An Adaptive Learning System Integrated with Fuzzy Logic to Improve Higher-Order Thinking Skills

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ABSTRACT

Adaptive learning systems utilize Artificial Intelligence (AI) to build intelligent learning systems. This study describes: (i) a model of an adaptive learning system to improve Higher-Order Thinking (HOT) skills, (ii) the use of fuzzy logic to provide appropriate learning activities, and (iii) an implementation to examine its effect on HOTs. The adaptive learning model includes student, adaptation, content, communication, and instructional models. Fuzzy logic is applied to the adaptation model with four variables: quizzes, individual activities, group assessments, and forum discussions. Then, it produces a learning material that automatically adjusts to the student's thinking skills level. This study involved 164 undergraduate students in the first-year programming course. The four variables produced a t-test significance below 0.05, thus significantly influencing HOT skills, namely evaluating, analyzing, and creating. The results show that experimental classes using adaptive learning have higher thinking skills than traditional learning in control classes. Further research can optimize technical support, including infrastructure, bandwidth connections, and server capability.

Keywords-adaptive learning; fuzzy logic; higher order thinking skills; programming; smart learning systems

I. INTRODUCTION

Information technology has been the driving force behind the development of educational information systems, leading to significant improvements in online learning platforms. However, this system still has drawbacks. First, e-learning presents the same learning materials or exercises to each student, assuming that all students have similar learning needs [1]. Second, education authorities, schools, and academic institutions lack a comprehensive plan to develop learning platforms, so they employ general and less specific learning patterns tailored to their characteristics [2]. Third, there is a lack of standardization of online learning platforms [3]. Integrated research on student learning growth, behavior, specific learning paths, learning outcomes, and reflections is not typically carried out in traditional e-learning. So, it is challenging to record, monitor, evaluate, and predict students' learning progress.

The primary purpose of an online learning system is to facilitate learning for everyone at any time [4]. The process of organizing learning materials in a specific way to create a connection between content and learning objectives is known as a learning path. This series of learning exercises improves students' comprehension or proficiency in a given subject.

Traditional e-learning is often unable to adapt to students' needs. The ability to modify the amount, kind, and complexity of educational activities offered to students is called domain knowledge adaptivity. An intelligent learning system supported by Artificial Intelligence (AI) that provides a personalized learning experience based on the abilities of the students is called an adaptive learning system [5, 6]. An adaptive system follows a predefined path, with the learning sequence being modified to accommodate the specific needs of each student. In addition to serving the entire learning community and advancing equity in education, the adaptive learning paradigm enables students to find learning resources and run systems that meet their personalized learning needs within an intelligent environment.

The Revised Bloom Taxonomy (RBT) offers a framework for categorizing learning outcomes based on students' cognitive abilities into six hierarchical levels: remembering, understanding, applying, analyzing, evaluating, and creating [7]. RBT can be utilized to identify a suitable learning activity for learners. RBT addresses the formulation of learning outcomes that pertain not only to the subject matter being taught but also to the profundity of understanding that students are required to attain. RBT levels are categorized into two categories: Higher-Order Thinking Skills (HOTs), including creation, evaluation, and analysis, and Lower-Order Thinking Skills (LOTs), including applying, understanding, and remembering.

The CoI framework highlights online learning experiences associated with text-based, asynchronous forms and overall satisfaction with online education. This framework aims to attain significant education by amalgamating teaching, social, and cognitive presences within a constructivist instructional paradigm. CoI is defined as the method by which students generate knowledge through continuous communication, employed to analyze students' experiences, learning processes, collaborative reflection, and problem-solving skills [8].

This study combines methods and pedagogical theories to provide students with adaptive instruction in computer programming, specifically Java programming. In particular, it uses fuzzy logic for rule-based decision-making and incorporates HOT skills according to the RBT. Adaptive learning techniques provide customized educational experiences for computer programming students based on their knowledge levels and the specific parameters and quantities of the assigned tasks and tests. Fuzzy weights are chosen due to their ability to function efficiently in situations characterized by ambiguity and unpredictability [9]. HOT skills are utilized as part of RBT to achieve educational outcomes that focus not only on the subject matter associated with the domain being instructed, but also the level of comprehension students are expected to achieve [10]. The main contributions of this study are threefold. First, proposes a model that provides an adaptive learning system and integrates with fuzzy logic to improve HOT skills in programming courses. Second, constructs fuzzy rules in an adaptive learning system to support students in achieving HOT skills. Third, the proposed system is implemented in an experiment class and evaluated to examine its effects on HOT skills.

