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ORIGINAL ARTICLE

An Adaptive E-Assessment for Self-Learning: A Sustainable Education Model in the Post COVID-19 ERA of Digital Media

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ABSTRACT

The integration of information and communication technologies in education has exploded various opportunities in learning and assessment. The state-of-the-art electronic learning and assessment systems are confined to delivering instructional content without focusing on learning analytics. Hence, more objective assessment systems are required that can keep track of the performance of students, especially for self-learning in the post-COVID-19 digital era. These assessment systems need to be optimized so that students can receive an accurate prescription in a limited time during the unavailability of teachers. Therefore, this study intends to propose an adaptive e-assessment model for learning and assessment. The proposed model comprises components including a domain model, student model, and assessment adaptation engine. The features of fuzzy logic have been utilized to address uncertainty and analyze student performance using a learner-centric approach. The prototype has been verified by deploying it on a computer science course offered at a degree-level program of an open university. The results reveal the improved performance of learners using the adaptive e-assessment system. The study also facilitates by providing a roadmap for the researchers to develop a generalized and personalized e-learning system for other courses.

Keywords: Adaptive System, E-Assessment, Student Model, E-Learning, Digital Media

Author`s Contribution	Address of Correspondence	Article info.
[1,2,3,4] *Data analysis, interpretation, and manuscript writing, Active participation in data collection, Conception, synthesis, and planning of research. Interpretation and discussion*	*Shahid Farid* *Email: shahidfarid@bzu.edu.pk*	*Received: May 14, 2023* *Accepted: Nov 09, 2023* *Published: December 30, 2023*

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INTRODUCTION

The advancement in Information and Communication Technology (ICT) is providing many opportunities to facilitate the learners of the 21st century [1]. One of the openings is in the form of e-learning [2], which is the electronic delivery of multimedia instructions using ICT [3], 2019). These digital instructions are used to support teaching and learning processes outside the boundaries of classrooms [4], which has become inevitable after the Coronavirus pandemic [5]. It can be considered an innovative approach in digital learning to modernize the contents, monitor and analyze the participation, and improve the interaction with the digital platforms [6]. The aim is to employ a systematic learning path, taking off with the existing knowledge of the learners [7]. Most of the work in e-learning is concentrated on the development of multimedia tutorials and their delivery over the net, and less attention has been given to assessment systems. E-assessment is part of an e-learning system, which is an electronic way of conducting tests.

Electronic assessment also termed as computerized assessment or online assessment is the use of ICT for conducting formative and summative examination tests [8]. Formative assessment is a process of collecting, analyzing, and interpreting complete facts to observe how the student's knowledge level matches with the instructor's prospects and curricular goals [9]. It may take a variety of forms e.g. informal questions, practice quizzes, exercises, and self-paced learning [10]. Summative assessment is a type of assessment that is used to assess the outcome of a course of studies or a program [11]. It involves measuring the student's achieved level of learning at the end of the learning process. It is associated with grades [10]. An enormous amount of data is required in this assessment type to thoroughly check the student's level of learning. It normally does not involve providing feedback to students. Therefore, the conduction of formative and summative assessment through technology is a research challenge. The concept of e-learning is associated with "anytime" and "anywhere" learning but the same does not apply to e-assessment due to the non-availability of specialized and adaptive assessment systems.

Adaptive assessment is a specialized assessment system [12] that can tailor the presentation of assessment objects to match the knowledge level & personality of an individual or a group of learners [13]. It can help in offering learner learner-centered approach by providing an individualized, self-paced, and responsive learning environment and making an exhaustive learning process dependent on the insight level of the learners [14]. The development of such specialized assessment has become inevitable as the existing systems are focused on content presentation rather than objective assessment. It is important to determine which assessment object is required at what time and to which learner [15] in a distant and isolating learning environment [16]. These challenges have motivated us to undertake the current research study and present a generalized model of adaptive e-assessment for self-learning of students.

LITERATURE REVIEW

The initial e-learning systems were only capable of presenting the static contents to an individual or group of learners [17]. These systems were unable to judge the actual needs and knowledge requirements of the learners. The same analogy was with assessment where the same set of questions were to be presented to all the learners without knowing about their learning deficiency and assessment needs [18]. With the evolution of technology, the need was felt to incorporate the adaptive capability among learning and assessment systems [7]. The complexity of applications paved the way to define the taxonomy and set the standards for learning and assessment systems. The two main categories of adaptive e-learning systems were introduced [19] i.e. Intelligent Tutoring Systems (ITS) and Adaptive Hypermedia (AH). ITS is an adaptive learning system that provides instant and customized content based on user interaction and feedback [20]. It is a machine-based tutor that works without the involvement of a teacher. AH is also an adaptive system that is more oriented toward the presentation of multimedia content interlinked through a user modeling approach [21].

AH systems are further adapted towards teaching and learning in the form of Adaptive Educational Hypermedia (AEH). AEH has three core components i.e. domain model, learner model [22], and instructional model [23]. The domain model is curriculum-specific and is composed of learning and assessment objects. The learner model stores information about students regarding their interests, goals, learning styles, interaction, and assessment. The pedagogical model makes use of learner and domain models and adapts teaching and assessment strategy. Assessment has a key role in AEH which is conducted as Computerized Adaptive Test (CAT) and is an integral part of each AEH sub-component [24].

The question databank is a collection of assessment objects that reside in the domain model. Each test has initial, termination, and grading criteria which are controlled by the learning algorithm in the pedagogical model. The record of previous and ongoing assessment activities is stored in the learner model which is updated with each new test entry. The assessment adaptation is carried out by tailoring of learning path for an individual student keeping in view his/her existing knowledge and competency of students.

