
An adaptive assessment: Online summary with automated feedback as a self-assessment tool in MOOCs environments

Saida Ulfa

Ence Surahman

Agus Wedi

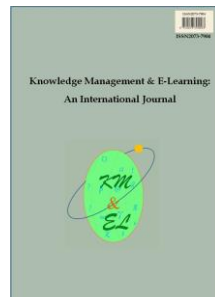
Universitas Negeri Malang, Indonesia

Izzul Fatawi

Universitas Terbuka, Indonesia

Rex Bringula

University of The East, Philippines



Knowledge Management & E-Learning: An International Journal (KM&EL)
ISSN 2073-7904

Recommended citation:

Ulfa, S., Surahman, E., Wedi, A., Fatawi, I., & Bringula, R. (2025). An adaptive assessment: Online summary with automated feedback as a self-assessment tool in MOOCs environments. *Knowledge Management & E-Learning*, 17(1), 88–113. <https://doi.org/10.34105/j.kmel.2025.17.004>

An adaptive assessment: Online summary with automated feedback as a self-assessment tool in MOOCs environments

Saida Ulfa* 

Faculty of Education
Universitas Negeri Malang, Indonesia
E-mail: saida.ulfa.fip@um.ac.id

Ence Surahman 

Faculty of Education
Universitas Negeri Malang, Indonesia
E-mail: ence.surahman.fip@um.ac.id

Agus Wedi 

Faculty of Education
Universitas Negeri Malang, Indonesia
E-mail: agus.wedi.fip@um.ac.id

Izzul Fatawi 

Faculty of Education and Teacher Training
Universitas Terbuka, Indonesia
E-mail: izzul.official@ecampus.ut.ac.id

Rex Bringula 

College of Computer Studies and System
University of The East, Philippines
E-mail: rex.bringula@ue.edu.ph

*Corresponding author

Abstract: Online assessment is one of the important factors in online learning today. An online summary assessment is an example of an open-ended question, offering the advantage of probing students' understanding of the learning materials. However, grading students' summary writings is challenging due to the time-consuming process of evaluating students' writing assignments. Particularly, if the course is delivered in a Massive Open Online Courses (MOOCs) platform where the number of students is massive. Therefore, the purpose of this research is to develop a feature that can analyze student summary results and provide feedback. The feedback given varies for each student as it depends on the results of the summary assessment. The algorithm employed in the online summary with an automated feedback feature was Cosine similarity which is part of text similarity in natural language processing (NLP). To measure

the effectiveness, usability, and student satisfaction of this feature, 100 students were involved as research participants. The results of this study indicated an increase in student learning outcomes. In conclusion, student responses to the use and satisfaction of this feature are good.

Keywords: Adaptive assessment; Automated feedback; Online summary assessment; Open-ended questions; Massive open online courses (MOOCs)

Biographical notes: Saida Ulfa PhD is an Associate Professor at the Educational Technology Department, Faculty of Education State University of Malang, Indonesia. She obtained her master and doctoral degree from Saga University, Japan in the year 2005 and 2009, respectively. In the year 2010, she received the Keizo Obuchi Research Fellowship Program to conduct research at the Information Engineering Department, Faculty of Engineering, Hiroshima University, Japan. Then, she continues to focus her research in the learning engineering area. Currently, her research interests are soft computing in education, adaptive learning, automated assessment and personalization in online learning systems. She has published papers in *Smart Learning Environment*, *Journal of Educational Computing Research*, *Electronic Journal of e-Learning International*, *International Journal of Distance Education Technologies (IJDET)*, *Journal of Learning for Development*, and others.

Ence Surahman PhD is an assistant professor in the Educational Technology Department, Faculty of Education, State University of Malang, Indonesia. He obtained his PhD in Education and Learning Technology from the National Tsing Hua University in Taiwan. His research interests include STEM education, adaptive mobile learning, online collaborative learning, and online assessment. He has published papers in *Journal of Computer Assisted Learning*, *Teaching and Teacher Education Journal*, and *Electronic Journal of e-Learning*. He also serves as a voluntary reviewer of several international journals including *IEEE Access*, *International Journal of Human-Computer Interaction*, *Cogent Education*, *International Journal of Information and Education Technology*, *International Journal of Evaluation and Research in Education*, and others.

Dr. Agus Wedi is an assistant professor in the Educational Technology Department, Faculty of Education, State University of Malang, Indonesia. He obtained bachelor's, master's and doctor's degrees from Universitas Negeri Malang. His research interests include learning technology, learning design, and learning strategy.

Dr. Izzul Fatawi is an assistant professor in the Faculty of Education and Teacher Training, at Universitas Terbuka, Indonesia. He obtained doctor degree from Instructional Technology, Universitas Negeri Malang. His research interests include learning analytics, instructional design, distance learning, and AI in education. He has published papers in *Electronic Journal of e-Learning*, *Ubiquitous Learning: An International Journal*, *International Journal of Emerging Technologies in Learning (iJET)*, and *International Journal of Distance Education Technologies (IJDET)*.

Rex Bringula, PhD is a researcher in the College of Computer Studies and System, University of The East, Philippines. His research interests include computing education, educational technology, environment research, IT education, and portals. He has published papers in *Smart Learning Environments*, *Journal of Educational Technology & Society*, *Computers & Education*, *Journal of Information Technology & Politics*, *Journal of Educational Computing*

1. Introduction

The term “*Massive Open Online Courses*” (MOOCs) was coined by Stephen Downes and George Siemens. It has been identified as one of the emerging educational technologies between 2010 and 2014 (Zawacki-Richter & Naidu, 2016). It became a popular buzzword during the COVID-19 pandemic again, after previously being considered stagnated before 2020 (Ossiannilsson, 2021). Currently, the number of MOOCs users has increased, especially during the COVID-19 outbreak (Impey & Formanek, 2021; Impey et al., 2021). This surge was due to COVID-19 restrictions for outdoor physical activities. Hence, MOOCs became a solution because they offer flexibility in learning which makes it different from formal education formats in general and we know that MOOCs are really changing the way in which people use and share digital knowledge (Cirulli et al., 2016). However, in recent years MOOCs have transformed to meet formal learning qualifications through recognition, accreditation, and certification. Several universities have recognized courses taken at MOOCs held by other institutions through the provision of formal credit (Despujol et al., 2022). Several countries including the European Union, Indonesia, India, and Malaysia are categorized as the early adapters in providing recognition to courses held by other institutions (Garcia et al., 2021). MOOCs accreditation has also been carried out at one of the conventional universities in China, but the implementation of MOOCs accreditation at that university still has challenges and requires future improvement (Wang et al., 2019). Garcia et al. (2021) also confirm that granting academic credit or credit transfer provides at least three benefits to an institution including cost efficiency and resource efficiency by expanding access to higher education without having to open new courses. In addition, another benefit is improving the quality of higher education by utilizing course content offered by well-known experts or professors at other institutions.

Since the beginning of the MOOCs trend, many researchers have begun to focus on implementing MOOCs in traditional classrooms (Israel, 2015). Numerous MOOCs are used as stand-alone online courses without formal credit but are open to anyone or used for registered students in academic institutions that provide MOOCs. In recent years several studies have made MOOCs a complementary resource that blended it with a traditional classroom in order to achieve a better learning outcome (Bralić & Divjak, 2018; Feitosa de Moura et al., 2021).

However, along with the popularity of MOOCs in formal education, the challenges still remain, including how to assess learning in MOOCs (Bayne & Ross, 2014; Bozkurt, 2021; Chauhan, 2014). With a large number of MOOCs users, it is not possible to carry out the process of assessing learning outcomes and providing feedback to students manually one by one. Some MOOCs providers use multiple-choice questions to gauge students' mastery of the concept and peer assessment (Suen, 2014). Alternative approaches for online evaluation include automatic essay scoring (AES) or calibrated peer review (Balfour, 2013).

Summary writing can be viewed as an essential assessment to gauge the students' understanding of the learning materials (Krathwohl, 2002). However, grading students' writing and providing individual feedback to each student is very difficult and time-

consuming for teachers. Therefore, this research objective is to develop an online summary analyzer with automated feedback. The research questions are as follows:

RQ1: How is the design of the online summary framework with automated feedback in the MOOCs?

RQ2: How are the student learning outcomes using online summaries with automated feedback features in MOOCs?

RQ3: What is the students' perceived usefulness of online summary with automated feedback feature in MOOCs?

RQ4: How satisfied are the students with the use of online summaries with automated feedback feature in MOOCs?

2. Literature review

2.1. Assessment in massive open online courses (MOOCs)

Assessment is one important factor in the learning process (Kearns, 2012). An assessment is not only aimed at assessing the performance and progress of student learning, but an assessment must be able to provide motivation to students (Bennett & Wynne, 2006). Based on the results of an assessment, a teacher can reflect on student learning outcomes. It can be said that an assessment can enhance learning (Andrade & Heritage, 2017). Birenbaum et al. (2015) explain that assessment generally has three main missions, namely as an assessment of learning (to assess learning outcomes), assessment for learning (to improve learning), and assessment as learning (as a means of learning). In the higher education environment, assessment is one of the core elements in education that informs all relevant stakeholders about the learning outcomes and the journey to attain the required qualification. Lecturers are the frontline as central stakeholders needing to be directed towards meeting the student needs and that is one of the major goals of assessment (Rocco, 2007; Rocco & Muselli, 2007). Assessment has been described as “*the heart of the student experience*” and is “*probably the single biggest influence on how students approach their learning*” (Rust et al., 2005).