II. LITERATURE REVIEW

The path within an adaptive learning framework provides personalized educational material to each student, considering their preferences and individual characteristics [11]. Fuzzy logic is one way to reflect the human subjectivity that characterizes the determination of student knowledge and the learning requirements [12]. This paradigm is constructed on detailed conceptual models and was created from the adaptive environment. Each student's knowledge elements are used to plan and arrange learning paths according to their requirements, automating and predicting the construction of learning paths. The adaptive learning system was developed through multiple learner factors, including learning styles [13], influence models [14], cognitive skills [15], behavior [16], and trait thinking [17].

Several studies have employed and evaluated RBT in the relevant academic literature [18-23], as it explores the educational objectives established in the instructional exchange between students and teachers. Learning performance can be improved by identifying student characteristics through personalized learning situations, depending on their cognitive development. This system offers a flexible learning environment to execute distant adaptive pedagogical activities while preserving a teacher-student connection to improve learning quality. However, previous studies have not utilized fuzzy weights to achieve adaptivity in decision-making, failing to integrate learning theories to maintain pedagogical affordance. This study presents a method for developing a suitable learning path tailored to students' cognitive capacities, utilizing the CoI framework and employing fuzzy logic. The cognitive presence in CoI indirectly facilitates HOTs. The cognitive presence relates to the learners engaging in collaborative, critical, and practical inquiry with other students. The teacher's responsibility is to promote and stimulate communication among learners by creating educational exercises that improve HOT skills.

III. ADAPTIVE LEARNING MODEL

Adaptive learning models provide personalized learning materials adapted to individual learners' requirements, resources, and learning settings. Figure 1 illustrates the adaptive learning model. The student or learner model is the basis for creating an adaptive learning system and environment. The student interface is the entry point for students into an e-learning system [24]. The student profile maintains information collected at the beginning of the registration procedure for each student, such as full name, email address, age, and phone number. This information becomes an initial phase of deciding the student's direction, followed by personalizing learning data to track specifics and document student behavior in the system. This information is integrated with regularly updated findings regarding student learning progress. Using student models has been a significant factor in providing adaptive instruction that focuses on problem-solving domains [25].

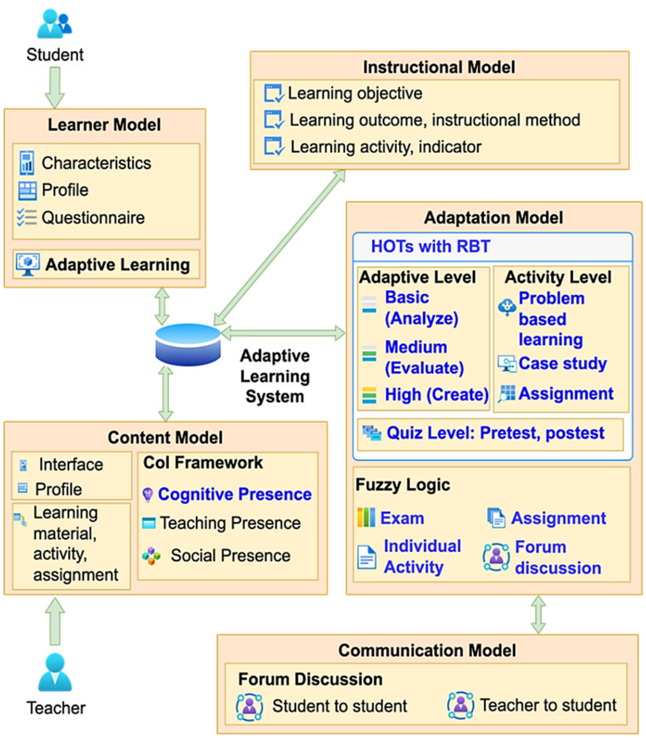

Fig. 1. Adaptive learning model.

