# The use of intelligent algorithms to adapt learning

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**Abstract**
In an era of rising technology, online learning is one of the priorities. The use of intelligent algorithms in online learning will not only allow students to gain knowledge remotely, but also takes into account their individual characteristics, which, in turn, will allow them to adapt learning, creating a unique trajectory for each student. This article discusses ant colony optimization and Bayesian knowledge tracing algorithms that will help personalize learning for each student, taking into account their personal characteristics such as learning style, information perception, and prior knowledge. The research results demonstrate various developments, achievements, and challenges in this area.
The article presents an original methodology that includes designing the architecture of an adaptive learning system based on a combination of ACO and BKT algorithms. This architecture allows you to create a personalized learning trajectory that adapts learning depending on the level of knowledge and learning characteristics. Comparative characteristics of online learning systems, as well as intelligent algorithms such as the genetic algorithm with the presented combination of ACO and BKT in this field are presented. The key components of adaptive systems are described: the learner model, the domain model, and the adaptation model. Comparing the effectiveness of adaptive learning algorithms allows us to evaluate the effectiveness of intelligent algorithms.

**Keywords**
online education; learning style; intelligent algorithms; ant colony optimization (ACO); ACS (Ant Colony System); Bayesian knowledge tracing (BKT); learning trajectory; adaptive system, individualization

## 1 Introduction

In the era of technological progress, the education system is also actively implementing technological solutions, such as online learning platforms and mobile applications, which in turn not only offer knowledge, but also develop certain skills. However, many existing systems provide only materials for study, without taking into account the individual needs of students, which leads to a decrease in the effectiveness of the acquired knowledge, which in turn leads to a problem in this area. The solution to these problems is adaptive learning systems that adapt the learning process taking into account the various characteristics of the learner. Adaptive systems are based on intelligent algorithms that analyze the level of knowledge, individual characteristics, taking into account the learning style, and the student's progress on topics, which allows them to identify complex topics specifically for them and builds a unique personalized path for everyone.

S. Kurt notes in his research that adaptive learning, unlike a universal curriculum, meets individual needs through personalized learning trajectories, effective feedback, and additional resources [1]. According to a study by Hanover Research, students participating in individual programs demonstrated greater academic growth in mathematics and reading compared to those who attended similar programs based on a more traditional approach [2]. The research data shows the distinctive advantages of adaptive learning systems, which includes an individual approach that takes into account the needs and learning style, increasing motivation through personalized content.

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In general, adaptive learning provides better and more effective education by meeting the needs of each student. This study is devoted to the analysis of intelligent algorithms used in the development of digital educational content in accordance with the principles of adaptive learning.

## 2 Research methodology

The methodological basis of the research is based on methods of knowledge analysis and management, which in turn is an integrated approach for the development and evaluation of educational content using intelligent adaptive learning algorithms:

- Study of intelligent algorithms used in adaptive learning – analysis and comparison of popular online learning platforms and implemented intelligent algorithms in them, which take into account individual characteristics (learning style, initial knowledge, etc.) to ensure a personalized approach.
- Development of the concept of adaptive learning and identification of its key components, their interrelationships and functional features.
- The study of a combination of ACO and BKT algorithms for optimizing learning trajectories and adapting learning in an electronic environment.
- Development of an architectural solution that makes it possible to form individual learning trajectories based on individual student data – the level of knowledge, perception style and learning style.
- Conducting an experiment in which virtual students with different levels of knowledge and learning styles worked with an adaptive system in which the BKT algorithm updated the level of knowledge, and the ACO algorithm optimized the order of topics.

## 3 Theoretical justification

Online educational learning resources include a variety of interactive materials that contribute to a more comprehensive understanding of the subject. However, many of them do not take into account the individual characteristics of students, which leads to insufficient flexibility of the system. This leads to a lack of personalization, when all students receive the same materials, and information overload due to excessive content [3]. The solution to these problems is to provide an individual approach that will take into account the learning style, initial knowledge of the subject and the learning style of the student, using these data to structure the educational content, builds a personal learning path, while avoiding unnecessary information and delving into the materials not learned.

Individual characteristics include different learning styles of students, so it is important to offer materials that match these styles. Several intelligent solutions have been developed for this purpose [3], such as automatic generation of conceptual maps [4], adaptive pedagogical pathways [5], and dynamic learning systems [6]. The proposed systems make it possible to analyze student behavior, evaluate academic performance, and recommend optimal learning materials.