Several research studies have been conducted to explore the development of CAT and different techniques have been employed to model the learner activities. One of the techniques is the Item Response theory (IRT), which is a psychological and educational measurement technique. IRT has been used to select the bespoke test items for individual learners [2], evaluate the rational ability of job applicants [25], conduct a trust-based assessment [26], and requirement-based real-time testing with academic standards [27]. IRT provides a basis for measuring the ability of test participants and items based on responses, however analysis of only correct responses is not enough to measure the ability, therefore some additional parameters may be looked into. Another technique is the Bayesian network which forms an acyclic graph of contributing factors with conditional probabilities. It has been used to Implement assessment systems based on learning analytics [28], question generations while considering success & failure [29], and adaptive grading systems [30] during online learning. Each node represents student knowledge as learned or not learned. This approach may lead to a hypothesis based on previous facts [6]; however, students may have learned a domain but part of it may still be unlearned.

Another important technique is the Markovian model which allows moves from one state to another using probabilistic rules. It has been used to compare the performance of learners and the classification of questions [30, 31], for adaptive e-assessment. The important characteristic of the Markov chain is that the probability of arriving at the present state depends only on the previous state and not on any of the preceding states. Furthermore, it assigns the Boolean value yes or no to each state indicating student knows or does not know the element. A review of the above-mentioned work illustrates that adaptive assessment and learning models vary in design, complexity, and student modeling approaches. The majority are more focused on enhancing the instructional guidance for learners and less attention has been paid to evaluating uncertainty in the student's knowledge level through assessment for providing learner-centered guidance [32].

Keeping in view these challenges, we are going to propose a model of learner-centered adaptive assessment for self-learning of distant learners in the post-COVID-19 era of digital media. The fuzzy logic has been selected to model the activities [33] to deal with the ambiguities in student behaviour.

RESEARCH METHODOLOGY

Proposed Adaptive E-assessment Model.

The proposed model is derived from the research challenges found in the literature review and also is the extension of the model presented in [7]. This model is comprised of three main modules: The Domain model, the Student Model, and the Assessment Adaptation Model as shown in Figure 1. The explanation of each of these models is given following subsections:

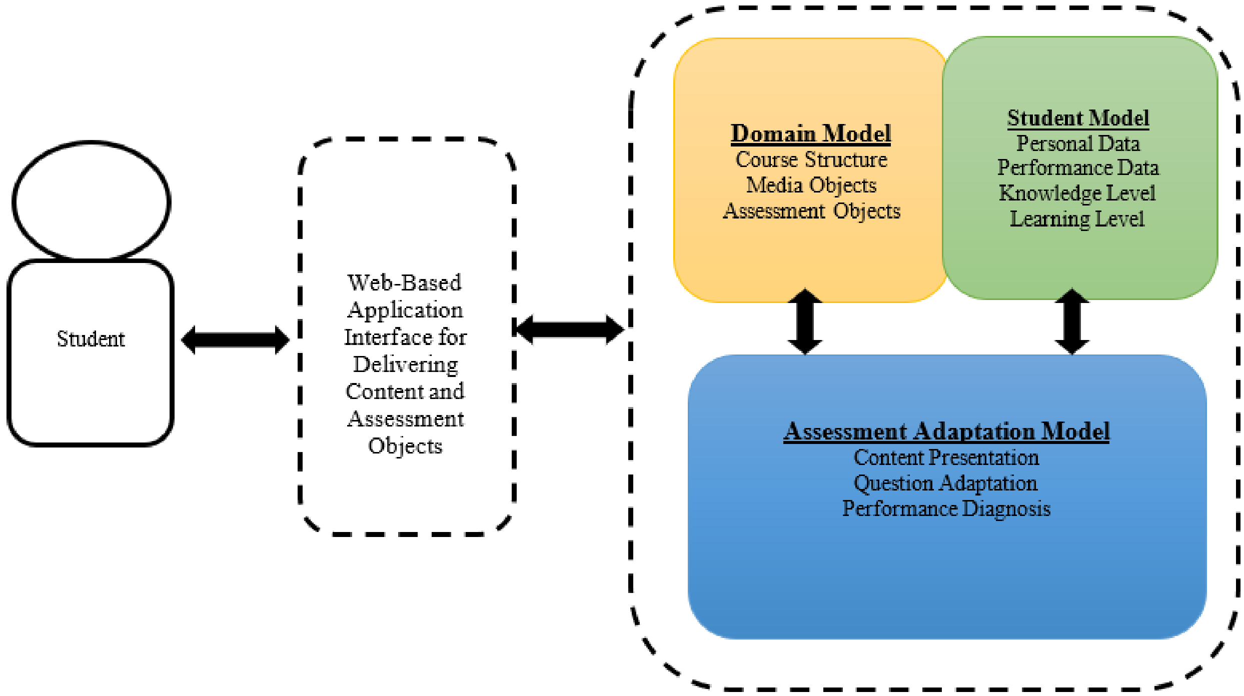


Figure 1. Proposed Model of Adaptive E-Assessment

Domain Model

The domain model is one of the core components of our proposed Adaptive E-assessment system. It encapsulates course structure, content hierarchy (depth and breadth), media & assessment objects.

Course Structure

The course structure has been defined as per the standard format of an open university. The course is divided into nine units and each unit is composed of topics and sub-topics hierarchically. The subject expert was engaged to define the content breadth & depth and set the difficult level, as shown in Figure 2. The hierarchical structure of the courses is shown in Figure 3.

Media and Assessment Objects

The course tutorials were developed by the subject expert in the form of text, animations, and multimedia objects. The assessment questions were also developed and mapped with each level of tutorial. The knowledge base was linked through a machine-based string of commands used by the student level and adaptation engine.

