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Smart MOOC integrated with intelligent tutoring: A system architecture and framework model proposal

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ABSTRACT

Massive Open Online Courses (MOOCs) are a type of Learning Management Systems (LMSs), but it seems that the influence of the instructor in these systems is minimal or simply lacking. These systems present the learning content and materials to all learners attending the course in the same way and fail to offer individualized instruction that recognizes the individual differences and needs of the learners. It is reported that such problems can be eliminated by making the new generation intelligent learning systems. However, there is still an ongoing search for making such systems intelligent and a conceptual discussion concerning them. Integrating an intelligent tutoring system (ITS) with learning analytics, this study seeks to design and present the framework of an ITS with open access that a) identifies the learning needs of learners through adaptive mastery testing and guides learners based on these needs, b) overcomes learning deficiencies, monitors learners' interactions with content through learning analytics and offers suggestions, c) supports learning with dynamic assessment processes and d) tests learners' learning competencies. This article aims to explain the conceptual and system framework for the design of an adaptive, dynamic, intelligent tutoring system (SMIT), supported by learning analytics, which is a product of the project, which aims to integrate LMS and ITS, on the idea of how to make systems such as MOOCs smarter. In line with the findings obtained from the research, various suggestions were made for the design of smart Moocs.

1. Introduction

Today, massive open online courses (MOOCs), free online courses that are accessible to everyone and have large numbers of students enrolled, have become popular. The number of MOOCs providers and learners enrolling in courses here is constantly increasing (Castaño-Muñoz & Rodrigues, 2021). In the traditional sense, the courses in MOOCs are structured consisting of a curriculum and related learning objectives, course materials, an assessment system, and a certification process (Stracke & Trisolini, 2021). The pedagogical model on which MOOCs are based has generally focused on delivering learning content through short videos. Along with short videos, the learning process is sometimes enriched with additional reading materials and discussions among participants and/or with instructors and teaching assistants in online forums. Due to the large number of participants in MOOCs, manual grading of assignments and exams is not possible. To evaluate participants' performance, instructors rely on tools that allow automatic grading (Gamage et al., 2021).

Since the courses in MOOCs are structured, they often do not offer student-specific individualized learning. Since there are many students in the lessons in MOOCs, the teacher can conduct the lessons with asynchronous videos and materials. Therefore, the limitation of student-teacher interaction is among the problems experienced with MOOCs. Students need scaffolding support, especially in lessons that require problem-solving skills such as statistics, not just lectures. MOOCs are suitable environments for students with advanced self-directed learning skills. However, students whose self-directed learning skills are not sufficiently developed may encounter problems such as not knowing

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what to do in MOOCs, not knowing where to start studying, and not getting the necessary help when they need help. In MOOCs, students are often not adequately guided and informed during activities (Julia & Marco, 2021). Another problem experienced in MOOCs is related to student-content interaction. The pedagogical approach of MOOCs is mostly based on student interaction with the content. However, this interaction remains very limited in existing systems. Content needs to provide detailed interactions and feedback to students to improve student-content interaction (Barthakur et al., 2021; Julia & Marco, 2021). Such problems experienced by students in MOOCs can cause students to drop out of classes, decrease motivation, and have undesirable learning processes and results (Borrella et al., 2022; Zhang et al., 2021).

Providing individualized education to the student, providing scaffolding support like a teacher during problem-solving, and increasing the quality of formative feedback and interaction are seen as open aspects of MOOCs today. In order to solve these problems related to MOOCs, the idea of integrating artificial intelligence support into MOOCs emerges. With the support of artificial intelligence, it is possible to get to know the student, provide personalized education support, give advice and guidance, and provide scaffolding support during problem-solving. Researchers state that the current studies in the literature are about detecting the obstacles and weaknesses in MOOCs. However, they emphasize that there is a need for research that demonstrates the best educational practices in MOOCs and sets concrete examples (Julia & Marco, 2021). Based on this need in the literature, our research reveals a concrete product to make MOOCs smart by providing artificial intelligence support to overcome the problems experienced in MOOCs. This research aims to provide individualized education to learners in MOOCs with artificial intelligence support by integrating an intelligent tutoring system (ITS) into traditional MOOCs systems. For this purpose, an adaptive dynamic intelligent tutoring system (SMIT) supported by learning analytics was designed and evaluated within the scope of the research. Developed within the scope of the research, SMIT offers conceptual and methodological implications for the design of new generation MOOCs. In this respect, it is thought that the research will guide instructional designers, system developers, researchers, and educators. The conceptual framework and design dimensions of SMIT developed within the scope of the research are explained in detail in the theory article's 'Theoretical Background and Literature' section this purpose, the SMIT supported by learning analytics was designed and evaluated within the scope of the research. Developed within the scope of the research, SMIT offers conceptual and methodological implications for the design of new generation MOOCs. In this respect, it is thought that the study will guide instructional designers, system developers, researchers, and educators.

When the studies on artificial intelligence in education are examined, it is seen that the number and diversity of research on the subject have increased in the last ten years (Chen et al., 2022). In addition, researchers state that the effect of using artificial intelligence technologies such as ITSs and recommender systems should be examined in order to increase the quality of the teaching process, and the effect of using more complex systems by combining different artificial intelligence technologies should be examined (Chen et al., 2020, 2022). In this article, a smart MOOC system that combines ITS, learning analytics, recommendation system, adaptive mastery test (AMT), dynamic evaluation, adaptive learning, educational data mining, and machine learning componeares is modeled. In this respect, it is thought that the research will contribute to the field of artificial intelligence in education at the point ofintegratingf artificial intelligence technologies. In addition, it is hoped that this research will contribute to the literature in terms of creating a bridge between artificial intelligence technology and pedagogy in terms of pedagogical use of artificial intelligence technologies. It is thought that the results obtained will be usehelpfulr practitioners and academicians working on artificial intelligence in education.

2. Theoretical Background and Literature

One of the primary purposes of instructional technologies is to design technological applications to facilitate learning and enhance performance. An extensive study by Bloom (1984) emphasizes that learning can be boosted by two standard deviations above the average performance through a) mastery learning and b) one-to-one tutoring. Learners need support, that is, intervention, during their learning process (Sahin & Yurdugul, 2020a, 2020b). Especially given that new generation learning environments lack lecturers, digital systems need to provide this support. Here, the concept of support is two-fold: a) support in the learning process and b) support during problem-solving. Supporting learners during problem-solving is modeled with ITS. It is essential to highlight that ITS and structured learning systems (e-learning systems) are two separate concepts. While learning systems (such as learning management systems) provide enriched learning environments following the course's objectives and instructional design, ITS primarily seeks to support learners during problem-solving. The system architecture proposed in this study supports the learning process through learning analytics and the problem-solving process through ITS.

