Optimizing the Usage of Educational Tools for Effective Online Learning: A Proposed Optimization Model for Physics and Other Basic Science Courses

Delara Jafari [a] and Zahra Shaterzadeh-Yazdi[a*] and Amin Ghodousian[a]

[a] *School of Engineering Science, College of Engineering, University of Tehran, 16 Azar St., Enghelab Sq., Tehran, Iran, Postal code: 14155-6619*

E-mail address and phone numbers of the authors: *delara.jafari@ut.ac.ir (+989125286559), zahra.shaterzadeh@ut.ac.ir (+989203211676), a.ghodousian@ut.ac.ir (+989127849352)*

Corresponding author: *Zahra Shaterzadeh-Yazdi*

Abstract:

Online education has become increasingly popular in academic and scientific communities, and the COVID-19 pandemic has accelerated its adoption worldwide, particularly in developing countries. However, many instructors were unable to effectively utilize the available learning management system educational tools due to their lack of experience, leading to less effective online education compared to traditional face-to-face teaching. To address these challenges, we propose an effective model for optimizing the usage of learning management system (LMS) educational tools by instructors. The proposed model is developed using Fuzzy logic and the Genetic optimization algorithm, and a flowchart is designed to facilitate its implementation. The model is applied to an undergraduate Physics course, and the output results are analysed using statistical methods. Our findings demonstrate the positive impact of the proposed model on students' performance. The outcomes of this study can aid in the optimal design of online-course plans based on the utilized LMS educational tools while simultaneously improving students' learning. The proposed model has the potential to be adapted for use in various theoretical and, with slight modifications, for practical courses across different disciplines, contributing to enhancing the effectiveness of online education in the post-pandemic era.

Keywords: Learning management system, Fuzzy logic, Genetic optimization algorithm, Online education, COVID-19 pandemic, Undergraduate Physics course, Post-pandemic era

1. Introduction

Popularity of online resources in academic and scientific communities has been increasing over the past few decades, but virtual and online education has only recently received more attention [1-4]. It is necessary to consider the advantages of online education and identify the institutional and individual barriers to its widespread adoption. Recent research indicates that web-based educational platforms have positively impacted the teaching-learning process by providing easier, less expensive, and quicker education [5,6].

The global outbreak of Covid-19 and subsequent governmental quarantines have significantly altered face-to-face education, necessitating the adaptation of education and learning, resulting in the increased use of online education platforms, particularly in developing countries [7-9]. Many universities worldwide have adopted online educational resources based on the learning management system to keep up with these changes and ensure the survival of education and learning [10].

The learning management system (LMS) encompasses a wide collection of online educational tools [11,12]. However, there is no any standard criterion for the optimal use of these tools. Instructors may choose to use certain educational tools based on personal experience and preferences, while others may use different tools, or similar tools differently for the same course [13]. Given the importance of virtual education, it is critical to further examine the effectiveness of such online educational systems.

The optimization of online education is a complex and time-consuming task, primarily due to the multitude of educational configurations available. Some studies suggest that combined optimization methods yield superior results compared to trial-and-error methods [14,15]. However, these studies have been limited to comparisons with other studies based on pedagogical methods [16,17]. Consequently, rigorous scientific research is yet to be conducted for the optimization of online teaching, including system modelling and the optimization of educational tools.

We address this research problem by developing an effective educational model, referred to as the JSG-Learn model, for optimizing the usage of LMS educational tools, concurrently enhancing students learning outcomes. The model is based on Fuzzy logic [18] and Genetic algorithm optimization method [19].

The proposed model is validated by applying common educational tools, used in LMS, to Physics taught to students from various engineering fields. Physics is selected as a representative of theory courses due to its characteristics of conception, comprehension and reasoning calculation, making it a suitable representative for a broad range of theory and basic science courses such as Mathematics, Differential equations, Chemistry, etc. To facilitate the implementation of the proposed model, the JSG-Learn flowchart is also presented.

Overall, **three research questions** are investigated in this study: **1.** How to develop a model for online teaching that optimizes the use of LMS educational tools to improve students learning outcomes? **2.** Given the optimized model, what combination of educational tools would be best suited for online teaching of Physics, as a representative of basic science courses? **3.** How effective is the implementation of Physics based on our proposed model, in enabling students to achieve higher level of educational proficiency?

The proposed model is a significant contribution to the field of online education, as it optimizes the use of educational resources and incorporates relevant learning theories. It takes the form of an optimized integrated multimodal approach that builds upon Picciano's model [20] with the specific aim of preventing both excessive educational pressure and insufficient workload for instructors and students.

2. Research Background

2-1. Research Background on Electronic Learning

In the late 1980s, the advent of affordable and advanced computer technology led to the development of computer-based learning, which is now considered the foundation of modern electronic learning (e-learning) [21]. The increasing popularity of internet networks and new technologies, coupled with their widespread use in various countries, has led to the emergence of electronic education as a new educational method that has caught the attention of top universities. The development of university curricula in electronic form has also become an important agenda item for educational institutions [22].

Research has shown that it is necessary and effective for teachers to become familiar with online classroom technology [23,24]. The use of technology facilitates interaction and enhances the quality of education between instructors and students, improves interaction among students, and ultimately enhances student learning [25]. Most research in the field of e-learning has focused on appropriate teacher-learner interaction in the teaching-learning process and evaluated students in learner-oriented, energetic, and highly interactive activities [25,26].

