Adaptive Learning Model and Analysis of Existing Systems

Zhansaya Bekaulova[1], Nurzhan Duzbayev[1], Gulnar Mamatova[2], Mukhamedi Bersugir[3] and Nurbek Bekaulov[1]

[1]*International IT University, Manas St. 34/1, Almaty, 050000, Kazakhstan*
[2]*Kazakh National University, Al-Farabi 71, Almaty, 050040, Kazakhstan*
[3]*Abai Kazakh National Pedagogical University, Dostyk 13, Almaty, 050010, Kazakhstan*

Abstract

Adaptive learning is a learning process using special algorithms for building an individual learning path using selected resources that meet the unique needs of students. Currently, technologies such as e-learning, m-learning, and blended are used to modernize the current educational process by introducing new teaching methods, training, and others. As a result, the system helps shift the teacher-centred approach towards the student-centred approach. However, it is noted that the role of the teacher is not levelled, but rather the teacher acts as a mentor who will be able to maximize their potential with the help of intelligent technologies. The article discusses adaptive learning systems such as Knewton, Smart Sparrow, etc., which allow based on the results of testing to determine the degree of assimilation of knowledge and assess the extent of research material, identify gaps in knowledge, selection of parts of the course, additional the training which will allow getting rid of these gaps by building a learning strategy.

Keywords

e-learning, adaptive learning, smart technologies, m-learning, blended-learning, graph theory

1. Introduction

The development and emergence of new technologies and solutions in one area can lead to a chain reaction in another. For example, increasing the amount of memory in the computer at one time led to the creation of the ability to store new data formats, such as digital images, audio, and video recordings. The development of the Internet has led to the possibility of instant dissemination of information around the world. Over the past few decades, with the advent of new IT technologies, the direction of virtual learning has been developing. In developed countries, such as the United States, South Korea, and the United Kingdom, virtual education systems are being created, which have several significant advantages over the traditional form of education. In the Republic of Kazakhstan, virtual learning has just begun to gain momentum.

Becker et al. review that the modern learning environment began with the “class-based teaching system” of Comenius. With the development of technology, technology-enhanced learning has gradually entered classrooms and experienced four changes discussed by Adu & Poo [2]. There are e-learning, m-learning, u-learning, and s-learning (Smart Learning). Against such a background, the technology-enhanced learning environment has also evolved from an e-learning environment to a smart learning environment (SLE). Kinshuk mentioned that personalized learning and adaptive learning are two kinds of effective learning that SLE mainly focuses on in an interview by Yang et al. [3]. The typical event of personalized technology-empowered personalized learning is the appearance of Skinner’s teaching machine and program teaching theory is discussed by Wleklinski [4]. Since then, personalized learning has begun to have the characteristics of adaptability.

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zhaanka@gmail.com (Zh. Bekaulova); nurzhan@gmail.com (N. Duzbayev); mamatovag@gmail.com (G. Mamatova) bersugir68@mail.ru (M. Bersugir); nbekaulov@gmail.com (N. Bekaulov)
0009-0000-9339-9222(Zh. Bekaulova); 0000-0002-7989-9463 (N. Duzbayev); 0009-0007-6338-6093 (G. Mamatova); 0000-0003-0889-2069 (M. Bersugir); 0009-0002-8862-3191 (N. Bekaulov)

In recent years, it has become popular to get an education online. Besides, due to the emergence and spread of coronavirus around the world in late 2019 and early 2020, most companies stopped operating or switched to online operations. The same applies to educational institutions from schools to universities. The sudden increase in attention and examples of practical applications or the transition to an online format has led to more productive growth in the number of e-learning research. Ebner et al. [5] analyzed the process of transition of the educational process from the traditional offline to online format in the example of the Austrian University Graz University of Technology (TU Graz). In China, the government initiated the "School's Out, But Class's On" campaign, which involves creating a large-scale online educational application for students from all over the country as discussed by Zhou et al. [6]. Because of the quarantine, more than 270 million Chinese students were forced to go online. For the systems to support the load from such a large number of users, cloud technologies were used, which allow you to develop solutions designed for very large loads. This is not an isolated example of using cloud technologies in e-learning. The article by El Mhouti et al. [7] reviews existing e-learning solutions based on cloud technologies.