A wide variety of ITSs has been developed hitherto. Some of them are as follows: Cognitive Tutors (Aleven et al., 2009), ALEKS (Falmagne et al., 2013), AutoTutor (Graesser, 2016), DeepTutor (Rus et al., 2013), GuruTutor (Olney et al., 2012), SKOPE-IT (Nye et al., 2018), ElectronixTutor (Graesser et al., 2018), ASSISTments (Heffernan & Heffernan, 2014), GIFT (Aleven et al., 2017). Among these systems, GIFT and SKOPE-IT stand out in that they are integrated with a learning system called EdX. As in the examples of GIFT and SKOPE-IT, systems integrated with learning systems are now preferred over stand-alone ITSs. Baneres, Caballé, and Clarisó (2016, July) underlined that MOOC systems such as EdX, Coursera, Canvas, UdaCity, in particular, are supported by limited learning analytics. It is necessary to render these systems more comprehensive, integrate them with ITSs, and further integrate the data of both systems to ensure that learners are supported during problem-solving. This study seeks to present a learning platform designed to offer further support (support in both the learning process through learning analytics and problem-solving through the ITS module) to learners by integrating a learning system with ITS and describing the design process's steps.

This design has incorporated support in problem-solving differently than in other ITSs. ITSs are typically based on the ontological relations (the concept network formed by the relations between knowledge structures) of knowledge components such as concepts and subjects in the knowledge space and shape the system behavior through these relations. The recently designed ITSs benefit from the Bayesian knowledge tracing method, which combines dynamic Bayesian networks and hidden Markov processes, thus emphasizing the network structure of concepts. This design uses a different algorithm based on the mastery tests of learners via sequential probability ratio test, as knowledge (concepts) is linearly addressed.

The designed system incorporates main components: a) AMT, b) learning content and learning experiences, c) educational data mining and learning analytics and intervention in learning experiences, and d) dynamic assessment module. Further information on these components is presented under the system components section.

2.1. *Support in learning systems and learning analytics*

Learning systems were first configured with Web 1.0 technologies and then used more effectively with Web 3.0 and now with Web 4.0 technologies. The effectiveness of these systems aims to support and improve learners' learning experiences by providing data-based support to them. Learners need mainly two different supports, help in the learning process and problem-solving. In other words, intervention in learning systems provides learners crucial information on the learning process and efforts. It is known that learning behaviors obtained from the log data of learners in both descriptions and predictions to support or interfere with learners' learning experiences are addressed by learning analytics.

Learning analytics refers to the measurement, collection, analysis, and reporting of learner data to better understand learning and the context of learning (Siemens, 2013; Siemens & Long, 2011). At the 1st International Conference on Learning Analytics and Knowledge (LAK, 2011), learning analytics was defined as collecting, analyzing, and reporting data on learning contexts where learning occurs. Indeed, learning analytics allow for a) following the learning process of learners, b) discovering and examining learner data, c) identifying problems, d) discovering patterns, e) identifying the preliminary indicators of success, poor grade or system drop-out, f) evaluating the usability of learning materials, g) increasing awareness, reflection, and self-reflection, h) enhancing understanding of learning environments, i) managing, intervening learning, resources, and learning environments, and making suggestions and guiding learners (Karaoglan Yilmaz, 2022). Likewise, learners use learning analytics to observe their own learning activities, interactions, and learning processes in the learning system, compare their own actions with those of other learners, raise awareness, and increase their participation in discussions, learning behaviours, and performance.

2.2. Support in intelligent tutoring systems and dynamic assessment

Learners also need critical support during problem-solving. Timely support for learners who cannot solve a problem contributes to their learning. Such support is closely linked to the social constructivist learning theory proposed by Vygotsky (1978). As Vygotsky argues, it is possible to bridge the gap between what a learner can do as an unaided individual and what they can achieve with the help of a more knowledgeable other through dynamic assessments. In this regard, the difference between dynamic assessments and different types of assessments can be explained using the concept of feedback. Feedback for the performance in an assessment task in dynamic assessment is provided through scaffolds, which leads learners to the correct answer, rather than through cognitive, affective, and motivation information on learners' performance. Daniels (2001) defines scaffolding as assistance provided to incompetent learners during problem-solving. These two statements imply that incompetent learners are led to exhibit the right behaviors during problem-solving with the help of someone else. When such assistance is not provided, learners can still solve problems by showing learned behaviors; when learners cannot solve problems posed during an assessment task, providing them with guiding questions or hints as feedback is considered dynamic assessment (Tzuriel, 2000). ITS, thus, seeks to support learners during problem-solving through scaffolding based on hints. Narciss and Huth (2004) report different types of instructional guidance. This study benefits from feedback (adaptive feedback) as a type of instructional guidance.

2.3. Adaptive mastery testing and sequential probability ratio test

Mastery tests are performed to classify learners as masters or non-masters on a subject based on test results (Vos & Glas, 2000). These tests are typically used to obtain a certification (such as a certificate or a license) and make a pass-fail decision. Mastery tests can be administered using predetermined or varying length forms. Different mastery tests with different lengths and numbers of items are administered to individuals to reveal their mastery of the relevant subject. Two main approaches are followed in mastery tests with a variable number of items: sequential and AMT (Vos & Glas, 2000). Sequential mastery tests benefit from Bayes decision theories, while AMT decides the length of the test considering individuals' estimated level of mastery (Kingsbury & Weiss, 1983). The essential advantage of these tests over fixed-length tests is that they allow for classifying individuals with a certain level of mastery (low or high) by applying shorter tests (consisting of fewer items) (Vos & Glas, 2000). This study draws upon the AMT approach. The AMT was used for main two goals such as a) determining the mastery level of the learner at the beginning of the process and assigning the learner to the appropriate module, and b) questions based on the algorithm within the scope of the mastery test that the learner has at the end of the relevant module and ITS will apply the decision-making rules by assessing these test results.

The solution of hidden Markov models entails using optimization and differential equation analysis (such as Viterbi, Baum-Welch algorithms). These methods involve iterative processes, which require runtime and burden the processor. Computerized Adaptive Testing (CAT) based on item response theory (IRT) as a measurement theory is considered an alternative to these analysis methods with low predictive performance. CATs are used to determine learning levels (in exams such as TOEFL GRE) and in individualized learning systems and ITSs (Armendariz et al., 2014). In this regard, Fig. 1 presents the correlation identified between Bayesian Knowledge Tracing (BKT) and CAT processes (Deonovic et al., 2018).

As Deonovic et al. (2018) described, BKT and CAT serve the same purpose based on item response theory. However, CAT requires many quests to decide on learners and needs an item pool with many items calibrated (Conejo et al., 2004; Van der Linden, & Glas, 2000). In addition to these, IRT and, therefore, CAT applications yield the mastery scores of learners' mastery (a continuous variable) as a scale value. Whether it is reasonable to convert such a score into a dichotomy of master-non-master or pass-fail using a cut score to indicate learning remains a controversial issue.

