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Abstract:

The rapid evolution of mobile technology has necessitated the integration of innovative teaching methods into computer education. This paper presents a fuzzy intelligent learning system (FILS) to improve mobile app development skills for computer teacher students. The proposed methodology uses a self-learning system based on fuzzy logic from data that represents learners' knowledge and skill capabilities and their educational requirements. FILS is used to improve knowledge delivery based on individual learners' characteristics as it adapts during the learning situation and content delivery. A total of 70 students were randomly assigned to either a control group or an experimental group, with each group consisting of 35 students. The control group received traditional instruction methods, while the experimental group engaged with the proposed fuzzy intelligent learning system. The methodology embraced a quasi-experimental design, focusing on comparative analysis between the pre-test and post-test results of both groups. The FILS was tailored to adjust the learning content dynamically based on the fuzzy logic inference system, which considered individual learning pace and understanding levels. Results indicated a significant improvement in mobile app development skills within the experimental group compared to the control group. Statistical analysis showed that the experimental group’s post-test scores were significantly higher, suggesting that the FILS effectively facilitated a deeper understanding and proficiency in mobile app development.

Keywords: Fuzzy Logic, Artificial Intelligence, E-Learning, Fuzzy Intelligent Learning System, Mobile App Development Skills, Computer Teacher Students.

1. Introduction

University education revolves around evaluating a student's capacity to achieve success in courses of study. This evaluation analyzes a student's expected educational achievement and then concentrates on teaching them the skills and information required to reach the level of success indicated. Teachers use evaluation to learn about how well their students are performing in university [1]. This data can assist teachers ensure that students get the most out of their education. The evaluation process begins with determining what pupils need to learn to attain their objectives. Then a judgment has made to assess if those aims have met [2]. Numerous studies confirm that computer Teacher students urgently need to enhance their programming skills, particularly in mobile application development. A study by Kim and Park (2020) highlighted a significant gap between the skills students possess and the skills demanded by the job market. The study pointed out that students often lack proficiency in modern programming languages and mobile application development techniques. The findings suggested that updating curricula to include advanced courses in mobile app programming is essential [3].

Another study by Lee et al. (2019) emphasized the importance of hands-on and practical learning in developing students' programming skills. The study demonstrated that students who engage in practical projects related to mobile app programming show marked improvement in their abilities. The researchers concluded that incorporating real-world projects into the curriculum can significantly enhance students' readiness for industry demands [4].

The rapid growth of multimedia systems, networking technologies, online learning, and large-scale learning methods has led to the emergence of e-learning. E-learning improves the education process by delivering knowledge and skills via Internet technology. It provides students with the necessary capabilities for online learning [5]. It facilitates distance learning and online knowledge sharing. The development of Information and communications technology (ICT) in education has expanded new teaching methods, improved the flexibility of learners and teachers, and facilitated the expansion of new teaching methods in learning systems [6].

Today, with the increasing number of students who use e-learning, this has resulted in the importance of having effective methods to evaluate their results. E-learning provides students with flexibility and easy access to learning resources. Evaluating students' knowledge and skills affects the learning process and motivates students to achieve more. However, the assessment process faces many challenges that may cause distortion of student results. These challenges include verifying students' knowledge and skills, assessment requirements, limited time to check assignments, and other factors [7].

Artificial intelligence (AI) can enhance e-learning systems by delivering specific and targeted content to each learner according to the learner's strengths and weaknesses. Using an e-learning system based on AI to provide customized content through several methods, including adaptive learning and adaptable learning. Personalization here means that the learner is taught individually and assessed [8]. Intelligent E-learning platform systems have more advantages such as easy updating, content availability, interest stimulation, easy goal setting, and human-computer interaction, strengthening education supervision [9].

The integration of AI and adaptive e-learning has many benefits including:

- Personalized learning: This integration enables personalized learning by tailoring the learning experience according to the interests and skills of individual learners. Integration allows to more diverse learning materials. This creates a dynamic and engaging learning environment.
- Improving learning outcomes: AI techniques track and analyze learner performance to identify knowledge gaps and provide appropriate content

to address these gaps. It also works to improve learning outcomes by focusing on the skills the learner needs for further support and practice.
- Real-time feedback: AI techniques provide real-time feedback, enabling learners to understand their mistakes and make appropriate corrections.
- Enhanced Engagement: AI techniques provide engaging, interactive learning experiences to increase student motivation. It helps enhance the learning process [10].

Rule-based systems use traditional IF-THEN rules to model human problem-solving behavior. Zadeh invented fuzzy sets address the imprecision and uncertainty present in the knowledge representation. Fuzzy Rule-Based Systems (FRBSs) are created by combining fuzzy sets with rule-based systems. These systems handle uncertainty, treat fuzzy statements as antecedents and consequents, and are more robust than traditional rule-based systems. FRBSs use Linguistic Variables to express features in antecedents, allowing rules to be interpreted by humans [11].

Mamdani approach is the foundation of classical fuzzy systems. The fuzzification module creates a mapping between real-valued input data and fuzzy values using a membership function. Similarly, the defuzzification module creates a mapping between fuzzy values and the real-valued output domain. The database comprises the linguistic variables (LV) and the membership function that corresponds to them. Rules are commonly used to organize knowledge in natural language [10]. A database and a rule base are common components of a knowledge base (KB). Mamdani's rules include the use of LVs both beforehand and afterwards. A rule is defined by a set of linguistic factors and an associated outcome; for example, a rule may have several inputs and only one output. The rule base stores the rules for a certain application. Rule bases can be represented in a variety of formats. A rule base is made up of either a list of rules or a decision table, which is a concise representation of rules. The fuzzy inference engine computes the fuzzy output from the inputs by applying the rules specified in the Rule Base.

Uncertainty fuzzy logic has used to evaluate students' knowledge and skills. Fuzzy logic systems (FLS) are widely used to model nonlinear problems with uncertainty. FLS are a mathematical tool that takes the form of fuzzy IF-THEN linguistic rules that are easy for humans to understand. FLS facilitate a wide range of applications due to their ability to build accurate predictive models from imprecise data with transparency and interpretability [12]. Applying fuzzy logic in e-learning has helped for making better decisions. These tools and experiences are vital to student success, as traditional e-learning methods do not deliver high-quality learning and have problems with student assessment and group study [13].

Despite the growing demand for mobile app development skills in the education sector, computer teacher students often face significant barriers to effectively acquiring and mastering these skills. Traditional educational models in technology training typically offer rigid, one-size-fits-all curricula that do not account for individual learning paces or adapt to the diverse educational needs of students. Additionally, these models lack real-time feedback mechanisms that are crucial for the iterative learning processes required in app development.

Current educational methods also struggle to incorporate advanced pedagogical approaches like fuzzy logic, which can offer nuanced assessments and adaptive learning pathways, crucial for the complex and rapidly evolving field of mobile app development. The absence of such intelligent systems hampers the ability of future educators to proficiently teach mobile app development, thus impacting their effectiveness in the classroom and ultimately, the preparedness of their students for a technology-driven world.

This research aims to address these challenges by proposing an intelligent fuzzy learning system specifically designed to enhance mobile app development education for computer teacher students. This system will aim to tailor learning experiences to individual needs, provide instant and actionable feedback, and foster a more engaging and effective learning environment. The ultimate goal is to equip computer teacher students with robust, adaptable app development skills that can be effectively passed on to their future students, thereby bridging the current gap in technology education.

The problem of the current research arose when they observed the researcher teaching some courses related to mobile phone application development to the computer teacher's students at the university. There is a weakness in the level of quality of smartphone projects prepared by students, and there is also a weakness in the knowledge and skills necessary to develop mobile phone applications among students. The researcher also noted that the method of presenting the educational content of courses related to skills related to developing mobile phone applications through traditional learning environments has many problems, including not taking into account individual differences, nor common characteristics among learners, and not paying attention to previous knowledge among learners, which is reflected in the quality of their design projects. Mobile phone applications, which requires the need to find a solution to develop the student's skills and increase the quality of the projects they design.