An analysis of recent research shows that intelligent technologies can analyze student behavior, evaluate their academic performance, and recommend optimal learning stages. One of the main applications of artificial intelligence in the online learning environment is adaptive learning. Adaptive algorithm-based systems help to adjust the content, complexity, and formats of learning according to the individual needs of students, using a variety of personal factors such as data on their knowledge, motivation, and learning pace. Such systems provide personal recommendations, taking into account the achievements, mistakes and learning characteristics of each student [7, 8]. This approach allows us to consider online education as an optimization task, the purpose of which is to find the most effective learning path for each student. The adaptive learning system defines learning models within specific groups of students and adapts appropriate learning paths accordingly. These group learning models represent a form of collective intelligence that can provide a high level of adaptability for other similar learners in such a dynamic learning environment [9].

In order to adapt the system, the system must have an idea of the students' knowledge and level of understanding. Decisions on the supply of material by the system should be made based on an adaptation algorithm that takes into account the various characteristics of the user interacting with the system. These characteristics shape the user's model, including their interests, learning preferences, and effectiveness. The system builds and continuously updates the student's model throughout the interaction, providing adaptive learning that personalizes learning materials [10].

The principles of adaptive learning were developed to determine how students with different learning styles can be connected to the most useful content, forming an optimal learning trajectory [11]. Thus, adaptive learning should provide access to educational materials that differ from traditional ones, allowing each student to find the most appropriate content. Many teachers and researchers emphasize the importance of taking into account the characteristics of students and their learning needs when developing educational materials. Therefore, it is crucial to provide a variety of learning resources appropriate to different learning styles.

The system should be able to recommend educational content appropriate to the preferences of students, their level of knowledge and learning style [12]. Each person processes information in their own way: while some learn information better through visual representations, others through text and reading, some excel in theoretical study, and others through experiments and practical examples. Also, everyone has their own level of knowledge – someone knows and understands the educational content well, in-depth material is important for them, while others may have minimal thresholds of knowledge of the subject that require basic knowledge. Understanding these diverse learning styles and initial knowledge allows for the development and implementation of approaches tailored to the individual needs of each student. Learning styles represent individual differences that play a crucial role in education.

According to Ennouamany and Mahani (2019), the design of any adaptive learning system is based on the interaction of three main components: student models, domain models, and adaptation models [13].

A domain model is a set of knowledge organized into a logical structure consisting of blocks representing various learning concepts and topics. These blocks use various methods such as exercises, explanations, or tests, and each of them has a unique identifier that can be used by both humans and computer systems to process information [14]. The system allows you to combine various elements of the discipline and create transitions between them. For logical structuring of the content, it is necessary to arrange the structure in the appropriate sequence to ensure effective student learning. Standards that ensure compatibility are used to encode these sequences. The most popular standards for structuring e-learning content are SCORM, xAPI, IMS Global Learning Consortium and AICC [15].

The student's model is formed using an electronic portfolio or a questionnaire [16]. Based on this data, a student's model is created, including his level of knowledge, learning style and preferences, as well as characteristics of understanding the material (such as common mistakes, task completion rate and motivation). The student model allows the system to adapt the learning process in the future, providing an individual approach that meets the individual needs of each student.

The system adaptation model is based on data analysis methods and algorithms using a forgetting curve and an iterative approach. These algorithms create different learning paths, offering students the most appropriate one. Methods such as dynamic fuzzy networks, multi-criteria decision-making systems, ant colony systems, genetic algorithms, neural networks, machine learning, and Bayesian knowledge tracing are used to automatically determine the optimal course sequence.

Effective adaptive learning algorithms take into account the individual characteristics of students, analyzing their academic performance and learning style, which makes the learning process personalized, effective and exciting. In educational environments, teachers upload materials to digital platforms, while students study and complete tasks, interacting with a system that adapts learning using intelligent algorithms. The table below shows educational platforms and the algorithms they use to adapt to learning.