One of the limitations of MOOCs is evaluating and providing feedback on open-ended assignments (Admiraal et al., 2015; Galikyan et al., 2021; Huisman et al., 2018; Pilli & Admiraal, 2017; Wei et al., 2021). MOOCs are to play a role in the future of higher education. It is imperative that we critically examine how they are currently organizing and providing education. In particular, questions persist about the role MOOCs will play in the future of formal accredited learning. As the focus turns from informal and free to formal, accredited, and paid greater scrutiny will be brought to bear on the quality of the courses themselves.

Self-assessment is an important part of any learning process, including MOOCs (Admiraal et al., 2015). Self-assessment can help students check their understanding of course material, identify areas for further study, and measure their progress against learning objectives (Lepp et al., 2017; Ventista, 2018). Self-assessment can also provide students with a sense of accomplishment, helping them to stay motivated and engaged in the course. Self-assessment can take many forms, such as multiple-choice questions, short answer questions, or open-ended questions (Lepp et al., 2017). Each type of question can measure

different aspects of understanding and provide different levels of feedback. As an example, multiple-choice questions can provide students with a quick assessment of their knowledge, while open-ended questions can give them an opportunity to deepen their understanding of the material. Self-assessment can also be used to check progress against course learning objectives, which can be helpful for students who are working towards a specific goal. Self-assessment can be beneficial for both students and instructors (Ventista, 2018). Students can use self-assessment to identify areas of confusion, adjust their study strategies, and track their progress. Instructors can use self-assessment to gain insight into how well students comprehend the material and to identify areas that need to be better explained or expanded upon. In conclusion, self-assessment is an important tool for both students and instructors in an MOOC. It can help students identify their strengths and weaknesses, track their progress, and stay motivated. It can also help instructors gain insight into how well their students understand the material (Admiraal et al., 2015; Lepp et al., 2017; Ventista, 2018).

Self-assessment has been recorded to have moderate to high internal consistency (Admiraal et al., 2015). Concerning self-image bias, adults can usually distinguish effort from ability. Even if they cannot, it does not contradict the construct or consequential validity of the assessment as long as the self-assessment remains formative. On the contrary, the belief that the amount of effort does not necessarily lead to a superior result can decrease the motivation of the students. Therefore, the inclusion of effort can even be considered desirable.

MOOCs with huge enrolments make it impossible to afford the luxury of student-instructor interaction. MOOCs, therefore, depend on automated assessments to not only grade but also provide automated feedback to the students. In that sense, automated assessments therefore provide the student with a unique advantage of anywhere, anytime grading and feedback (Reeves, 2000). Rich feedback also can encourage students to self-reflect and improve the quality of their work (Chao et al., 2014). Research has shown that assessments based on Item Response Theory (IRT) can be used effectively in online assessments (Baylari & Montazer, 2009; Chen et al., 2005). These tests are designed to automatically adapt to student learning and ability in order to measure student performance and learning outcomes. The tests include different levels of difficulty and based on the response of the student to each test item, the difficulty level decreases or increases to match the student's ability and potential (Meyer & Zhu, 2013). The final score is based on the difficulty level of the correct answer (Challis, 2005). The advantage of using adaptive assessments is that based on the final score, course content can be tailored to meet individual student needs (Baylari & Montazer, 2009). Since MOOCs participants are not limited to a geographical location and include different background knowledge and skills, designing learning modules that use adaptive assessment can go a long way in making learning relevant and meaningful to participants who enroll in MOOCs.

2.2. Automated feedback

One of the important parts of the teaching and learning process is feedback (Cavalcanti et al., 2021). In online learning, feedback is more essential as online activities are solitary (Jensen et al., 2021). Automated feedback systems are widely utilized in MOOCs to provide students with rapid and efficient feedback. It provides students with personalized and immediate feedback on their submitted work, increasing their motivation to learn and ultimately leading to improved learning outcomes (Olaniran et al., 2018). Automated

feedback systems can also be used to assess student performance and provide timely feedback on incorrect answers for example using concept maps and machine learning (Bleckmann & Friege, 2023). This type of feedback helps to increase student motivation and engagement in MOOCs (Beheshti et al., 2016). Automated feedback systems are typically integrated into MOOCs to provide students with personalized feedback and support in the form of auto-graded quizzes, automated peer feedback, and automated essay feedback (Gabbay & Cohen, 2022). Automated feedback systems assess student work and provide detailed feedback on areas of improvement. This feedback can be used to inform students of their progress and areas that need further attention, allowing them to take corrective action and improve their learning outcomes (Olaniran et al., 2018). The automated feedback contains information that can aid students in making decisions (Loh et al., 2010). Automated feedback systems can also be used to provide personalized feedback on incorrect answers, helping to increase student engagement and motivation in MOOCs (Beheshti et al., 2016).

In addition, automated feedback systems can be used to provide personalized feedback to students in the form of automated peer feedback. Automated peer feedback allows students to receive feedback on their work from peers in their MOOC, providing them with valuable insight and guidance on areas of improvement (Gabbay & Cohen, 2022). Automated peer feedback also allows students to receive feedback from a variety of different perspectives, allowing them to gain a deeper understanding of their work and the topics being studied (Olaniran et al., 2018). Moreover, automated feedback in MOOCs is an important learning design to help students determine and achieve their learning goals (Phan, 2023).

2.3. Similarity algorithm in natural language processing

Text similarity is an important aspect in the field of Natural Language Processing (NLP). Similarity measurement in data mining refers to the distance in a dataset with dimensions that indicate features of the data object. There will be a high degree of similarity if this distance is small, but a low degree of similarity if this distance is large. Text similarity is widely used for plagiarism detection (El-Rashidy et al., 2023). The phrase “*reusing someone else’s prior ideas, processes, results, or words without specifically recognizing the original author and source*” is defined by IEEE to characterize text plagiarism (Causser, 2011).

According to Gomaa and Fahmy (2013), words can be similar in two ways: lexically and semantically. Words are lexically similar when their character sequences are identical, however, words are semantically similar when their context-specific meanings are the same. With that being said, according to Gomaa and Fahmy (2013), the Classification framework of similarity algorithms uses String-Based algorithms for lexically similar words while Corpus-Based and Knowledge-Based algorithms are used for semantically similar terms. Whereas Wang and Dong (2020) classify text similarity measurements based on the evolution of semantic similarity technology, in that similarity calculations are split into two, namely text distance and text representation.

One of the most popular similarity algorithms is cosine similarity (Sohangir & Wang, 2017). Cosine similarity is a size-independent metric for comparing the similarity of data objects. The cosine similarity metric considers each data object in a dataset to be a vector. The Cosine of the angle between any two non-zero vectors in an inner product space

is used to determine the similarity of the vectors. The following formula depicts cosine similarity:

$$\text{Cosine similarity} = \frac{(A \cdot B)}{(\|A\| \times \|B\|)}$$

According to the formula above, cosine similarity returns one when two texts are similar, or zero when the texts are completely dissimilar. There are four levels of textual similarity using a corpus of plagiarized texts, namely highly similar text, lightly reviewed texts, heavily reviewed texts, and highly dissimilar texts), Thompson et al. (2015) concluded that Cosine similarity performed best on lightly and heavily reviewed text. Previous research has also confirmed that Cosine is most effective when used for similarity measurement between texts of different lengths (Hoad & Zobel, 2003).

3. Experimental design

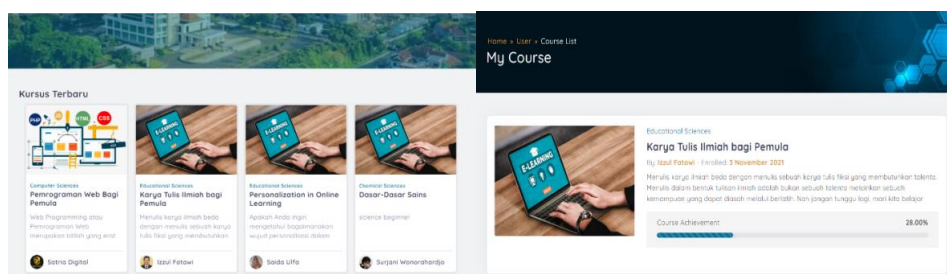
3.1. Research participants

The study involved 100 participants who were second-year students of the Educational Technology Department, State University of Malang, East Java, Indonesia.

3.2. Research procedures

Researchers developed MOOCs platform and the online summaries with the automated feedback feature embedded in MOOCs. The development process was carried out using the waterfall model of the system development life cycle (Kramer, 2018).

After the process of developing the MOOCs platform and the online summary with automated feedback feature was completed, further testing was carried out using a pre-experimental design with one group pre-post-test design. The participants were assessed twice at the pretest and again after they completed treatment (post-test). According to Thyer (2012), this research design is feasible, even if the average score on the post-test was significantly improved relative to the average score for the pre-test, then we could legitimately claim that the hypothesis was corroborated.



(a) Several courses

(b) One course

Fig. 1. MOOCs interface of (a) several courses and (b) one course

Furthermore, students used MOOCs which have been equipped with the Online Summary with Automated Feedback feature by registering for the Scientific Writing Course (see Fig. 1). After that, students accessed learning content using a self-paced

method so that the speed of completing the course differed from one student to another. Although the method was self-paced, in this study, students had the opportunity to complete each module in one week.