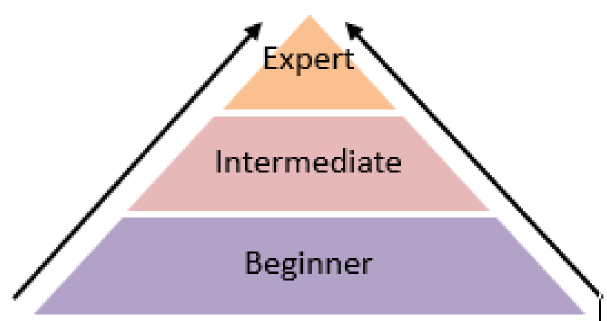


Figure 2. Content Difficulty Level

Moreover, to adapt assessment items and assess student's knowledge level, multiple choice questions are used. The questions are divided into three difficulty levels (beginner, intermediate and difficult) by the course expert. A further description of questions block difficulty level is presented in following sub-section of Assessment Adaptation Model.

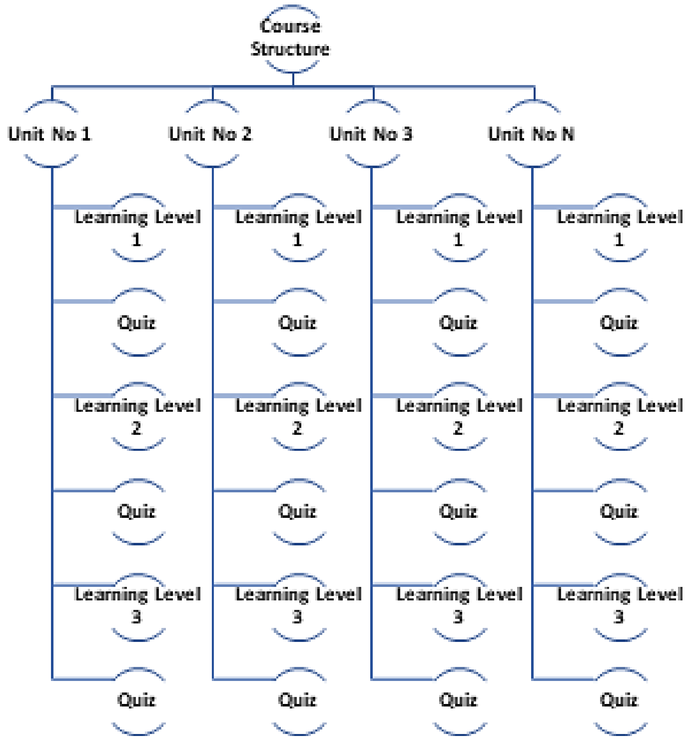


Figure 3. Hierarchical Structure of Course

Student Model

The student model stores the static and dynamic profiles of students. Static information includes students' personal and demographic data, while dynamic information comprises progress on assessment and unit history as shown in Figure 4. The assessment results are stored in the form of student responses (i.e. how many correct answers have been given by a student in a specified quiz), time spent on each quiz, and knowledge level of the student (detail is mentioned in the following Sub-Section of assessment adaptation model). This static and dynamic information is part of the initialization and updation phases.