Instructors in e-learning use a LMS to upload course materials, assign homework, assess student participation and discussion, provide feedback, and evaluate student activities [27]. Learning management systems also enable universities and educational institutions to collect, store, and extract data for descriptive analysis and appropriate prediction of course performance.

Moodle is one of the most well-known open-source LMS platforms that has been employed as a tool for evaluating student learning performance in various studies [28]. Between 2009 and 2013, data extracted from Moodle was utilized to investigate the educational performance of students in a university complex. Students' learning outcomes were assessed based on the scores awarded to their assignments and exams, as well as their participation in forums [29-31]. In 2016, Park identified significant indicators for predicting progress in an educational course, such as regular study habits, homework submission delay, and the number of sessions attended. In 2018, Jamil presented an educational model that encompassed a set of interconnected online educational networks aimed at enhancing the educational level of computer programming courses. The architecture of this network was named Open School [32].

Massive open online courses, first proposed in 2008, are another type of online education that provides open online courses accessible to a large number of users. Massive open online courses (MOOCs) effectively use website and network technologies to create learning opportunities for tens of thousands of learners [32,33]. The rapid development of MOOCs has attracted attention not only from university instructors and students, but also from educational researchers, and the media [24,34-37]. Nowadays, open and extensive MOOC online courses have provided global learning opportunities for a large number of students and those interested in learning, enabling them to benefit from education at any time and in any place [31,38-40].

2-2. Theories of Online Learning

One influential model in online education is the integrated multimodal model, which is based on the theory that individuals learn more effectively when exposed to multiple modes of learning, such as visual, auditory, and kinesthetic experiences [20,41]. By incorporating diverse modalities, this model offers a more engaging and personalized learning experience, accommodating different learner preferences and improving educational outcomes [42].

Another integrated model that has gained popularity in recent years is the Community of Inquiry (CoI) framework, which emphasizes the importance of social presence, cognitive presence, and teaching presence in online learning [43]. The framework provides a structured approach to online learning that facilitates interaction and collaboration among learners and instructors.

The SAMR (Substitution, Augmentation, Modification, Redefinition) model is another integrated model that has been used to enhance the effectiveness of online learning [44]. The model provides a framework for integrating technology into teaching and learning in a way that enhances the learning experience. The model emphasizes the importance of moving beyond simple substitution of technology for traditional teaching methods and instead focuses on enhancing the learning experience through technology.

Online collaborative learning (OCL) is another approach to online learning that emphasizes collaboration and interaction among learners [45]. The OCL framework provides a structured approach to online learning that facilitates collaboration among learners and instructors. The approach is based on the theory that learning is a social process that is enhanced through collaboration and interaction.

While integrated multimodal models have the potential to enhance the effectiveness of online education, the success of these models depends on the optimization of educational tools. In order to provide an engaging learning experience, educational tools must be designed to facilitate interaction among learners and instructors, and to accommodate diverse preferences for learning. Moreover, educational tools must be optimized to remove pressure from instructors and learners, who may feel overwhelmed by the demands of online learning.

3.Theoretical Framework

3-1. Statement of the Problem

To address the challenge of optimizing online education, this study proposes an optimal model for web-based online education that takes into account three common educational tools: online classes, homework and test modules, and educational videos.

By employing a fuzzy system method and a suitable optimization algorithm, the study aims to determine the optimal percentage of each educational tool that should be used to minimize instructor time and energy while maximizing student learning.

To validate the educational model, the study implemented it for another academic semester on a Physics course and compared the results with the state before applying the model. The research method employed is practical, executive, experimental, and quantitative, with data analysis playing a crucial role in determining the effectiveness of the proposed model.

3-2. Proposed Model for Optimization of Online Education: The JSG-Learn Flowchart

This study presents the proposed JSG-Learn flowchart, as shown in **Figure 1**, which outlines the steps required to determine the relative contribution of each educational tool to improve the quality of the teaching-learning process in online education. According to the flowchart, the first step is to extract the special features of the subject in question, known as "Feature Extraction." This step involves specifying whether the desired course is theoretical or practical, or a combination of both. Next step, known as "Set the Learning Method," the educational tools targeted for teaching on the LMS should be specified. These tools include synchronous and asynchronous online classes, assignments, e-books, videos, animations, forums, tests, and more.

The third step, "Fuzzy System," involves using the instructors' skill data obtained in online teaching as input data in the fuzzy system. The student's final scores are considered as the output data in the fuzzy system. By using the fuzzy system method based on a proper table look-up [18,46,47], a suitable educational model as a function of used educational tools is developed.

The next step is optimization, known as "Optimization and Change Features" in the flowchart. The goal is to optimize the educational model by choosing more suitable features for the input data to improve the student's final score as a measure of evaluating the level of learning. The proposed model is optimized by employing a genetic algorithm (GA). Meta-heuristic search methods can move towards the global optimization of the problem. Evolutionary methods are one of the methods that can lead to global optimization of the problem [19].

After extracting the output data in "Extract Results" and analysing the changes made compared to the previous data in "Data Analysis," the input features of the "Fuzzy

System" can be changed appropriately, and its effect on optimization can be reassessed. The assessment of the result of changing the input characteristics and its impact on the output data continues variationally until an acceptable optimal model is reached for the course.