The adaptation model records and analyzes data on the student learning process, providing information on student preferences. Student performance provides a comprehensive view of all student activities, including current activities, learning paths, processes, and learning outcomes. These data are dynamically updated based on each student's cognitive growth throughout the learning process [24]. The adaptive scaffold module modifies problem-solving with higher-order questions for each student, namely, analyze, evaluate, and create [26]. The pedagogy module offers the material in project-based learning and assignments using HOT skills from RBT. The repository for assessment test data holds all test information utilizing HOT question items. Process evaluation is typically a complicated interplay of lecturers, content specialists, and technologists who create, configure, and deploy subject matter expertise for operational use in adaptive assessments [27]. Students receive test questions, selected dynamically from the repository based on their level of thinking. Implementing a pedagogy module that incorporates problem-based learning has been shown to facilitate active learning among students. This approach also promotes the development of HOT skills as students engage in problem-solving [28].

The communication model illustrates collaborative student-to-student and student-to-teacher interactions using the CoI framework. Adaptive learning systems incorporate communication models that facilitate communication in both asynchronous and synchronous modes [29]. This model gathers information regarding the number of student interactions, comments, questions, and answers on online discussion forums [30].

The content model, or domain knowledge, includes the presentation of learning content to students, instructional teaching, learning strategies, and learning materials. This content maps the knowledge acquired through learning objects and is instructed through knowledge structures [31]. The instructor populates this model with data through the teacher interface. The teacher profile offers general information about the teacher and class performance history.

The content and adaptation model connects students, teachers, learning resources, forms of curriculum design, teaching, and the learning environment through information technology. The adaptive system design is adaptable to various characteristics of the students and can be dynamically customized for each learner. The communication model provides students with the opportunity to experience, absorb, and investigate content to gain a deeper understanding. The CoI framework offers an interactive online function for individuals and groups focused on student-to-student and student-to-teacher engagement.

Adaptation models can facilitate personalized learning by computing and analyzing data using clustering, mining, and analysis tools. Exploring students' personal information, learning process data, interaction process data, and teacher teaching data can provide relevant learning paths for students. The database provides users with access to various data sources, including student, teacher, and administrative information, as well as learning behavior, teaching, and learning resources. It transforms into a storage management function that allows data mining and sharing.

The proposed system uses fuzzy logic to identify students' HOT skills as the basis for personalized learning paths, input and output variables, and range layouts. First, students access an adaptive system that retrieves and filters student information data from the database. Second, the system executes a fuzzifier to predict fuzzy sets using crisp input with membership degrees between 0.0 and 1.0 for the four components: quiz grade (high, medium, low), individual activities with HOTs (analyze, evaluate, create), group assessment with HOTs (analyze, evaluate, create), and forum discussion with the CoI framework (trigger, exploration, integration, resolution). Third, the fuzzy inference engine utilizes 108 rules based on fuzzy input sets and the Mamdani method to estimate the degree of membership. This inference engine employs the AND operator, which is applied in the membership function, and then, in the IF antecedents' part, the output is used in the linguistic variable in the THEN consequent part. Last, a defuzzifier evaluates the rules and identifies student learning outcomes based on their cognitive level with a crisp output (analyze, evaluate, create).

The fuzzy weights represent a student's current expertise in the subject matter taught in Java programming, as shown in Table I. The values of these fuzzy weights, which range from 0 to 1, are determined using the membership functions. When the knowledge level is equal to 1, the student has mastered the subject and is fully familiar with it. As a result, the total value of each divided fuzzy set, which is equal to 1, represents the level of knowledge of a domain learning unit. Hence, the equation of assignments

$$\mu_{K_{Analyze}}(x) + \mu_{K_{Evaluate}}(x) + \mu_{K_{Create}}(x) = 1$$

is valid. In addition, the equation of the discussion forum

$$\mu_{D_{Trigger}}(x) + \mu_{D_{Exploration}}(x) + \mu_{D_{Integration}}(x) + \mu_{K_{Create}}(x) = 1$$

is also valid.

