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

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Appendix A: Collecting instructors' skill data to construct the model

Educational data is necessary for use in system modelling in the fuzzy part. The collection of skill data including (online classes, examinations, and educational videos) has been done from the learning management system, with the help of Physics professors for 4 consecutive semesters from 2019 to 2020 **(Tables A.1 and A.2)**. These data make the inputs of the desired fuzzy system. The collection of final scores of the Physics course was done through the educational system of the University of Tehran, known as the Golestan system. These scores are related to the outputs of the fuzzy system. Previously, in Section 3, we introduced how to model the system with the help of fuzzification. Also, it is necessary to determine the level of the final scores and analyse the scores of the Physics course.

Table A.1: Educational information of the Physics course, in terms of the instructors. The columns show the number of Adobe online classes, the number of educational videos, and tests given during the semester. The rows represent the selected course instructors and the semesters.

Term	Adobe Connect	Films	Exams
Winter 2019	16	33	7
Fall 2020	-	-	-
Winter 2020	20	31	13
Winter 2019	26	0	7

Fall 2020	26	26	4
Winter 2020	14	26	3
Winter 2019	24	5	5
Fall 2020	28	0	9
Winter 2020	20	16	9

Table A.2: The table shows the sum of educational information for three Physics instructors.

Term	Adobe Connect	Films	Exams
Winter 2019	66	38	19
Fall 2020	54	26	13
Winter 2020	54	73	25
Total	174	137	57

Appendix B: Determining students' learning level using statistical data

The statistical parameters that are necessary to evaluate the scores for use in the construction of the fuzzy model are mean, standard deviation, median, and the percentage of students' scores above 10 (out of a maximum score of 20). A low mean value can indicate poor educational quality and a high mean indicates good educational quality, provided that the standard deviation and median values are also reasonable. The standard deviation shows how far the data is from the mean value. The small value of the standard deviation indicates that the data has little dispersion. The low dispersion and over-concentration of students' scores show that exams are not a good criterion for distinguishing students' learning and have resulted in most students to get low or high scores. This shows that the existing scores are not reliable and are not very useful in the process of assessing the educational level. On the other hand, the high value of the standard deviation shows that the dispersion of scores is high, which shows that the exams and evaluations have been successful in distinguishing the students' learning level.

Therefore, to determine the level of educational quality, it is important to have a reasonable standard deviation for the set of scores, in addition to a high mean.

In addition to the mean and standard deviation, another characteristic necessary to evaluate the quality of statistical data is the median value. The median indicates the skewness of the data to the right or left. A high mean along with a low median value indicates that we have a lot of outlier data that caused the mean to increase if the majority of the statistical population have got lower scores. Therefore, the best statistical results that can be obtained from students' scores are achieved when we have a high mean as well as a high median for the set of scores.

Of course, in order to increase the quality of education, we expect that the educational combination used during the semester will increase the mean scores. Therefore, it can be concluded that the mean standard deviation is the best state on the one hand, it shows the effectiveness of the educational combination and on the other hand, it shows the acceptability of the data.

The parameters mentioned above are general statistical parameters. In this research, the score of 10 (out of a maximum score of 20) is of particular importance, because it is the borderline between passing the course and not passing the course. Therefore, for logical analysis of statistical data, it is better to consider this parameter as well. A very high percentage of scores greater than 10 may indicate the ease of the tests as well as the evaluation criteria. On the other hand, the low percentage indicates the difficulty of the evaluation method and the high level of the tests; in both cases the results are less reliable.

B.1 Fuzzy model conditions for determining educational levels using statistical parameters at the input

To build a fuzzy model, the input parameters must be phased based on logical analysis. With logical analysis, the phases related to each of the parameters can be considered as

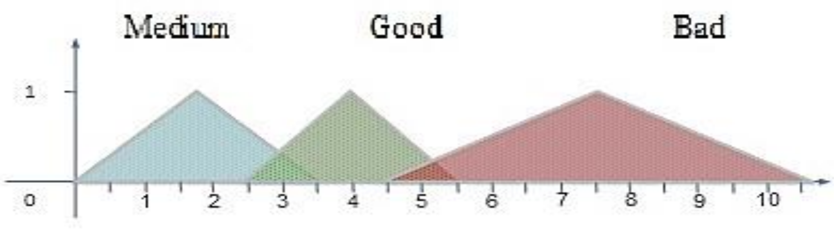

Figure B.1: Different phases of standard deviation input for three levels: good, bad, and medium.