4. Research Methodology

This paper presents a study consisting of three phases: modelling, implementation, and meta-analysis. The first phase involves the creation of the JSG-Learn platform model by combining fuzzy-based modelling and optimization using Genetic algorithm. The second phase involves the implementation of the obtained optimal model on a selected course in a classroom. Finally, a meta-analysis is performed on the output data to evaluate the JSG-Learn educational platform and the proposed model. The system's modelling and optimization are carried out using MATLAB software, while SPSS software is used to analyse the extracted data and the results of applying the proposed model. This section provides a detailed description of the method used to model the system.

4-1. The Fuzzy Logic

Fuzzy logic is a method used to formulate human knowledge, which can be divided into conscious and unconscious knowledge. Conscious knowledge can be expressed in words, while unconscious knowledge is known only to experts who possess the information on how to perform a task but cannot articulate it in words. Fuzzy logic was introduced by Zadeh in 1965 and is widely used in decision-making, decision-control, and decision-prediction systems to describe uncertain and unspecified phenomena [48].

In the fuzzy logic method, the expert can express conscious knowledge using a set of defined fuzzy rules and transform it into a fuzzy format. However, with unconscious knowledge, the expert knows what task should be done, but cannot express it in the form of an instruction describing how the task can be done [18]. Unconscious knowledge can also be framed and modelled using the appropriate fuzzy logic method [48].

To formulate unconscious knowledge, the expert's performance is considered a black box, and input-output data pairs are created to model the behaviour of the system. Therefore, the unconscious knowledge of the person becomes a set of input-output pairs, with which a suitable fuzzy system can be built. For the system in question, the set of input data is $\left(x^i, g\left(x^i\right)\right)$ and the function defining the behavior of the system, i.e. $g(x)$, is unknown. A limited number of input-output pairs $\left(x^i, g\left(x^i\right)\right)$ is available, and the goal is to design a fuzzy system to construct a model for the unknown function $g(x)$ [49].

The Mamdani model is the most well-known method for building a fuzzy system, which includes a fuzzifier, rules, an inference engine, and a defuzzifier. This method converts input values into fuzzy sets through fuzzification, executes applicable rules from the fuzzy rules set, produces fuzzy outputs using the inputs and rules governing the fuzzy model, and finally defuzzifies the output fuzzy functions to obtain real output values [49]. The advantage of this approach is that the resulting model can then be used for similar cases. **Appendix C** in the supplementary material provides more details on the method of producing the fuzzy system.

4-2. Applying Fuzzy Model to Online Education

The scheme for applying the fuzzy system method to online education is depicted in **Figure 2**. To build a fuzzy model, a fuzzifier, fuzzy rules and product inference engine singleton, and centre average defuzzifier are employed [49]. Skill data collected from the desired course is used as "inputs". If the available input data is insufficient for properly modelling the system of interest, it is necessary to use a method to modify and optimize the structure of the fuzzy model over time.

As illustrated in Figure 2, the components of the fuzzy model that can be improved using an optimization algorithm include a fuzzifier, rules, and defuzzifier. The optimization algorithm modifies these components by utilizing the inputs and outputs of the fuzzy model as well as real test data. Once the optimal state is reached, a new educational program can be designed and applied for the course based on the obtained model. The learning level of students can be assessed and analysed based on the output results.

The fuzzy model initially obtained based on the test data is approximate and requires modification and optimization over time by using the results of the model's efficiency at the end of each academic semester. The fuzzy model obtained for the target system is solely a tool that determines the educational level based on inputs and is practically unable to improve the results by itself. Therefore, an algorithm that changes each of the obtained parameters in the model is needed to optimize the results. For this purpose, the genetic algorithm is used [50].

5. Results

In this section, we present the results of implementing our proposed model for online teaching of a Physics course using the employed educational tools. Subsequently, we optimize the degree of use for these educational tools to increase the level of students' learning. To achieve this goal, we first use the existing skill data for this course as a test dataset to obtain the optimal model. We then apply the obtained optimized values for the educational tools during an educational semester. Finally, we statistically analyse the results of the proposed model's implementation.

5-1. The Fuzzy Model for Online Teaching of a Physics Course

The production of the desired fuzzy model involves following several steps [18,46,47]. In the first step, we define fuzzy sets to cover input and output fuzzy spaces. To form input-output pairs, data related to educational semesters are required. The data was collected experimentally from the LMS at the University of Tehran and is presented in **Appendix A**, in the supplementary material**.**

We consider the number of input fuzzy sets to be three, i.e. $A_i = \{A_i^j\}$ for $i = 3$. The input fuzzy sets comprise three educational tools: live online classes (on the Adobe Connect platform), educational videos, and tests. The index j represents the number of times the fuzzy set i has been used during an educational semester. The range of j for three input fuzzy sets, based on the available data are: Online Classes $= \{1,...,28\}$, Films $= \{1,...,33\}$, and Exams $= \{1,...,13\}$. The maximum values in the aforementioned fuzzy sets indicate the maximum number of online classes conducted during the semester, number of educational videos used, and number of tests administered during the semester.