This study highlights AMT, which benefits from sequential probability ratio testing (SPRT) as an alternative to IRT and CAT, which are challenging to apply, as mentioned above. AMT is a solution that allows for more consistent and optimal results with fewer questions (as the hypothesis H_0 is tested with type I and type II errors in this algorithm) and yields dichotomous results (master/non-master) on learner learning (Spray & Reckase, 1996). As this approach classifies learners as master or non-master at the end, AMT is also called computerized classification testing by some.

It is easier to model the BKT approach with the SPRT algorithm based on AMT. Below is the presentation of this process, which incorporates maximum likelihood estimation and hypothesis testing with BKT notations.

H_0: L = L_0 → Learner mastered the subject (master)

H_1: L = L_1 → Learner failed to master the subject (non-master)

$$\mathrm{Likelihood}(Q1, Q2, \ldots Qk|L0, L1) = \frac{P(Q_1=1|L_1)P(Q_2=1|L_1)\ldots P(Q_k=1|L_1)}{P(Q_1=1|L_0)P(Q_2=1|L_0)\ldots P(Q_k=1|L_0)}$$

This likelihood function continues as long as it produces values between $(1\text{-}\beta)/\alpha$ and $\beta/(1\text{-}\alpha)$. Here a indicates Type I error [P(H_1 is selected | when H_0 is true)] and b indicates Type II error [P(H_0 is selected | when H_1 is true)]. If the likelihood function is more significant than $(1\text{-}\beta)/\alpha$, then the decision is P(L) = 1 (learner is master). If the likelihood function is lower than $\beta/(1\text{-}\alpha)$, then the decision is P(L) = 0 (learner is non-master). Thus, it seems that AMT, which draws on the SPRT algorithm based on the Bayesian approach, produces more consistent and dichotomous results through fewer questions, making it more effective than the hidden Markov analyses of BKT, particularly in terms of cost, performance, and consistency.

2.4. The teaching model of smart MOOC integrated with intelligent tutoring

This study aims to design and present the framework of an intelligent tutoring system that a) identifies the learning needs of learners through AMT and guides learners based on these needs, b) overcomes learning deficiencies, monitors learners' interactions with content through

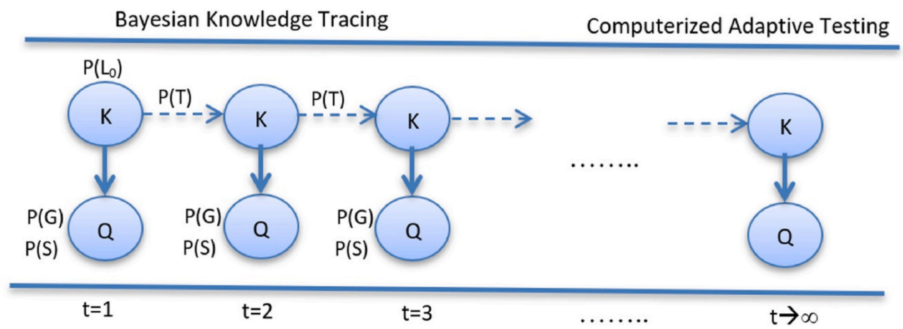

Fig. 1. Correlation between bayesian knowledge tracing and computerized adaptive testing.

learning analytics and offers suggestions, c) supports learning with dynamic assessment processes and d) tests learners' learning competencies. The system architecture proposed is inspired by the mastery learning process introduced by Bloom (1968). Fig. 2 and Fig. 3 show the traditional and teaching models based on mastery learning (Moore, 2014).

As shown in Figs. 2 and 3, the traditional teaching model starts with the objectives of a module and ends with an assessment to determine whether these objectives are achieved or not. The teaching model based on mastery learning starts similarly with the goals of a module but ends with the transition to the next module based on the assessment. Formative assessment is made following the teaching process, and individuals are directed to either alternative learning or enriched teaching based on the result of this assessment. Following this second teaching experience, learning is assessed, and if the learner is a master, they can move on to the next module. Fig. 4 presents the model used in this study.

This system basically consists of a) AMT, b) LA & EDM, c) MOOC, and d) ITS (Dynamic Assessment). The AMT module is integrated with the system for pre-testing and assessment of learning; the MOOC and LA & EDM module is integrated with it for the teaching process. The ITS module is integrated for the enrichment and alternative learning steps. The system architecture section offers detailed information on the links between the operation of the system and the components.

2.5. System architecture of smart MOOC integrated with intelligent tutoring

The mastery learning model inspires the model's design process proposed in this study. It is based on a new learning model supported by AMT and dynamic assessment through scaffolding. Fig. 5 presents the processes of this teaching model and relationships.

Case 1: Outcomes of the Subject

The subjects in the curriculum (as defined in modules) are shown. For example:

Course: Statistics	**Unit**: 1. Descriptive Statistics
Subject: 1.1. Measures of central tendency	**Item Type**: Multiple choice
Information A: 0.84	**Information B**: 0.17
Information C: 0.23	**Information D**: 0.78
Course: Statistics	**Unit**: 1. Descriptive Statistics
Question: What are the mean and median values of 7, 4, 2, 5, 7 datasets, respectively?	
Choice A) Mean=4 and Median=4	
Choice B) Mean=4 and Median=5	
Choice C) Mean=5 and Median=4	
Choice D) Mean=5 and Median=5	
Choice E) Mean=4.5 and Median=4.5	
Correct Answer: D	
Hint 1: The first step in calculating the median is to sort the data from smallest to largest; while calculating the mean, we have to rely on our aggregation ability.	
Guiding Question 1: What is the Median of 5 siblings of different ages?	
Worked Example: The median of 1,2,3,4,5 data is 3 and the mean is 15/5.	

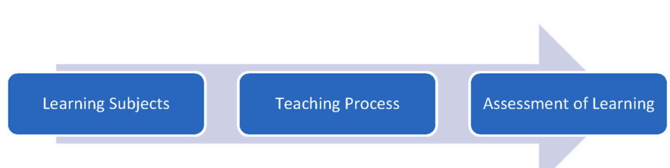

Fig. 2. Traditional teaching model.

Case 2: Adaptive Mastery Testing

Upon entering the system, a learner can activate, for example, the subject of 'central tendency measures' in the module of 'descriptive statistics' (which is one of the subjects in the statistics curriculum) through the navigation menus; then, the system tests if the learner is master on this subject through AMT. SPRT algorithm is used for AMT. SPRT is an approach that continues testing learners by considering their response patterns based on the decision-making theory or classifies them based on a threshold value.

$P_{ij}\,(x_i = 1 \mid \theta_{j+})$: the probability of the user, who is a master on subject j., answering item i. Correctly.