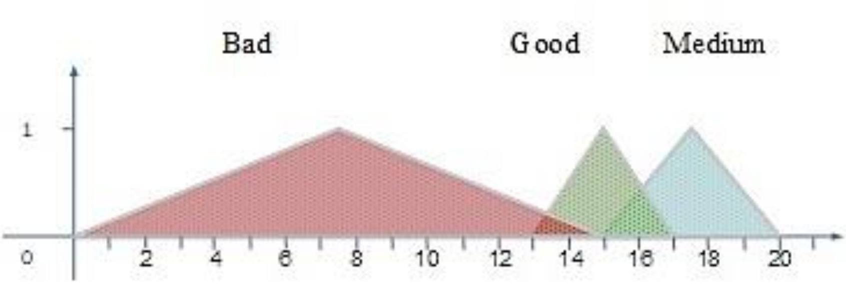

Figure B.2: Different phases of averaging input with three levels of good, bad, and medium

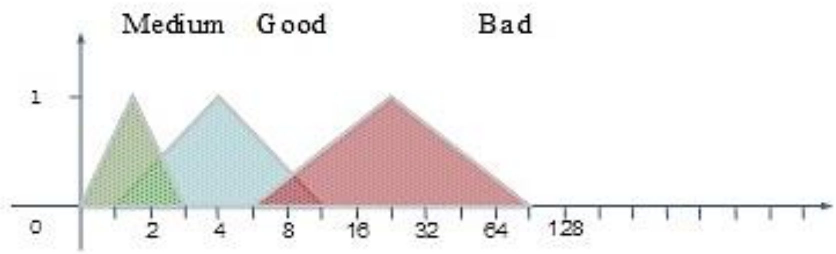

Figure B.3: Different phases of mean input with three good, bad and medium levels

follows. The lower limit and upper limit of the standard deviation for scores from 0 to 20 are 0 and about 11, respectively. The upper limit is reached when half of the students get a score of 20 and the other half get a score of 0, the probability of which is practically zero. The standard deviation can be divided into three parts: the first phase (between 0 and 3), which indicates the accumulation of scores around a point; the second phase (the standard deviation between 3 and 5), which indicates a reasonable dispersion of the data; and the third phase (between 5 and 11), which shows the high dispersion of scores. These three phases should also have overlap, and the intervals can be considered from 0 to 3.5, from 2.5 to 5.5, and from 4.5 to 11. **Figure B.1** shows the different input phases of standard deviation.

Mean can take any numbers between 0 and 20. The mean between 0 and 14 indicates the weak scores and the mean between 16 and 20 indicates the simplicity of the exams and the professor's assessment method. Therefore, three different phases for this parameter can be shown as follows. **Figure B.2** shows the different phases of the mean input. The phases related to the median can also be done in the same way.

Based on the survey that we had from the percentage of scores above 10, the phases of this parameter can be considered as logarithmic percentages so that the phases can be better defined. The figure below shows the phases of this parameter with logarithmic steps. **Figure B.3** shows different input phases of standard deviation.

Appendix C: Fuzzification and optimization

C.1 Fuzzy system construction method

In the fuzzification stage, a number of fuzzy sets are defined and then the input values of the target system are assigned to fuzzy sets with a certain degree of membership, which can have any value between 0 and 1. A membership degree of 0 (zero) means that value does not belong to the target fuzzy set. A membership degree of 1 (one) means that the value belongs to the target fuzzy set). These fuzzy sets are usually explained in words.

In this scaling, the three logical values are attributed to each final score in the course; these values indicate with what degree of membership that score is in each of the three fuzzy sets. According to **Figure C.1**, according to the degree of membership that can be considered for each final score, fuzzy sets are often defined by triangular or trapezoidal shapes.

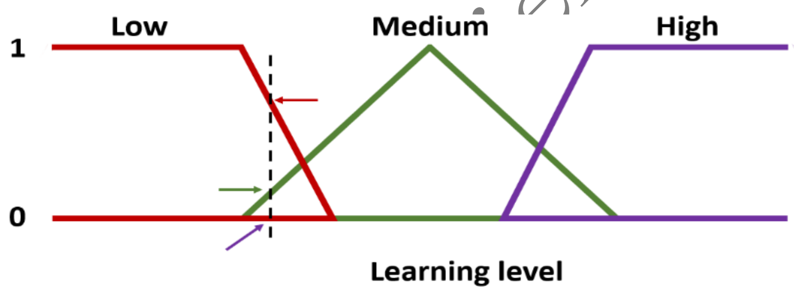

Figure C.1: lesson based on the learning level scale, the fuzzy sets can be considered as three learning levels: "low", "medium" and "high".