Furthermore, three output fuzzy sets are considered to specify three levels of learning. To determine these levels, students' final scores obtained from four consecutive semesters of teaching Physics courses are used. To evaluate the quality of education in each class, it is necessary to calculate the educational level of that class based on the available assessment information. For this purpose, statistical parameters related to students' scores at the end of each semester are used to examine the atmosphere governing the problem and evaluate the validity of the data and resulting educational levels. Details about the analysis of scores for the levels of learning are provided in **Appendix B**, in the supplementary material. Based on the analysis of the available final scores for Physics, the range of scores for the level of learning is considered to be **Level 1:** $10 \le n < 12$**,** **Level 2:** $12 \le n \le 15$**,** and **Level 3:** $15 \le n \le 20$**.**

As the next step, we define an IF-THEN rule for each input-output pair and assign a degree of membership for each rule given by $\mu_{A_i^j}(x)$. As shown in **Equation(1),** the rules are defined as:

IF Adobe is $A_1^{j_1}$ and Film is $A_2^{j_2}$ and Exam is $A_3^{j_3}$, $THEN$ the output is B

where,

$$
\begin{gathered}
j_1 = \{1, \ldots, 28\}, \\
j_2 = \{1, \ldots, 33\}, \\
j_3 = \{1, \ldots, 13\}, \\
B = \{Level1, Level2, Level3\}
\end{gathered} \tag{1}
$$

Figure 3 shows the plots obtained for the range of membership functions for the input and output fuzzy sets. After the defuzzifier step, the $f(x)$ fuzzy system model is built based on the obtained values. The calculations and construction of the $f(x)$ model function was performed using MATLAB software. The $f(x)$ model function is obtained based on the following equation:

$$
f(x) = \frac{\sum_{j_1=1}^{N_1} \sum_{j_2=1}^{N_2} y^{-j_1 j_2} (\mu_{A_1^{j_1}}(x_1) \mu_{A_2^{j_2}}(x2))}{\sum_{j_1=1}^{N_1} \sum_{j_2=1}^{N_2} (\mu_{A_1^{j_1}}(x_1) \mu_{A_2^{j_2}}(x2))} \tag{2}
$$

As shown in **Equation(2),** the fuzzy-made function $f(x)$ is a polynomial function of three parameters, namely online classes, educational videos, and tests. The coefficient associated with each parameter determines the percentage of its contribution to the students' learning level. The next step involves optimizing the coefficients of these parameters using the Genetic algorithm to achieve the highest level of learning.

The function $f(x)$ is sensitive to changes in the parameters and conditions of the fuzzy model. Specifically, it is sensitive to: 1. input variability: modifications in the number of online classes, educational videos, or tests influence the degrees of membership assigned to each input variable. This, in turn, alters the output learning levels calculated by $f(x)$, 2. fuzzy set definitions: adjusting the definitions or ranges of the fuzzy sets can impact the membership functions, leading to different output levels. For instance, if we redefine the thresholds for what constitutes a “high” or “low” learning level, the resulting $f(x)$ will reflect these changes. 3. optimization of coefficients: the coefficients associated with each parameter in $f(x)$ can be optimized using algorithms such as the Genetic Algorithm. This optimization process aims to maximize the learning level outputs based on the input parameters.

5-2. Optimization of the Fuzzy Function $f(x)$ with the Help of Genetic Algorithm

Optimization is achieved using the Genetic algorithm, with settings such as population size and number of repetitions [19]. MATLAB software is used for optimization, with the population size increased from 200 to 1000 and the number of repetitions from 100 to 1200. After several repetitions of $f(x)$ function simulation, the values of the function in the output remained constant, and there was no change in the values. As a result, optimized values for the target training parameters were obtained. Details of optimization calculations are provided in **Appendix C**, in the supplementary material.

Table 1 presents the results obtained after the optimization operation. The first row shows the optimization results for the required number of online classes, educational videos, and exams to increase the level of learning. According to several implementations of the educational JSG-Learn model, applicable values are found to be within the range shown in the second row of the table. Therefore, 24 to 26 sessions of online classes, 22 to 25 educational videos, and 9 to 11 exams are recommended for online teaching of the Physics course.

The optimized values resulting from the optimization process, as presented in Table 1, were implemented for one academic semester in two Physics classrooms with the same syllabus and instructor, to test the JSG-Learn educational model. The following section presents the results of the implementation of the educational model and the assessment and comparison of the results before and after applying the proposed model.

5-3. Statistical Analysis and Comparison of Student Performance Before and After Implementation of the Proposed Optimal Model for the Physics Course

In this section, we assess the results obtained by the implementation of the optimized values and compare them with the results before their application.

Table 2 presents the results associated with learning levels, obtained through statistical analysis, before and after the implementation of the proposed JSG-Learn model. Prior to the model's implementation, data were collected on the final scores of engineering students in six classrooms over three consecutive semesters, where all classes were taught by the same instructor and had similar teaching methods and syllabi. The learning level achieved in each classroom was assessed using the three levels given in Equation 2, which were obtained through initial data analysis and used as the output of the fuzzy model. Weak, mean, and strong performance of students were represented by $Level1, Level2,$ and $Level3$, respectively.

The results in Table 2 indicate that prior to applying the proposed model, one class had weak performance, three classes had average performance, and two classes had strong performance. After applying the model, all classes achieved $Level3$ performance. Important insights can be gleaned from the results of Table 2, which will be discussed in the following section

To further analyse the results of the JSG-Learn model implementation, we conducted statistical analysis using SPSS software. Two groups of students, consisting of 152 individuals, were considered for this analysis. The first group, referred to as the control group, received online training prior to the implementation of the proposed JSG-Learn model. The second group, referred to as the target group, received online training after the implementation of the proposed model. In this analysis, the independent variable was the educational method, while the dependent variable was the scores obtained after the implementation of the JSG-Learn model. Additionally, we considered scores from the pre-test stage and before the implementation of the educational model as a covariate variable. The results of this analysis are presented in **Table 3**.