It is worth noting the role of the state in the development of e-learning in the country. For example, in China, as part of the "School's Out, but Class On" campaign, the government made adjustments at the legislative level to implement a large-scale project to provide an e-learning training format for the entire country. Among the most interesting changes in the laws is that now the learning process is not focused on the teacher (teacher-centric) but moves to a student-centric orientation (student-centric), and the teacher acts as a mentor and mentor. This approach was used by innovators from India who developed a SMART mobile Android app is discussed by Haidar et al. [8]. The main idea of this app is that to implement the m-learning learning process, you need to switch from the teacher-centric approach to the student-centric one. These changes will provide an opportunity to personalize the learning process, build an individual learning path, and conduct adaptive testing. the positive aspects of implementing SMART technologies in the learning process. In addition, this concept, like smart education, needs to adhere to the view that “technology promotes education rather than leads education is discussed by Zhu et al. [9]. This is because, so far, few technologies have been created for teaching, and the convenience pursued by technology is not what education seeks are reviews Zhu & Wei [10] which is the effectiveness of promoting human development.

The most advanced type of e-learning system is adaptive e-learning. The main idea of which is to personalize the learning path for each student. For the system to be adaptive, various approaches can be applied. Tseng et al. [11] used the concept maps theory developed by Novak and Musonda in 1991. The development allows you to select the next material/course individually from a specific set of training materials or courses based on the available data about the student.

Abdullah et al. [12] proposed a model of an adaptive educational system, in which the assessment process is adaptive, i.e. adaptive e-assessment. The system can be integrated with other solutions, as it is developed as a separate module. In the case of the authors, the solution was integrated with LMS Moodle. The authors argue that it is impossible to create an adaptive educational system if it does not adopt the assessment process, i.e. feedback from the student to the teacher. We fully agree with this statement and one of the main components of our system is adaptive e-assessment.

In general, adaptability in learning is understood as a personification of the educational process based on the creation of electronic courses that take into account the individual characteristics of students, including the level of initial knowledge, speed of perception, and psychological characteristics. Under the influence of data-intensive science, personalized adaptive learning has become the fifth-generation educational technology research paradigm proposed by Zhu & Shen [13]. Based on big data, it has become an important part of a digital learning environment discussed by Zhu & Guan [14]. However, this field has not yet revealed all its secrets and a significant number of researches are in progress in the field of adaptive learning because, at this stage, no unanimously recognized methods to study learning environments using the principles of adaptive learning and many issues remain unelucidated are proposed by Fontenla-Romero, & Guijarro-Berdiñas [15].

This is a type of goal-oriented requirements engineering that personalizes the learning process and focuses on the needs of the learner. An ALT can provide each learner with course materials that match their learning style as proposed by Dounas et al. [16]. Studies on ALT systems that focus on cognitive learning styles reveal improved student learning as discussed by Dhakshinamoorthy & Dhakshinamoorthy [17]. With ALT, students work at their own pace. Truong [18] reviews the teaching environment becoming "personalized". Universities are now able to promote a learner-directed environment proposed by Gebhardt [19]. Cai [20] reviews that colleges and universities are turning to adaptive learning as a solution to the antiquated one-size-fits-all approach to teaching.

Thanks to such information and educational technologies, it is possible to organize the educational process at all stages of working with students at a higher level, systematically evaluating their subject achievements, and forming knowledge, skills, competencies, and skills. Also, the computer system of adaptive learning is a kind of "teacher" and "psychologist" in the development of several important properties and qualities of students, the formation of their all-required skills, abilities, and professional competencies.

The main contributions are summarized as:

- This study provides a theoretical basis for the development of adaptive learning systems.
- This study is the students' recognition ability of better understanding and promotes self-evaluation as a means of adaptive learning of the system model.
- This study is the literature on adaptive e-learning systems used for learning efficiency and satisfaction of the empirical investigation contributes significantly to it.

The remainder of the paper is organized as follows:

Section II contains problem identification. Section III includes the features of the existing literature. Section IV describes the system model of adaptive testing. Section V proposed the student competency evaluation algorithm based on Adaptive learning. Section VI presents the experimental results and implementation. Section VII gives a discussion of the results. The last Section VIII concludes the paper.

2. Problem identification

The problem of creating computer-based training programs that can effectively organize the content of the training course, as well as learning strategies and modes of active interaction between the student and the computer, is one of the most important issues of computer-based learning. This type of training also has disadvantages, which include the following:

The need to detail the training course and duplicate its elements with varying degrees of detail in the presentation of the material, which leads to a significant increase in the complexity of developing the training course;

The need to perform frequent knowledge monitoring. To have as much objective information as possible about the current level of knowledge of the student, therefore, it is necessary to frequently conduct testing in various sections of the course. This disadvantage can be mitigated by using adaptive knowledge testing algorithms, which can reduce the testing time, reducing the load on the learner.