In Figure C.1, the dotted vertical line represents a specific score (e.g. score 11 out of 20) and three arrows show the logical value of this score in each of the three fuzzy sets. The purple arrow points to the logical value of zero for the desired score in the fuzzy set attributed to the "high" learning level and indicates that this score does not have a place in the high learning level. The green arrow, which points to approximately 0.2, indicates that this score with a membership degree of 20% belongs to the "medium" fuzzy set, and the red arrow, which indicates approximately 0.7, indicates that the score with a membership degree of 70% belongs to the fuzzy set attributed to the "down" the learning level.

Fuzzy rules are IF-THEN rules that relate the calculated input logic values to the output logic values. In other words, assuming that the fuzzy sets with $A_j = \{A_j^1, A_j^2, \dots A_j^i, \dots, A_j^{N_i}\}$, where $j = \{1, 2, \dots, n\}$ represents the number of defined fuzzy sets and $i = \{1, 2, \dots, N\_i\}$ represents the number of logical input values in each fuzzy set, then the result is an output logical value in $\{B\}$ fuzzy sets:

$$RU^{i_1 i_2}: IF\ x_1\ is\ A_1^{i_1}\ and\ x_2\ is\ A_2^{i_2}, THEN\ y\ is\ B^{i_1 i_2} \qquad (C.1)$$

The total number of definable IF-THEN rules is $M = N_1 \times N_2 \times \dots \times N_i$. For example, assuming that two fuzzy sets $A_1$and A_2 are defined, for the logical values x_1 and x_2 that are in these two sets respectively, the following rule can be written that $B^{i_1 i_2}$ is the logical output value [18].

Usually, the number of generated input-output pairs is large, and considering that each pair creates a rule, it is possible that during the creation of rules, conflicting rules will arise, that is, rules that have the same IF but different THEN. To resolve this conflict, a membership degree can be obtained for each of the rules created in the group of conflicting rules by using the following formula where the coefficients μ represent the degree of membership of the input fuzzy sets A^{ij*} and output B^{l*} and the sign " $*$ " indicates that the fuzzy set for the input (as well as the output) is considered that has the largest membership value.

$$D(rule) = \prod_{i=1}^{n} \mu_{A_i^{j*}(x_{0i}^p)\mu B^{L*}(y_0^p)} \qquad (C.2)$$

After determining the degree of membership for the rules in the group of contradictories rules, we keep only the rule with the highest degree and remove other weak and contradictory rules. In this way, the problem of rule contradiction is eliminated and the number of rules is greatly reduced [18].

In the last step, by implementing "de-fuzzification", we get a continuous function of fuzzy logical values. Since all logical output values are obtained discretely, a function should be chosen that has the best fit and coordination with the desired logical values. For this purpose, using the generated rule M, and product inference engine, singleton fuzzifier, centre average defuzzifier.

$$f(x)=\frac{\sum_{j_1=1}^{N_1}\sum_{j_2=1}^{N_2} y^{-j_1 j_2}(\mu_{A_1^{j_1}}(x_1)\mu_{A_2^{j_2}}(x_2))}{\sum_{j_1=1}^{N_1}\sum_{j_2=1}^{N_2}(\mu_{A_1^{j_1}}(x_1)\mu_{A_2^{j_2}}(x_2))} \qquad (C.3)$$

In this formula, $\mu_{A_j^{N_i}}$ is the degree of membership of each of the input data N_j in the fuzzy sets A_j, and $y^{-j_1 j_2}$ is the center of the fuzzy set B, $B^{j_1 j_2}$, which is equal to the value of the function $g(x)$ at the point $x=(e_1^{i_1}, e_2^{i_2})$. The values of $e_j^{i_{N_j}}$ are at the centers of fuzzy sets $A_j^{N_j}$.

Functions describing physical or social systems are differentiable and continuous, therefore, the function $g(x)$ is continuous and differentiable. Based on a theorem, it can be proved that the obtained function $f(x)$ can be approximated with any precision with respect to the unknown but continuous and differentiable function $g(x)$, and in other words, the obtained function $f(x)$ is universal. The fuzzy sets can be defined for the target system, and as a result, the more rules are defined, the more accurate fuzzy function $f(x)$ can be obtained for the target system. In the next section, we use the fuzzy system method to model online education.