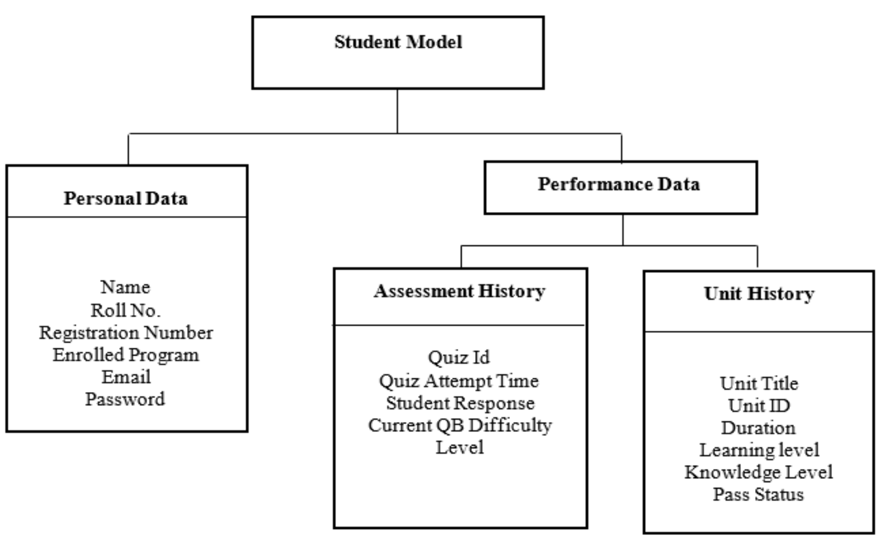


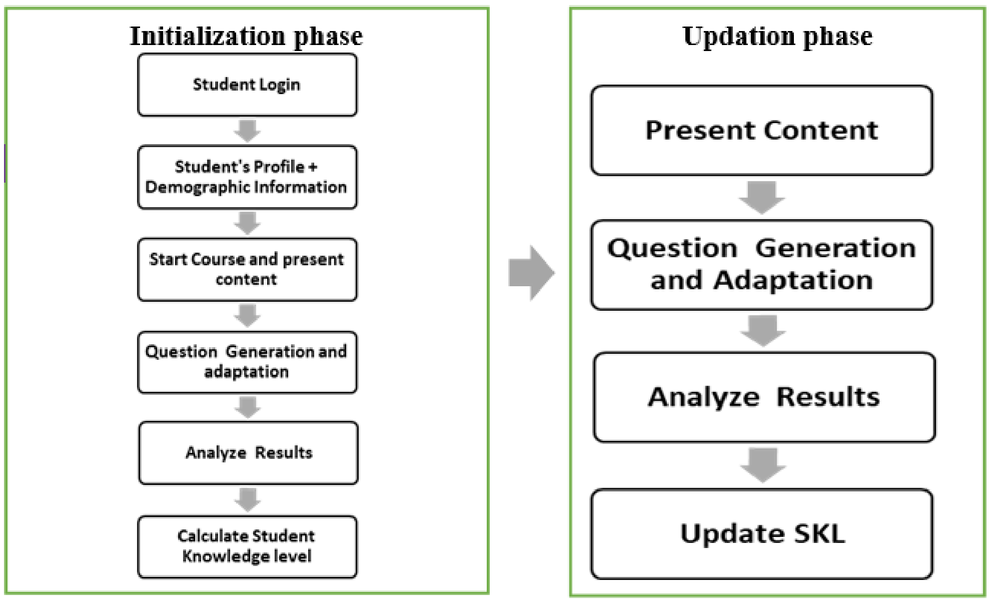
Figure 4. Student Model

Initialization Phase

The initialization phase commences with the enrolment of students in the course. Students are registered and admitted as per the criteria. After admission confirmation, they are allocated login credentials for an adaptive assessment system. Here the initialization phase starts, and they are directed to a survey questionnaire. They fill up the questionnaire and submit the responses. The system collects and analyses the responses and they are invited to start the course with an initial level of the content followed by the assessment quiz. The system analyses the results and places them in the appropriate knowledge level.

Updating Phase

The updating phase starts with the current knowledge level and the matching content is presented to the learners. After the end of the current topic, the questions of the relevant difficulty level are generated as adapted to their knowledge level. Students with different competencies are evaluated with these questions. The adaptation of the following question is driven by the learner's reaction to the former question. The data from the initialization and updation phases, as shown below in Figure 5, are stored in the student model.



SKL= Student Knowledge Level

Figure 5. Initialization and Updation Phase of Student Model

Assessment Adaptation Model Based on Fuzzy Logic

The assessment adaptation Model is the core component of our proposed model of study. It uses the domain and student model to predict student performance throughout the course. It keeps track of the learner's actions during navigation and detects their scoring level with the analysis of their strengths and weaknesses in understanding the concepts. It is used to adapt content and assessment according to the learner's needs to optimize the learning path in the presented domain. The adaptive strategy used in this paper is based on fuzzy logic.

Parameters for Quiz Item Selection and Student Performance Level Diagnosis

The parameters that are used in our fuzzy logic model are discussed below. The quiz item selection and knowledge level of a student are determined by these parameters and hence their performance is evaluated.

Question Block Difficulty Level: The parameter is part of the domain model and is divided into the current and next question difficulty blocks. The difficulty level helps in tailoring the testing process to per specific knowledge abilities of the student. Each question has a difficulty level between the interval of 0 and 1 [34]. The response of students in the current question block difficulty level influences the selection of the next question by the system.

Student Response: The response made by a student for each question helps in identifying his/her learning level regarding a certain concept. The student's response may be right or wrong. The proportion of the right and wrong answers indicates their performance [35]. The information is stored in the student model.

Time Taken: This parameter is also part of the student model that determines how much time is taken by a student to answer a quiz. A time rate is determined by dividing the time taken by a student to solve a question block by the total time of a quiz [36]. A longer time interval indicates that the student is not well prepared for the exam.

Student Knowledge Level: This is the output parameter that indicates the attained knowledge level of the student after examining the quiz results. The value of this parameter is dependent on the above-mentioned parameters [37].

Description of Proposed Fuzzy Logic Model for Item Selection and Student Performance Level Diagnosis

The proposed fuzzy logic model is composed of three main components i.e. Fuzzifier, Inference Engine, and Defuzzifier. as shown in Figure 6.

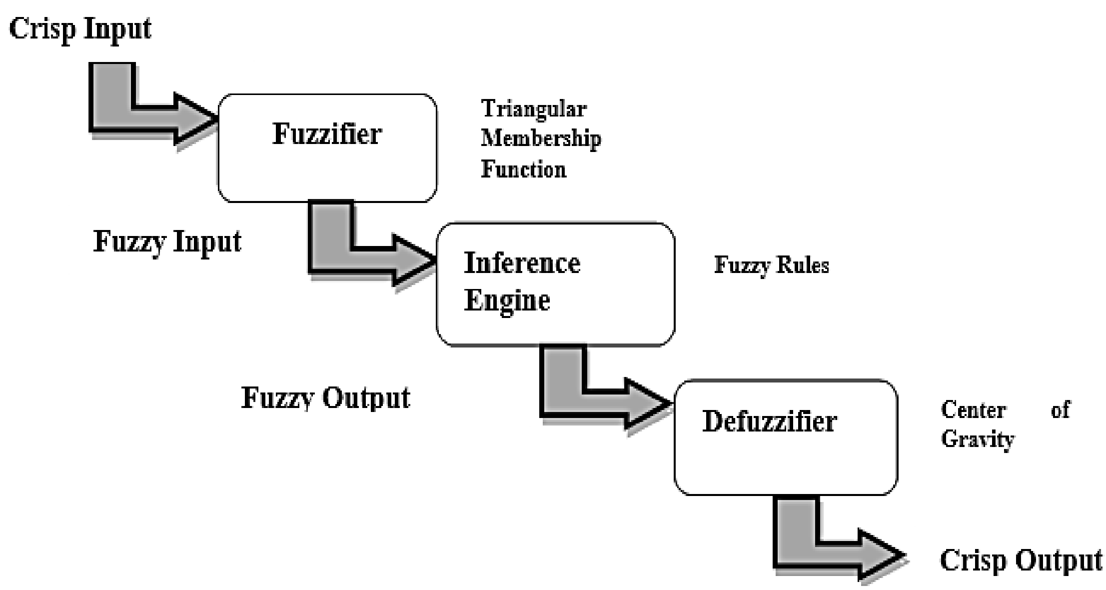


Figure 6. Fuzzy Logic Model

Fuzzifier

Whenever a student attempts a quiz, this component gets the crisp value and converts it into a fuzzy set using the membership function. There are three crisp input values i.e. 'current question block difficulty level', 'student response', and 'time is taken to solve a quiz'. The table 1 shows the fuzzy input variables, their linguistic terms and intervals as adopted from the literature [34-37].