Thus, thanks to intelligent adaptive learning systems, you can improve the quality of training and reduce the costs that are necessary for organizing an online educational process.

3. System model of adaptive testing

The principle of the working adaptive learning model consists of a few competencies of students and these skills form a hierarchy. At the top level must be a final result or a target competency that the student aims to reach. Then this hierarchy is divided into simple skills. In the lower level of the hierarchy, you can observe the simple and indivisible skills. In this model provided that a student does not have low-level skills, he can completely avoid high-level skills and vice versa. We use a platform to evaluate each skill. Enter and evaluate the right and wrong scale of the correct answer, we assess the likelihood of the "Yes-No" scale. Taking into account the skill presentation and evaluation of test projects can lead to many truly gifted. This reduces the number of input elements. However, it is not always possible to reduce the amount of product. Therefore, it is also recommended to use complex test tasks to reduce the number of test tasks, as well as take into account the skill hierarchy. The difficulty of the next test task should correspond to the student's skill level. This will help to eliminate deliberately set simple or complex test objects and evaluate so many skills with a test item. Figure 1 shows the adjustment test process of the proposed method. The process is iterative. Each iteration selects topics, and (after the answer) some relevant methods can be evaluated. For this purpose, our test consists of a complex task (writing a test project), qualification level (a specific model of the student), and skill (subject model). Tests can be stopped when all competency of students are completed. For a final set of assessment techniques, we select only those for which students do not pass.

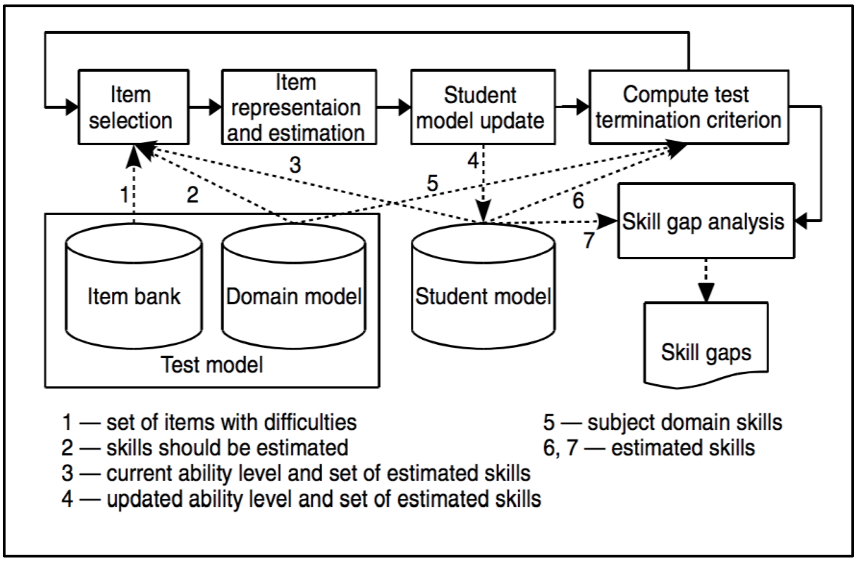

Figure 1: Scheme of the adaptive testing process

4. Related work

In this section, the salient features of existing approaches are summarized.

The main tools of the Knewton adaptive learning system, founded by Jose Ferreira were introduced in [21]. Knewton has come up with courses that continuously adapt to the characteristics of each student. With traditional methods, gaps in knowledge grow like a snowball–it is necessary to understand one topic as soon as the other is taken. However, the authors failed to define and implement this idea properly.

Henderson [22] introduces another tool of an adaptive learning system called SmartSparrow that allows teachers to develop interactive courses themselves and use the system's intelligent capabilities to adapt the curriculum to each student. More than a dozen courses have already been created based on this platform, mainly at the university level. Thus, SmartSparrow is a powerful online platform for creating a new generation of interactive and adaptive courses. Although it contains an impressive collection of sources, this tool does not provide constant and immediate adaptability, rendering it a great resource, but one with less horsepower was introduced in [23].