A3-2 A Table look-up scheme for designing fuzzy systems from input-output pairs

In the current research, the model construction of the target system has been implemented with the help of fuzzy system design method using table look-up and input-output pairs. This method includes the following 5 steps [18]:

Step 1. Definition of fuzzy sets to cover input and output fuzzy spaces.

Step 2. Generating a rule for each input-output pair.

Step 3. Assign a score to each rule created in step 2.

Step 4. Creating a database of fuzzy rules

Step 5. Building a fuzzy system based on the database of fuzzy rules [18].

Below, some basic and noteworthy points about the above 5 steps are presented:

Unlike other methods, in which we should be able to determine the exact output function $g(x)$ for each input $x \in U$, in this method (fuzzy system design method using table look-up and input-output pairs), the input points cannot be freely chosen for an input-output pair an exit. Also, in this method, it is not necessary to know the information about the adverbs of the first and second derivatives of the obtained estimated function.

The number of rules in the final fuzzy rule base is limited by two values, which are N (the number of input-output pairs), and $\prod_{j=1}^{n} N_j$ is the number of all possible combined states of the phase sets defined for the input parameters. Of course, the number of rules in the database of the fuzzy system is much less than these two adverbial values N and $\prod_{j=1}^{n} N_j$.

A3-3 Optimization with the help of genetic algorithm

In this research, function $g(x)$ is the ultimate modelling function of our problem, and we approximate the function $g(x)$ to the function $f(x)$ [18]. This function is not defined at first. The function $f(x)$ is obtained after modelling and analysing the behaviour of the system. According to the input-outputs and fuzzy rule base of the model, the function of the desired model, i.e. the function $f(x)$, is obtained. The function $g(x)$ is a polynomial and we can optimize it with one of the optimization algorithms such as the genetic algorithm. Consequently, the appropriate model for optimizing online education resources is obtained.

The function's optimization has been administered by employing the genetic algorithm and with different populations and different number of repetitions. The final result of different executions is shown in Figures C.2 and C.3. By changing the population and the number of repetitions, no particular change in the output occurs, and again the same results are obtained in the output.

Figure C.2 is a graph showing the function value according to the number of repetitions. The graph shows that after several executions; the function values remain

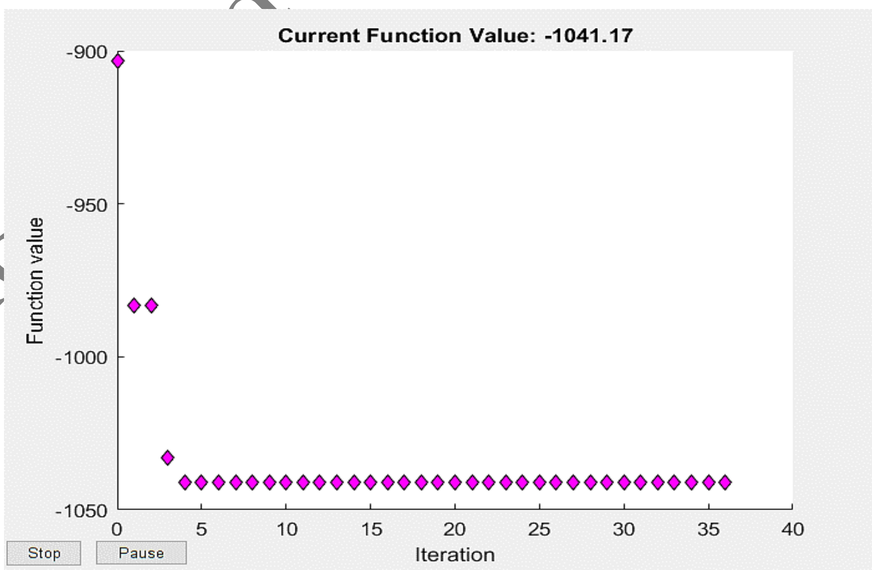

Figure C.2: The graph shows the values of the function $f(x)$ versus the number of iterations.

constant in the output and no change is seen in the output values. **Figure C.3** shows the fitness value of the function compared to the generated population. The best fitness value of the function is equal to -1041.17 and the mean fitness value is equal to -1041.1