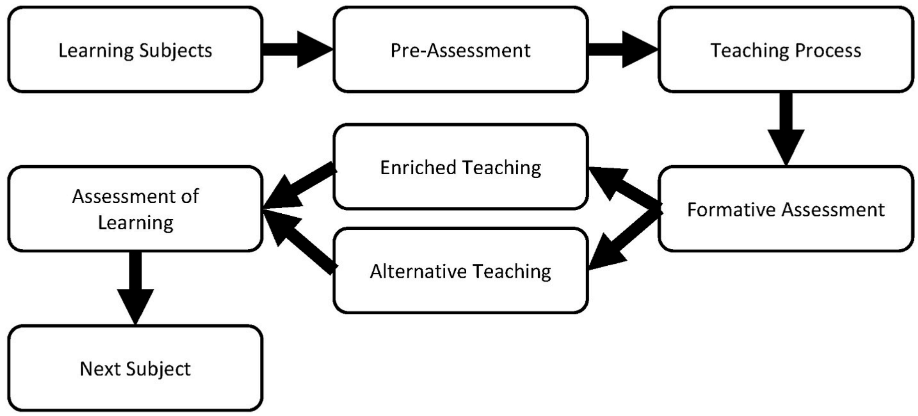

Fig. 3. A typical teaching model based on mastery learning.

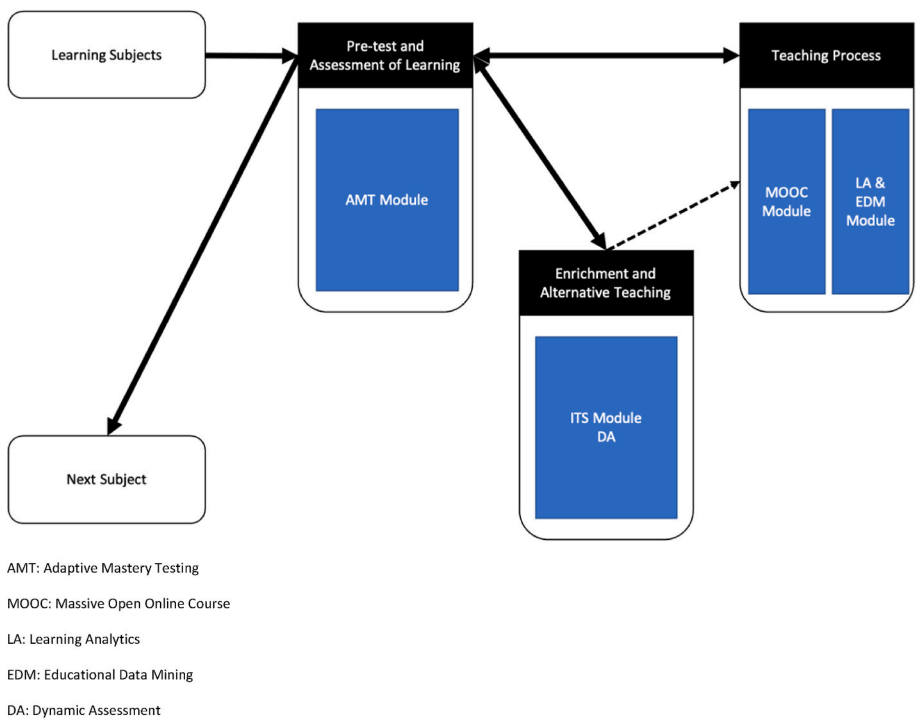

Fig. 4. The teaching model of the proposed model.

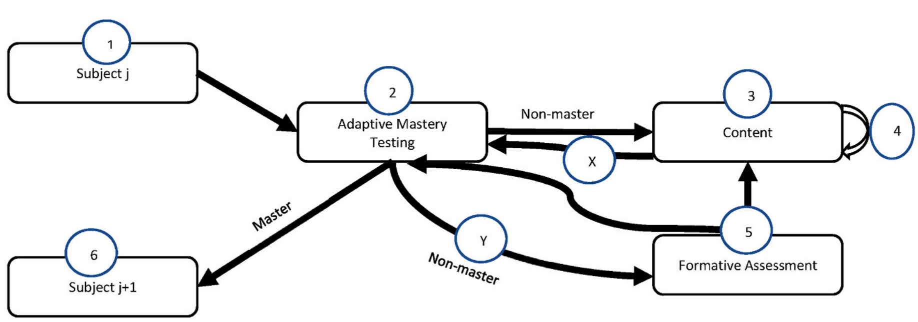

Fig. 5. Components and processes of the Smart MOOC integrated with an intelligent tutoring system.

P_{ij} $(x_i = 1 \mid \theta_{j-})$: the probability of the user, who is not a master on subject j., answering item i. Correctly.

Where xi indicates the correct ($x_i = 1$) or incorrect ($x_i = 0$) answer given to item i.; further, θ_{j+} and $\theta_{j\text{-}}$ represents the mastery or non-mastery or master and non-master levels of the user on the subject j.

Hence, the probability of a question according to the Binomial distribution principle,

Table 1
Meta-data structure of the items in the question bank.

Course: Statistics	Unit: 1. Descriptive Statistics
Subject: 1.1. Measures of central tendency	**Item Type**: Multiple choice
Information A: 0.84	**Information B**: 0.17
Information C: 0.23	**Information D**: 0.78
Course: Statistics	**Unit**: 1. Descriptive Statistics
Question: What are the mean and median values of 7, 4, 2, 5, 7 datasets, respectively?	
Choice A) Mean = 4 and Median = 4	
Choice B) Mean = 4 and Median = 5	
Choice C) Mean = 5 and Median = 4	
Choice D) Mean = 5 and Median = 5	
Choice E) Mean = 4.5 and Median = 4.5	
Correct Answer: D	
Hint 1: The first step in calculating the median is to sort the data from smallest to largest; while calculating the mean, we have to rely on our aggregation ability.	
Guiding Question 1: What is the Median of 5 siblings of different ages?	
Worked Example: The median of 1,2,3,4,5 data is 3 and the mean is 15/5.	

$$P(x_i|\theta)=P_i^{x_i}(1-P_i)^{1-x_i} \tag{1}$$

And the joint probability under the assumption of independence for k items is:

$(x1, x2, x3,\ldots, x_k\,|\theta) = (x_1|\theta).\ (x_2|\theta).\ (x_3|\theta)\ \ldots\ P(x_k\,|\theta)$

$$P(x_1,x_2,x_3,\ldots,x_k|\theta)=\prod_{i=1} kP(x_i)^{x_i}(1-P(x_i))^{1-x_i}) \tag{2}$$

where Equation (2) is also known as the likelihood function. Accordingly, the likelihood ratio function (LR) is obtained by proportioning for non-master and master users.

$$LR=\frac{P(x_1,\ x_2,\ x_3,\ \ldots x_k|\theta_-)}{P(x_1,\ x_2,\ x_3,\ \ldots x_k|\theta_+)}=\frac{\prod_{i=1}^{k}P(x_i|\theta_-)^{x_i}(1-P(x_i|\theta_-))^{1-x_i}}{\prod_{i=1}^{k}P(x_i|\theta_+)^{x_i}(1-P(x_i|\theta_+))^{1-x_i}} \tag{3}$$

Using type I and II error relations, a hypothesis test was designed for the decision processes of the likelihood ratio test.