Two expert lecturers, who teach computer programming, validated the weight values and function thresholds using fuzzy logic. More specifically, they were asked to identify the stages at which a learner's level of success in acquiring each of these knowledge levels varied during their whole process of learning Java. The validators with more than 15 years of expertise in teaching programming languages in academic settings can accurately represent students' skill levels.

TABLE I. FUZZY MEMBERSHIP FUNCTIONS

	Membership Function
Input	
Individual assignment, group assignment, and quiz	$\mu_{K_{Analyze}}(x) = \begin{cases} 1, & x \leq 0.9 \\ \frac{0.9-x}{0.3}, & 0.9 \leq x \leq 1.2 \\ 0, & x \geq 1.2 \end{cases}$ $\mu_{K_{Create}}(x) = \begin{cases} 0, & x \leq 1.9 \\ \frac{x-1.9}{0.3}, & 1.9 \leq x \leq 2.2 \\ 1, & x \geq 2.2 \end{cases}$ $\mu_{K_{Evaluate}}(x) = \begin{cases} 0, & x \leq 0.9 \text{ or } x \geq 2.4 \\ \frac{x-0.9}{0.2}, & 0.9 \leq x \leq 1.1 \\ 1, & 1.1 \leq x \leq 1.9 \\ \frac{2.4-x}{0.3}, & 1.8 \leq x \leq 2.4 \end{cases}$
Forum discussions	$\mu_{D_{Trigger}}(x) = \begin{cases} 1, & x \leq 0.9 \\ \frac{1.1-x}{0.2}, & 0.9 \leq x \leq 1.1 \\ 0, & x \geq 1.1 \end{cases}$ $\mu_{D_{Exploration}}(x) = \begin{cases} 0, & x \leq 0.9 \text{ or } x \geq 2.1 \\ \frac{x-0.9}{0.2}, & 0.9 \leq x \leq 1.1 \\ 1, & 1.1 \leq x \leq 1.9 \\ \frac{2.1-x}{0.2}, & 1.9 \leq x \leq 2.1 \end{cases}$ $M_{D_{Resolution}}(x) = \begin{cases} 0, & x \leq 2.9 \\ \frac{x-2.9}{0.2}, & 2.9 \leq x \leq 3.1 \\ 1, & x \geq 4 \end{cases}$ $\mu_{D_{Integration}}(x) = \begin{cases} 0, & x \leq 1.9 \text{ or } x \geq 3.1 \\ \frac{x-1.9}{0.2}, & 1.9 \leq x \leq 2.1 \\ 1, & 2.1 \leq x \leq 2.9 \\ \frac{2.9-x}{0.2}, & 2.9 \leq x \leq 3.1 \end{cases}$
Output	
HOT skills	$\mu_{B_{Analyze}}(x) = \begin{cases} 1, & x \leq 0.3 \\ \frac{0.4-x}{1}, & 0.3 \leq x \leq 0.4 \\ 0, & x \geq 0.4 \end{cases}$ $\mu_{B_{Create}}(x) = \begin{cases} 0, & x \leq 0.6 \\ \frac{x-0.6}{0.2}, & 0.6 \leq x \leq 0.8 \\ 1, & x \geq 0.8 \end{cases}$ $\mu_{B_{Evaluate}}(x) = \begin{cases} 0, & x \leq 0.3 \text{ or } x \geq 0.8 \\ \frac{x-0.3}{0.1}, & 0.3 \leq x \leq 0.4 \\ 1, & 0.4 \leq x \leq 0.6 \\ \frac{0.8-x}{0.2}, & 0.6 \leq x \leq 0.8 \end{cases}$

Learning exercises are used to teach each chapter regarding the instructional strategy. Therefore, the rules allow the system to determine which learning activities must be provided to each student. The two validators, described above, established these regulations. The rationale behind creating rules is that improving student performance demonstrates knowledge acquisition and the student's capacity to advance HOT skills. As a result, learning exercises become more complicated in the higher RBT levels. For example, for a student with:

- Input variable: individual assignment $\mu_K = 0.5$ at the level $\mu_{K_{Analyze}}$,
- Input variable: group assignment $\mu_K = 1.0$ at the level $\mu_{K_{Evaluate}}$,
- Input variable: quiz $\mu_K = 1.0$ at the level $\mu_{K_{Evaluate}}$,
- Input variable: forum discussion $\mu_K = 2.9$ at the level $\mu_{K_{Resolution}}$,

the fuzzy membership function produces an output variable for the student's HOT skills' level of $\mu_K = 0.7$ at the level $\mu_{K_{Evaluate}}$. The system then automatically provides material according to the student's level of thinking.