Table 3 presents the teaching method used in the Physics classrooms, including the mean, standard deviation, and number of students. A comparison between the mean values associated with the two methods shows that after applying the JSG-Learn model, the mean scores increased by almost 2 points compared to the scores achieved before the application of the model. However, the value of the standard deviation remained almost the same.

Furthermore, **Figure 4** illustrates the distribution of students' scores before and after the implementation of the proposed JSG-Learn model and the resulting academic achievement. A comparison between the two graphs reveals that after the implementation of the JSG-Learn educational model, 60 students reached learning $Level3$, whereas only 31 students reached $Level3$ in the graph describing the scores before the implementation of the model. These results indicate that the learning level has doubled, and the mean scores have significantly increased.

Moreover, it is apparent that the distribution of scores after running the model is less skewed than the distribution of scores before running the model. In other words, the scores have a more balanced distribution, which is more desirable. Details of the meta-analysis of training data before and after the implementation of the JSG-Learn platform are provided in **Appendix D**, in the supplementary material.

6. Discussion

According to the results for the optimization of the educational model presented in Table 1 and also the results of applying the JSG-Learn model for the course of Physics presented in Table 2, some important points can be deduced. In this section, we will first discuss the important points extracted from Table 1 and then present the important points from Table 2.

In Table 1, the number of exams obtained from our proposed model is from a minimum 9 to a maximum 11. On the other hand, the syllabus of the Physics course consists of 11 chapters. Hence, to increase the student's learning level, it is necessary to take a test from students after completing each chapter, so that their learning rate is measured. Although one can speculate that taking more tests would be beneficial for students learning, our interest is on the optimal value of the number of tests, for which less time and energy are taken from both instructor and students.

Moreover, during an academic semester, 32 sessions are planned for teaching Physics. After analysing the data obtained for the number of online sessions, it is concluded that holding a maximum of 26 online sessions during the semester is enough for optimal teaching, provided that educational videos are used as supplementary resources for teaching the content. On average, two educational videos should be considered for each chapter. However, the number of videos assigned may vary depending on the difficulty level of each chapter. For easier chapters, one educational video can be assigned, while three educational videos can be assigned for more difficult chapters. These conclusions were reached after comparing the range of values obtained for the number of educational videos with the number of chapters.

From Table 2, it can be seen that the mean values for the winter semester classes in 2019 and 2020, which are both considered the main semesters for the Physics course, are at $levels$ 2 and 3, while the mean scores for the fall semester classes of 2020 and 2021, which are considered as the second semester for the desired course of Physics, are located in $levels$ 1 and 2. This point shows that students performed better in the main semester than in the second semester.

In winter semesters, most of the students who are taking Physics are in the first year of their studies. Hence, according to the university's established educational program, they have taken this course in the second semester of their studies, while this is not the case for fall semesters. Most of the fall semester students are those who have retaken the course, or have taken the course in the last year of their studies, since this course is not a prerequisite for any other courses, in their field of study. Therefore, either they are weak in physics or they do not consider it a priority course and do not have the necessary motivation to study the course seriously.

Another important point that can be inferred from Table 2, by comparing the results before and after the implementation of the proposed model, is the significant increase in the mean scores of the classes, and the placement of both classes of the fall semester 2021, at learning $level$ 3. These results were obtained in the fall semester, which is the semester when most students have lower performance. Compared to the previous fall semester (before the implementation of the JSG-Learn model), the class mean score has increased from 11.60 and 12.12 to 15.46 and 16.33; the mean score increments by 4 to 5 points indicating the successful performance of our proposed model. Also, the number of students who reached the highest learning level improved from 31 students in the old method to 60 students after the implementation of the proposed model.

The mean score of one class is higher than the other class in each academic semester, while the conditions for each class were completely the same during the semester. This is due to the difference in the statistical distribution of different engineering fields in the two classes. The analysis of the effect of the field of study on the results is not considered here in this paper and will be discussed in another paper.

Overall, the study's findings indicate that the implementation of the JSG-Learn platform has been successful, leading to academic progress in the teaching process of Physics 2. The proposed model has the potential to enhance student learning outcomes and improve the quality of online education.

7. Conclusion

The JSG-Learn model proposed in this research study is a valuable tool for educators seeking to improve their online teaching practices. The model has been proven effective in improving students' academic achievement in online Physics classes, as evidenced by a significant increase in mean scores and the number of students who reached the highest learning level. This study aimed to find optimal values for the LMS educational tools that would be less time and energy-consuming for both parties. Practical recommendations for other educators include using the JSG-Learn model, following the flowchart provided in the study.

The JSG-Learn model holds promise for adaptation to practical and experimental settings. By incorporating specific modifications—such as refining feature extraction to include hands-on components, tailoring educational tools for practical environments, and customizing the optimization algorithm—the model can address the unique demands of experiential learning. While the potential for broader application is evident, it is essential to acknowledge the need for additional training for instructors to ensure the successful implementation and optimization of the LMS educational tools.

Furthermore, the JSG-model has potential applications across various academic disciplines, highlighting its adaptability. Regardless of discipline categories, all courses within each discipline fundamentally consist of theoretical, experimental, or practical (a blend of both) elements. The JSG-Learn model, primarily applied to Physics as a representative theoretical course, can be strategically modified for practical and experimental courses. Furthermore, many courses are common across global academic systems, suggesting that our model can be beneficial for diverse disciplines in various educational contexts worldwide [51-53].