The course being tried out was a compulsory course presented to second-year students in the Educational Technology department. The course was presented online only focusing on providing students with a basic understanding of the basic concepts of research methods in scientific writing. While several other chapters were presented face-to-face which were not included in this study. Learning content in the Scientific Writing Course consists of three chapters, namely 1) Introduction to Scientific Writing, 2) Scientific Knowledge and Scientific Method in Research, and 3) Bibliometric Method.

Each chapter has a formative evaluation, with two types of evaluation methods namely making a summary and multiple choice (see Fig. 2). The questions given in both tests focused more on factual knowledge. The questions provided for the multiple-choice type and online summary were intended to measure the level of remembering and understanding based on the six levels of cognitive processes from Bloom's Theory, respectively (Krathwohl, 2002).

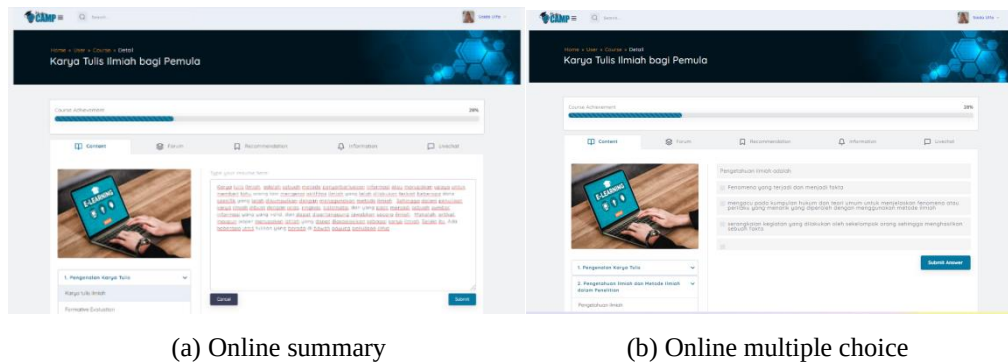


Fig. 2. Formative evaluation system of (a) online summary and (b) online multiple choice

Summary evaluation is intended to determine students' mastery of understanding of the main ideas in the learning content presented (see Fig. 2.b). These main ideas are also used as material for questions in the formative evaluation in the form of multiple-choice questions (see Fig. 2.a). These main ideas are part of the achievement of learning objectives in each chapter. This automated feedback feature analyzes the summary writings of each student and provides feedback in real-time (see Fig. 3). The automated feedback feature in this online summary provides an opportunity for students to improve their summary writing skills through multiple practices. This feature will return two pieces of feedback to the students, the summary score and comment that inform students whether they need to revise their summary or not. This type of feedback is categorized as verification feedback, it is simple feedback, but it also can help the students monitor their learning progress (Demaidi et al., 2018), enabling them to continue analyzing the summary they have created until they achieve the maximum score.

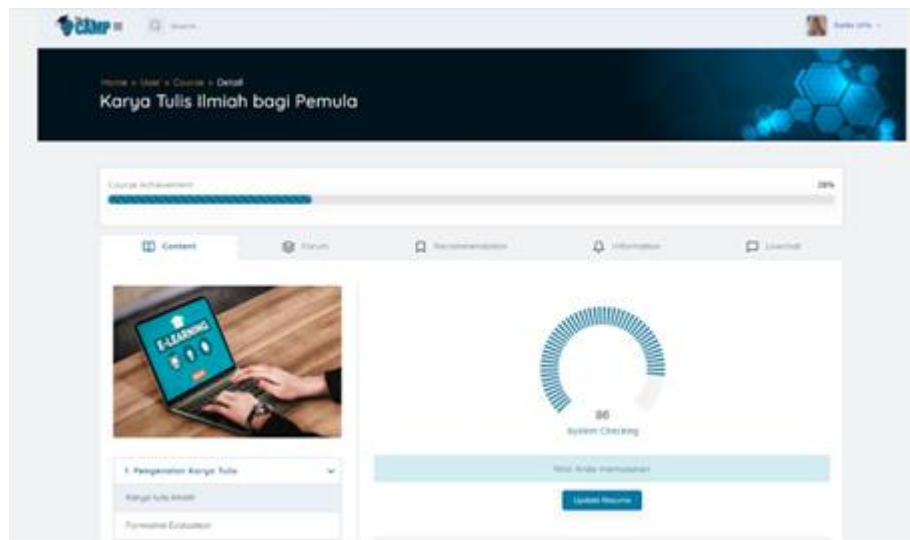


Fig. 3. Online summary with automated feedback interface

4. Research findings and discussions

4.1. System framework

RQ1: How is the design of the online summary framework with automated feedback in the MOOCs?

A framework system was developed (as described in Section 3.2, and the framework is illustrated in Fig. 5) for adaptive assessment into three parts, namely the interface module or visualization module, the MOOCs platform, and the online summary analyzer. The visualization module includes a teacher's dashboard as shown in Fig. 4, a learning dashboard as shown in Fig. 6, and a learning analytics dashboard (see Fig. 7.a and Fig. 7.b). The second part of the framework system is the MOOCs platform which consists of several modules, namely:

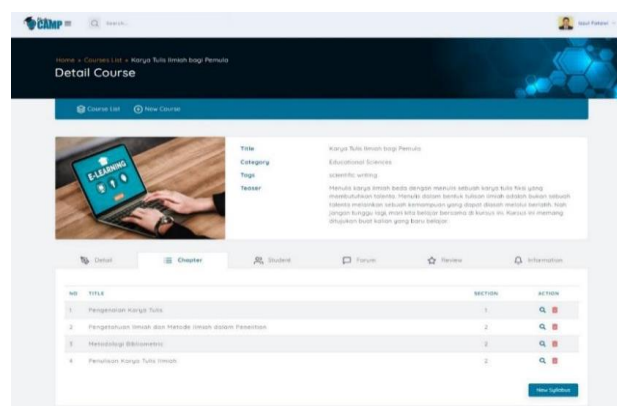


Fig. 4. Teacher's dashboard

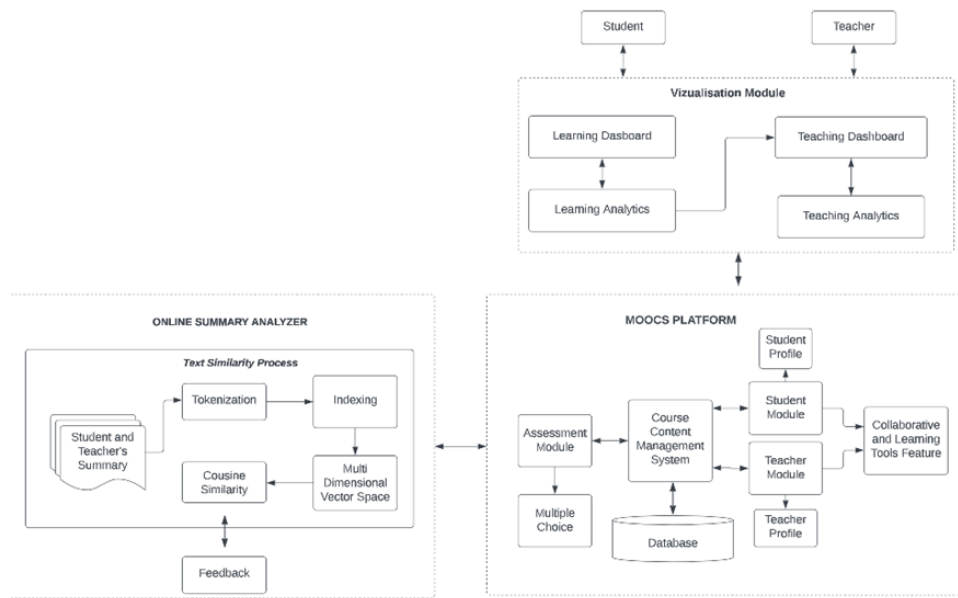


Fig. 5. Framework of MOOCs online summary-automated feedback feature

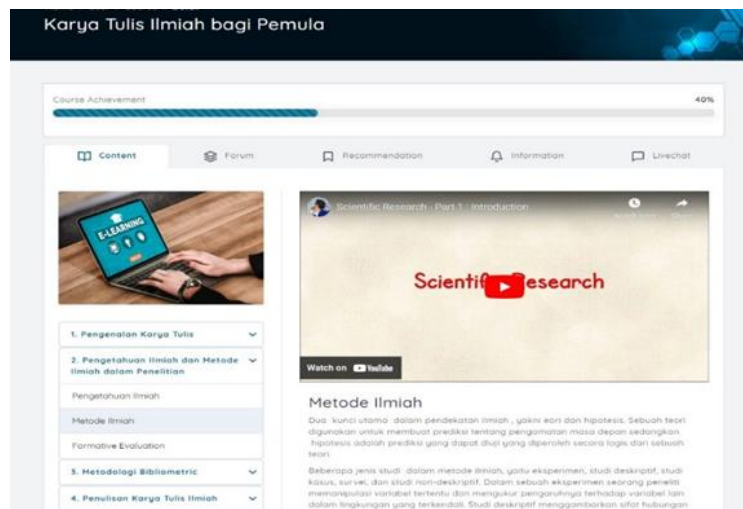


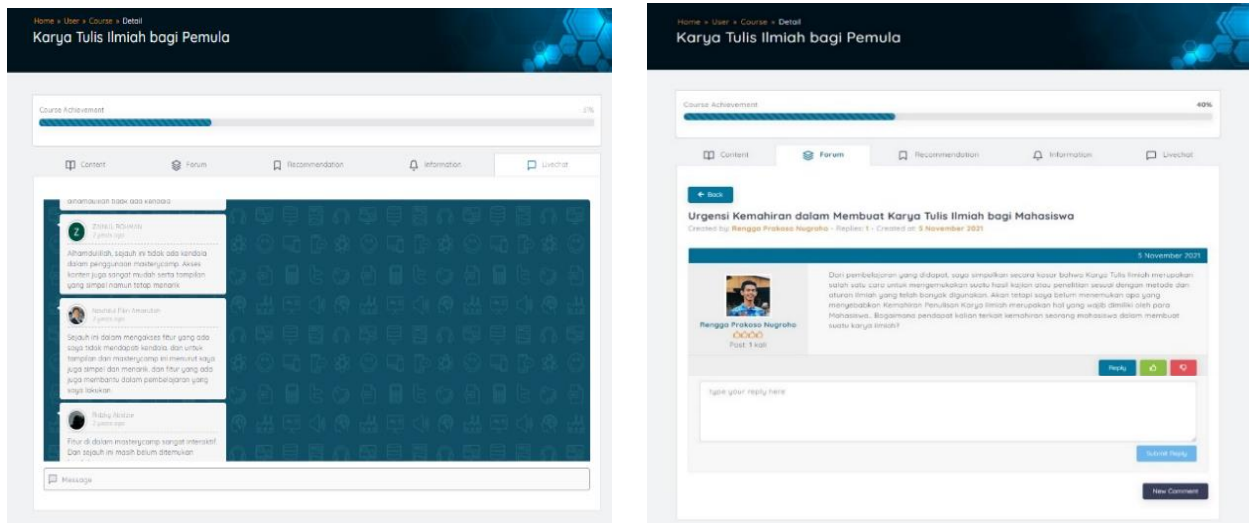
Fig. 6. Learning dashboard

4.1.1. Course management system

CMS (course management system) is a module that manages the learning system in general. The purpose of developing this module is to integrate all existing learning features so that it does not require additional external devices to organize existing classes (see Fig. 1.a).

4.1.2. Student and teacher module

This module contains the results of the authentication process, authorization process, and organizations that are intended as user privacy data so that the system recognizes the user, enabling the system to distinguish the role of the user whether logging in as a student or teacher. In addition, all online learning activities for each student are stored in this student module (see Fig. 8.a). On the teacher's side, it provides the summary of all student data in the course (see Fig. 8.b).



(a) Live chat interface

(b) Forum interface

Fig. 7. Interactive features of (a) live chat interface and (b) forum interface

4.1.3. Multiple choice tool

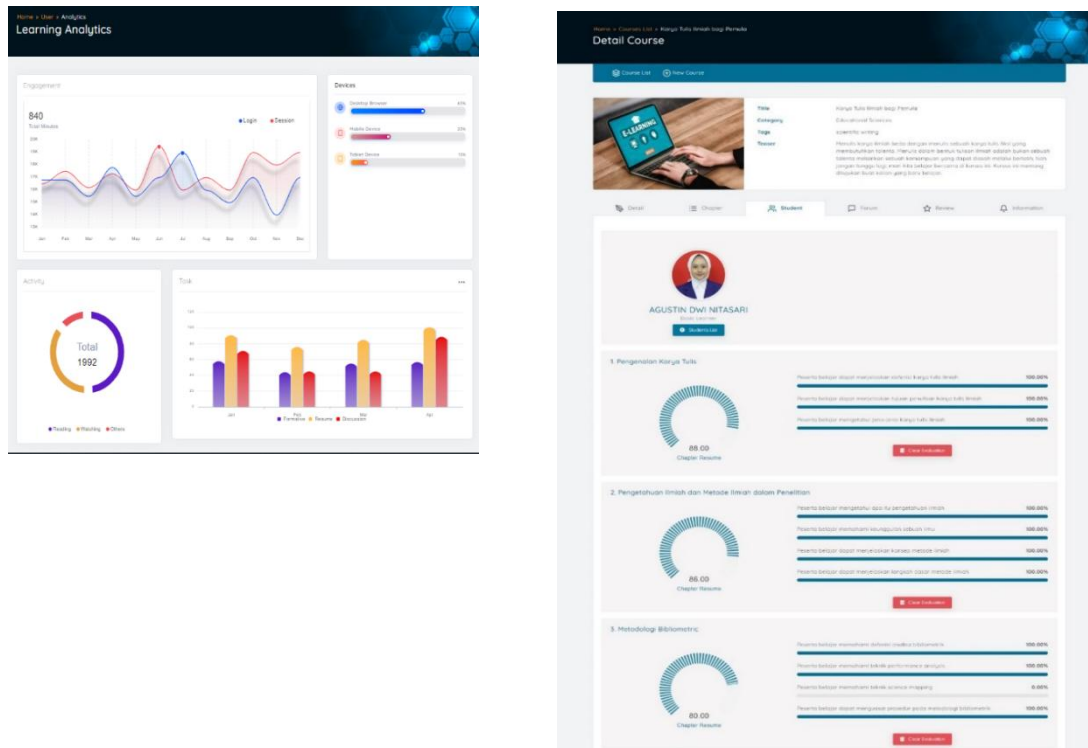
This section is a tool used to measure formative assessment. This module specifically provides evaluation or assessment in the form of multiple-choice questions (see Fig. 2.b).

4.1.4. Collaborative learning tool

The MOOCs system is equipped with collaborative learning tools in the form of discussions, live chats and forums. The live chat is intended to facilitate direct communication with teachers in asynchronous mode (see Fig. 8.a). Meanwhile, the forum feature is intended to allow students to interact with other students and with lecturers. Several features are provided on the forum, namely creating new topics, posting comments, responding to comments, and rating comments in the form of likes and dislikes (see Fig. 8.b).

4.1.5. Databases

The database in this system is used to store data for all modules such as user profiles, organization of course materials, assignments, evaluation results, and user access traces, all of which are stored in the database. All data collected will later be processed again by the system to then appear as useful information for all users, both students and instructors.



(a) Student's progress in student's dashboard (b) Student's learning progress in teacher's dashboard

Fig. 8. Learning analytics of (a) student's progress in student's dashboard and (b) student's Learning progress in teacher's dashboard

MySQL, a relational database management system (RDBMS), was employed for its ability to connect tables and reduce duplicate data with the data normalization process when planning this learning management system. This decision was made as each data entity is connected to other entities, such as the relationship between the user table that has the role of the student and the course, enrollment, and task tables such as summary and multiple-choice evaluations. In addition, MySQL supports SQL in order to facilitate data traffic management and queries between table relations. The entity relationship diagram (ERD) of the database is shown in Fig. 9.

The third part of this framework is the Online summary analyzer. This module uses one of the text mining algorithms in analyzing students' summaries, particularly using text similarity measurement. It compares the text with available references to estimate the degree of similarity between those texts, and it plays an important role in the NLP task (Wang & Dong, 2020). One of the text similarity algorithms used in this online summary with an automated feedback feature is Cosine similarity. It is intended to measure the similarity between two vectors by taking the cosine of the angle of the two vectors by calculating their dot product space divided by the product of their lengths. If the angle is zero, their similarity is one, the larger the angle yields the smaller their similarity. It is often used to measure the similarity of two documents in text analysis (Han et al., 2012).

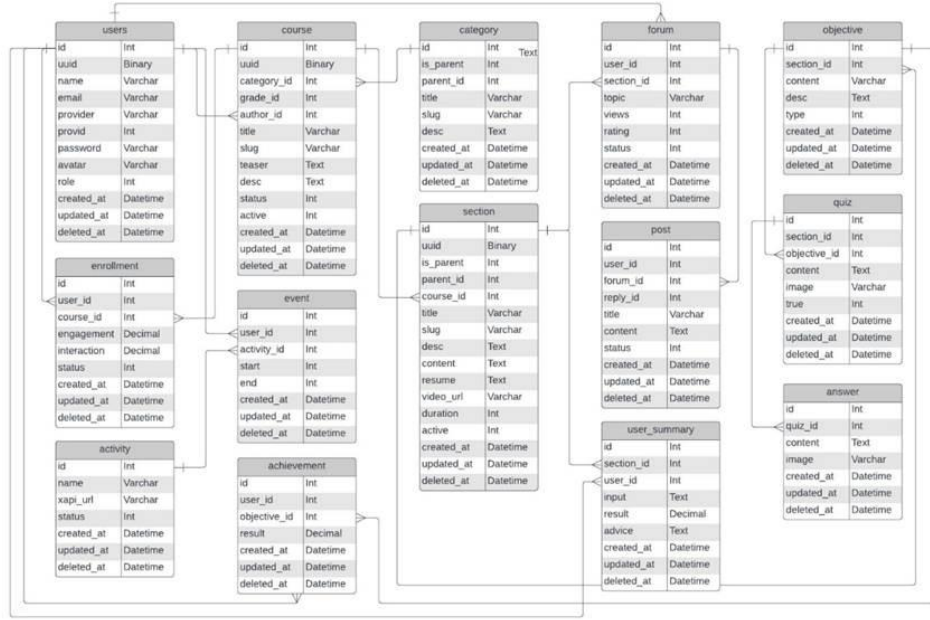


Fig. 9. Entity relationship diagram

The following are the stages of analyzing the students' summary process:

Text similarity process:

- Students and teachers' summary: The teacher prepares a summary to be used as a reference. Furthermore, the results of the student summary are compared with the teacher's summary. The teacher's summary and student's summary in this case are categorized as different documents.
- Tokenization: At this stage the texts that will be compared (student and teacher summary) separately will be split into separate pieces or some other meaningful elements called tokens.
- Multidimensional vector space: The results of the tokenization process for the two documents are stored in vector form using the bag-of-words model. Next, calculate the term frequency-inverse document frequency (*tf-idf*) which is a statistical measurement to evaluate how relevant a word is to a document in a collection of documents. Here is Equation 1 to calculate *idf* for a term (*t*) in a document (*D*) is given as (Rahman et al., 2018):

$$idf_{t,D} = \log_2 \frac{N}{|\{d \in D : t \in d\}|} \quad (1)$$

where *N* is the number of documents in the collection, and $|\{d \in D : t \in d\}|$ is the number of documents where the term *t* occurs.

$$tf - idf_{t,D} = tf_{t,D} * idf_{t,D} \quad (2)$$

Equation 2 is used to calculate the *tf-idf* score, which is then used to calculate cosine similarity.