**Table 1**
Platforms and Used Algorithms

| Platform | Used algorithms | Algorithm Description |
|---|---|---|
| Khan Academy | Machine learning algorithms | Analyzes lessons, tests, and other data to personalize content and recommendations |
| Duolingo | Fuzzy logic and machine learning algorithms | Assesses performance and adapts material complexity based on success and experience |
| Coursera | User behavior analysis and ranking algorithms | Recommends personalized courses based on interests and preferences |
| Smart Sparrow | Fuzzy logic, machine learning, and intelligent agents | Adapts content in real-time based on student progress |
| Plario.ru | Bayesian Knowledge Tracing and genetic algorithm | Diagnoses knowledge gaps, creates a digital twin of the student, and predicts material mastery |
| Beiym.ai | Genetic algorithm | AI assistant analyzes requests, adapts tasks and materials, and personalizes learning |

The table demonstrates the growing popularity of educational resources that adapt learning materials for students using preference analysis algorithms. BKT in these systems is used to determine whether a student has successfully mastered skills (i.e., correctly answered elements or tasks) in a skill set. BKT has become a successful model in this field, providing significant achievements [17]. ACS uses swarm intelligence to find optimal learning paths by mimicking the behavior of ants. The nodes in the system represent the elements of learning (lessons, exercises, tests), and the connections between them have weights reflecting the probability of choosing the next stage of learning [18]. The ACO algorithm optimizes these weights, helping students find the most effective learning path. The pheromones in the system reflect the successes and failures of students, which allows you to adapt the learning route accordingly. The ACS and ACO approaches ensure the reliability and adaptability of online learning by creating personalized learning paths. The main comparative differences of the systems in which intelligent algorithms for learning adaptation are implemented are given below.

**Table 2**
Comparative Characteristics

| Criterion | Existing Systems (Coursera, Duolingo,) | Proposed System with ACO and BKT |
|---|---|---|
| Adaptation to knowledge gaps | Diagnosis is performed, but not always at a deep level | In-depth diagnostics with the creation of an accurate student model (digital twin) |
| Learning path formation | Based on past behavior or general preferences | Uses an optimized ant colony algorithm to construct a personalized learning path |
| Path adjustment during the process | Often requires manual tuning or limited automatic restructuring | Automatic adaptation after each attempt/error made by the student |
| Intelligent navigation | Tasks are offered sequentially or by level | Optimal path selection to the goal: the system selects the most efficient tasks |
| Consideration of individual traits | Partially implemented on some platforms (motivation, style, interests) | Integration of multiple factors: knowledge level, perception style, intelligence type, motivation |

From the analysis of the table, it can be concluded that the ACO and BKT algorithms are often used in learning adaptation systems, which demonstrates high efficiency when combined with other algorithms.

The scientific novelty of the author's approach lies in the use of a combination of ACO and BKT algorithms for the dynamic adaptation of educational content depending on the level of knowledge, the pace of learning and student preferences, which allows you to form individual learning trajectories in real time. BKT will be used to update the probability of learning after each answer, and ACO will be used to build the optimal learning route.

## 4 Results

Students learn in different ways: some absorb visual material better, while others prefer text. Some favor theoretical explanations, while others grasp concepts more easily through experiments and examples. By understanding various learning styles, an adaptive system provides tools for developing and delivering personalized learning trajectories [19].

The concept of an adaptive educational system is based on analyzing fundamental knowledge and individual characteristics such as perception, intelligence, and motivation.