Table 1. Fuzzy Input Set

Variable	Linguistic term	Symbol	Interval
Current question block difficulty level (QDL)	Difficult Intermediate Easy Difficult	DFC IMD ES	[0.7-1.0] [0.3-0.8] [0-0.4]
Student response	Not good	NG	[0-40]

(SR)	Good Excellent	G E	[30-70] [60-100]
Time taken (TT)	Short Medium Long	SH M LG	[0-0.15] [0.1-0.25] [0.2-0.35]

All input values are in crisp or numeric format. They are converted into fuzzy values by using the triangular membership function. Equation 1 shows the fuzzy variable representation of the triangular membership function for each linguistic expression of the question block difficulty level variable, whereas Figure 7 shows its graph. It reveals that the fuzzification of a crisp value may result in multiple fuzzy values with different weights.

$$\mu\,ES\,(x) = \begin{cases} 0 & x \leq 0 \\ \dfrac{x}{0.2} & 0 \leq x \leq 0.2 \\ \dfrac{0.4 - x}{0.2} & 0.2 < x < 0.4 \\ 0 & x \geq 0.4 \end{cases}$$

$$\mu\,IMD\,(x) = \begin{cases} 0 & x \leq 0.3 \\ \dfrac{x - 0.3}{0.25} & 0.3 \leq x \leq 0.55 \\ \dfrac{0.8 - x}{0.25} & 0.55 < x < 0.8 \\ 0 & x \geq 0.8 \end{cases}$$

$$\mu\,DFC\,(x) = \begin{cases} 0 & x \leq 0.7 \\ \dfrac{x - 0.7}{0.15} & 0.7 \leq x \leq 0.85 \\ \dfrac{0.8 - x}{0.2} & 0..85 < x < 1.0 \\ 0 & x \geq 1.0 \end{cases}$$

…………….. (1)

The variable x indicates the crisp value obtained during the runtime. μES maps the EASY linguistic value of learning. Similarly, μIMD and μDFC characterize INTERMEDIATE and DIFFICULT levels of learning.

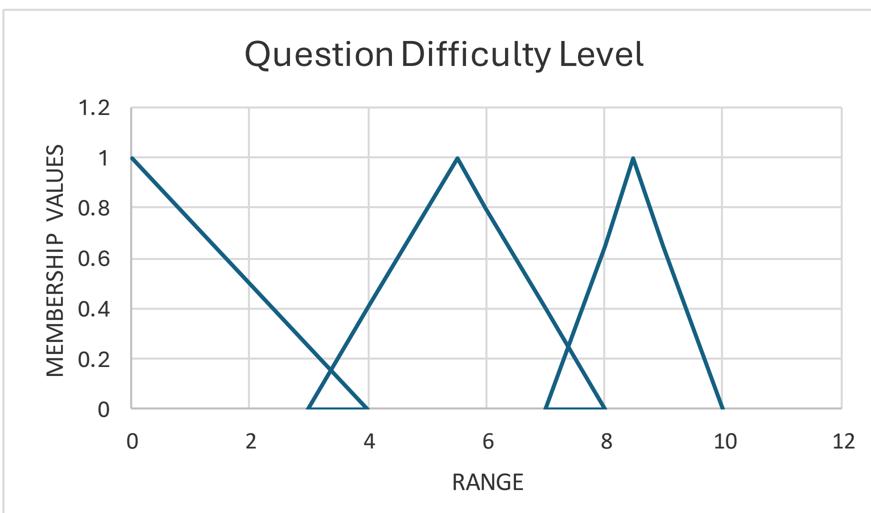


Figure 7. Question Block Difficulty Level Graph

Concerning the output generated by the fuzzy model, it provides the subsequent adaptation and assessment of the student's performance based on the fuzzy input set and the corresponding fuzzy rules. Table 2 presents the fuzzy output variable with its linguistic terms and their intervals.

Table 2. Fuzzy Output Set

Variable	Linguistic term	Symbol	Interval
Next question blocks difficulty level (QDL)	Difficult Easy Intermediate Easy	DFC IMD ES	[0.7-1.0] [0.3-0.8] [0-0.4]
Student Knowledge Level	Unknown Unsatisfactory Known Learned	Un Uk K L	[0-60] [55-75] [70-90] [85-100]

Inference Engine

The Inference engine produces the value of the output variable (presented in Table 2) by applying fuzzy rules on fuzzy input sets (presented in Table 1). Some sample rules are as follows:

If the current QDL is ES SR is E and TT is SH then SKL is L and the next QDL is IMD
If the current QDL is ES SR is G and TT is LG then SKL is K and the next QDL is IMD
If the current QDL is ES SR is G and TT is M then SKL is Uk and the next QDL is ES
If QDL is ES SR is NG and TT is SH then SKL is Un and the next QDL is ES

These rules analyze the attempted answers and suggest the next item selection by using the following defuzzification process.

Defuzzifier

This stage performs the reverse process of fuzzifier to convert the vague output value obtained by the inference engine into a crisp / non-fuzzy output. We used the centroid method to defuzzify our output value. The equation of this method is as follows:

Centroid of area ZCOA= $\frac{\int_z u_A(z) z\, dz}{\int_z u_A(z)\, dz}$

μA(z) is the membership value of a student's knowledge level, where the value of z is ranged [0-100].