Cosine similarity:

The following is the equation used to measure cosine similarity.

$$\text{cosine similarity}(d1, d2) = \frac{\vec{v}(d1) \cdot \vec{v}(d2)}{|\vec{v}(d1)| |\vec{v}(d2)|} \quad (3)$$

Equation 3 is a formula to measure the similarity between two documents $d1$ and $d2$. It computes the cosine similarity of their vector representations and where the numerator represents the dot product of the vectors, whereas the denominator is the product of their Euclidean lengths.

Feedback: Corrective feedback was employed. The feedback given to students was the summary score information obtained from the calculation of cosine similarity. If a student scored below a score of 70, the student would be asked to revise the summary until the score reached above 70.

4.2. Student learning outcomes using online summary with automated feedback

The research procedure in sub-section 3.2 was carried out by the researcher to answer the following research questions (RQ).

RQ2: How are the student learning outcomes using online summaries with automated feedback feature in MOOCs?

The need for online assessment since the outbreak of the COVID-19 outbreak has increased rapidly and is expected to continue after COVID-19 in the new normal era. Although the use of the e-learning platform in conducting online assessments is not mandatory, the majority of online assessments are supported by the Moodle e-learning platform (Topuz et al., 2022). This is due to the large number of online assessment plugins that support Moodle (Huerta et al., 2022). Whereas on the MOOCs platform, multiple choice questions are one type of assessment commonly used in MOOCs which are used to test students' declarative knowledge (Admiraal et al., 2015), and enable representative sampling of course content (Costello et al., 2018). Thus, in this study, a type of MCQ assessment was also employed.

Both formative tests using online summaries and multiple-choice questions with automated feedback were conducted at the end of the chapter to measure learning outcomes. The results of these two tests will be used as a benchmark to see differences in the use of online summaries in terms of learning outcomes.

The obtained learning outcome data carried out a normality test to determine the type of test that will be used next whether it is a parametric or non-parametric test. Based on Table 1 ($p < 0.05$) shows the results of the normality test using the Kolmogorov-Smirnov test. Hence, to analyze the effectiveness of formative evaluations using online summaries compared to multiple-choice question evaluations, a non-parametric test is used. This study used the Wilcoxon Signed Rank Test (WSRT). This test is a non-parametric equivalent of the parametric paired t-test which is suitable for comparing two correlated samples that do not meet the assumption of normality, as seen in. Tests in this study compared two data sets of learning outcomes from the same participant.

Table 1

Test of normality

Variables	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistics	df	Sig.	Statistics	df	Sig.
Chapter 1	.250	100	< .001	.870	100	< .001
Chapter 2	.100	100	.016	.969	100	.017
Chapter 3	.146	100	< .001	.949	100	< .001

It is very appropriate for a repeated measure design where the same subjects are evaluated under two different conditions. The Wilcoxon signed rank is more powerful than the sign test. This statistic differs from the sign test in that it considers the magnitude of the difference while the sign test does not. It uses more information from the set of scores than the simple sign test. Since it uses more information, it is considered to be more precise than the sign test (Scheff, 2016).

In Table 2, the average online summary scores are higher than the multiple-choice scores, except in chapter 1, where the material presented includes a very general discussion that participants may have already mastered, namely the introduction to scientific writings; thus, the multiple-choice average score is higher. In addition, the online summary standard deviation value is slightly lower than the multiple-choice questions in all chapters. This shows that online summary scores are more clustered around the mean. With a smaller SD value, it can be assumed that student learning outcomes in this class are almost uniform. This can be considered good if the mean value obtained is also high. As shown in Table 2, the Mean and SD values in chapters 2 and 3 for learning outcomes using online summary with feedback show a higher mean value than the multiple-choice questions with a lower SD value than the multiple-choice questions.

Table 2

Descriptive statistics comparison of online summary and multiple-choice scores

Chapter	Type of tests	N	Min	Max	Mean	Standard deviation	Variance
Chapter 1	Multiple choice	100	33.00	100.00	91.00	16.83	283.01
	Online summary	100	49.00	92.00	81.41	9.07	82.35
Chapter 2	Multiple choice	100	20.00	100.00	68.93	18.01	324.32
	Online summary	100	41.00	92.00	74.92	10.72	114.90
Chapter 3	Multiple choice	100	25.00	100.00	70.35	14.46	209.22
	Online summary	100	45.00	92.00	75.70	8.49	72.03

As seen in Table 3, a comparison of the multiple-choice score to the online summary score is obtained with a negative rank value greater than a positive rank ($z = -4.486$, $p < .05$), so it can be concluded that there is a difference in scores, but with the online summary score lower than the multiple-choice score. In chapters 2 and 3, negative rank values were lower than positive rank ($z = -2.968$, $p < .05$ and $z = -3.618$, $p < .05$). In conclusion, it can be concluded that online summary with automated feedback created a positive difference in student learning outcomes. Several previous studies have also revealed that training in summary writing can help students improve learning outcomes (Franzke et al., 2005). Learning through summary can deepen comprehension skills by identifying important ideas in a text (Garner, 1982). Specifically, Sung et al. (2016) demonstrated the effectiveness of online summaries with semantic feedback in improving

students' writing skills. With automated feedback, students will spend more time working on their summaries (Wade-Stein & Kintsch, 2004).

Table 3

Wilcoxon signed-rank test results for multiple-choice questions and online summary scores

Chapter	Categories	<i>N</i>	Mean rank	Sum of ranks	<i>Z</i>	Asymp. sig. (2-tailed)
Chapter 1 – Test	Negative rank	78	49.09	3829.00	- 4.486	< .001
	Positive rank	22	55.50	1221.00		
	Ties	0				
	Total	100				
Chapter 2 – Test	Negative rank	38	40.84	1552.00	- 2.968	0.003
	Positive rank	59	54.25	3201.00		
	Ties	3				
	Total	100				
Chapter 3 – Test	Negative rank	32	39.81	1274.00	- 3.618	< .001
	Positive rank	62	51.47	3191.00		
	Ties	6				
	Total	100				

4.3. Students' perceived usefulness of online summary with automated feedback

RQ3: What is students' perceived usefulness of online summary with automated feedback feature in MOOCs?

To measure the perceived usefulness of online summary with automated feedback on the developed MOOCs learning system, researchers used a six-item questionnaire as presented in section Appendix I (items no. 8-13). The eight items were adopted from several studies (for example, Alqahtani et al., 2022; Gashi et al., 2022; Joo et al., 2018; Kumar Sharma et al., 2014) using five Likert scales as many as 100 users have provided answers (see Table 4).

Table 4

Descriptive statistic data

Item	<i>N</i>	Minimum	Maximum	Mean	SD
PU1	100	3	5	4.02	.586
PU2	100	2	5	4.17	.697
PU3	100	2	5	4.04	.695
PU4	100	2	5	3.98	.724
PU5	100	3	5	3.97	.643
PU6	100	2	5	3.90	.759
Valid <i>N</i> (listwise)	100				

To measure the reliability of research instruments (see Appendix I) Cronbach's Alpha (CA) value was used as a reference. By using 50 respondents, the CA value of the research instrument was 0.921. According to Hair et al. (2019), if the CA value is greater than 0.9, it is categorized as excellent.

To measure the perception of the usefulness of online summary with automated feedback on MOOCs, researchers used a six-item questionnaire as presented in section appendix 1 (items no. 1-6). The items were adopted from several studies (e.g., Alqahtani et al., 2022; Gashi et al., 2022; Joo et al., 2018; Kumar Sharma et al., 2014) by using 5-point Likert scales, with 100 research participants (see Table 4). In general, the students as the research participants mostly agreed and strongly agreed with each item asked (see Fig. 10).