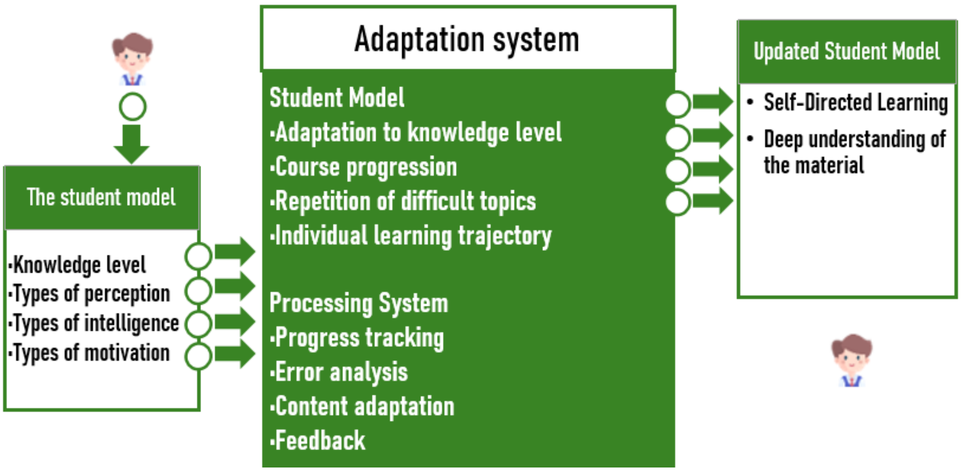


**Figure 1:** Concept of an Adaptive Educational System.

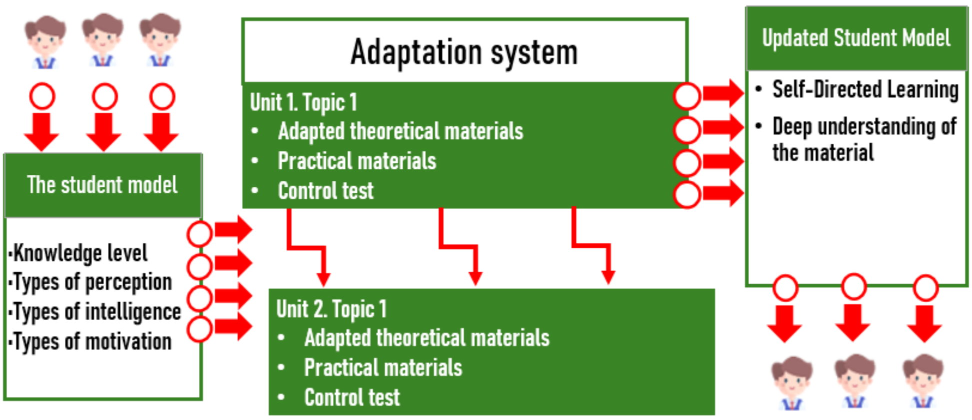


**Figure 2**: Learning path of each student.

Even if the student makes mistakes, learning continues, and the system adapts the process by returning to topics that have not been mastered in subsequent sections. Each student follows an individual learning trajectory that takes into account their unique characteristics. As a result, by the end of the course, the material is fully absorbed, and success becomes maximum.

To ensure such flexibility and adaptation of materials in the e-learning environment, ant colony and BKT algorithms will be used.

Bayesian Knowledge Tracing (BKT) for knowledge tracking, evaluates a student's current knowledge on each topic and updates probabilities after students complete assignments. Parameters [20]:

- *P*(known): the probability that the student already knows the skill;
- *P*(will learn): The probability that a student will learn a skill at the next practice opportunity;
- *P*(slip): the probability that a student will give an incorrect answer despite knowing the skill;
- *P*(guess): the probability that the student will give the correct answer, despite the fact that he does not know the skill.

An ant-like algorithm for optimizing the student's learning paths, helping them choose the best set of tasks to maximize learning progress. Key Elements of the Ant Colony Algorithm:

- Pheromones: Tasks with higher pheromone levels indicate "good" assignments for students. The pheromone level increases when a task helps a student better understand the material.
- Heuristic Information: Assignments are evaluated based on difficulty and contribution to learning.
- Pheromone Evaporation: Tasks that have not been used for a long time or have proven less useful gradually lose their pheromone levels.

In the ACO learning model, each student is represented as an "ant" moving through a graph. As they complete exercises, they leave behind "success pheromones" (*S*) or "failure pheromones" (*F*), influencing the selection of future learning paths.

The pheromone evaporation formula for success pheromones (*S*) (with a similar formula for *F*) is defined as follows.

The pheromone evaporation formula for success pheromones (*S*) is:

$$S_t = \tau^x S_{t-1} \tag{1}$$

The pheromone evaporation formula for failure pheromones (F) is:

$$F_t = \tau^x F_{t-1}, \tag{2}$$

$S_t$ – Amount of success pheromone on the edge between vertices;

$F_t$ – Amount of failure pheromone on the edge between vertices;

$t$ – Evaporation rate, a key parameter of the system;

$\tau$ – Constant used to adjust the evaporation rate;

$x$ – time elapsed since the last visit to this node or the evaporation period, indicating how often evaporation is calculated, remaining constant throughout the learning process.

These pheromones spread with decreasing intensity, reflecting the influence of past experiences [21]. Pheromone evaporation prevents getting stuck in local optima, and their levels are regularly updated.