Future research could explore the effectiveness of combining the JSG-Learn model with other optimization methods to further enhance student learning outcomes. Additionally, it would be valuable to investigate the impact of the JSG-Learn model on student motivation and engagement in online learning. Exploring innovative methods for optimizing online education, such as machine learning algorithms or artificial intelligence-based approaches, could also yield promising results [54, 55].

In addition, our study significantly contributes to the field of blended learning by providing a robust fuzzy model that evaluates the effectiveness of various educational tools, including those associated with both online and in-person learning environments. By incorporating a comprehensive range of input variables, our model captures the complexities of student engagement and learning outcomes, enabling educators to make informed decisions about instructional strategies. This approach not only optimizes blended learning experiences, but also facilitates personalized learning tailored to individual student needs. Furthermore, our findings pave the way for future research exploring the application of fuzzy logic in educational contexts, enhancing the overall effectiveness of blended learning environments. This model aligns with recent studies emphasizing the integration of diverse educational tools to foster improved learning outcomes and student satisfaction [56-58].

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Availability of data and materials

The supplementary material and the raw data used for some initial analyses can be accessed via the following DOI link: https://doi.org/10.6084/m9.figshare.26377735

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The supplementary data is available at:
file:///C:/Users/pc/Downloads/Supplementary%20material-revised.pdf

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List of Captions

Figure 1: The proposed JSG-Learn flowchart for optimizing online education. It shows the steps required to be taken to obtain an appropriate optimized model for any online education.

Figure 2: The scheme of online education, which comprises the fuzzy model and the e-learning steps. The fuzzy model consists of three components: fuzzifier, fuzzy rules and inference engine, and defuzzifier. An electronic learning plan is generated based on the output of the fuzzy model. The plan is then applied throughout one or more semesters, and the output results are obtained, analysed, and used as input to improve the fuzzy model.

Figure 3: Plots for the range of membership functions for the input fuzzy sets (adobe classes, films, and exams) and the output fuzzy set (students' score).

Figure 4: Distribution of students' scores in Physics before and after the implementation of the JSG-Learn model. The diagram compares the number of students achieving each learning level.

Table 1. The optimal values of the three educational tools, used for the Physics course, based on the proposed JSG-Learn model.

Table 2. Results from the analysis of students' scores and determination of learning level, before and after implementation of the proposed JSG-Learn optimal model for 4 academic semesters from 2019 to 2021.

Table 3. Mean and standard deviation of pre-test and post-test scores before and after applying the proposed JSG-Learn model for the academic semester of 2023-2024. The control group received online training prior to model implementation, while the target group received online training after implementation.