Algorithm for Content and Quiz Automation

Figure 8 depicts an algorithm for selecting content and quizzes. It uses indices i, j, and k to represent unit, content level, and learner knowledge, respectively. Beginner content is presented first for each unit. The presentation of contents is followed by an evaluation quiz to assess the knowledge level of students. Steps 1,2 and 3 of the following algorithm present the generalized steps of fuzzy logic and indicate how it helps in assessing the achieved knowledge level of learners (Unknown, Unsatisfactory, Known, Learned) in each learning level of a unit. Learners must review the content and retake the quiz if they achieve an Unknown, Unsatisfactory, or Known level of knowledge. This process continues until they reach the Learned level. After completing the three knowledge levels within a unit, learners can progress to the next unit. The adaptation rules (steps 6-9) in the algorithm manage the assessment data from the student model.

1. Initialize unit number i=1
2. Initialize content level j=1 and student knowledge level k=1
3. Present level j content of unit i
4. Take quiz (quiz duration is preset to 10 mnts)

$$Initialize\ question\ block\ level\ q = 1$$

$$Present\ question\ level\ q;$$

$$\underline{1.\ Attain\ values\ of\ the\ fuzzy\ input\ variables}$$

$$\underline{student\ response, time\ taken\ and\ current\ question\ block\ difficulty}$$

$$\underline{2.\ apply\ fuzzy\ rules}$$

$$\underline{3.\ attain\ the\ value\ of\ next\ question\ block\ difficulty\ and\ student\ knowledge\ level}$$

$$Increase\ question\ block\ difficulty\ level\quad (if\ question\ level = 3\ then\ ask\ questions\ from\ same\ level)$$

$$Else$$

$$Decrease\ question\ level\ \ (if\ question\ level\ = 1\ then\ ask\ questions\ from\ same\ level)$$

System continues asks questions until stopping criteria met (time expires or question limit follows, whichever occurs first)

5. Aggregate all the rules to obtain the output parameter student knowledge level SKL value using defuzzification method.
6. Evaluate student knowledge level k by using the following rules.

a. $If\ SKL \leq 55\ then\ k = 1.$

b. $Else\ if\ SKL\ > 55\ and \leq 70\ then\ k = 2$

c. $lse\ if\ SKL > 70\ and \leq 90\ then\ k = 3$

d. $Else\ k = 4$

e. $End\ if$

7. $If\ k < 4$

$$Present\ level\ j\ content\ of\ unit\ i$$

$$Else\ if\ j = 3\ then$$

$$i = i + 1 \qquad //\ next\ unit$$

$$go\ to\ step\ 2$$

$$else$$

$$j = j + 1 \qquad go\ to\ step\ 3$$

Figure 8. Algorithm for Content and Quiz Automation

Implementation and Experimental Results

A course in Computer Science was selected to be converted into adaptive e-assessment mode. The subject expert was hired to develop the tutorials and assessment objects. A prototype was developed using PHP with the latest version of the Laravel framework. MySQL was used as a backend database server to store the student data. The interface was designed using the web framework bootstrap version 4.0 to make it responsive. The user (student and teacher) modules enabled them to log in and use the system by using any web browser. The selected screenshot is shown in Figure 9, which is composed of a student interface with a navigation bar showing the course content, the graph of previous quiz attempts, and the other screen navigation buttons."

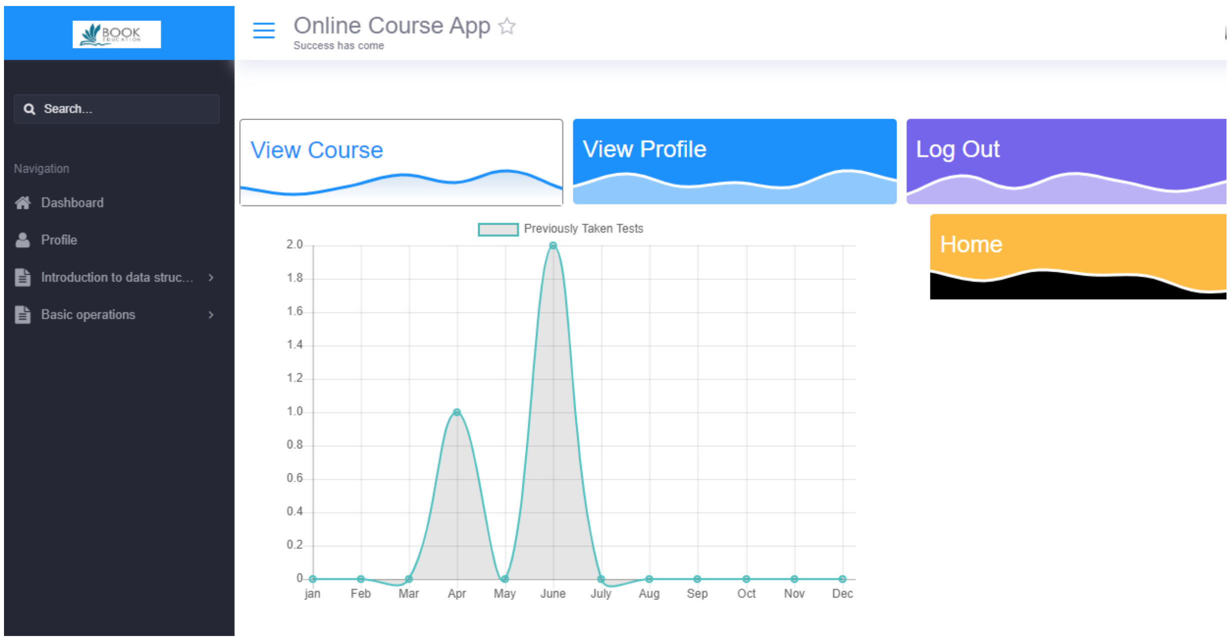


Figure 9. Screenshot of Adaptive E-assessment Prototype

The effects of the Adaptive E-assessment system were observed by experimenting.