The researcher conducted a pilot study to determine the validity of the problem. The pilot study was conducted by interviewing a random sample other than the study sample, which consisted of 20 computer teacher students at the Faculty of Specific Education, Zagazig University, Egypt. Several questions were asked about the difficulties they encountered while learning the skills of designing smartphone applications, and the reasons for the weakness and lack of quality of projects designed in mobile programming languages. It turns out the following:

- The students agreed by 90% that they have problems learning and acquiring mobile application development skills due to not giving practical examples, and that the content does not take into account the previous knowledge that they want to remember, and that the content does not take into account individual differences between them.
- The students agreed by 95% that their preferred method is to provide them with content electronically in the form of knowledge levels that suit their abilities and ends with tests and applied examples and allows them to

evaluate themselves to ensure that they have correctly acquired the necessary skills.

- The students agreed by 90% that the difference in their previous experiences related to the development of mobile applications may hinder participation and understanding between them in the production and design of mobile applications.
- Students agreed 100% on the desire to learn through smart, adaptive learning environments.

On the same sample of the pilot study, An evaluation rubric was prepared for use in assessing the skill test was conducted to determine the extent of the varying levels of students' prior skills related to programming to produce mobile phone projects and applications. The results were:

- 30% of students are familiar with the concepts and basics of programming.
- 15% of students have the ability to employ previous knowledge in designing and producing mobile phone projects.
- 55 % of students do not have knowledge of the basics of application programming, through which they can be used in producing mobile phone projects and applications, and these students also have difficulty understanding it and have difficulties in employing it.

The problem of the study can be formulated in this main question:

"How can a Fuzzy Intelligent Learning System be developed to enhance Mobile App Development Skills for Computer Teacher Students ?"

2. Research Objective

The primary objective of this research is to improv the mobile app development skills of computer teacher students by design, develop, and evaluate an intelligent fuzzy learning system. This system will leverage fuzzy logic to facilitate a dynamic and adaptive learning environment that is capable of personalizing the educational experience according to individual student profiles and their learning progression. By incorporating fuzzy logic into the learning platform, the system aims to provide nuanced assessments and adapt educational content and challenges in real time, thereby improving student engagement and learning outcomes.

3. Research Importance

By applying this research, the following benefits can be realized:

- Enhancing Learning Outcomes: By providing a personalized learning experience, the system aims to improve the retention and comprehension of mobile app development concepts among computer teacher students. This personalized approach helps in addressing specific learning needs and overcoming individual weaknesses, thereby enhancing overall academic performance.
- Preparation for the Digital Age: As digital literacy becomes increasingly crucial in the educational sector, equipping future educators with robust app development skills is vital. This system prepares computer teacher students to not only excel in their careers but also to effectively teach and inspire their future students in the realm of mobile technology.
- Real-Time Feedback and Adaptation: One of the significant advantages of using fuzzy logic in an educational context is its ability to handle uncertainties and provide feedback that is not strictly binary (right or wrong). This approach allows for more nuanced feedback on student work, which can contribute to more detailed and constructive learning progressions.
- Research Contributions: The development and study of this fuzzy learning system contribute to the academic field by providing empirical evidence on the effectiveness of fuzzy logic in education technology. It opens pathways for further research on adaptive learning systems and their impact on technological education.
- Bridging the Technology Education Gap: By implementing advanced technologies in teacher education, the system addresses the gap between current teaching methodologies and the evolving technological landscape. This ensures that future teachers are well-prepared to integrate technology

into their teaching practices, thereby enhancing the learning experience for the next generation.

4. Research Delimitations

This research is limited to the following parameters:

- **Human Delimitations:** The sample consists of 70 second-year computer teacher students from the Faculty of Education, Zagazig University.
- **Subject Delimitations:** This research focuses solely on developing mobile app development skills among computer teacher students.
- **Spatial Delimitations:** The research is conducted at the Faculty of Specific Education, Zagazig University.
- **Temporal Delimitations:** The main research experiment was conducted over a period of 60 days during the second semester of the 2022-2023 academic year.

5. Research Methodology

This research follows two methodologies:

- **Descriptive Methodology:** To analyze and address the theoretical framework of the research, build the research tools, identify appropriate statistical methods, and interpret the research results.
- **Quasi-Experimental Methodology:** To develop a Fuzzy Intelligent Learning System for enhancing mobile app development skills among computer teacher students.

6. Research Variables

1. **Independent Variable:** Fuzzy Intelligent Learning System.
2. **Dependent Variable:** Mobile App Development Skills.

7. Research Hypotheses

The main study hypotheses were the following:

- **H1**: There are statistically significant differences between the mean scores of the students in the control group and the experimental group in the posttest measurement of the cognitive test, favoring the experimental group.

- **H2**: There are statistically significant differences between the mean scores of the students in the control group and the experimental group in the posttest measurement of the skills test, favoring the experimental group.
- **H3**: There are statistically significant differences between the mean scores of the students in the experimental group in the pretest and posttest measurements of the cognitive test, favoring the posttest measurement.
- **H4**: There are statistically significant differences between the mean scores of the students in the experimental group in the pretest and posttest measurements of the skills test, favoring the posttest measurement.

8. Measurement Tools

- **Cognitive Test:** To measure the cognitive aspects related to the mobile app development skills intended to be developed.
- **Skill Test:** To measure the performance aspects related to the mobile app development skills intended to be developed.
- **Rubric Evaluation Checklist:** For grading the skill test.

9. Experiment Design

A quasi-experimental design was adopted in the present study, a pretest-posttest control group design was selected to examine the impact of the proposed intelligent fuzzy learning system on enhancing mobile app development skills among computer teacher students. Participants were randomly assigned to two groups: an experimental group (Exp), which received the innovative treatment, and a control group (Con), which experienced traditional instructional methods. Both groups underwent cognitive and skill assessments before and after the intervention to measure the potential effects of the treatment as shown in Figure 1.

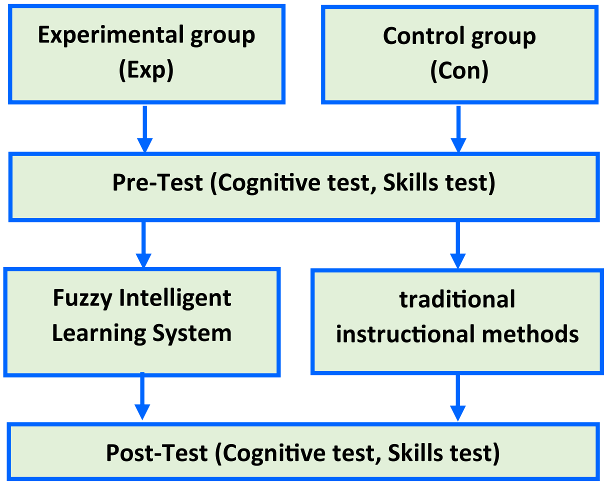

Figure 1. The Experimental Design.

10. Participants

The participants were 70 students from the Computer Teacher Department at the Faculty of Specific Education, Zagazig University, during the second semester of the academic year 2022/2023. The participants were randomly divided into a control group and an experimental group, each comprising 35 students.

11. Literature Review

Research have dealt with intelligent fuzzy learning systems (FILS) to move towards to adaptive e-learning. This approach has considered the most appropriate method for providing learning methods that suit students' varying abilities.

Fan and Wang (2024) proposed the Fuzzy Logic System (FLS)-based Persistent Appraisal Assessment Model (PA2M) to improve English language learning. The model uses personal attributes, progressive appraisal, and Fuzzy Logic-based appraisal to assess students' English learning capabilities. The model uses fuzzification approaches to reduce variations in appraisal verification and links personal attributes with performance. The PA2M approach merges prior and current data, resulting in precise improvements and evaluations based on student ability. Experimental data shows that the proposed model enhances recommendation rates, appraisal verification, convergence factor, error ratio, and verification time by 9.79%, filling gaps in knowledge and practice. This innovative approach fills gaps in the body of knowledge and practice in English language learning [14].

