future studies should consider applying the proposed AI-based evaluation system to other MOOCs to validate its effectiveness using larger datasets. The improved system could incorporate the feature of sending notifications to students to help them accurately evaluate their current study patterns before a course ends. This would give them the opportunity to optimize their learning behaviors. Finally, future works could combine other affect-detecting systems such as student response systems (Li, & Wong, 2020) with our proposed system to obtain real-time affective factors. By analyzing student responses, teachers can take prompt action to improve learning and teaching (Hwang et al., 2020).

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