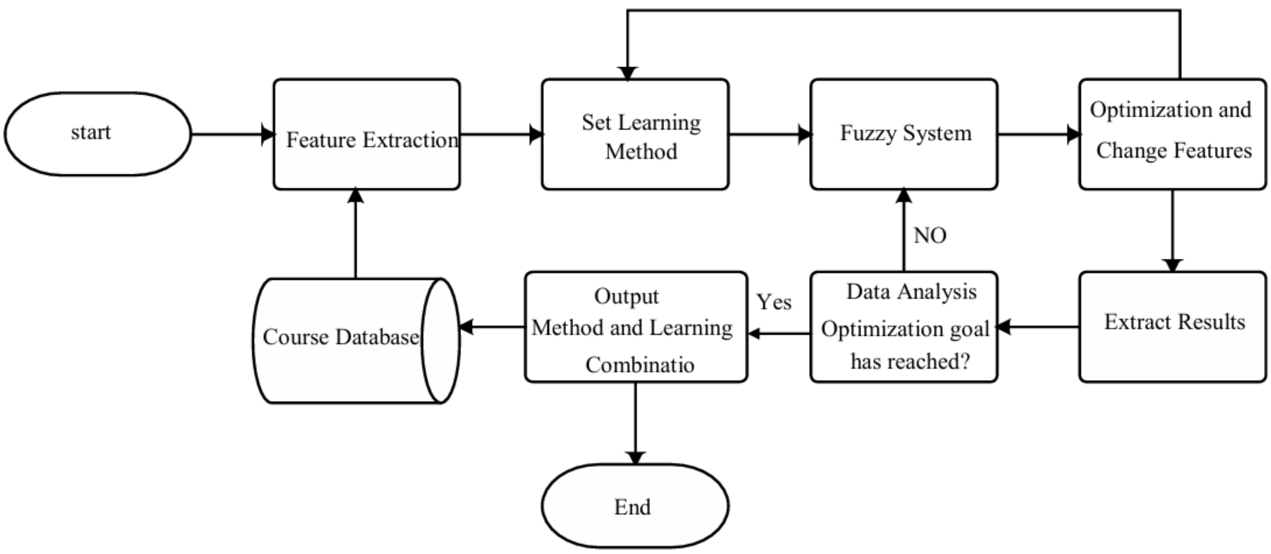
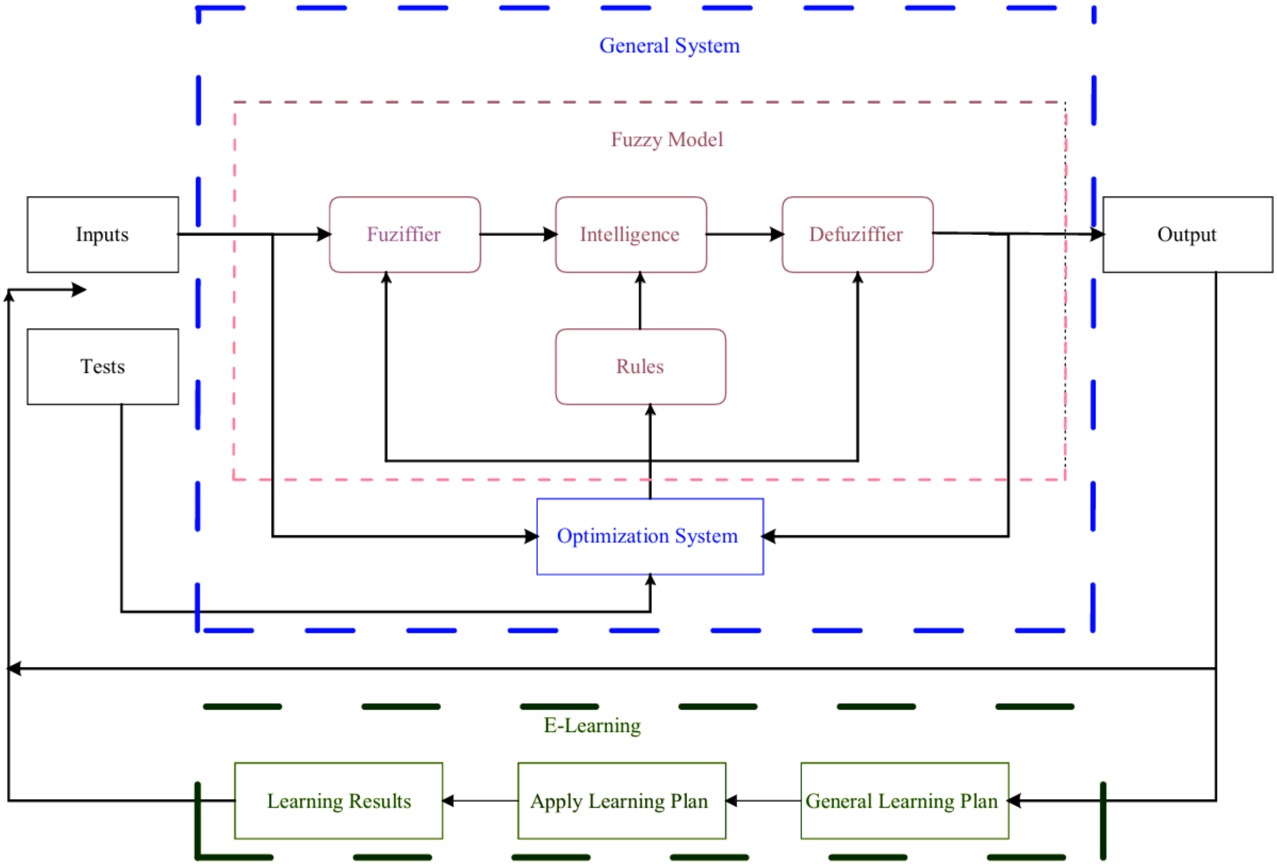


Figure 1


General System
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Output
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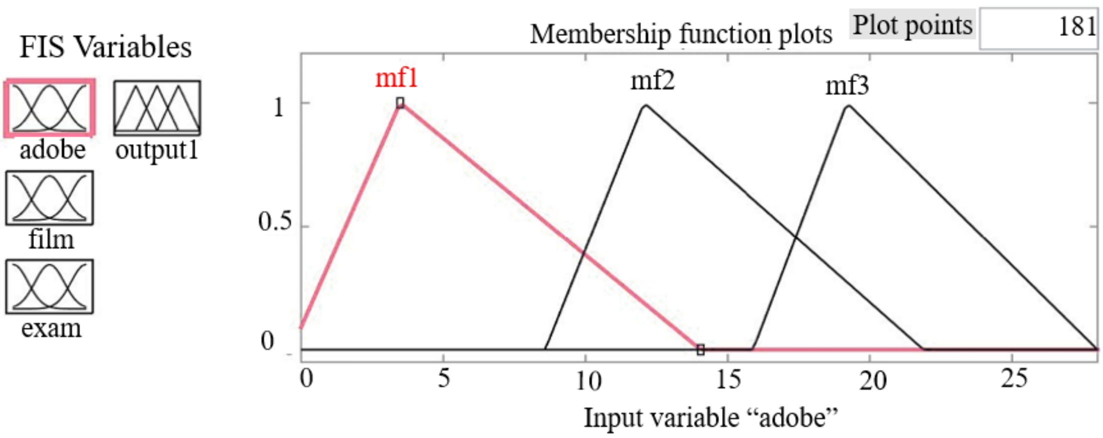
Rules
Optimization System
E-Learning
Learning Results
Apply Learning Plan
General Learning Plan