$H_0 : \theta=\theta_+$

$H_1 :\ \theta=\theta_-$

What is H_0 refers to situation where the θ mastery level of the user corresponds to θ_+ state of where for refers to situation where the θ mastery level of the user corresponds to θ_- state of non-mastery.

α: Type I error; The probability of making a wrong decision on a user who is a master on the subject j.
β: Type II error; The likelihood of making a wrong decision on a user who is a non-master on the subject j.

Considering the likelihood ratio (LR) statistic for the answer of the user to the question k.

If $(LR) \geq \log\frac{1-\beta}{\alpha}$ H_1 is accepted, and if $Log(LR) \geq \log\frac{\beta}{1-\alpha}$ H_0 is accepted; for values other than these, the test continues with the k+1st question, as there is still uncertainty.

This process goes on until H_0 is accepted or rejected. At the end of this process, if the user is a master on the subject j, they move on to the next subject (j+1); otherwise, that is, if the user is a non-master on to the content module on the subject j., which is the case 3.

The common processes and algorithms of adaptive tests are, respectively, as follows: a) item pool, b) starting the test, c) item selection algorithm, d) scoring, and e) stopping.

2.5.1. Item pool

The item/question bank is presented in the database along with the questions and meta-data. Table 1 below shows an example of these questions and meta-data.

Information A: The rate of those who are master and answered this question correctly $\Sigma\ (x = 1\ |\ \theta_+)/n$.

Information B: The rate of those who are master and failed to answer this question correctly $\Sigma\ (x = 0\ |\ \theta_+)/n$.

Information C: The rate of those who are non-master and answered this question correctly $\Sigma\ (x = 1\ |\ \theta_-)/n$.

Information D: The rate of those who are non-master and failed to answer this question correctly $\Sigma\ (x = 0\ |\ \theta_-)/n$.

After each relevant question is raised, information A, B, C and D are updated based on the application data.

As shown in this architecture, the question bank that contains questions structured with meta-data is suitable for use in mastery tests and dynamic assessments. However, each question is used in only one of these two processes (either in the AMT or dynamic assessment). For that reason, the last two meta-data (hints and guiding questions) are used in dynamic assessment and processed when the user gives an incorrect answer. A key point here is the number of questions in the item pool. Studies have shown that AMT can only decide on the mastery of learners with an average of 8-9 questions. Considering the repeated AMTs, designing 40 items per subject is reasonable. Also, for dynamic assessment, 15 questions on each subject are sufficient.

2.5.2. Starting the test

In this stage, which involves determining the nature of the question to be pulled first from the pool when the user starts the test, this question is randomly selected through the RND function since no data are available at the beginning of the study. If enough data is collected to run the algorithm, prior knowledge is utilized for Bayesian statistics. For example, considering the user's performance on the (j-1)th subject or their performance on the previous AMT, the test may start with more difficult or easier questions.

2.5.3. Item selection algorithm

Various item selection algorithms for AMT are available. The most widely used ones are the random item selection algorithm and intelligent item selection based on expert systems. This approach, developed by Weiss and Kingsbury (1984) and called maximum information search and selection (MISS), obtains the discriminating power of the item through the following correlation:

$$D_i=P(xi=1|\theta_+)-P(xi=1|\theta_-)$$

where θ (+) refers to the learner's mastery of the subject i. While θ (−) indicates non-master learners. The larger this value is, the higher the item's quality is (in terms of distinguishing between learners who master the subject and others). Information A, B, C, and D mentioned above in the item meta-data schema serve this purpose. It is necessary to measure the item/examine incompatibility, in addition to the item discrimination index, for the item selection algorithm:

$$I_{ij}=\left[1-\frac{n.P(x=1|\theta_+)+1}{(n.P(x=1|\theta_+)+n.P(x=1|\theta_-)+2)}-\frac{n.P(x=1|\theta_+)+1}{(n.P(x=1|\theta_+)+n.P(x=1|\theta_-)+2)}\right]$$

The item discrimination index and item/examine incompatibility are assessed together for item selection to yield:

Item benefit index: $U_{ij} = \frac{D_i}{(I_{ij}-\delta)}$

Where delta is a constant value close to 0 (e.g., delta = 0.0001) to avoid zero division error, another important consideration is administering the questions for parameter estimations related to the questions. Accordingly, the I. and II. type error values of the questions are fixed at 0.05 and the questions were administered directly under SPRT.

Case 3: Learning Content and Learning Experiences

Learning experiences are the interactions of learners/users with the components in the learning environment. In this stage, the user, who has already been considered a non-master on the subject j., is directed to video-based or text-based content based on the curriculum. She/he interacts with the content on the subject of central tendency measures in the module of descriptive statistics, as given in the example above. However, the interaction data (video metrics, text-based content metrics, etc.) are recorded in the database. For this reason, this study has designed a video player intended to record video metrics. Videos are primarily presented to learners for learning experiences. The system further incorporates textual documents, presentations, and infographics. Learners can also interact with learning tasks and extra content under each subject.

Case 4: Intervention in Learning Experiences through Educational Data Mining and Learning Analytics

Autonomous learners are learners with high learning awareness, who can take responsibility for their own learning and manage their own learning processes (Ribbe & Bezenilla, 2013). While such learners effectively learn the subject in the absence of a teacher, non-autonomous learners need continuous educational intervention to enhance their own learning. Interventions based on learning analytics are made to allow such learners to gain a deeper understanding. Learning analytics refers to understanding and improving learners and learning environments through data. This study benefits from educational data mining and learning analytics for intervention in learning experiences to ensure that non-master learners can interact with the content more effectively and learn the subject better. The correlation between analysis and analytics can explain the link between educational data mining and learning analytics. As known, while analysis refers to the analysis of patterns and correlations in data, analytics is the purposeful use of these patterns and correlations, such as for communication or interaction (Sahin & Yurdugul, 2020a, 2020b).

Before considering the relevance of this to the example above, one may recognize that Case 3 and Case 4 are intertwined. That is to say, if non-master learners, who fail the mastery test on central tendency measures of the descriptive statistics module, for the sake of example, fast-forward while watching the video or move on to other content without viewing the video, then learning analytics can interfere with them and give appropriate feedback to them on "the probability of being successful or failing if they keep doing so."