Leal-Ramírez et al. (2024) presented a tool for evaluating learning activities based on the fuzzy inference system that aims to evaluate the development of the student's abilities and skills. This proposed fuzzy inference system acts as an expert to interpret the pointers provided in the integrated instructions. This work aims to evaluate, explain and operationalize this tool to objectively assess students' skill development without assigning biased assessments [15].

Dwivedi et al. (2023) presented an effective adaptive online learning system based on a fuzzy logic (FL) to assess students understanding levels. The feedbacks have generated to address gaps in students' understanding [16].

Jan et al. (2023) introduced AI and FL system for students' shortcoming and advantage detection. They relied on performance analysis and evaluation on a set of student characteristics (knowledge, problem-solving skill, etc.) [17].

Szczepański and Marciniak (2023) proposed an e-learning system based on FL. They relied on AI courses. The system aims to support the integration between adapting academic content and methods that suit student learning. The proposed fuzzy system works in the absence of information and fuzzy control at the expense of student activity in the course in order to determine exam questions. The fuzzy system has proven its worth when there is uncertainty in students' learning styles [18].

Marciniak et al. (2023) presented adaptive e-learning content based on FL. This system adapts the content to the student's specific level of proficiency and then directs him to the specific educational path. The system steps and learning personalization control have completed using a rule-based system. The system has introduced through design based on web [19].

Papakostas et al. (2023) proposed an adaptive augmented reality training system for engineering students that attempts to increase spatial ability and motivation. The system use fuzzy sets to accurately reflect students' knowledge levels, and it adjusts the amount and difficulty of learning activities as students' progress. The approach prioritizes the learner and offers a flexible educational experience [20].

Syaifudin et al. (2023) investigated that the increasing demand for Android application developers has led to a need for students to learn programming languages, including XML, for designing user interfaces. However, many courses lack specific topics in this area, and teachers struggle to verify source codes. This study proposes a self-learning system for designing Android application UI using XML code, utilizing a pedagogical model and 20 learning topics. The system uses an integration testing mechanism on Android applications for automatic source code verification and learning assistance. A study of 80 IT students from Indonesia confirmed the system's effectiveness in supporting self-learning, appropriate learning materials, and high user satisfaction. The system has successfully led all students to master UI design skills on Android applications using XML code, despite initial poor coding experience [21].

FLS includes four procedures: fuzzing all inputs, fuzzy inference process and de-fuzzing system to obtain the output in the form of human concept. In this context, Abdul et al. (2023) relied on four procedures to apply FL in order to generate a learning path for the student and provide appropriate educational materials to each student based on his or her knowledge [22].

Chrysafiadi et al. (2022) presented a mobile-assisted learning model based on Machine Learning (ML) and FL for English and French language learning. The model diagnoses and identifies student errors such as spelling and verb errors. FL provide feedbacks for students based on their learning needs. The results of the model evaluation were positive regarding the effectiveness learning process [23].

Eryılmaz and Adabashi (2020) developed a fuzzy Bayesian intelligent tutoring system (FB-ITS) to adaptively support students in learning environments. Analysis of covariance (ANCOVA) was used based on 120 university students in the pre-test and post-test scores. The results showed that students who studied using FP-ITS had significantly higher academic performance on average compared to students who used the traditional e-learning system. The results indicated that the time taken to take the post-test was less for students who studied using the system compared to other students who studied with the traditional e-learning system. The system contributed that the speed of completion of the skills that be learned and the speed of performing the final exam [24].

Most of the related work presented by researchers relied on providing adaptive instructions on electronic content, but not on the changes that occur in the level of knowledge according to the content requirements presented to the learner. Therefore, the proposed intelligent fuzzy learning system (FILS) provides adaptive instruction, updates the knowledge level in relevant topics and evaluates learners' real knowledge. Many existing learning environments lack the capability to provide real-time, actionable feedback that students can use to immediately improve their understanding and skills. The proposed system could incorporate fuzzy logic to assess student responses and projects more intuitively and offer instant feedback.

This research work focuses on the following several key aspects of e-learning in order to enhance the learning ability of learners through the proposed system:

- Conduct a careful analysis of the learners and prepare the system that suits the characteristics of the learner.
- Presenting preferences to the learner according to the context of the e-learning content.

- Modeling and designing a new e-learning system that adapts to each learner in the context.

12. Fuzzy Intelligent Learning System module

Developing students' computer application skills to increase their productivity and overcome their shortcomings, as students' knowledge levels vary depending on their different types of preferences. Hence the learning content and content sequence should not be the same for all students. This is due to the fact that some students are familiar with topics they do not need to learn, while new students must learn the content of these topics. The design of intelligent learning systems depends on students' adaptation to the learning system. When designing these systems, they must contain data on the knowledge level of students in order to provide adaptive educational content [24].

Adaptive learning systems are crucial tools that customize the learning experience based on the needs and preferences of learners. These systems use artificial intelligence and data analysis techniques to adjust and tailor educational content and pacing to match the learner's performance and knowledge level. Traditional adaptive systems primarily rely on conventional algorithms to assess learner progress and provide recommendations or educational content based on predefined and static data.

In contrast, the proposed system based on fuzzy logic offers an advanced level of adaptation and personalization. The fuzzy intelligent learning system (FILS) uses representative data to dynamically and continuously measure learners' knowledge and skill capabilities. This system is characterized by its ability to handle uncertainty and significant variations in learners' understanding levels. By adjusting the learning content and delivery method in real-time according to the fuzzy logic inference system, FILS provides a more tailored and effective educational experience. This approach ensures that the learning process is more flexible and responsive to individual learning paces and comprehension levels, resulting in improved learning outcomes. Figure 2 shows the adaptive learning environment for students.

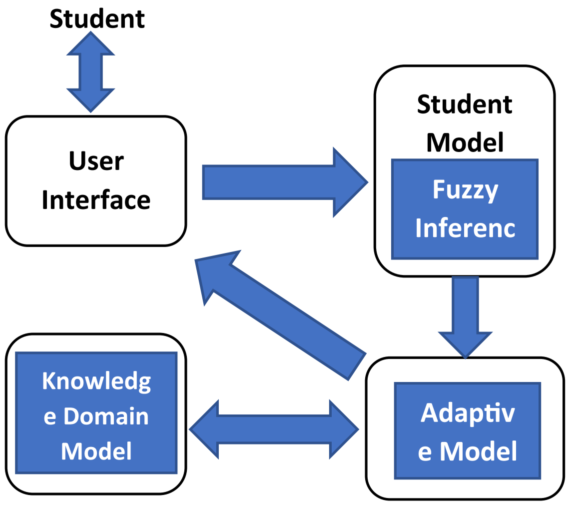

Figure 2. Architecture for Intelligent learning system [24]

Hence, the primary focus is the necessity of developing an intelligent fuzzy learning system that provides dynamic adaptation to all students in this system individually. Figure 3 shows the structure of the proposed system.