The results of quiz no.1 (learning level 1, unit no 1) of three students in the form of student response, time spent, and current block difficulty level are presented in table 3 and Figure 10 [38]. Student A starts with an easy set of tutorials & problems, he/she completes it in a short time and is placed in known SKL, and therefore next difficulty level was set as intermediate. He was provided with the intermediate content followed by the same level of quiz. The student again showed excellent performance but took intermediate time, and again placed in known SKL. During the third time, he was presented with the advanced level of content and then a quiz, which he attempted in a short time and therefore placed in learned SKL showing the end of the current topic. The learning path is shown by white arrows in Figure 10. The performance of student B is different. His performance was not good during the second round therefore he was presented with intermediate content to learn the concept. The black arrow shows backtracking towards the intermediate level of content before attaining the required level. Student C started with low performance; therefore, he was given easy content twice and then he moved towards intermediate level. He took a longer time and therefore again presented an intermediate level of content. The learning path is shown by the gray arrow.

Table 3. Adaptive Quiz Generation Result of Three Students

Student	Input Variables			Output Variables	
	Current QB difficulty level	Response	Time spent	Next QB difficulty level	SKL
A	Easy	Good	Short	Intermediate	Known
	Intermediate	Excellent	Medium	Difficult	Known
	Difficult	Excellent	Short	Difficult	Learned
	Difficult	Good	Short	Quiz stopping criteria met	Learned
B	Easy	Good	Short	Intermediate	Known
	Intermediate	Not good	Medium	Intermediate	Unsatisfactory known
	Intermediate	Good	Short	Intermediate	Known
	Intermediate	Good	Short	Difficult	Learned
C	Easy	Not good	medium	Easy	Unknown
	Easy	Good	Medium	Intermediate	Unsatisfactory known
	Intermediate	Good	Long	Intermediate	Known
	Intermediate	Good	Short	Difficult	Learned

Current QB Difficulty Level= Current Question Block Difficulty Level
Next QB Difficulty Level= Next Question Block Difficulty Level
Response= Student Correct Responses **SKL =** Student Knowledge Level
Quiz Stopping Criteria= Time limit expires / maximum question attempt limit expires

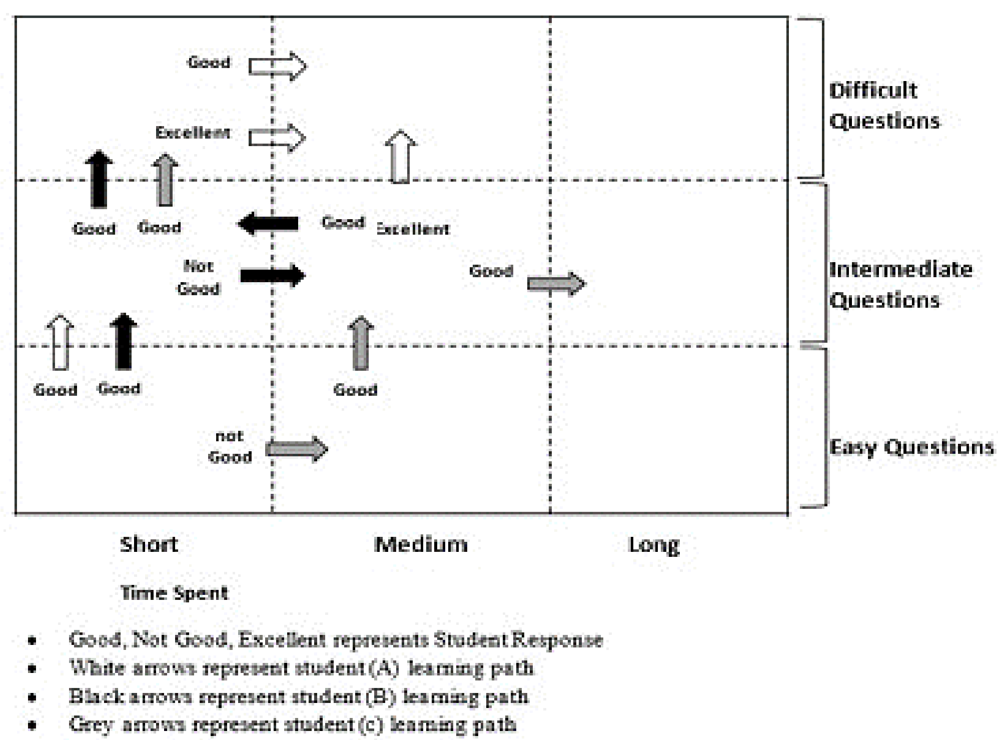


Figure 10. Grid Representation of Assessment Adaptation

Average Number of Attempts in Quizzes: The students interacted with the systems by browsing the contents and appearing in the quizzes. Their average performances in nine quizzes are shown in Figure 11.