Englisch et al. [24] described the use of an Adaptive learning system called as Math Garden system which serves to improve math skills and is an online environment for students to practice math at their level. This service is available to families, schools, and other educational institutions. However, there is one shortcoming – the utility only works to improve math skills.

5. Skill estimation using adaptive testing

To perform the following concept, we develop the following algorithms. Skill estimation is important for generating a sequence of test items to assess the performance of students. This process consists of two phases.

1. Item Selection
2. Update assessments of domain skills

A. Item Selection

This algorithm solves the problem of generating a set of tests to assess students' skills.

Thus, algorithm 1 depends on the answer of the student and we can determine several related skills in the field of science and calculate a new level of student skills.

	Algorithm 1: Item Selection Algorithm
1.	**Initialization:** {S_j: a competency that has been evaluated at the previous iteration, j ∈ {1 and n} (n total number of skills that has been assessed at the previous iteration); GS: original set of skills, L_s: a label for skill S; the label can have one of three values "undefined", "possesses" and "does not possess", G_{s_k}– the minimal set of unrelated skills, which a student does not possess, $S_{analyze}$: skill that have to be assessed at the current iteration }
2.	**Input:** {S_j, L_s, GS, G_{s_k}}
3.	**Check and analyse:** S_j
3.1.	**If** n = 0
3.2.	**Set** $S_{analyse}$ = GS
3.3.	**Else If** n>0 && (L_{s_k}= "undefined" or L_{s_k} = "does not possesses") where k ∈ {1 and n}
3.4.	**Set** $S_{analyse}$ = S_k where k ∈ {1 and n} && L_{s_k}= "undefined"
3.5.	**Else if** n>0 && L_{s_k}= "possesses" for all k ∈ {1 and n
3.6.	**Set** $S_{analyse}$ = G_{s_k}
3.7.	**End if**
4.	**Output:** {$S_{analyse}$}

Algorithm 1 selects the next test item that assesses several skills concurrently. The relatedness of skills, the difficulty of test items, and the current student's ability level are considerable points.

Step -1 initializes variables for the item rating process. Steps 2-4 give the input and output processes respectively. Step 3 analyses a set of skills $S_{analysis}$, which can be judged in the current moment. We can evaluate 3 cases. Steps 3.1 – 3.2 proposed the first case that the test has just begun, therefore the set $S_{analyse}$ is equal to the original GS. Steps 3.3 -3.4 determined that the student does not possess the skill S_k. In this step, the set $S_{analyse}$ include inherited skills for S_k which have the label L_{s_k}= "undefined". Steps 3.5-3.6 determined that the student possesses the skill S_k. In this case, the set $S_{analyse}$ consists of subject skills that have not yet been evaluated, therefore, there is a L_{s_k}= "undefined".

B Update assessments of domain skills

During testing in a student model, we have to rely on the student's ability or not. Backup information and information for students. This component determines the skill level/competence of the student. In addition, the model should reflect the current skill level of the student for whom the next test item is selected. Therefore, the student model is described in algorithm 2.

Algorithm 2: Update assessments of domain skills	
1.	**Initialization:** {S_j: a competency that has been evaluated at the previous iteration, j ∈ {1 and n} (n total number of skills that has been assessed at the previous iteration); $S_{analyze}$ – current skill under analysis; Q_i – the represented test item (it is associated with the skill S ; G – assessment of response to test item Q_i; L – the current ability level}
2.	**Input:** {S_j, G, L}
3.	**Update** S_j
3.1.	**If** G = "correct"
3.2.	**Set** $L_{S_{analyse}}$ = "possesses"
3.3.	**Set** L_{S_k} = "possesses" where k ∈ {1 and n} && S_k in child of $S_{analyse}$
3.4.	**Else If** G = "incorrect"
3.5.	**Set** $L_{S_{analyse}}$ = "does not possess"
3.6.	**Set** L_{S_k} = "does not possess" where k ∈ {1 and n} && S_k in child of $S_{analyse}$ && L_{S_k} = "undefined"
3.7.	**End if**
4.	**Output:** {$L_{S_{analyse}}$}

Algorithm 2 represents the current student's ability level, by which the next test item is selected. In step 1, the variables are initialized for the student model update. Steps 2-4 give the input and output processes respectively. In step 3, update the student's ability skill. Steps 3.1 – 3.3 determined that the answer is correct, it should be assumed that the student has this skill, that is, for all generations S_j, which are labelled as "undefined" set the label "possess". Steps 3.4 – 3.6, determine that the answer is incorrect, it should be assumed that the student has this skill, that is, for all generations S_j, which are labelled as "undefined", set the label "does not possess".