The movement history (*H*) helps account for the frequency of node visits, reducing the likelihood of revisiting already mastered topics. Each time a node is confirmed, a history variable *H* is created and stored for each "ant" in the database, initially set to $h_1$ = 0.5 in the case of successful confirmation and $h_2$ = 0.75 in the case of failure. This value will later be used as a multiplier to reduce the probability of revisiting that node. When revisiting eventually occurs, *H* is again multiplied by $h_1$ or $h_2$. Like *S* and *F*, *H* also evaporates over time and gradually returns to 1 according to:

$$H_t = H_{t-1}\left(1 + \frac{1-H_{t-1}}{H_{t-1}} \cdot \frac{1-e^{-\tau x}}{1-e^{-\tau x}}\right) \quad (3)$$

where τ is a constant used to adjust the evaporation rate, and x is the amount of time that has passed since the last visit to this node. τ should be calibrated to match the variability of students' memory:

$$\tau = \frac{1}{x}\ln\left(\frac{1+\alpha}{1-\alpha}\right), \quad (4)$$

$$\alpha = \frac{H_t - H_{t-1}}{1-H_{t-1}}. \quad (5)$$

Suppose it is defined what is meant by "forgetting an exercise." For example, if the value of $H$ for an exercise that initially has $H_{t-1} = 0.5$ (one successful visit) increases again to $H_{t-1} = 0.9$, this means $\alpha \approx 2.2$. Then, the expert (teacher) only needs to estimate the time required for "forgetting the exercise" – for example, one week ($x = 604800$ sec, giving $\tau \approx 3.6E - 6$).

The fitness function $f(\alpha)$ determines the optimal learning path by considering successes, mistakes, and teacher recommendations. The system dynamically adapts, adjusting the student's trajectory for maximum success.

$$f(\alpha) = \mathrm{H}(\varpi_1 W + \varpi_2 S - \varpi_3 F) \quad (6)$$

The higher the fitness value, the more "attractive" the corresponding edge will be, and therefore, the more likely it is to be suggested to the student. An edge is considered attractive when:

- Its endpoint has not been visited or was visited a long time ago ($H$ is close to 1);
- It is encouraged by teachers (high $W$);
- There is a strong atmosphere of success around this edge (high $S$);
- There have been few failures around this edge (low $F$).

Additionally, the relative influence of different factors can be adjusted by tuning the values of $\omega_i$. Once a node is confirmed, the outgoing edges are sorted according to this computed fitness value. One edge is then selected from the list using one of the described selection procedures and proposed as the next lesson for the student.

## 5 Architecture of an adaptive educational course structure

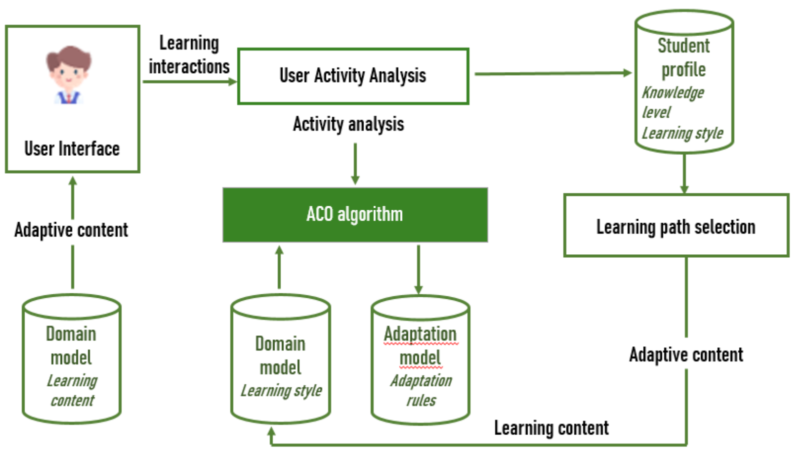


**Figure 3:** Adaptive Learning Architecture with ACO.

This architecture is an adaptive educational system based on BKT and ACO algorithms. The user interacts with the system through the adaptive learning system interface, which records learning activities. This data is analyzed by the activity module to build a student profile that includes the level of knowledge and learning style. The profile is used to define personalized learning paths. The system integrates intelligent BKT and ACO algorithms. BKT tracks initial knowledge, evaluates current knowledge after each topic is completed by a student, and updates probabilities after students complete assignments. The ACO algorithm uses information from the subject area, learning models, and adaptation to calculate the most effective route. The result is adaptive content that provides a customized trajectory. The system provides personalized learning by dynamically adapting to the characteristics of the student, thereby increasing the effectiveness of the educational process. Thus, the system automatically adapts based on the student's behavior using an algorithm.