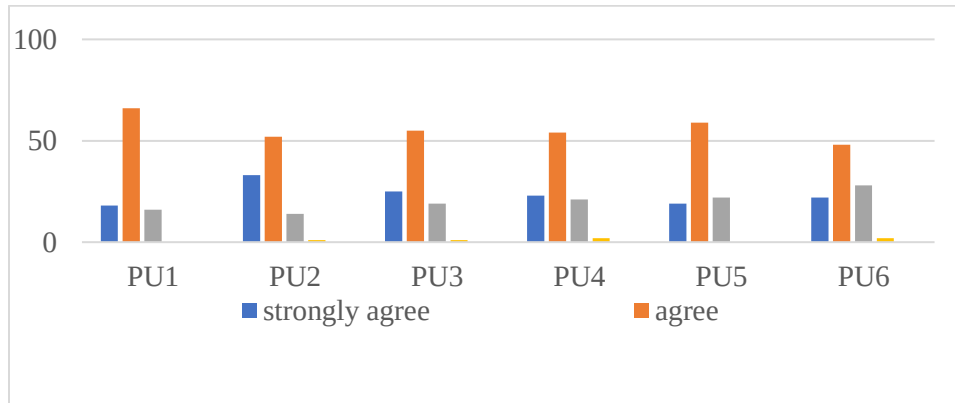


Fig. 10. Students' perceived usefulness (PU) of online summary with automated feedback

The data in Table 4 and Fig. 10 show that the online summary-automated feedback feature is beneficial to students. In detail, they confirm that the online summary-automated feedback feature helps them understand the learning material, practice writing summaries, monitor their learning progress, notify parts of the learning material that they have not yet understood, provide feedback services according to student needs, and increase personalized learning. These findings are in line with other reported findings that an automated summarization provides students with personalized and immediate feedback on their submitted work, increasing their motivation to learn and ultimately leading to improved learning outcomes (Olaniran et al., 2018). In addition, it can increase student motivation and engagement in MOOCs (Beheshti et al., 2016), provide students with personalized feedback and support in the form of auto-graded quizzes, automated peer feedback, and automated essay feedback (Gabbay & Cohen, 2022), allowing them to take corrective action and improve their learning outcomes (Olaniran et al., 2018), as well as providing personalized feedback on incorrect answers, helping to increase student engagement and motivation in MOOCs (Beheshti et al., 2016). Overall, the automated feedback system is a valuable tool for MOOCs, providing students with personalized and timely feedback that can be used to improve their learning outcomes, assess student performance, provide personalized feedback on incorrect answers, provide automated peer feedback, and increase student motivation and engagement in MOOCs, ultimately leading to improved learning outcomes.

4.4. Student satisfaction on the online summary with automated feedback

RQ4: How satisfied are the students with the use of online summaries with automated feedback feature in MOOCs?

In this study, there is a question about the satisfaction level of using the online summary with automated feedback feature, namely: “*I am satisfied with the performance of the feedback generated by the online summary-automated feedback feature*”. Based on these questions, an average mean of 4.07 was obtained (using a 5-point Likert scale) with a standard deviation of 0.7. This shows that research participants in this case are students who are satisfied with the Online Summary with Automated Feedback feature in general.

Student satisfaction refers to the favorability of a student’s subjective evaluation of the various outcomes and experiences associated with education (Oliver, 1989). Student satisfaction is an important factor influencing the adoption of the use of technology in online learning, especially in a MOOCs platform. Several factors affect students’ satisfaction with MOOCs, which include course delivery, course assessment, and course support (Kumar & Kumar, 2020). Enabling learning with the help of technology is rising, which has been evident from the way the current courses have been developed. The students themselves demonstrate how adopting the technology has led to successful learning. A detailed analysis of students’ satisfaction survey will help the educators understand students’ expectations from the course and they can work on these factors which leads to increasing the students’ satisfaction with MOOCs and thereby addressing high-dropout rates from MOOCs (Pande & Mythili, 2021).

The online exam during the COVID-19 pandemic was a significant factor in determining student satisfaction (Basuony et al., 2021). In line with research conducted by (Martín Rodríguez et al., 2019) which says that one of the component effects of student satisfaction in online learning is how the lecture assesses student performance, and the assessment method used must be able to access knowledge and skills acquired during the learning process. In addition, during the COVID-19 pandemic, various online assessment features have been used by educators around the world to conduct online learning assessments. Multiple choice is one of the prominent features of an online learning environment. Research conducted by Topuz et al. (2022) shows a 63.6% use of multiple choice and a 50% essay use in online assessments. However, according to Yuksel and Fidan (2019), there are several weaknesses of multiple-choice questions including 1) they cannot be used to express expressions, in particular, they cannot measure students’ abilities at the level of synthesis and evaluation; 2) more time is consumed by reading questions and looking for answers to questions.

Meanwhile, questions in the form of open-ended writing tests such as essay tests and summaries have advantages that are not accommodated by multiple-choice questions. For example, an essay test can be used to explore students’ reasoning abilities (Schuwirth & van der Vleuten, 2004). As with the summary assessment, it can provide opportunities for students to express the main ideas in the text briefly (Downing, 2002). However, assessing student summary results requires individual feedback which is very time-consuming for teachers (Sung et al., 2016). Therefore, the existence of Online Summary with Automated Feedback which is the object of this research provides a new breakthrough in conducting online assessments, especially open-ended essays in MOOCs-based learning environments.

5. Conclusion

The increasing number of online learning implementations currently has implications for the implementation of online assessments. Close-ended questions remain the foremost

online assessments, particularly in the form of multiple-choice questions. Although it is easy to give an assessment, one of the weaknesses is that it cannot measure students' reasoning abilities, so open-ended questions such as summary assessments are an option. However, giving a manual summary assessment is time-consuming, especially if the course is held in a MOOCs platform, making it impossible to be carried out one by one. Therefore, the results of this study in the form of an online summary with automated feedback feature embedded in the MOOCs platform are very promising and can significantly help teachers provide real-time assessments to students.

To measure the effectiveness of using the online summary with automated feedback feature, trials have been conducted on a group of students by measuring their learning outcomes. The results of this study have indicated an increase in student learning outcomes using this feature. This also shows that this feature can help students briefly write down the main ideas in a text. In short, with the automated feedback provided, student self-regulated learning can be promoted where this variable is one of the components that can increase success in learning.

Measurement of students' perceived usefulness and satisfaction was also carried out in this study. The results of statistical analysis have proven that the average student agrees that the online summary-automated feedback feature can facilitate learning material, provide practice in making summaries, help monitor individual learning progress, grade their summary, provide services according to student needs, and increase learning independence. Based on these findings, it can be concluded that this feature is useful to increase student motivation and learning outcomes. Measuring the level of satisfaction is very important to see how satisfied students are after using this feature. The level of satisfaction greatly influences the chances of using a system in the future. The results of the students' perception measurement on the satisfaction of this feature have indicated that this feature can be used in general.

There are two limitations in this study, namely the summary checker feature and the automated feedback feature. The summary checker tool that was developed in this study still relied on the manual summary provided by the teacher because the system compared the students' summary to the teacher's summary by using a similarity algorithm. The automated feedback provided in this study is categorized as verification feedback that only confirms the student's work. In this study, the system automatically displayed the summary grading with a comment. In order to make the evaluation system more effective the system should be equipped with sophisticated feedback that can give detailed information about the student performance.

Author Statement

The authors declare that there is no conflict of interest.

Acknowledgements

This research was funded by Universitas Negeri Malang's Internal research grant (Number 3.3.16/UN32/KP/2020). All procedures performed in studies involving human participants were in accordance with the ethical standards of Universitas Negeri Malang.

ORCID

Saida Ulfa  <https://orcid.org/0000-0002-2302-7172>

Ence Surahman  <https://orcid.org/0000-0002-8850-4275>

Agus Wedi  <https://orcid.org/0000-0001-9579-6459>

Izzul Fatawi  <https://orcid.org/0000-0003-2550-2923>

Rex Bringula  <https://orcid.org/0000-0002-1789-9601>

References

- Admiraal, W., Huisman, B., & Pilli, O. (2015). Assessment in massive open online courses. *Electronic Journal of E-Learning*, 13(4), 207–216. Retrieved from <https://academic-publishing.org/index.php/ejel/article/view/1728>
- Alqahtani, M. A., Alamri, M. M., Sayaf, A. M., & Al-Rahmi, W. M. (2022). Exploring student satisfaction and acceptance of e-learning technologies in Saudi higher education. *Frontiers in Psychology*, 13: 939336. <https://doi.org/10.3389/fpsyg.2022.939336>
- Andrade, H. L., & Heritage, M. (2017). *Using formative assessment to enhance learning, achievement, and academic self-regulation*. Routledge. <https://doi.org/10.4324/9781315623856>
- Balfour, S. P. (2013). Assessing writing in MOOCs: Automated essay scoring and calibrated peer review™. *Research & Practice in Assessment*, 8, 40–48. Retrieved from <https://www.learntechlib.org/p/157940/>
- Basuony, M. A. K., EmadEldeen, R., Farghaly, M., El-Bassiouny, N., & Mohamed, E. K. A. (2021). The factors affecting student satisfaction with online education during the COVID-19 pandemic: An empirical study of an emerging Muslim country. *Journal of Islamic Marketing*, 12(3), 631–648. <https://doi.org/10.1108/JIMA-09-2020-0301>
- Baylari, A., & Montazer, G. A. (2009). Design a personalized e-learning system based on item response theory and artificial neural network approach. *Expert Systems with Applications*, 36(4), 8013–8021. <https://doi.org/10.1016/j.eswa.2008.10.080>
- Bayne, S., & Ross, J. (2014). MOOC pedagogy. In K. Paul (Ed.), *Massive Open Online Courses* (pp. 33–55). Routledge. <https://doi.org/10.4324/9781315848655>
- Beheshti, J., Bilal, D., Mackey, T. P., Limberg, L., Bartlett, J. C., Gwizdka, J., Jacobson, T., & Ishimura, Y. (2016, October). Information literacy: Bridging the gap between theory and practice. In *Proceedings of the Association for Information Science and Technology* (pp. 1–6). Wiley. <https://doi.org/10.1002/pra2.2016.14505301019>
- Bennett, S., & Wynne, K. (2006). *Special education transformation: The report of the co-chairs with the recommendations of the working table on special education: Final report to the Minister of Education*. Ontario Ministry of Education. Retrieved from <https://coilink.org/20.500.12592/qvqjhd>
- Birenbaum, M., DeLuca, C., Earl, L., Heritage, M., Klenowski, V., Looney, A., Smith, K., Timperley, H., Volante, L., & Wyatt-Smith, C. (2015). International trends in the implementation of assessment for learning: Implications for policy and practice. *Policy Futures in Education*, 13(1), 117–140. <https://doi.org/10.1177/1478210314566733>
- Bleckmann, T., & Friege, G. (2023). Concept maps for formative assessment: Creation and Implementation of an automatic and intelligent evaluation method. *Knowledge Management & E-Learning*, 15(3), 433–447.