An adaptive learning algorithm Is based on taking into "ccount th" natural proces" of forgetting information by a person over time, which can be mathematically described as:

$$R(t) = e^{-\frac{s}{t}} \tag{1}$$

where R – is the amount of residual knowledge; s – is an individual parameter for each person that characterizes the speed of forgetting information; t – is the interval of time.

Herman [25] showed that the more time passes since a person acquires information, the less it remains in memory exponentially. Studies show that an average person forgets 60-70% of the received information in 24 hours, and in a month the residual level of knowledge is 20% of the initial one. A well-known method of fixing knowledge at the required level is iterative learning, which involves repeated repetition of the studied material to fix it in long-term memory. Let's assume that the student was asked to teach a certain amount of information, which he successfully coped with. Then, over several days, the student repeated the studied material several times.

Krechetov & Kruchinin [26] described the main idea of adaptive learning is to build an optimal trajectory for students to study course modules. A module is a logically complete minimal unit of educational information that reveals one or more terms or concepts and is related to other units.

The module can be represented by text, contain graphics, video, or audio, as well as any other interactive forms of information representation. Building a trajectory from modules is a multicriteria optimization problem. However, given the specifics of the University's curriculum, namely that the time allotted for studying the course is fixed, the criterion of optimality can be considered to be obtaining the maximum level of knowledge at the end of the course with the minimum time for studying the course modules, or

$$F(PTcon) = TM/(R(Tcon))) \rightarrow min \tag{2}$$

here, P is the learning path, TM is the total time of learning modules, and R is the level of residual knowledge. Since the end time of the Tcon course is a constant, it can be omitted when writing the objective.

Moreover, the solution space of the problem is highly discretized: as will be shown below, not every sequence of course modules is valid. Therefore, the constraints of the problem can only be written in terms of discrete mathematics as relations on sets. Classical optimization algorithms are not well suited for solving such problems, so a genetic algorithm was chosen to solve it. At the planning stage of the practical implementation of the adaptive learning model, the following design decisions were made.

1. The client-server architecture was chosen. Desktop software solutions in e-learning are currently almost not used. All universities involved in the development of distance learning are focused on online systems.
2. All the tools for creating and running it was decided to perform adaptive training courses in the form of a cloud service such as SaaS. This will make it possible to provide this tool to all interested universities and other organizations, regardless of the type of distance learning system they use, as well as simplify the maintenance and support of the software component of the service.
3. It is assumed that modules and competencies do not initially belong to any particular course, i.e. they are universal. All of them are stored in a common database, and when necessary, they can be used in the formation of a particular training course.

6. Discussion of results Adaptive testing

The proposed method for adaptive learning is to accurately determine the level of knowledge in a certain subject individually for each student by a minimum number of test questions. The central component is a “knowledge tree” similar to the Knowledge Structure tree. The advantages of the method “Knowledge Structure tree” based on the results of the study are the student will have the opportunity to finish teaching or re-reading the material and come ready for the next lesson. The most important advantage of using the system for the teacher is that there is no need to manually check homework from students' notebooks. The system will automatically check all students and send a detailed report on the development of the material. Also, the system will be able to send additional information personally for each student on the list of topics that are most likely not mastered or forgotten. This will allow the teacher to devote time freed up due to the automatic check of students' homework assignments to improve the educational material and work with lagging students.

Another advantage of this tool is that a sufficient degree of freedom in forming their schedule for passing theoretical material and testing develops students' independence and responsible attitude to learning. During the experiment, there was an increase in motivation to study the course, which ultimately had a positive impact on learning outcomes.

Thus, it can be stated that adaptive learning is not just a different approach to the formation of the educational process, but also provides higher learning outcomes that can be measured quantitatively, as well as personal interest and involvement of students in the learning process.

An experiment with adaptive training has been done of 10 students in one discipline using electronic information and an educational environment. At the same time, the second group of 12 people studied the same course also using electronic information and an educational environment. However, students of the second group were trained traditionally, and the electronic information and educational environment were used only for the digital presentation of theoretical material in the form of lecture notes and automated knowledge control through tests.

Naturally, the content of the course was identical, but the form of presentation of the material and, consequently, the test questions were different. At the same time, for the second group, the content for all students was the same, designed for a student with average real educational opportunities, while for the first group, several forms of presenting theoretical material to the student were provided, depending on its results.