Figure 2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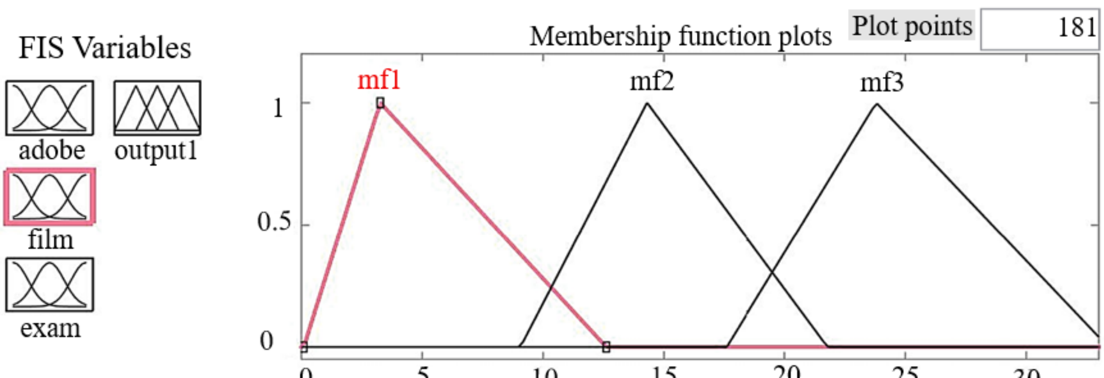
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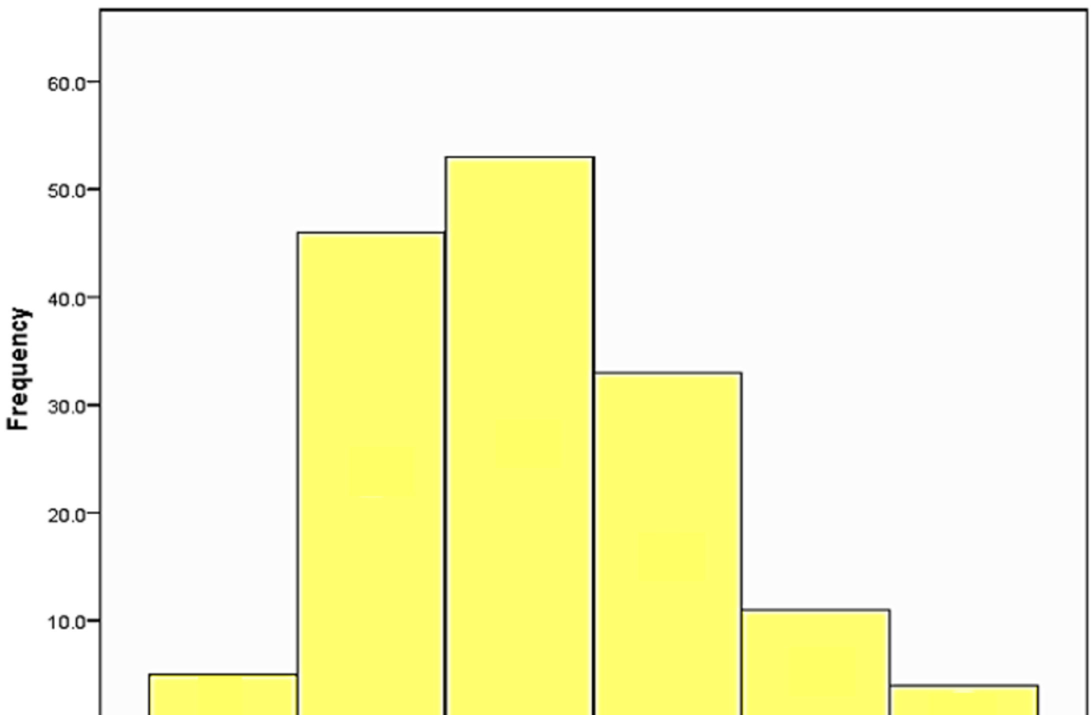
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Frequency

Table 1.

Variables	**Online Classes**	**Films**	**Exams**
Simulated values with the help of Genetic algorithm	25.6021	22.6511	10.3180
Applicable values based on the training JSG-Learn model	24-26	22-25	9-11

Table 2.

Class number	Semester	Number of students	The mean value of students' scores	Level of learning	
1	Winter 2019	73	15.531	3	Before implementation
2	Winter 2019	62	14.983	2	
1	Fall 2020	94	12.125	2	Before implementation
2	Fall 2020	95	11.602	1	
1	Winter 2020	83	15.573	3	Before implementation
2	Winter 2020	84	12.714	2	
1	Fall 2021	80	15.461	3	After implementation
2	Fall 2021	76	16.327	3	

Table 3.

Descriptive Statistics			
Method	**Mean**	**Std. Deviation**	**N**
New platform (JSG-Learn)	14.8816	2.19639	76
The old method	12.9474	2.31708	76

Authors Biography

Mrs. Delara Jafari is a PhD candidate at the University of Tehran. She is also a faculty member at Farhangian University for over 20 years. Mrs. Jafari's PhD research project is about the optimization of educational tools for effective teaching and learning.

Dr. Zahra Shaterzadeh-Yazdi is a faculty member in the College of Engineering, at the University of Tehran. With nearly 20 years of experience in education, she has dedicated her career to teaching a diverse array of engineering students. In addition to her other research interests and expertise, Dr. Shaterzadeh-Yazdi is passionate about enhancing educational methodologies, with a particular focus on optimizing the teaching-learning process.

Dr. Amin Ghodousian is a faculty member in the College of Engineering, at the University of Tehran, specializing in optimization and fuzzy systems. Since beginning his academic career, he has made significant contributions to the field, with his first publication dating back to 2006. Dr. Ghodousian has an H-index of 12 and has garnered 695 citations, reflecting the impact of his research within the academic community. He is dedicated to educating engineering students, teaching a variety of mathematics-related courses.