- <https://doi.org/10.34105/j.kmel.2023.15.025>
- Bozkurt, A. (2021). Surfing on three waves of MOOCs: An examination and snapshot of research in massive open online courses. *Open Praxis*, 13(3), 296–311. <https://doi.org/10.5944/openpraxis.13.3.132>
- Bralić, A., & Divjak, B. (2018). Integrating MOOCs in traditionally taught courses: Achieving learning outcomes with blended learning. *International Journal of Educational Technology in Higher Education*, 15(1): 2. <https://doi.org/10.1186/s41239-017-0085-7>
- Causser, C. (2011). The way ahead. *IEEE Potentials*, 30(4), 3. <https://doi.org/10.1109/MPOT.2011.942130>
- Cavalcanti, A. P., Barbosa, A., Carvalho, R., Freitas, F., Tsai, Y. S., Gašević, D., & Mello, R. F. (2021). Automatic feedback in online learning environments: A systematic literature review. *Computers and Education: Artificial Intelligence*, 2: 100027. <https://doi.org/10.1016/j.caeai.2021.100027>
- Challis, D. (2005). Committing to quality learning through adaptive online assessment. *Assessment & Evaluation in Higher Education*, 30(5), 519–527. <https://doi.org/10.1080/02602930500187030>
- Chao, K. H., Lan, C. H., Chang, K. E. & Sung, Y. T. (2014). Implementation of a mobile peer assessment system with augmented reality in a fundamental design course. *Knowledge Management & E-Learning*, 6(2), 123–139. <https://doi.org/10.34105/j.kmel.2014.06.009>
- Chauhan, A. (2014). Massive open online courses (MOOCS): Emerging trends in assessment and accreditation. *Digital Education Review*, 25, 7–17. Retrieved from <https://raco.cat/index.php/DER/article/view/278125/387378>
- Chen, C. M., Lee, H. M., & Chen, Y. H. (2005). Personalized e-learning system using Item Response Theory. *Computers & Education*, 44(3), 237–255. <https://doi.org/10.1016/j.compedu.2004.01.006>
- Cirulli, F., Elia, G., Lorenzo, G., Margherita, A., & Solazzo, G. (2016). The use of MOOCs to support personalized learning: An application in the technology entrepreneurship field. *Knowledge Management & E-Learning*, 8(1), 109–123. <https://doi.org/10.34105/j.kmel.2016.08.008>
- Costello, E., Holland, J., & Kirwan, C. (2018). The future of online testing and assessment: Question quality in MOOCs. *International Journal of Educational Technology in Higher Education*, 15(1): 42. <https://doi.org/10.1186/s41239-018-0124-z>
- Demaidi, M. N., Gaber, M. M., & Filer, N. (2018). OntoPeFeGe: Ontology-based personalized feedback generator. *IEEE Access*, 6, 31644–31664. <https://doi.org/10.1109/ACCESS.2018.2846398>
- Despujol, I., Castañeda, L., & Turró, C. (2022). MOOCs as a massive learning resource for a Higher Education Community. The universitat politècnica de valència experience using the EdX remote access program. *Education and Information Technologies*, 27(9), 12999–13020. <https://doi.org/10.1007/s10639-022-11140-2>
- Downing, S. M. (2002). Assessment of knowledge with written test forms. In G. Norman et al. (Eds.), *International Handbook of Research in Medical Education* (pp. 647–672). Springer. https://doi.org/10.1007/978-94-010-0462-6_25
- El-Rashidy, M. A., Mohamed, R. G., El-Fishawy, N. A., & Shouman, M. A. (2023). An effective text plagiarism detection system based on feature selection and SVM techniques. *Multimedia Tools and Applications*, 83, 2609–2646. <https://doi.org/10.1007/s11042-023-15703-4>
- Feitosa de Moura, V., Alexandre de Souza, C., & Noronha Viana, A. B. (2021). The use of massive open online courses (MOOCs) in blended learning courses and the

- functional value perceived by students. *Computers & Education*, 161: 104077. <https://doi.org/10.1016/j.compedu.2020.104077>
- Franzke, M., Kintsch, E., Caccamise, D., Johnson, N., & Dooley, S. (2005). Summary street®: Computer support for comprehension and writing. *Journal of Educational Computing Research*, 33(1), 53–80. <https://doi.org/10.2190/DH8F-QJWM-J457-FQVB>
- Gabbay, H., & Cohen, A. (2022). Exploring the connections between the use of an automated feedback system and learning behavior in a MOOC for programming. In I. Hilliger et al. (Eds.), *Educating for a New Future: Making Sense of Technology-Enhanced Learning Adoption* (pp. 116–130). Springer. https://doi.org/10.1007/978-3-031-16290-9_9
- Galikyan, I., Admiraal, W., & Kester, L. (2021). MOOC discussion forums: The interplay of the cognitive and the social. *Computers & Education*, 165: 104133. <https://doi.org/10.1016/j.compedu.2021.104133>
- Garcia, M., Perez, L. D., & Hayashi, R. (2021). *Accreditation of online courses in higher education – Early adopters in the European Union, India, Indonesia, and Malaysia*. Asian Development Bank. <http://doi.org/10.22617/BRF210411-2>
- Garner, R. (1982). Efficient text summarization costs and benefits. *The Journal of Educational Research*, 75(5), 275–279. Retrieved from <https://www.jstor.org/stable/27539909>
- Gashi, A., Zhushi, G., & Krasniqi, B. (2022). Exploring determinants of student satisfaction with synchronous e-learning: Evidence during COVID-19. *The International Journal of Information and Learning Technology*, 41(1), 1–20. <https://doi.org/10.1108/IJILT-05-2022-0118>
- Gomaa, W. H., & Fahmy, A. A. (2013). A survey of text similarity approaches. *International Journal of Computer Applications*, 68(13), 13–18. <https://doi.org/10.5120/11638-7118>
- Hair, J., Page, M., & Brunsveld, N. (2019). *Essentials of business research methods*. Routledge. <https://doi.org/10.4324/9780429203374>
- Han, J., Kamber, M., & Pei, J. (2012). Getting to know your data. In J. Han et al. (Eds.), *Data Mining* (pp. 39–82). Elsevier. Retrieved from <https://myweb.sabanciuniv.edu/rdehkharghani/files/2016/02/The-Morgan-Kaufmann-Series-in-Data-Management-Systems-Jiawei-Han-Micheline-Kamber-Jian-Pei-Data-Mining-Concepts-and-Techniques-3rd-Edition-Morgan-Kaufmann-2011.pdf>
- Hoad, T. C., & Zobel, J. (2003). Methods for identifying versioned and plagiarized documents. *Journal of the American Society for Information Science and Technology*, 54(3), 203–215. <https://doi.org/10.1002/asi.10170>
- Huerta, M., Caballero-Hernández, J. A., & Fernández-Ruiz, M. A. (2022). Comparative study of moodle plugins to facilitate the adoption of computer-based assessments. *Applied Sciences*, 12(18): 8996. <https://doi.org/10.3390/app12188996>
- Huisman, B., Admiraal, W., Pilli, O., van de Ven, M., & Saab, N. (2018). Peer assessment in MOOCs: The relationship between peer reviewers' ability and authors' essay performance. *British Journal of Educational Technology*, 49(1), 101–110. <https://doi.org/10.1111/bjet.12520>
- Impey, C., & Formanek, M. (2021). MOOCs and 100 days of COVID: Enrollment surges in massive open online astronomy classes during the coronavirus pandemic. *Social Sciences & Humanities Open*, 4(1): 100177. <https://doi.org/10.1016/j.ssaho.2021.100177>
- Impey, C., Formanek, M., Buxner, S., & Wenger, M. (2021). Science knowledge and attitudes of lifelong learners in an astronomy massive open online course. *International*