This adaptive system uses fuzzy logic to assess and investigate e-learning system data because it can perform human-like decision-making reasoning. Fuzzy logic provides the advantage of causal cognitive mapping, an effective way to acquire and capture expert knowledge, and an intuitive way to represent knowledge that is easy to maintain, modify, or extend by adding new concepts or relationships by modifying their weights [32, 33]. The adaptive system delivers the appropriate content to the students in a proper time and manner, following the learning instructions. Compared to previous adaptive systems, it can mine learning data, gather, analyze, and present data, and provide structured feedback to strengthen HOTs within the CoI framework.

IV. RESULTS

The assessment of educational software's effectiveness and acceptance is crucial, particularly for student outcomes, and is regarded as a fundamental stage in its developmental process. A qualitative study was carried out to analyze various aspects of the system, aiming to evaluate the effectiveness of an adaptive system to improve HOT skills with a fuzzy logic algorithm.

A. Participating Population

This system was implemented and evaluated in a public university, the University of Bengkulu, Indonesia. The system was used in the Java Programming course, and the evaluation took place for one semester in the 2023/2024 academic year. The evaluation involved 164 first-year undergraduate students and the two lecturers. The population was divided into two groups: control and experimental classes. The lecturers and validators carefully deliberated on the constitution of groups to ensure a high-quality assessment (see Table II). During the semester, students in the control group (Group 1) received conventional instruction, using the same learning materials as the experimental group. In contrast, the experimental group (Group 2) engaged in a learning process that involved using a personalized system through adaptive learning activities.

TABLE II. POPULATION

Characteristics	Group 1	Group 2
Class	Control	Experiment
Age	19 – 20	19 – 20
Gender	16 females 22 males	76 females 50 males
Total	38 students	126 students
Semester	First semester in the 2023 – 2024 academic year	
Computer skills	Standard knowledge of the use of computers	
Prior level of knowledge	All students have graduated from senior high school in the first year of their studies at the university.	
Motivation	All students attended the "Computer and Programming" course and wanted to achieve a high grade.	

B. Evaluation of HOT Skills

A non-parametric statistical hypothesis test was utilized to evaluate HOT skills in two groups. Table III shows the statistical significance of the pre-test and post-test results according to the control and experimental groups. The two-tailed asymptotic significance value was determined to be 0.00, indicating statistical significance at a level below the value of 0.05. Thus, it can be inferred that H_a is upheld, indicating a substantial disparity in the pre-test and post-test scores in two classes. The observed dissimilarity suggests that implementing adaptive online learning had a discernible impact on the experimental group. The primary research goal is to investigate the effects of utilizing an adaptive learning system during the educational process and determine whether it can enhance student academic achievement. The academic performance of students who utilized the online learning system in the experimental group was contrasted with those who received traditional instruction in the control group. Table IV presents ANOVA test results for the dependent variable.

TABLE III. NON-PARAMETRIC TEST RESULT

	Pre-test	*Post-test*
Mann-Whitney U	43995	16367
Wilcoxon W	61761	34133
Z	-5.53	-15.25
Asymp. Sig. (2-tailed)	0.00	0.00

a. Variable grouped by class_control_experiment

TABLE IV. ANOVA RESULTS

Model	Sum of squares	df	Mean square	F	Sig.
Regression	21.27	4	5.31	120.38	0.00
Residual	5.28	120	0.04		
Total	26.62	125			

a. Dependent variable: HOT skills level
b. Independent variables: average discussion forum, average quiz, average group, average individual assignment

The ANOVA test results indicate a significant difference based on the test variable, as evidenced by a p-value of 0.00. Variations in cognitive abilities impact the evaluation of discussion forums, final examinations, individual activity, and group performance assessments. Moreover, the t-test evaluates the statistical significance of each independent variable in isolation and its impact on the dependent variable. Table V displays the t-values and their corresponding p-values in the t and Sig.