In this regard, classification algorithms are primarily utilized in the context of data mining to create profiles of successful or unsuccessful learners based on their behaviors. In this process, the steps above are followed after the data pre-processing step:

a) Inquiry is performed (particularly through entropy levels, information gain coefficients and so forth) on levels of information provided by attribute variables (video analytics, number of logins, time per page, etc.) on success (master-non-master) as a class variable for feature extraction.
b) After identifying the important feature variables, the performance of the classification algorithms for master and non-master learners is assessed and compared. Although the algorithms predicted here differ by the nature of the feature (categorical or numerical), they will be limited to Naive Bayes, Gaussian Bayes, KNN, SVM, artificial neural networks, decision trees (ID3, C4.5, CART, etc.), logistic regression and discriminant analyses. Following these analyses, the classification algorithm with the best performance will be identified with the help of the confusion matrix to be created for classification validity. Where the classification accuracy does not differ significantly in determining the classification algorithm, algorithms without iteration may be preferred, considering the processor performance as well. One of the reasons for this is perhaps that the PHP coding language is used to develop the SMIT system and that the machine learning functions of PHP are lacking. Another consideration of classification algorithms is that such algorithms are incorporated in the supervised learning model and training data are required to establish these models. To that end, content is uploaded to LMS to create training data, and the interaction data of the learners are collected through these systems.
c) In addition to these mechanisms, which intend to identify the profiles of master and non-master learners and intervene in at-risk learners based on classification algorithms, Markov chains or lag sequential analysis methods are also used to reveal learners' navigation strategies. It is further planned to present various suggestions to learners through k-means or hierarchical clustering algorithms under unsupervised learning when deemed necessary.

2.5.4. Cases X and Y: transitions

Once the experiences of non-master learners based on their interaction with the content are completed, transition X occurs with the assumption that learners have learned the subject in line with the indicators in learning analytics; in other words, learners are again subjected to an AMT. If the test process yields that a learner is a master on the relevant subject, then, she/he can move on to Case 6 (the next subject). If a learner is still considered as non-master on the relevant subject in the AMT, then transition Y takes place. Transition Y is when a non-master learner moves on to (instead of being re-directed to the content with activities that she/he has already completed) the dynamic assessment module, that is, Case 5, which is an assessment-centered teaching process.

Case 5: Dynamic Assessment Module

To improve their learning, learners who have not yet become masters in the relevant subject despite interacting with the content, interact with instructional assessment activities for enriched learning. Intelligent tutoring systems are essentially systems that support learners, and they usually intend to teach a subject by helping learners solve problems they cannot solve. Through such support, learners are often presented with hints to develop strategies for problem-solving. Similarly, the social learning theory, as a learning theory, also aims to make learners master using so-called scaffolds. In this context, scaffolds may sometimes be a hint, a question, or an explanation, and when such assistance is provided within the scope of an assessment, this is called a dynamic assessment. These also correspond to learner-directed help strategies, and hint-based help strategies are often used in intelligent tutoring systems. To improve learning, the SMIT system asks learners questions on the subject from the item pool, but these questions are not designed to test mastery, but rather seek to support learning through hints, scaffolds, and sample solutions, among other help strategies associated with the question (specified in the item/question previously defined based on its metadata). Based on a dynamic assessment, there is a finite number of such strategic assistances in problem-solving, and the optimum number is determined in further research. The initiative to choose the type of assistance is left to learners in dynamic assessment.

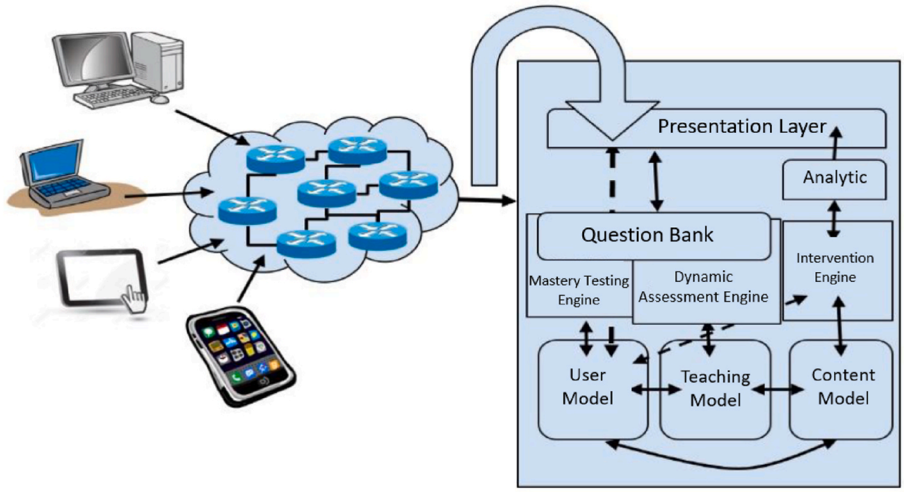

Fig. 6. Instructional system architecture.

Case 6: Next subject

When any learner masters the previous subject (subject j.), the next step she/he moves on to is the next subject. Fig. 6 shows the architecture of this step. The static and situational details of learners are available in the user model. The details of a learner entering the system are checked here to allow him/her to log in, and the last activities of the learner can be monitored here. The assessment model further includes the meta-data on what learners have mastered as well as other items. Algorithms in the mastery test engine work based on the questions in the assessment model during the sequential learning of a learner on the subject j., and the learner's mastery of the subject is tested. The assessment model is also used in the dynamic assessment.

The teaching model is the model that incorporates the modules, subjects, and concepts in the curriculum of the course. This model is further used to associate the course, module, and subject knowledge in the question meta-data presented in Table 1. The content model is the model that includes learning materials on the subjects in the modules in the curriculum as learning objects. The information in the meta-data structure of the learning objects is associated with the modules and subjects in the teaching model. On the other hand, the dynamic assessment engine consists of algorithms that recognize learners and offer them the most appropriate help strategy. Lastly, the intervention engine is a module that incorporates educational data mining algorithms and is structured based on learning analytics; this engine monitors learner interactions with the content and recommends strategies to support them to master the subject.

3. Discussions

In the context of technology integration in education, the use of educational technology in the classroom and out-of-class learning processes is increasing (Backfisch et al., 2021). Students use technology for purposes such as practicing in classroom learning processes, performing collaborative learning activities, structuring knowledge through online discussions, and differentiated instruction (Zervoudakis et al., 2020). In the context of out-of-class learning processes, educational technology is used for purposes such as accessing course content and materials, repetition and practice, and evaluation of what has been learned (Tsai & Tsai, 2019; Wilson et al., 2020). Within the scope of instructional practices such as flipped classroom, which is becoming more and more common today, students use technology to access course content and materials before the face-to-face course process and study these content and materials. Thus, students come prepared for face-to-face lessons. In the face-to-face class, activities such as collaborative learning and problem-solving activities are carried out by using educational technology tools. Thus, it is ensured that the information obtained before the lesson is transformed into a skill in the classroom environment through technology (Karaoglan Yilmaz & Yilmaz, 2022; Ustun et al., 2021). In all these processes, educational technology tools and environments are used effectively.