- Journal of Science Education*, 11(2), 110–126. <https://doi.org/10.1080/21548455.2021.1903114>
- Israel, M. J. (2015). Effectiveness of integrating MOOCs in traditional classrooms for undergraduate students. *The International Review of Research in Open and Distributed Learning*, 16(5), 102–118. <https://doi.org/10.19173/irrodl.v16i5.2222>
- Jensen, L. X., Bearman, M., & Boud, D. (2021). Understanding feedback in online learning – A critical review and metaphor analysis. *Computers & Education*, 173: 104271. <https://doi.org/10.1016/j.compedu.2021.104271>
- Joo, Y. J., So, H. J., & Kim, N. H. (2018). Examination of relationships among students' self-determination, technology acceptance, satisfaction, and continuance intention to use K-MOOCs. *Computers & Education*, 122, 260–272. <https://doi.org/10.1016/j.compedu.2018.01.003>
- Kearns, L. R. (2012). Student assessment in online learning: Challenges and effective practices. *Journal of Online Learning and Teaching*, 8(3), 198–208. Retrieved from https://jolt.merlot.org/vol8no3/kearns_0912.pdf
- Kramer, M. (2018). Best practices in systems development lifecycle: An analyses based on the waterfall model. *Review of Business & Finance Studies*, 9(1), 77–84. Retrieved from <https://ssrn.com/abstract=3131958>
- Krathwohl, D. R. (2002). A revision of bloom's taxonomy: An overview. *Theory Into Practice*, 41(4), 212–218. https://doi.org/10.1207/s15430421tip4104_2
- Kumar, P., & Kumar, N. (2020). A study of learner's satisfaction from MOOCs through a mediation model. *Procedia Computer Science*, 173, 354–363. <https://doi.org/10.1016/j.procs.2020.06.041>
- Kumar Sharma, S., Kumar Chandel, J., & Madhumohan Govindaluri, S. (2014). Students' acceptance and satisfaction of learning through course websites. *Education, Business and Society*, 7(2/3), 152–166. <https://doi.org/10.1108/EBS-08-2013-0032>
- Lepp, M., Luik, P., Palts, T., Papli, K., Suviste, R., Säde, M., Hollo, K., Vaherpuu, V., & Tõnisson, E. (2017). Self- and automated assessment in programming MOOCs. In D. Joosten-ten Brinke & M. Laanpere (Eds.), *Technology Enhanced Assessment* (pp. 72–85). Springer. https://doi.org/10.1007/978-3-319-57744-9_7
- Loh, S., Lichtnow, D., Kampff, A. J. C., & de Oliveira, J. P. M. (2010). Recommendation of complementary material during chat discussions. *Knowledge Management & E-Learning*, 2(4), 385–399. <https://doi.org/10.34105/j.kmel.2010.02.028>
- Martín Rodríguez, Ó., González-Gómez, F., & Guardiola, J. (2019). Do course evaluation systems have an influence on e-learning student satisfaction? *Higher Education Evaluation and Development*, 13(1), 18–32. <https://doi.org/10.1108/HEED-09-2018-0022>
- Meyer, J. P., & Zhu, S. (2013). Fair and equitable measurement of student learning in MOOCs: An introduction to item response theory, scale linking, and score equating. *Research & Practice in Assessment*, 8, 26–39. Retrieved from <https://eric.ed.gov/?id=EJ1062822>
- Olaniran, O. R., Abdullah, M. A. A., Pillay, K. G., & Olaniran, S. F. (2018). Empirical bayesian binary classification forests using bootstrap prior. *International Journal of Engineering & Technology*, 7(4.30), 170–175. <https://doi.org/10.14419/ijet.v7i4.30.22104>
- Oliver, R. L. (1989). Processing of the satisfaction response in consumption: A suggested framework and research propositions. *Journal of Consumer Satisfaction, Dissatisfaction and Complaining Behavior*, 2, 1–16.
- Ossiannilsson, E. (2021). The new normal: Post COVID-19 is about change and sustainability. *Near East University Online Journal of Education*, 4(1), 72–77.

- Retrieved from <https://dergipark.org.tr/en/download/article-file/1576529>
- Pande, J., & Mythili G. (2021). Investigating student satisfaction with online courses: A case study of uttarakhand open university. *International Journal of Information and Communication Technology Education*, 17(3), 12–28. <https://doi.org/10.4018/IJICTE.20210701.0a2>
- Phan, N. T. T. (2023). Self-efficacy in a MOOC environment: A comparative study of engineering students in Taiwan and Vietnam. *Knowledge Management & E-Learning*, 15(1), 64–84. <https://doi.org/10.34105/j.kmel.2023.15.004>
- Pilli, O., & Admiraal, W. F. (2017). Students' learning outcomes in massive open online courses (MOOCs): Some suggestions for course design. *Journal of Higher Education*, 7(1), 46–71. Retrieved from <https://scholarlypublications.universiteitleiden.nl/access/item%3A2903812/view>
- Rahman, M. M., Riyadh, R. R., Khaled, S. M., Satter, A., & Rahman, M. R. (2018). MMRUC3: A recommendation approach of move method refactoring using coupling, cohesion, and contextual similarity to enhance software design. *Software: Practice and Experience*, 48(9), 1560–1587. <https://doi.org/10.1002/spe.2591>
- Reeves, T. C. (2000). Alternative assessment approaches for online learning environments in higher education. *Journal of Educational Computing Research*, 23(1), 101–111. <https://doi.org/10.2190/GYMQ-78FA-WMTX-J06C>
- Rocco, S. (2007). Online assessment and evaluation. *New Directions for Adult and Continuing Education*, 2007(113), 75–86. <https://doi.org/10.1002/ace.249>
- Rocco, C. M., & Muselli, M. (2007). Network reliability assessment through empirical models using a machine learning approach. In G. Levitin (Ed.), *Computational Intelligence in Reliability Engineering* (pp. 145–174). Springer. <https://doi.org/10.1007/978-3-540-37372-8>
- Rust, C., O'Donovan, B., & Price, M. (2005). A social constructivist assessment process model: How the research literature shows us this could be best practice. *Assessment & Evaluation in Higher Education*, 30(3), 231–240. <https://doi.org/10.1080/02602930500063819>
- Scheff, S. W. (2016). *Fundamental statistical principles for the neurobiologist: A survival guide*. Academic Press. <https://doi.org/10.1016/C2015-0-02471-6>
- Schuwirth, L. W. T., & van der Vleuten, C. P. M. (2004). Different written assessment methods: What can be said about their strengths and weaknesses? *Medical Education*, 38(9), 974–979. <https://doi.org/10.1111/j.1365-2929.2004.01916.x>
- Sohangir, S., & Wang, D. (2017). Improved sqrt-cosine similarity measurement. *Journal of Big Data*, 4(1): 25. <https://doi.org/10.1186/s40537-017-0083-6>
- Suen, H. K. (2014). Peer assessment for massive open online courses (MOOCs). *The International Review of Research in Open and Distributed Learning*, 15(3), 312–327. <https://doi.org/10.19173/irrodl.v15i3.1680>
- Sung, Y. T., Liao, C. N., Chang, T. H., Chen, C. L., & Chang, K. E. (2016). The effect of online summary assessment and feedback system on the summary writing on 6th graders: The LSA-based technique. *Computers & Education*, 95, 1–18. <https://doi.org/10.1016/j.compedu.2015.12.003>
- Thompson, V. U., Panchev, C., & Oakes, M. (2015, November). Performance evaluation of similarity measures on similar and dissimilar text retrieval. In *Proceedings of the 7th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2015)* (pp. 577–584). IEEE. Retrieved from <https://ieeexplore.ieee.org/abstract/document/7526978>
- Thyer, B. A. (2012). *Quasi-experimental research designs*. Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780195387384.001.0001>

- Topuz, A. C., Saka, E., Fatsa, Ö. F., & Kurşun, E. (2022). Emerging trends of online assessment systems in the emergency remote teaching period. *Smart Learning Environments*, 9(1): 17. <https://doi.org/10.1186/s40561-022-00199-6>
- Ventista, O. M. (2018). Self-assessment in massive open online courses. *E-Learning and Digital Media*, 15(4), 165–175. <https://doi.org/10.1177/2042753018784950>
- Wade-Stein, D., & Kintsch, E. (2004). Summary Street: Interactive computer support for writing. *Cognition and Instruction*, 22(3), 333–362. https://doi.org/10.1207/s1532690xc2203_3
- Wang, J., & Dong, Y. (2020). Measurement of text similarity: A survey. *Information*, 11(9): 421. <https://doi.org/10.3390/info11090421>
- Wang, X., Hall, A. H., & Wang, Q. (2019). Investigating the implementation of accredited massive online open courses (MOOCs) in higher education: The boon and the bane. *Australasian Journal of Educational Technology*, 35(3). <https://doi.org/10.14742/ajet.3896>
- Wei, X., Saab, N., & Admiraal, W. (2021). Assessment of cognitive, behavioral, and affective learning outcomes in massive open online courses: A systematic literature review. *Computers & Education*, 163: 104097. <https://doi.org/10.1016/j.compedu.2020.104097>
- Yuksel, M. E., & Fidan, H. (2019). A decision support system using text mining based grey relational method for the evaluation of written exams. *Symmetry*, 11(11): 1426. <https://doi.org/10.3390/sym11111426>
- Zawacki-Richter, O., & Naidu, S. (2016). Mapping research trends from 35 years of publications in Distance Education. *Distance Education*, 37(3), 245–269. <https://doi.org/10.1080/01587919.2016.1185079>

Appendix I

Table questions items

Questions	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Perceived usefulness					
1 By using the online summary-automated feedback feature, I can understand the material	☐	☐	☐	☐	☐
2 The online summary-automated feedback feature can train me to make a summary	☐	☐	☐	☐	☐
3 The online summary-automated feedback feature can encourage me to monitor my learning progress	☐	☐	☐	☐	☐
4 The online summary-automated feedback feature in general can help me understand which parts of the content I do not understand	☐	☐	☐	☐	☐
5 In general, the online summary-automated feedback feature can help personalize learning because it suits my learning needs	☐	☐	☐	☐	☐
6 Tests based on the online summary-automated feedback increase my learning independence	☐	☐	☐	☐	☐
Overall satisfaction					
1 I am satisfied with the performance of the feature of Online Summary-automated feedback	☐	☐	☐	☐	☐