TABLE V. T-TEST RESULTS

Model	Unstandardized coefficients		Standardized coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.062	0.112		0.557	0.579
Individual assignment	0.571	0.061	0.532	9.414	0.000
Group assignment	0.378	0.058	0.337	6.469	0.000
Discussion forum	0.140	0.034	0.191	4.146	0.000
Quiz	0.300	0.019	0.065	1.588	0.015

Table V shows the Sig. values for the four independent variables—individual, group, discussion forum, and quiz scores—that are less than the statistical significance threshold (0.05). All independent variables significantly impact student thinking ability. Adaptive systems have been found to facilitate the development of HOT skills. Acquiring HOT skills is not innate but requires deliberate cultivation through structured procedures [34, 35]. This entails a gradual progression of learning increasingly complex ideas as students progress to more advanced stages of cognitive development. The characteristics of the independent variables within the system have been incorporated to facilitate problem-solving processes that promote the development of knowledge, comprehension, practical application, analytical reasoning, creative synthesis, and evaluative judgment as integral components of HOTs.

Student engagement in discussion forums was enhanced by employing an adaptive learning system to enable them to adhere to the course and experience a sense of belonging to the community. The manifestation of cognitive presence within the online discussion depends on the active participation of students as integral members of a collaborative learning community [8, 30]. Individuals tend to exhibit more significant HOTs in online discussion forums than in face-to-face sessions. The CoI framework claims that cognitive presence indicates how learners engage in reflective and critical discourse to construct meaning [36]. This system made a significant difference in improving students' learning levels. An adaptive system with five models, including student, content, adaptation, communication, and instructional models, can optimize the learning process [37, 38]. Hence, the analysis of cognitive presence from CoI can aid educators in swiftly assessing the levels of HOT skills exhibited in forum discussions.

V. CONCLUSION

This study presents an innovative pedagogical approach that provides adaptive learning activities to students based on the theoretical framework of RBT. The proposed strategy utilizes fuzzy weights for decision-making. This method determines students' knowledge level by evaluating their scores in domain concepts and subsequently deduces the appropriate learning material. Consequently, individual students are provided with learning activities tailored to their knowledge level, which are also adjustable in quantity, format, and complexity. The findings of the evaluation system are encouraging, as they indicate a notable level of student satisfaction and improved academic performance. The novel teaching strategy was evaluated by the students and received a rating greater than 8.2 out of 10. This indicates that the educational activities offered were precise in terms of their knowledge level and suitable in quantity and complexity.

The pre-test and post-test assessments significantly improved students' academic performance, thereby validating the educational effectiveness of the proposed model. Compared with conventional learning in the control class, the findings indicate that the proposed system performs better in enhancing learning outcomes, intensifying the adopted adaptivity and RBT's efficiency, and validating the teaching strategy's efficacy through learning activities. This investigation focused on providing suitable educational exercises tailored to students' proficiency levels, with their level of proficiency as the primary factor influencing their adaptability. The adaptive system integrated fuzzy logic to improve HOT skills, providing a comprehensive instructional design with various resource presentations, helping lecturers address learning challenges, optimize learning processes, and design effective resources.

This study identifies important gaps that would assist future investigations. First, the study's sample size is limited in scope due to its size. Further investigation is expected to increase the sample size in several classes to find various impacts to improve HOT skills in college. Second, the development of adaptive learning with fuzzy logic requires experts' expertise to determine the membership function, enabling decisions on the proper learning flow based on students' thinking skills. Third, further research can optimize technical support, including infrastructure, bandwidth connection, and server capability to handle high demands. Research development can improve the efficiency of data structure forms for data storage. An adaptive learning system can be a recommendation to train the thinking process in problem-solving, improve students' skills, and guide strategies to improve HOT skills in college.

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