One of the educational technology tools and environments used effectively in the context of in-class and out-of-class teaching processes is LMSs. LMSs are mostly used in the process of delivering content and materials prepared by the teacher to the student. However, for students to benefit from LMS effectively, students' self-directed learning skills must be developed. Otherwise, the student who has not developed self-directed learning skills may experience problems such as not knowing what to do in LMS, not knowing what content and materials to study, not being able to focus on content and materials suitable for her/his level, and not knowing what to do to solve it when she/he has a problem. These problems are among the most common problems faced by students in today's LMS (KaraoglanYilmaz & Yilmaz, 2020a, 2020b; Ustun et al., 2021).

To solve these problems experienced by students in LMS, it is important to provide personalized advice and guidance to the student in LMS, and to provide appropriate instructional support during the problem-solving process. Considering the number of students in the course using the LMS, it is not possible for the teacher to follow and guide each student individually, and to provide instructional support when needed. However, thanks to artificial intelligence technologies, it becomes possible to perform this function of the teacher virtually on the LMS (Tepgec et al., 2021a, 2021b; 2021b). For this purpose, SMIT design was carried out in this research. In other words, a conceptual framework about how traditional LMS or MOOCs systems can be made smart has been tried to be put forward.

SMIT; learning analytics and dashboard, AMT, and dynamic assessment system based on ITS consists of basic components. SMIT's learning analytics and dashboard are designed as three separate panels: student, teacher, and administrator. At SMIT, analytical indicators in three different categories, video analytics, exam analytics and system usage analytics, are calculated based on students' interactions with the system and displayed on SMIT's dashboard. The individual indicator results of the student for each indicator are displayed on the dashboard, as well as the indicators related to the class average. Thus, the student was given the opportunity to compare his/her own situation according to the class average. Researchers report that the benefits of presenting learning analytics results to students may be limited. Because the student may have difficulty in understanding and interpreting the analytical result and may not know what to do based on the analytical result. In this case, it is stated that it would be appropriate for the system to give appropriate advice and guidance to the student (Jivet et al., 2017, 2018). From this point of view, it was ensured that individual advice and guidance specific to the student was made on the dashboard of SMIT, which was designed within the scope of this research. Students can organize their own learning and structure their learning process and study strategies according to the advice and guidance of SMIT.

AMT is a solution for achieving more consistent and optimal results with fewer questions and at the same time producing dichotomous results regarding student learning (Spray & Reckase, 1996). In some sources, AMT is also called computerized classification testing, especially since this approach makes decisions about the student as competent (master) or not-competent (non-master) at the end of the process. When there is only one breakpoint and two mastery groups, this type of CAT is often referred to as AMT (Sie et al., 2015). Chang (2005) states that AMT is a test used to predict the mastery level of an examine, as in the computerized adaptive test. The courses that will take place at SMIT, developed within the scope of this research, are structured as modular. The modules in a course include the subtopics of the relevant course. In the developed system, AMT is defined for each sub-topic of the course. After studying the subject, the student is directed to the AMT of the relevant subject to testing whether she/he is competent in that subject. AMT decides whether she/he is competent in the subject with the questions she/he asks. While the student who is determined to be competent is marked as successfully completing the subject, two options are offered for the unsuccessful student. The first option is to direct the student back to the course content and materials to study the subject. In the second case, the student may not have succeeded in AMT despite studying the subject contents. In this case, the student may need external support during problem-solving to better understand the subject. In this case, the system directs the student to ITS as a second option. Thanks to AMT, the system can decide whether the student is competent or not by asking as few questions as possible and personalized for each student (Karaoglan-Yilmaz et al., 2021; Sahin et al., 2021). A well-known stopping rule in AMT is to terminate the assessment when the test taker's ability confidence interval is completely above or below the cut-off score (Sie et al., 2015). When applying AMT, a zone should be specified around the boundary level. For this, it is not important whether the decision is successful or unsuccessful. This region is often referred to as the "indifference region". The closer the test taker's mastery level is, the more items will be required to make an accurate decision when the cut-off level is reached. Therefore, measures should be taken to ensure that the substance pool is not depleted (Chang, 2005).

The ITS component of the SMIT system developed within the scope of this research was developed to provide support to the student during problem-solving. In this context, if the student performs the AMT on the relevant sub-topic of the course and is not found to master according to this AMT result, the system offers the student two options: a) "return to the content", b) "get help while solving a question". If the first option is selected, the system directs the student back to the contents of the relevant topic. However, the student may think that she/he has studied the subject sufficiently and may want to improve her/his problem-solving skills and practice by getting support during problem-solving. In this case, the system directs the student to ITS. In ITS, support is provided to the student during problem-solving through dynamic assessment. Dynamic assessment is a general and inclusive concept that is used to explain different approaches, includes teaching, provides feedback in the assessment process, and differentiates based on individual performances (which differs according to the individual's performance) (Tuluk, 2019). In addition, the concept of dynamic assessment means evaluating perception, comprehension, problem solving, learning and thinking in the active learning process that aims to change cognitive functioning (Natalia et al., 2013; Tzuriel, 2000; cited in Tuluk, 2019). The dynamic assessment process aims to create changes in the cognitive and affective functions of the individual and to observe the potential change in the subjects learned during the assessment process (Natalia et al., 2013; cited in Tuluk, 2019). In accordance with the dynamic assessment approach applied in the ITS part of the developed system, students are asked five-choice multiple-choice questions. In the face of the student's wrong question, the system removes the wrong option from the answer options and gives a hint to the student. Similarly, the cycle continues this way for each student's wrong answer to the question. The system provides feedback to the student until the correct answer is reached. These feedbacks are in the form of 'hint', 'guiding question', 'sample solution' and 'detailed feedback'. The order in which this feedback will be presented to the student is determined by machine learning. As a result of machine learning, it is determined which type of feedback the student prefers the most, and the relevant feedback is presented to the student first. In other words, in dynamic assessment, feedback is presented to the student in an adaptive way based on machine learning. Thanks to this feedback, it is tried to ensure that the student learns during the assessment. Floratos et al. (2015) concluded in their research that formative assessment and feedback practices in MOOCs would improve students' participation in lessons. Kyaruzi et al. (2019) concluded that using formative assessment feedback practices contributed positively to students' performance. When the students' views on the pilot study of SMIT's dynamic assessment system developed within the scope of this research are examined, it is seen that the questions and hints in the dynamic assessment system are effective in teaching by reinforcing the subject, that it provides the opportunity to progress according to the individual speed and preference of the student, that it has a fun structure, that it facilitates learning, increases interest and curiosity about learning (Karaoglan-Yilmaz et al., 2021; Tepgec et al., 2021a, 2021b; 2021b). With these aspects, it can be said that integrating dynamic assessment applications based on ITS in MOOC environments can be beneficial.