At the end of the course, both groups passed the same test, which was designed to show the level of students 'assimilation of the material and demonstrate the advantages (or disadvantages) of adaptive learning in terms of students' assimilation of the knowledge component of the discipline. To compare the results, due to the different number of groups, the results of two students were randomly excluded from the second group. The test results of students in each group were arranged in non-decreasing order, which allowed us to visualize and compare the results obtained (Fig.3).

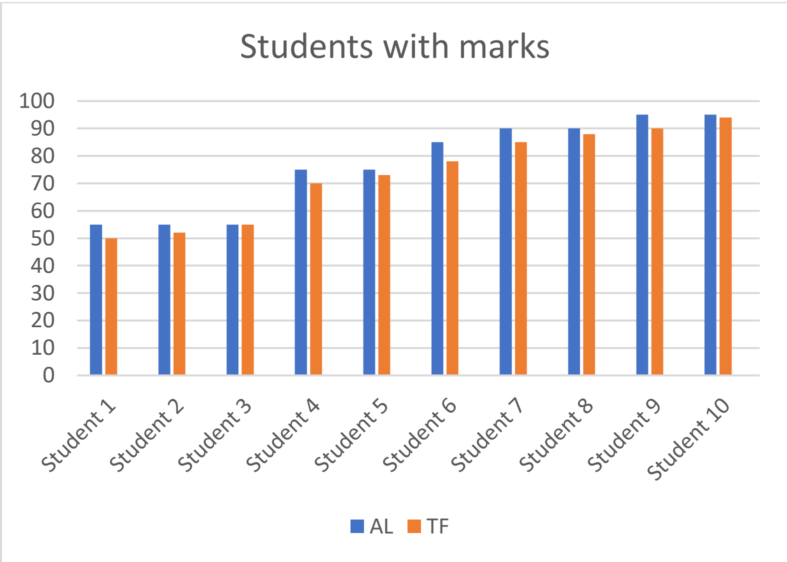

Figure 2: Results of testing (AL - Adaptive learning, TF - Traditional form of learning)

The results show that students who were trained according to the adaptive approach to learning showed higher results on the final test. Thus, out of 10 students, four received an "excellent" rating (80-100 points), while only 2 students who studied under the traditional model received an "excellent" rating. Scores show that in the vast majority of cases, students who were trained in adaptive learning answered the test questions better.

As you can see, students studying in the adaptation process have high grades. This fact is a practical proof, where with the adaptive learning has more effective than traditional training. Table 1 presents the results of the mean tests for two groups of students, means and standard deviations. According to Table 1, the group of students using the answer option has an average score 0.778912, but for the other group, it is 0.7188888. The median, mean absolute deviation and standard deviation values for the adaptive e-learning are respectively 80%, 14%, and 15.8%, while for the non-adaptive learning assessment, their values are 73.00%, 13.56%, and 15.6%. This data once again shows that learning an adaptive system is better than a traditional system.

7. Conclusion

The paper presents the concept of adaptive testing, to reduce the number of entered test tasks, for every student constructed individually by their hierarchical skill. Nowadays, in our universities, we have a lot of the newest such as the “bell for a student”. Also, this problem can be solved with an adaptive learning model. E-learning systems are considered adaptive when they can change dynamically in response to individual student differences. Online customers, researchers and teachers a better combination of theory and learning strategies with the system features and experimental research on the impact and value of these systems in real-time. To improve learning effectiveness for all research students in the development of e-learning systems based on the theoretical framework, the integration of adaptive learning strategy, the regional forest theory and self-assessment mechanism. Adaptive e-learning system accounts in the student's dynamic strength and all students in the relevant study material can provide.

The research aims to test the hypothesis that the knowledge gained in adaptive learning is formed and consolidated better due to higher independence, motivation, involvement, and responsible attitude to learning among students who have been trained in the adaptive learning format.

The results of this study can be useful for system developers, programmers, education, and related education staff in the hope of leading a successful adaptive e-learning environment. In particular, the results that teachers can use grades, and self-assessment tools to help students through a dynamic framework to perform student-centred e-learning.

This study, like many empirical studies, has limitations to address. First, the lack of generality is a clear limitation in the presence of data from participants. The results of this study from the same University selected for this study with participants in many populations can be summarized. This research still maintains an important space for growth. Future studies may consider different individual student files and provide dynamic wireframes for them.

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