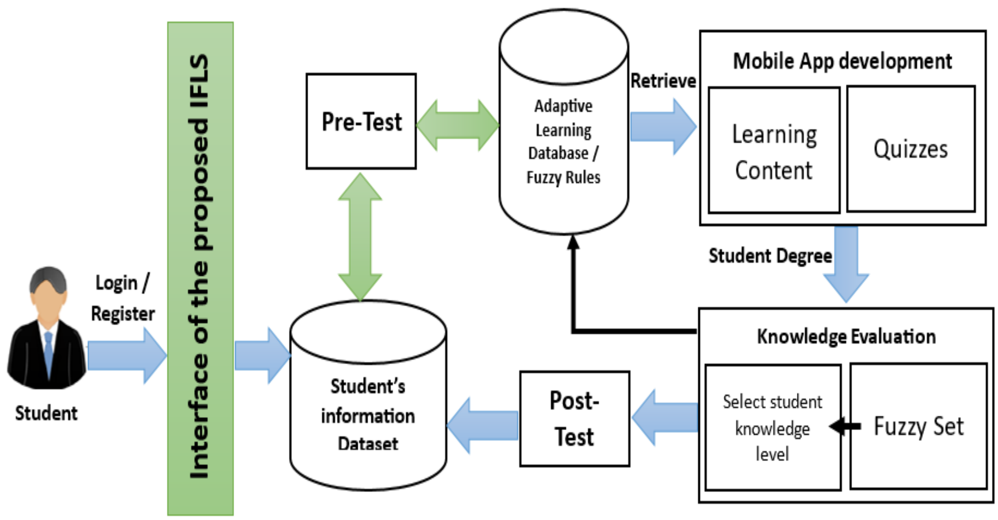

Figure 3. Architecture for the proposed FILS

12.1. Student Login

The first step is for the student to enter the system. If the student ID is valid, he is allowed to enter the learning system. If the student ID is invalid, he will not be allowed to enter the learning system and therefore must log in to the system. The student enters the system and registers his information at the cognitive level related to developing mobile application skills. All student information is stored in the student profile database. This information is used to determine and analyze students' current knowledge and to provide appropriate content to each learner based on this information. Information is constantly modified as the student studies through the system and learns new concepts**.**

12.2. Pre-Test

After the student logs into the system and registers information, the pre-test and pre- evaluation rubric are administered, and all student ratings are stored in the student ID database. Feedback on gaps and concepts unknown to the student is provided to the student, and then the learning content is demonstrated based on the concepts unknown to the student.

12.3. Learning Content for the Mobile App development

In this stage, the student selects and retrieves educational materials from the database for the purpose of learning. All learning resources are stored in a shared database. If the student needs any educational material according to the feedback issued by the system, it will be retrieved from the database. Once the learning process is completed by the student, the system has to conduct quizzes of the domain concept learned by the student. Whenever a student interacts with the system, a test is administered to evaluate the student's knowledge.

12.4. Membership Functions in the Knowledge Level for Mobile App development

Fuzzy rules are used to classify students' knowledge level. Each fuzzy node in the proposed FILS moves through three steps, as shown as Figure 4:

- **Step 1 (Fuzzification):** This stage converts inputs into fuzzy set membership values.
- **Step 2 (Inference):** In this step, inference is performed using the specified rule base in the form of IF-THEN statements.

- **Step 3 (Defuzzification):** In this process, fuzzy output values are converted to a single crisp value or final decision.

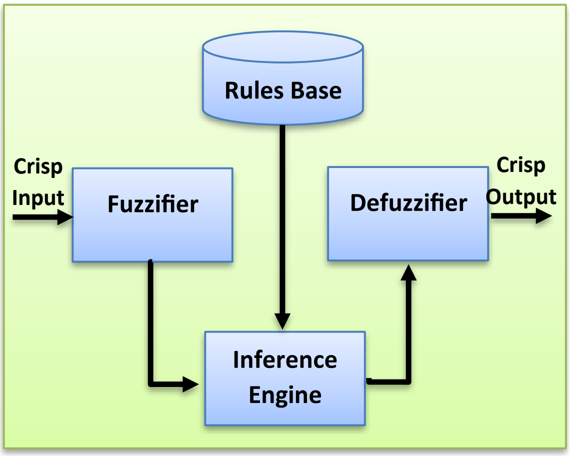

Figure 4. Architecture for fuzzy inference system

Table 1 shows five different fuzzy sets are used to represent students' knowledge based on information recorded in the database that includes information on the pre-test and quizzes on the learning topics.

Table 1. Membership Functions in the Knowledge Level for Mobile App development

Mobile App Knowledge Level	Membership Functions
Novice (*N*) passing grade from 0 to 45%	$\mu_N = \begin{cases} 1, & d \leq 35 \\ 1 - \dfrac{d-35}{10}, & 35 < d < 45 \\ 0, & d \geq 45 \end{cases}$
Advanced Beginner (*AB*) passing grade from 35 to 60%	$\mu_{AB} = \begin{cases} \dfrac{d-35}{10}, & 35 < d < 45 \\ 1, & 45 \leq d \leq 50 \\ 1 - \dfrac{d-60}{10}, & 50 < d < 60 \\ 0, & d \leq 35 \text{ or } d \geq 60 \end{cases}$

Mobile App Knowledge Level	Membership Functions
Competent (*C*) passing grade from 50 to 70%	$\mu_C = \begin{cases} \frac{d-50}{10}, & 50 < d < 60 \\ 1, & 60 \le d \le 65 \\ 1 - \frac{d-75}{5}, & 65 < d < 70 \\ 0, & d \le 50 \text{ or } d \ge 70 \end{cases}$
Proficient (*P*) passing grade from 65 to 80%	$\mu_P = \begin{cases} \frac{d-65}{10}, & 65 < d < 70 \\ 1, & 70 \le d \le 75 \\ 1 - \frac{d-75}{5}, & 75 < d < 80 \\ 0, & d \le 65 \text{ or } d \ge 80 \end{cases}$
Expert (*E*) passing grade from 75 to 100%	$\mu_E = \begin{cases} \frac{d-75}{10}, & 75 < d < 80 \\ 1, & 80 \le d \le 85 \\ 0, & d \le 80 \end{cases}$

The membership functions shown above are symmetric which provides a clear and easily interpretable way of representation. The current level of Mobile App development knowledge of a student is represented using the membership functions. These membership functions define the values of the fuzzy weights, ranging from 0 to 1. A value of 1 for the knowledge level indicates that the user has achieved mastery in the domain and possesses comprehensive knowledge. Consequently, the total value of each divided fuzzy set represents the knowledge level of a domain learning unit and sums up to 1, as shown by the equation:

$$\mu_N(x) + \mu_{AB}(x) + \mu_C(x) + \mu_P(x) + \mu_E(x) = 1$$

where $\boldsymbol{\mu_N}$, $\boldsymbol{\mu_{AB}}$, $\boldsymbol{\mu_C}$, $\boldsymbol{\mu_P}$ and $\boldsymbol{\mu_E}$ as novice, advanced beginner, competent, proficient, and expert.

Therefore, a fuzzy set with five membership values (A, AB, C, P, E) will clearly differentiate the knowledge level of the student for a particular concept (Fig. 5).

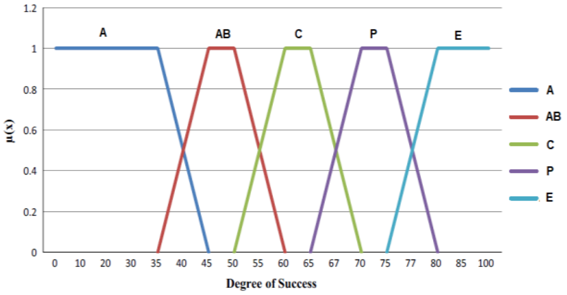

Figure 5. Membership function

An indicator of students' level of knowledge is recorded based on an assessment in the pre-test and a quizzes after each learning content. Moreover, the following fuzzy rules are used to determine the version of learning materials provided to individual students based on their recent learning status:

- ***R1: IF*** *Knowledge Level <= 35* ***Then*** *go to "Novice Level"****.***
- ***R2: IF*** *Knowledge Level > 35 and < 45* ***Then*** *go to "Advanced Beginner Level"****.***
- ***R3: IF*** *Knowledge Level > 45 and < 50* ***Then*** *go to "Advanced Beginner Level"****.***
- ***R4: IF*** *Knowledge Level > 50 and < 60* ***Then*** *go to "Competent Level"****.***
- ***R5: IF*** *Knowledge Level > 60 and < 65* ***Then*** *go to "Competent Level"****.***
- ***R6: IF*** *Knowledge Level > 65 and < 70* ***Then*** *go to "Proficient Level"****.***
- ***R7: IF*** *Knowledge Level > 70 and < 75* ***Then*** *go to "Proficient Level"****.***
- ***R8: IF*** *Knowledge Level > 75 and < 80* ***Then*** *go to "Expert Level"****.***
- ***R9: IF*** *Knowledge Level > 80 and < 100* ***Then*** *go to "Expert Level"****.***
- ***R10: IF*** *Knowledge Level >= 100* ***Then*** *go to "post-Test and pre-product evaluation card"****.***

The FILS helps students with different learning preferences and competencies as well as different levels of knowledge regarding mobile application development concepts and skills. Also, the role of the teacher does not exist in the learning system. Hence, the FILS must react according to students' preferences. The system can be made adaptive since knowledge classification using fuzzy set membership function is done based on the student's knowledge level in mobile application development concepts and skills. Initially, in the FILS, the student is new to the domain concept and student's knowledge level regarding the concept is completely unknown. But when the interaction continues for the next time, student may have learned some concepts that modify the student's knowledge level. When the student completes a particular concept before being allowed to move on to the next concept, the system administers a short quiz to assess the student's knowledge level. Depending on the performance on the practice test, the level of knowledge and classification of stereotypes changes. The test result will have an impact on the knowledge level of all other relevant mobile app development concepts and skills. Once the student's knowledge level reaches 100%, a test is administered to assess the e-learner for all concepts of the relevant fields.

The FILS adapts to learners' needs by dynamically adjusting the educational content and delivery based on individual learning profiles. Utilizing fuzzy logic, the system assesses the learners' knowledge levels, skill capabilities, and learning pace. This continuous evaluation allows FILS to personalize the learning experience in real-time. For instance, if a learner struggles with a particular concept in mobile app development, the system can provide additional resources, simplified explanations, or alternative instructional methods. Conversely, if a learner demonstrates proficiency, the system can introduce more advanced topics to challenge and further develop their skills. This adaptive approach ensures that each learner receives tailored support, promoting a more effective and efficient learning process.

12.5. Post-Test

After the student completes the special learning content on mobile application development skills, in addition to achieving 100% in knowledge levels through the proposed system. The student conducts the post-test and a post- evaluation rubric to measure the effectiveness and efficiency of the system and the extent of its impact on the students.

13. Data Collection and Measuring tools

13.1. Pre-Post Cognitive Test

In alignment with the overarching and procedural objectives, as well as the educational content of the proposed system, the cognitive test was designed and constructed. This test aimed to measure the cognitive aspect of mobile app development skills among the sample of computer science teacher students at the Faculty of Specific Education, Zagazig University. Initially, the cognitive test comprised 50 items, covering various cognitive aspects of the skills. To ensure content validity, the initial version of the test was reviewed by a panel of experts in computer science and educational technology.

The experts suggested modifications, including the rephrasing and reordering of some items. The final version of the test included 50 objective-type questions, divided into 30 true/false items and 20 multiple-choice items, each with an introduction and four options to minimize the effect of guessing. The test instructions were placed at the beginning, with an additional 10 minutes allocated for reading them before starting the actual 60-minute test. The total score for the test was 50 points.

A pilot study was conducted on a sample of 10 computer science teacher students from the Faculty of Specific Education, Zagazig University (not part of the main research sample). The objectives of the pilot study were as follows:

- **Validity**: The validity of the test was assessed through the calculation of internal consistency validity, which refers to the strength of the correlation between each question's score and the total score for the cognitive level it represents; Pearson's correlation coefficient was calculated. The correlation coefficients for all levels of the test were significant at the 0.01 level, ranging from 0.798 to 0.889, indicating a high degree of construct validity and internal consistency.
- **Reliability**: Cronbach's alpha was used to calculate the test's reliability coefficient. The overall reliability coefficient for the test was 0.805, indicating high reliability and suitability for application.
- **Item Difficulty and Discrimination Coefficients**: The difficulty coefficient for each item of the cognitive test was calculated, ranging from

0.42 to 0.76, indicating an acceptable level of difficulty. Discrimination coefficients for the pilot sample were also calculated, where scores were ranked and divided into two groups (upper and lower). The discrimination coefficients for the cognitive test items ranged from 0.61 to 0.79, indicating good discrimination and test suitability.

13.2. Pre-Post Skills Test

In line with the general procedural objectives and educational content of the proposed system, the skill performance test was designed and constructed to measure the skill level related to mobile app development among the sample. The initial form of the skill test consisted of a single task, where the student was required to develop a mobile application in the field of education. To ensure content validity, the test was reviewed by a panel of experts in computer science and educational technology, who affirmed its suitability for use. An evaluation rubric was prepared for use in assessing the skill test.

13.3. Evaluation rubric

An evaluation rubric was developed with its axes in the final form, based on research concepts and terms, and within the framework of the mobile app development skills to be developed. It included 23 statements divided into four main axes (Performance and Efficiency, Interface and User Experience, Content and Features, Security and Privacy, Compatibility and Integration, Support and Assistance), measuring the skill performance level of computer science teacher students. Responses were scored on a five-point scale (Yes, Sometimes, No), with a continuum of 1 to 5, depending on the direction of the statements (positive-negative). Table 2 shows details the scale by its factors:

Table 2. Factors of the Evaluation Rubric

Factors	N
Performance and Efficiency	5
Interface and User Experience	5

Factors	N
Content and Features	3
Security and Privacy	3
Compatibility and Integration	4
Support and Assistance	3
Total	23

- **Content Validity:** The initial version of the scale was reviewed by several professors in computer science and educational technology. This review focused on the accuracy of the language, the appropriateness of the content, the relevance of the statements to each axis, and the sufficiency of the statements to achieve the intended purpose. Modifications suggested included rephrasing some statements to ensure content validity.
- **Internal Consistency Validity:** To calculate the internal consistency validity of the scale, the skill test was administered to a pilot sample of 10 students (not part of the main research sample). Pearson's correlation coefficient was calculated between the axes and the total scale score. The correlation coefficients ranged from 0.775 to 0.801, indicating high construct validity and internal consistency.
- **Reliability**: Cronbach's alpha was used to calculate the reliability coefficient of the scale. The coefficients ranged between 0.881 and 0.844, with an overall reliability coefficient of 0.878, indicating high reliability and suitability for application.

14. Instructional Design

The Instructional design used in the proposed system is the Successive Approximation Model (SAM) as shown in Figure 6. This model follows a flexible and dynamic methodology aimed at improving the development process through iterative cycles of evaluation and successive refinements [25]. SAM emphasizes collaboration and ongoing interaction among team members to ensure the best educational outcomes are achieved.

SAM begins with a preparation phase, where educational goals are defined, and necessary information is gathered. Following this, the system moves into the design and development phase where prototypes of educational materials are created and evaluated iteratively. This approach facilitates the rapid development of instructional content that is closely aligned with the learners' needs and objectives, enabling effective and efficient educational experiences.