4. Conclusion

Although systems such as MOOCs are a kind of LMS, they can be expressed as learning systems in which the teacher's influence on the system is minimal or absent. In these systems, learning content and materials are presented to all learners in the same way, and individualized instruction cannot be provided in accordance with the individual differences and needs of the learners. For these reasons, the need to find solutions to the aforementioned problems has emerged by making the new generation of learning systems intelligent. However, the search for making such systems intelligent and the conceptual debates on this subject still continue. This study presents a learning environment framework that integrates the MOOC and LA with the ITSs. This framework is intended to support learners in the learning process and problem-solving. It is designed based on educational data mining and learning analytics to intervene with learners in their learning processes. It further incorporates the ITS module under dynamic assessment to provide support during problem-solving, which is made available for use by learners. The mastery or non-mastery of learners on a particular subject is determined through AMT. The architecture of the system can be explained as follows.

Learners first take an AMT, which draws on a learning objective's SPRT algorithm. If they are considered a master in this test, they move on to the next objective; otherwise, they move on to the relevant content on the objective. Case 3 refers to learning content and learning experiences, and learners interact with videos, visuals, textual content, and additional materials accordingly. The system makes some estimations based on educational data mining algorithms on metrics using learner interactions with the content. It intervenes learners based on learning analytics, following the patterns obtained. When the experiences of a learner based on their interaction with the content are completed, and the indicators in the learning analytics provide the assumption that the learner has mastered the subject, the learner is directed to AMT again. The learner responds to different items while taking the test a second time, and item selection algorithms are used to present different questions. If this second test again ascertains that the learner is non-master, the learner is this time, directed to a dynamic assessment environment instead of the learning content. To improve his/her learning, a learner who has not yet mastered the relevant subject despite interacting with the content interacts with instructional assessment activities for enriched learning. For the purpose of enhancing learning, the SMIT system asks learners questions on the subject from the item pool, but these questions are not designed to test mastery, rather seek to support learning through hints, scaffolds, and sample solutions, among other help strategies associated with the question (specified in the item/question previously defined based on its meta-data). Based on a dynamic assessment, there is a finite number of such strategic assistances in problem-solving, and the optimum number is determined in further research. The initiative to choose the type of assistance is left to learners in dynamic assessment.

Pilot assessment studies of the developed system were carried out within the scope of statistical methods in the education course. Assessment studies were conducted on 53 undergraduate students who took this course through SMIT. Participants stated that the developed system contributed to their academic success. It was revealed that the participants using the system were positive about the instructional support offered by ITS in the difficulties they encountered in solving the questions. Finally, the developed system was successful in identifying the needs and deficiencies of the students, it was effective in providing personalized education to the student with the advice and guidance offered through the learning analytics and the learning panel, and the support provided to the student in the dynamic assessment process enabled the student to learn the subject more effectively and reinforced the learned, and in general, the system facilitated the learning and fun, provides the opportunity to progress according to the individual speed and preference of the student, and enables the student to make self-evaluations with learning analytics. In general, students' satisfaction with SMIT was found to be high (Karaoglan-Yilmaz et al., 2021; Sahin et al., 2021; Tepgec et al., 2021a, 2021b; 2021b).

This study has some limitations, and research recommendations for these are discussed below. In this article, which firstly provides information on the conceptual design of SMIT, the pilot application studies of the developed system were carried out on undergraduate students within the scope of the "statistical methods in education" course. Therefore, the research results are limited to this course and the student group. In future studies, studies will be carried out to evaluate the optimization and effectiveness of the system developed with a wider audience. In addition, in future research, different types of courses, such as verbal and numerical courses, can be opened on the system and user evaluation can be made. In addition, the generalizability of the findings can be examined by carrying out studies to evaluate the system on different target groups such as high school students, secondary school students and adults. When the student characteristics of the developed SMIT are examined, it is limited to the level of competence, level of knowledge, motivation (task value and self-efficacy) and learner preferences. In addition to these student characteristics, student behaviors (number of logins, time spent in the session, time spent on the question, response time, time to find the right option after receiving instructional support, etc.) can also make students more sensitive in diagnosing/diagnosing. At SMIT, which was developed within the scope of this research, the most appropriate instructional support is offered as an intervention for the difficulties students encounter while solving questions. In other words, it helps to solve the question by adapting the instructional support to the individual with the data in the student model. ITS can be integrated into the very common MOOCs systems today. Such systems will combine MOOCs and ITS to create different systems and bring various studies. Thus, studies can be conducted on the effectiveness of a hybrid system in terms of platforms. Moreover, while solving questions on the ITS, student mistakes can be determined, and gains can be determined. Afterward, the student can be directed to various topics in MOOCs. Studies can be carried out to integrate the specified ITS into MOOCs or to reveal the techniques that suggest/guide the student on which subject they should study. In the tutorial model developed in SMIT, the weighted Jaccard technique from the collaborative filtering method was used. The main reason for this is due to the quantitative data types of the characteristics kept in the student model. Studies focusing on the design of the instructor model can be done by using different similarity or distance calculations (Aydın et al., 2020) according to student characteristics. In future research, studies can be conducted to determine the effect of SMIT on learning processes and outcomes such as student motivation, self-regulated learning skills, and academic performance. In future research, a clustering algorithm based on particle swarm optimization techniques introduced by Zervoudakis et al. (2020) for the classification of students can be used and its effectiveness can be examined. In addition, in future research, the effectiveness of the use of the SMIT system introduced in this research can be examined in the context of the differentiated instruction method (Zervoudakis et al., 2020).

This article aims to explain the conceptual and system framework of SMIT, which is a product of the project, which aims to integrate LMS and ITS, from the idea of how to make systems such as MOOCs smarter. The findings regarding the results of the pilot implementation of SMIT during the development process of the project are also partially discussed in the discussion and conclusion part of this article, and it reveals an idea about the applicability of the system put forward within the scope of the article.

Compliance with ethical standards

Necessary permissions have been obtained and ethical standards have been followed.

Authors' contributions

All authors participated in constructing the framework. The first author is the director of the project. All authors read and approved the final paper.

Availability of data and materials

N/A.

Research involving human participants and/or animals

The research doesn't involve human participants and/or animals.

Informed consent

Informed consent about the study is not required.

Declarations competing interest

The authors declare that they have no competing interests.

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