# 6 Experimental validation and discussion

## 6.1 Purpose and objectives

The purpose of this experiment was to evaluate the effectiveness of the proposed adaptive learning system architecture based on the integration of ACO and BKT algorithms. The validation aimed to demonstrate how the combination of these algorithms improves the personalization of learning trajectories and optimizes the educational process.

## 6.2 Experimental setup

The simulation involved a group of thirty virtual students with different levels of knowledge and learning styles. Each student interacted with an adaptive system consisting of twenty learning modules of varying complexity. In this experiment, the BKT algorithm regularly updated the probability of acquiring knowledge after each completed task, while the ACO algorithm dynamically optimized the sequence of topics according to the updated probabilities and pheromone traces.

The parameters used in the experiment were as follows:

Evaporation rate: $\tau = 3.6 \times 10^{-6}$

Success pheromone reinforcement: $S = 0.8$

Failure pheromone penalty: $F = 0.2$

BKT parameters:

$P$(known) = 0.6

$P$(will learn) = 0.3

$P$(slip) = 0.1

$P$(guess) = 0.15

## 6.3 Evaluation metrics

To assess the effectiveness of the proposed model, the following indicators were applied:

1. Adaptation Efficiency (AE) – the percentage of tasks dynamically adjusted based on learner interaction [11, 19].
2. Knowledge Retention (KR) – the increase in post-test scores compared to pre-test performance [12].
3. Path Optimization Rate (POR) – the reduction in redundant learning steps compared to a static system [11].
4. Time Efficiency (TE) – the average decrease in completion time for all modules [3, 132].

### 6.4 Experimental results

After ten adaptive iterations for each student, the system showed significant improvement in all indicators compared to systems that used only one algorithm.

**Table 3**
Experimental Comparison of Algorithms

| Model | AE (%) | KR (%) | POR (%) | TE Improvement (%) |
|---|---|---|---|---|
| BKT only | 60 | 18 | 10 | 9 |
| ACO only | 73 | 20 | 18 | 12 |
| Proposed ACO + BKT model | 85 | 27 | 32 | 18 |

The results show that the hybrid model of ACO with BKT has shown high efficiency, especially in terms of the speed of adaptation and knowledge retention. The integration of BKT with ACO ensured continuous adaptation of the system and effective modeling of the learner.

### 6.5 Discussion

The results obtained confirm that the combination of ACO and BKT algorithms provides a complementary interaction that increases the adaptability and accuracy of recommendations along the learning path. The BKT component provides real-time knowledge updates, while the ACO determines the most effective task sequence using heuristic information obtained from these updates. This interaction creates an adaptation with guided feedback, which will allow for continuous improvement of the individual learning trajectory.

Despite the fact that the presented test was performed in a simulated environment, the observed performance indicators demonstrate the high potential of the proposed approach for real-world e-learning applications. Future research will focus on integrating this hybrid model into existing adaptive learning platforms and testing its effectiveness on real-world student data to assess scalability and reliability.

## 7 Conclusion

Modern e-learning systems are more inclined to adapt learning, which helps to take into account the individual characteristics of each student. All adaptive platforms begin their work with diagnostics, which is the definition of initial knowledge and the identification of knowledge gaps that form the basis for creating a student model (often found as a digital twin or a digital student profile), which includes the level of knowledge, learning style and other characteristics. For this purpose, this study suggests using the BKT algorithm, then using the Intelligent Ant Colony Optimization Algorithm (ACO), a personalized learning trajectory is built. These algorithms dynamically adjust the learning process: depending on the student's success or mistakes in completing assignments, the route is revised, so the student returns to topics where mistakes were previously made. This ensures that the student's knowledge is corrected by analyzing the mistakes made during the knowledge test and offering materials that are most suitable for the learning style, which ensures deep and long-term assimilation of knowledge.

The developed learning system architecture effectively implements an approach to learning adaptation. The architecture includes modules for analyzing student activity, domain modeling, adaptation, and student profiling based on BKT and ACO algorithms. This structure provides not only personalized learning, but also dynamic adaptation. The learning content consists of managed content relevant to the learning objectives, which allows the system to provide appropriate resources. Experimental studies have been conducted to show the effectiveness of the proposed model based on the estimated results.

Thus, the proposed adaptive learning system serves as an effective tool that maximizes the effectiveness of the educational process by taking into account the individual characteristics and academic performance of each student.

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## Declaration on Generative AI

During the preparation of this work, the authors used ChatGTP-4 in order to grammar and spelling check. After using this services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content

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