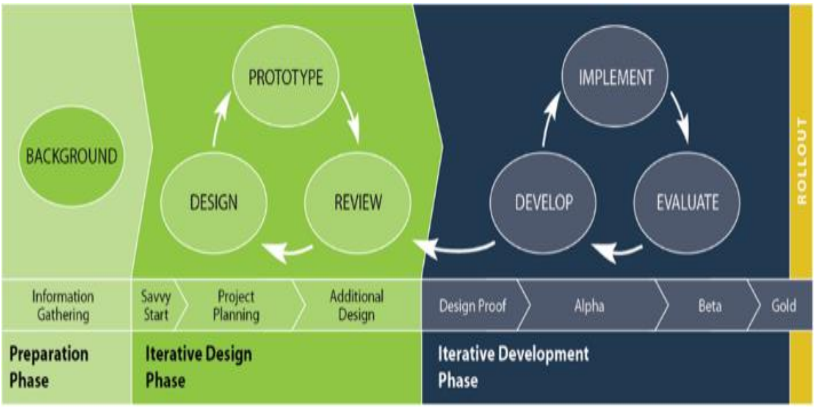

Figure 6. The Phases of SAM [25]

14.1. Preparation Phase:

In the SAM model, the Preparation phase involves initial planning and preparation, which aligns with the first phase discussed earlier. It includes:

1. **Analyzing Student Entry Requirements:** Evaluating existing skills among students, such as proficiency in using the internet, electronic devices, and web applications.
2. **System and Resource Evaluation:** Ensuring that all necessary resources, financial facilities, and technological requirements are available to support the deployment of the proposed system.
3. **Administrative Approvals:** Securing all necessary permissions from relevant authorities to proceed with the research experiment.

14.2. Iterative Design Phase:

This phase in SAM involves creating prototypes and continuously refining them based on feedback. It incorporates several tasks from the outlined phases:

1. **Setup and Requirement Analysis**: Addressing any deficiencies found in the technological infrastructure and determining the needs of the system.
2. **Design Specifications:**
   - Developing behavioral objectives based on the desired outcomes.
   - Designing appropriate scientific content and multimedia resources:

     1) Understanding Flutter Basics:
     - *Setting up the development environment.*
     - *Knowing the project structure in Flutter.*
     - *Handling packages and plugins.*

     2) Designing User Interface (UI) with Flutter:
     - *Using Flutter core widgets.*
     - *Designing responsive user interfaces.*
     - *Managing layouts and nested layouts.*

     3) State Management:
     - *Understanding the basics of state management.*
     - *Implementing simple state management techniques (e.g., setState).*
     - *Using advanced state management solutions (e.g., Provider, Riverpod, Bloc).*

     4) Navigation and Routing:
     - *Setting up navigation and routes.*
     - *Managing navigation stacks.*
     - *Implementing named and nested routes.*

     5) Working with APIs:
     - *Understanding RESTful APIs.*
     - *Making HTTP requests using packages like http or Dio.*
     - *Parsing JSON data.*

     6) Data Persistence:
     - *Using local storage solutions (e.g., SharedPreferences, Hive).*
     - *Integrating SQLite for complex data storage needs.*

- *Implementing data synchronization.*

7) Handling Forms and User Input:
- *Creating and validating forms.*
- *Managing form state.*
- *Handling user inputs and gestures.*

8) Animations and Transitions:
- *Understanding basic animations in Flutter.*
- *Implementing complex animations and transitions.*
- *Using animation libraries and packages.*

9) Testing and Debugging:
- *Writing unit tests and widget tests.*
- *Debugging Flutter applications.*
- *Using the Flutter DevTools.*

10) Deployment:
- *Preparing the app for release.*
- *Publishing to the Google Play Store and Apple App Store.*
- *Managing app updates and versioning.*

11) Performance Optimization:
- *Profiling and optimizing app performance.*
- *Reducing app size.*
- *Ensuring smooth UI performance*

12) Integrating Native Features:
- *Using platform channels to access native APIs.*
- *Integrating third-party native libraries.*
- *Handling device-specific features and permissions.*

- Crafting user interface designs and interaction mechanisms.
- Establishing assessment and evaluation tools.
- Creating detailed scenarios and storyboards to guide the development.

14.3. Iterative Development Phase:

The development phase in SAM is where the actual creation and continuous improvement of the system occur, which would integrate the production and evaluation phases described:

1. **Production**: This includes:
    - Developing multimedia content and educational activities.
    - Implementing user interfaces and interaction systems.
    - Setting up the registration, management, and support frameworks.
2. **Testing and Evaluation**: Conducting thorough testing of all system components, monitoring usage outcomes, and applying necessary adjustments based on user feedback and performance analysis.
3. **Final Adjustments and Deployment:** Making final tweaks to the system before full-scale implementation and preparing for broader deployment based on the system's effectiveness and user satisfaction.

15. System Implementation

The system was developed using C# 2022 and Python 3.6. The development and testing of the system were conducted on a Microsoft Surface Book 1 computer with the following specifications:

- Central Processing Unit (CPU): Intel(R) Core(TM) i5-6300U CPU @ 2.40GHz, 2.50 GHz.
- Random Access Memory (RAM): 8 GB.

These specifications were adequate to handle the demands of the development tools and the runtime requirements of the system. The choice of C# 2022 provided a robust framework for managing user interface and backend processing, while Python 3.6 was utilized for data handling and analytics, leveraging its extensive library support for statistical and machine learning computations. The combination of these technologies ensured a seamless and efficient system operation, optimized for educational purposes within the constraints of the hardware used. Figure 7 shows the login screen. Figure 8 shows the register new user screen. Figure 9 shows the proposed system main GUI. Figure 10 shows the proposed system main lessons GUI. Figure 11 shows the student-model GUI. Figure 12 shows the Communication system GUI.

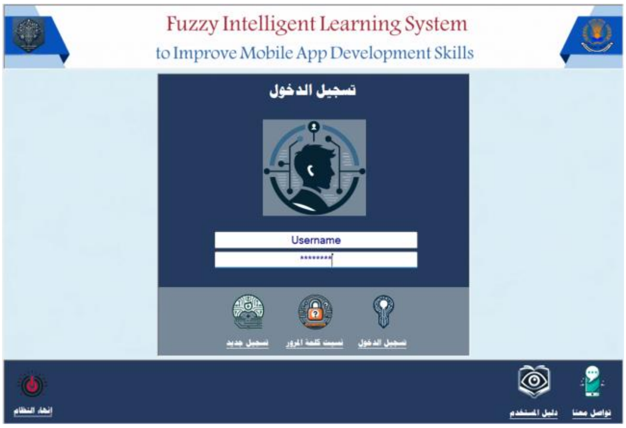

Figure 7. Login screen

Figure 8. New user screen

Figure 9. Main menu screen

Figure 10. Content screen

Figure 11. Student-model screen

Figure 12. Communication system screen

The following is an example of content adaptation according to the student's level. Figure 13 shows the content designed for a beginner student, while Figure 14 shows the same content but tailored for an advanced student. The content for the beginner student is presented in a simpler manner and with more detailed explanations compared to the advanced student.

Figure 13. Content designed for a beginner student.

Figure 14. Content designed for a advanced student

In cases where the content presented to the student is not suitable, they can access the intelligent assistant (Figure 15) built on generative artificial intelligence. This assistant allows the student to interact with it as if it were a private tutor. The benefit of generative artificial intelligence lies in its ability to improve the student's level by considering the capabilities of each student individually. This interactive system allows students to ask questions and receive explanations tailored to their level of understanding and educational needs, thereby enhancing the learning experience and increasing the effectiveness of grasping complex concepts in mobile app development.

Figure 15. Intelligent assistant screen

16. Experimental Procedure

Upon the completion of designing, constructing, and scientifically calibrating the measurement tools, and preparing the proposed fuzzy intelligent learning system, the researchers commenced the primary field experiment. Below is a detailed presentation of the process:

16.1. Preliminary Application of Measurement Tools

The research instruments were initially applied on Saturday, October 21, 2022, to the sample of computer science teacher students at the Faculty of Specific Education, Zagazig University. Following this preliminary application, scores were recorded in preparation for statistical analysis. This part focuses on the equivalence between the control and experimental groups, which was established through this initial application. A detailed overview follows:

- **Equivalence Between Students in the Groups (Control - Experimental) in the Preliminary Cognitive Test:**

The cognitive test to measure the cognitive aspect of mobile app development skills was administered to the computer science teacher students. All students achieved similar scores in the preliminary application of the test, indicating equivalence in the cognitive aspect of mobile app development skills between the research groups before the implementation of the proposed fuzzy intelligent learning system. To verify the equivalence between the control and experimental groups in the preliminary application of the cognitive test, an independent groups t-test was used to determine the significance of the difference between the group means. Table 3 shows that there is no statistically significant difference between the mean scores of the control and experimental groups in the preliminary application of the cognitive test related to mobile app development skills for computer science teacher students. The calculated T-value (1.359) is not significant, indicating equivalence in the pre-test cognitive performance related to mobile app development skills.