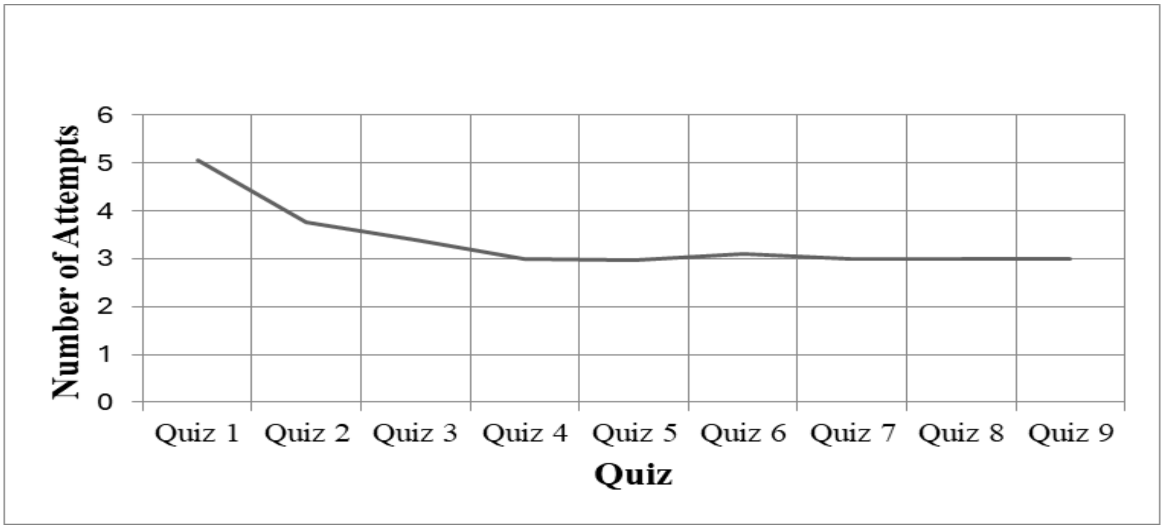


Figure 11. Average Number of Attempts in Self-Learning Quizzes

The analysis shows that initial interaction with contents and attainment of knowledge level required more quiz attempts. After getting through the matching contents and assessment objects their performance was improved.

Overall Improvement in Knowledge

Overall improvement in the knowledge of the adaptive batch and their comparison with the non-adaptive batch was analyzed. Randomly, students in several hundred-plus-ten students were picked out to observe and take inferences for the experimental survey. The students were distributed in two groups in a random fashion: experimental and control group and 55 students were included in each group. The comparison of grades for data structure course is shown in Figure 11. In this, 12.7 % of the students of the Adaptive batch obtained an A+ grade whereas 7.3 % of the Non-adaptive batch, showing improvement in highest grade. Grade results for the other experimental group were 10.9% scoring A, 16.4% scoring B and 25.5% scoring a C. Those in the control group showed results of 12.7% with A, 18.2% with B and 12.7% with C grades.

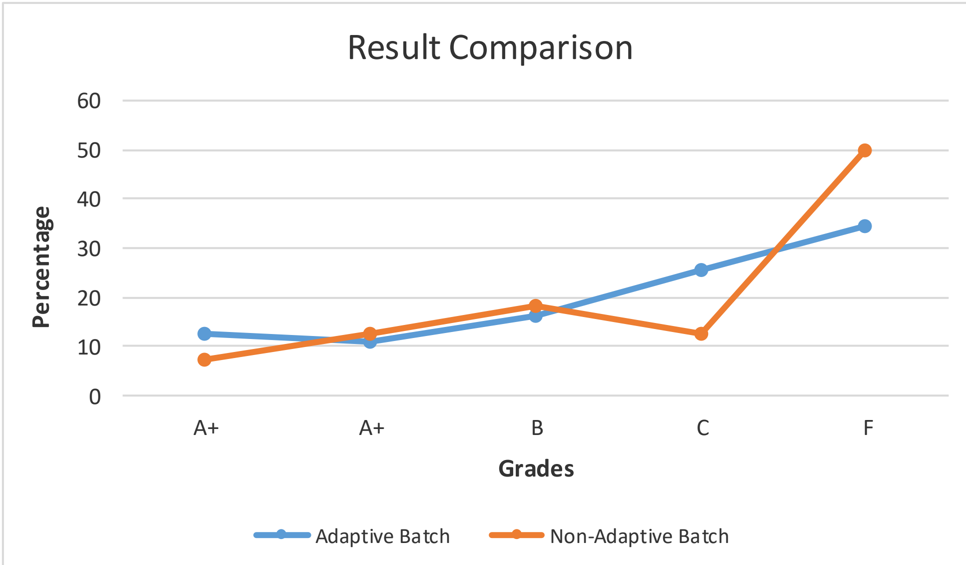


Figure 11. Result from Comparison of Data Structure Course

An important finding was a decline in the failure rate of the students which dropped down to 34.5% in the experimental group which was initially noted as 49.9% in the control group.

CONCLUSION

This paper presents a generalized model of an adaptive e-assessment for self-learning. The model has been proposed to present the personalized content followed by matching assessment quizzes to distant learners. Fuzzy logic has been used to analyze the assessment activities with quiz difficulty level, performance, and time taken to solve a quiz. The analysis has been used to evaluate the knowledge level and tailor a personalized learning path. The model has been implemented by designing the specialized contents for a computer science course and its presentation using a web-based application. A comparison was made between two sets of learners undergoing the course. The clear inference drawn by the end of this comparison was that the performance level of the set of learners using the Adaptive E-assessment technique was better as compared to the control group. In the overall improvement performance graph, clear progression in A+ grade holders was observed. A cutdown in the number of failures was seen, owing to the benefits of adopting this E-assessment tool. Similarly, the student's knowledge level in the adaptive assessment batch has also increased. The model may be implemented for other courses converted into distant learning mode, especially during the current pandemic.

Future Work

The future work deals with the development of a learning objects repository for adaptive content for different courses and programs. Future work also consists of maintaining a large databank of assessment objects and linking with learning objects to better adapt the content according to learner needs. A greater number of input parameters will be modeled to better classify the knowledge level of students.

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