Table 3. "T-test" for the Preliminary Cognitive Test

Group	N	Mean	Std.D	df	t	Sig
Con	35	20.37	2.951	68	1.359	0.179
Exp	35	19.34	3.369			

- **Equivalence Between Students in the Groups (Control - Experimental) in the Preliminary Skills Test:**

The skills test for measuring the practical aspect of mobile app development was administered. All students obtained closely matching scores in the preliminary application of the test, demonstrating equivalence in the skill aspect of mobile app development among the research groups before the implementation of the proposed fuzzy intelligent learning system. An independent groups t-test was used to check for significance between the mean scores of the groups. Table 4 shows that here is no statistically significant difference in the mean scores of the control and experimental groups for the sample in the preliminary application of the skills test for mobile app development. The calculated T-value (0.316) is not significant, confirming the equivalence of the groups in pre-test skill performance related to mobile app development.

Table 4. "T-test" for the Preliminary Skills Test

Group	N	Mean	Std.D	df	t	Sig
Con	35	58.31	5.656	68	0.316	0.753
Exp	35	57.83	7.127			

16.2. Conducting the Research Experiment

The following procedures were followed to conduct the research experiment:

- **Holding a Preparatory Session:** The researchers conducted an introductory meeting with the computer science teacher students (research sample) at the Faculty of Specific Education, Zagazig University, on Saturday, October 28, 2022. The session clarified the process of starting to learn the content, the instructions of the proposed fuzzy intelligent learning system, its objectives, the scientific content, the activities related to the content, how to use the available interaction tools, and how to upload and share files.
- **Clarifying the Educational Plan and Pathway for the Research Sample:** The educational plan and pathway for the research sample were clarified, adhering to the specified schedules. The educational pathways were provided on the system, while the schedules were set on the system's notice board, including a module for each week, making the experiment last six weeks.
- **Implementing the Main Research Experiment:** The main research experiment was conducted from Wednesday, February 15, 2023, to

Thursday, April 18, 2023. During this period, the following were accomplished:

- Organizing the teaching process according to the prepared timeline.
- Monitoring the students (study sample), responding to their posts, correcting them, and providing guidance electronically through the communication tools of the proposed fuzzy intelligent learning system, as well as monitoring the chat room and conversations.
- Some meetings were held electronically via Microsoft Teams as needed to explain and clarify some of the contents.
- Monitoring the students' (study sample) responses to the training activities, guiding them to the correct answers, and providing support.

16.3. Post-Implementation Application of Measurement Tools

After the specified period for conducting the main experiment, the post-implementation application of the measurement tools took place on Saturday, December 9, 2022. Following this application, scores were recorded in preparation for statistical processing.

17. Data Analysis

After the data were collected and processed, an analysis was conducted using the Statistical Package for the Social Sciences (SPSS). This analysis involved calculating mean values, standard deviations, and percentages. Pearson’s correlation coefficient was computed to assess the validity of the research instruments. Additionally, Cronbach’s alpha was calculated to evaluate the reliability of the research tools. Paired t-tests were used to examine the differences between the pre- and post-test mean scores of the research sample in both the cognitive and skills tests. Independent t-tests were also employed to highlight the differences between the post-test mean scores of the control and experimental groups in both the cognitive and skills assessments. Furthermore, Black’s adjusted gain equation was utilized to measure the effectiveness of the proposed system in enhancing both the cognitive and performance aspects of mobile app development skills among the research sample.

18. Experimental Results

18.1. Hypothesis One Results:

Hypothesis: "There is a statistically significant difference between the average scores of the control group and the experimental group in the post-test cognitive assessment in favor of the experimental group". To verify this hypothesis, an independent samples t-test was used, where the mean and standard deviation of the scores for both the control and experimental groups in the post-test cognitive assessment were calculated, and the corresponding t-value was computed.

Table (5) shows a statistically significant difference between the average scores of the two groups in the post-test cognitive assessment, with a calculated t-value of -72.118, significant at the 0.05 level with 68 degrees of freedom, favoring the experimental group with a higher mean (49.29). This result suggests that the proposed fuzzy intelligent learning system effectively improved the cognitive abilities related to mobile app development skills for computer science teacher students. This hypothesis is fully confirmed as shown in Figure 16.

Table 5. "T-test" for the Post Cognitive Test

Group	N	Mean	Std.D	df	t	Sig
Con	35	27.63	1.573	68	-72.118	<0.001
Exp	35	49.29	0.825			

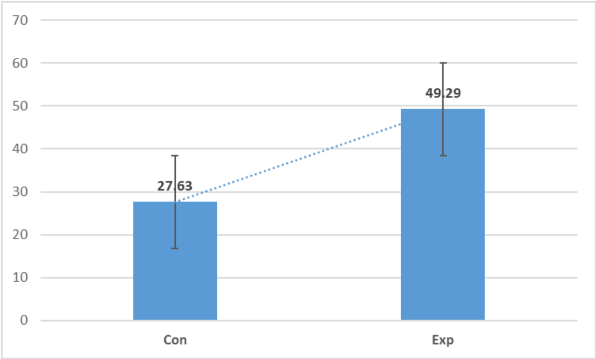

Figure 16. "T-test" for the Post Cognitive Test

18.2 .Hypothesis Two Results:

Hypothesis: "There is a statistically significant difference between the average scores of the control group and the experimental group in the post-test skills assessment in favor of the experimental group". An independent samples t-test was also used for this hypothesis, calculating the mean, standard deviation, and t-value for the differences between the two groups in the post-test skills assessment.

Table (6) shows a statistically significant difference between the average scores of the two groups in the post-test skills assessment, with a calculated t-value of -55.738, significant at the 0.05 level with 68 degrees of freedom, favoring the experimental group with a higher mean (108.83). This result indicates that the proposed fuzzy intelligent learning system significantly improved the mobile app development skills of the experimental group students. This hypothesis is fully confirmed as shown in Figure 17.

Table 6. "T-test" for the Post Skills Test

Group	N	Mean	Std.D	df	t	Sig
Con	35	62.89	4.391	68	-55.738	<0.001
Exp	35	108.83	2.121			

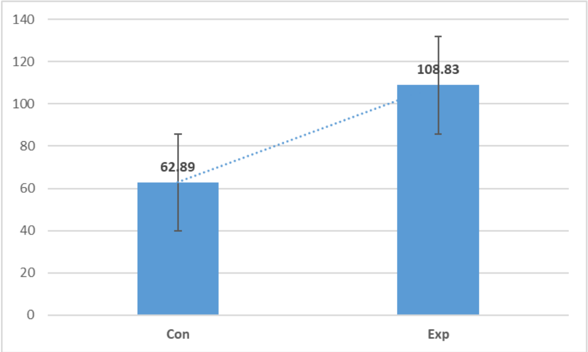

Figure 17. "T-test" for the Post Skills Test

18.3 .Hypothesis Three Results:

Hypothesis: "There is a statistically significant difference between the average scores of the experimental group in the pre-test and post-test cognitive assessments in favor of the post-test". A paired samples t-test was used to verify this hypothesis, where the mean, standard deviation, and t-value for the differences between the pre-test and post-test scores of the experimental group were calculated.

Table (7) shows a statistically significant difference between the pre-test and post-test average scores of the experimental group, with a t-value of -54, significant at the 0.05 level with 34 degrees of freedom, favoring the post-test with a higher mean (49.29). This result confirms that the proposed fuzzy intelligent learning system effectively improved the cognitive aspects of mobile app development skills for the experimental group students. This hypothesis is fully confirmed as shown in Figure 18.

Table 7. "T-test" for the Pre and Post Cognitive Test

Group	N	Mean	Std.D	df	t	Sig
Pre	35	19.34	3.369	34	-54	<0.001
Post	35	49.29	0.825			

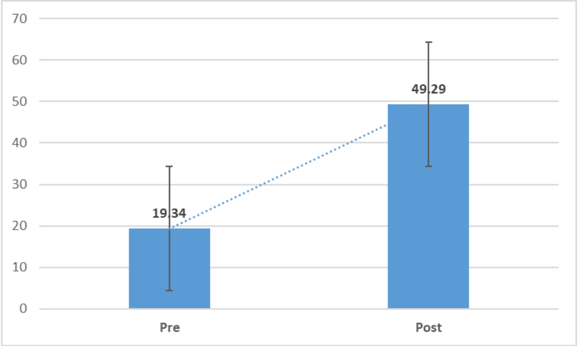

Figure 18. "T-test" for the Pre and Post Cognitive Test

18.4 .Hypothesis Four Results:

Hypothesis: "There is a statistically significant difference between the average scores of the experimental group in the pre-test and post-test skills assessments in favor of the post-test". A paired samples t-test was used here as well, calculating the mean, standard deviation, and t-value for the differences between the pre-test and post-test scores of the experimental group.

Table (8) shows a statistically significant difference between the pre-test and post-test average scores of the experimental group, with a t-value of -40.837, significant at the 0.05 level with 34 degrees of freedom, favoring the post-test with a higher mean (108.83). This result indicates that the proposed fuzzy intelligent learning system effectively enhanced the mobile app development skills of the experimental group students. This hypothesis is fully confirmed as shown in Figure 19.

Table 8. for the Pre and Post Skills Test

Group	N	Mean	Std.D	df	t	Sig
Pre	35	57.83	7.127	34	-40.837	<0.001
Post	35	108.83	2.121			

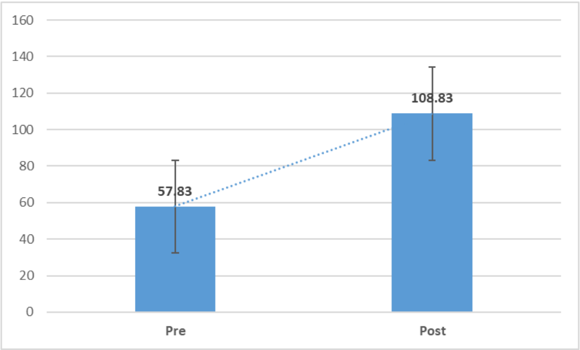

Figure 19. "T-test" for the Pre and Post Skills Test

18.5 .Effectiveness of the Proposed System:

The effectiveness of the system refers to the proportion of experimental group students who achieved the required level of learning for each objective of the proposed fuzzy intelligent learning system, as measured by their scores on the cognitive and skills tests. The effectiveness of the system was assessed using Black's adjusted gain formula, which Black defines as between (1-2) for acceptable system effectiveness. This ratio is calculated using the following Equation:

$$\frac{x_{Post} - x_{Pre}}{D - x_{Pre}} + \frac{x_{Post} - x_{Pre}}{D}$$

Where:

- X post is the average score of students after the intervention (post-test).
- X pre is the average score of students before the intervention (pre-test).
- D is the maximum possible score on the test.

Table (9) shows that the Black's adjusted gain ratio (1.58) falls within the range defined by Black, indicating a high proportion of students benefited and achieved the required level in the cognitive aspect associated with mobile app development skills for computer science teacher students, confirming the effectiveness of the proposed fuzzy intelligent learning system. Table (10) shows the calculation of Black's adjusted gain ratio for the skills test. table (6) shows that the Black's adjusted gain ratio (1.34) also falls within the range defined by Black, indicating a high proportion of students benefited and achieved the required level in the skill aspect of mobile app development for computer science teacher students, confirming the effectiveness of the proposed fuzzy intelligent learning system.

Table 9. Black's Adjusted Gain Ratio for Cognitive Test

X pre	X post	D	Adjusted Gain
19.34	49.29	50	1.58

Table 10. Black's Adjusted Gain Ratio for Skills Test

X pre	X post	D	Adjusted Gain
57.83	108.83	115	1.34

Conclusions and Future Works

Adaptive learning systems have a positive impact on the learning process because they suit the characteristics of the learner, which leads to increased efficiency and effectiveness for learners. In this regard, the integration of artificial intelligence methodologies and educational curricula in universities provides a more interactive learning environment that meets learners' preferences. The main objective of this paper is to provide an intelligent fuzzy learning system (FILS) for higher education to determine the knowledge level of learners dynamically. FILS represents the dependencies between concepts in the field improve mobile app development skills, which has structured in an electronic self-learning method. This system monitors learners' performance in improve mobile app development skills domain concepts and provides adaptive instruction to learners. The fuzzy logic used by the proposed system saves time in the learning process by evaluating the learner and covering the comments about the gaps, and thus the learner can quickly adapt and reach real knowledge.

This work focuses on the topic of mobile application development, and therefore the proposed system can apply as future work by considering knowledge assessment of more topics related to computer science and educational curricula. As scalability, design an intelligent fuzzy learning system based on smartphones for higher education students.

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تطوير نظام تعليمي ذكي ضبابي لتحسين مهارات تطوير تطبيقات الهاتف لطلاب معلم الحاسب الآلي

الملخص

أدى التطور السريع في تكنولوجيا الهواتف المحمولة إلى ضرورة دمج أساليب تعليمية مبتكرة في تعليم الكمبيوتر. يقدم هذا البحث نظام تعلم ذكي ضبابي (FILS) لتحسين مهارات تطوير تطبيقات الهاتف لطلاب معلم الحاسب الآلي. تستخدم المنهجية المقترحة نظام تعلم ذاتي يعتمد على المنطق الضبابي من البيانات التي تمثل معرفة وقدرات المتعلمين واحتياجاتهم التعليمية. يستخدم FILS لتحسين نقل المعرفة بناءً على خصائص كل متعلم، حيث يتكيف مع المواقف التعليمية وتقديم المحتوى.

كانت عينة البحث 70 طالبًا من طلاب معلم الحاسب الآلي تم اختيارهم عشوائيًا وتقسيمهم إلى مجموعتين: مجموعة ضابطة ومجموعة تجريبية، بحيث تضم كل مجموعة 35 طالبًا. تلقت المجموعة الضابطة طرق التدريس التقليدية، بينما شاركت المجموعة التجريبية مع نظام التعلم الذكي الضبابي المقترح. اعتمدت المنهجية على تصميم شبه تجريبي، مع التركيز على التحليل المقارن بين نتائج الاختبارات القبلية والبعدية لكلتا المجموعتين. تم تصميم FILS لتعديل المحتوى التعليمي ديناميكيًا بناءً على نظام استدلال المنطق الضبابي، الذي يأخذ في الاعتبار وتيرة التعلم ومستويات الفهم الفردية.

أظهرت النتائج تحسنًا كبيرًا في مهارات تطوير تطبيقات الهاتف ضمن المجموعة التجريبية مقارنة بالمجموعة الضابطة. كما أظهرت النتائج أن درجات الاختبار البعدي للمجموعة التجريبية كانت أعلى بشكل ملحوظ، مما يشير إلى أن FILS ساعد بفعالية في تعزيز فهم الطلاب وإتقانهم لمهارات تطوير تطبيقات الهاتف.

الكلمات المفتاحية: المنطق الضبابي، الذكاء الاصطناعي، التعليم الإلكتروني، نظام التعلم الذكي الضبابي، مهارات تطوير تطبيقات الهاتف، طلاب معلم الحاسب الآلي.