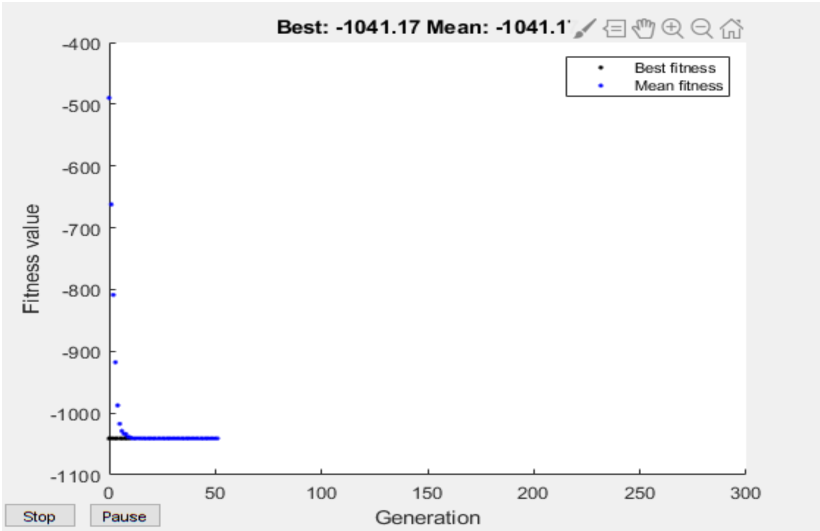

Figure C.3: The graph shows the fitness value of the function compared to the generated population.

Also, **Table C.1** shows the implementation of different types of population and number of optimization iterations.

Table C.1: Shows the value of the function relative to the number of iterations.

Number of iterations	Number of populations
100	200
300	300
500	500
1000	700
1200	1000

Appendix D:

D.1 Meta-analysis of educational data

Figure D.1 is the line graph and histogram of students' academic achievement in the course of Physics during 4 consecutive semesters, which was drawn with the help of SPSS software and using the data in the table.

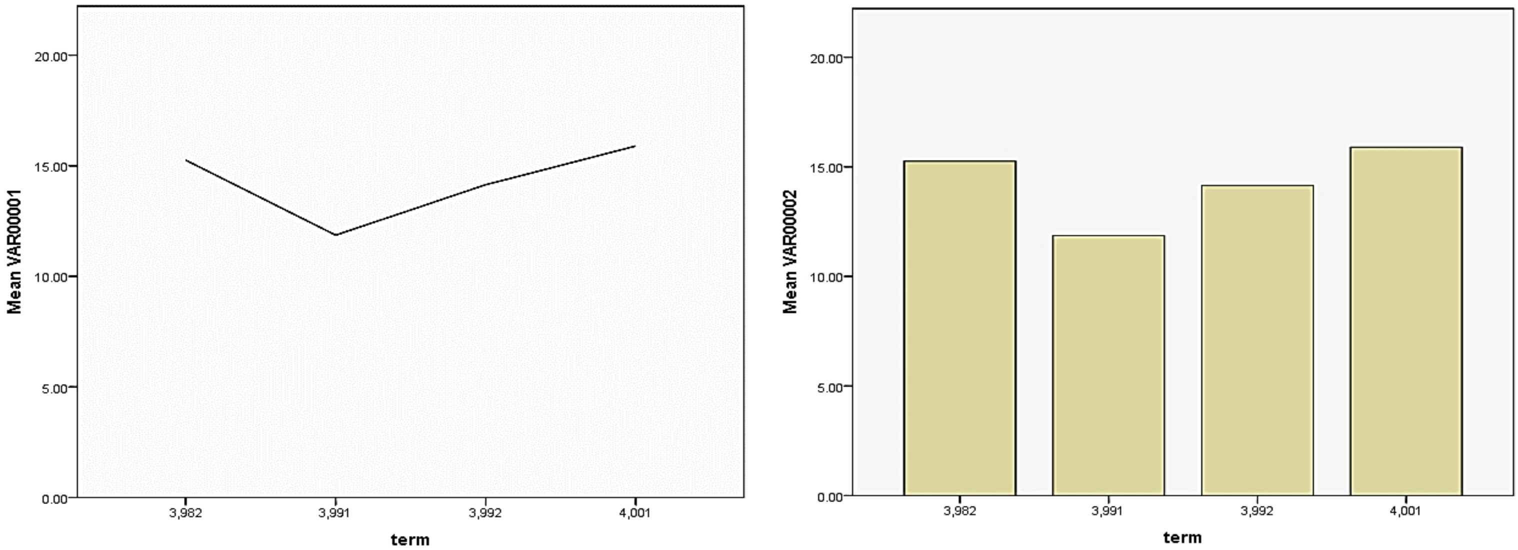

Figure D.1: Column and line graphs show the average academic achievement in the Physics course.

Figure D.2 shows the assessment of the proposed JSG-Learn model. The pretest and posttest charts are drawn with two methods before and after the model execution.

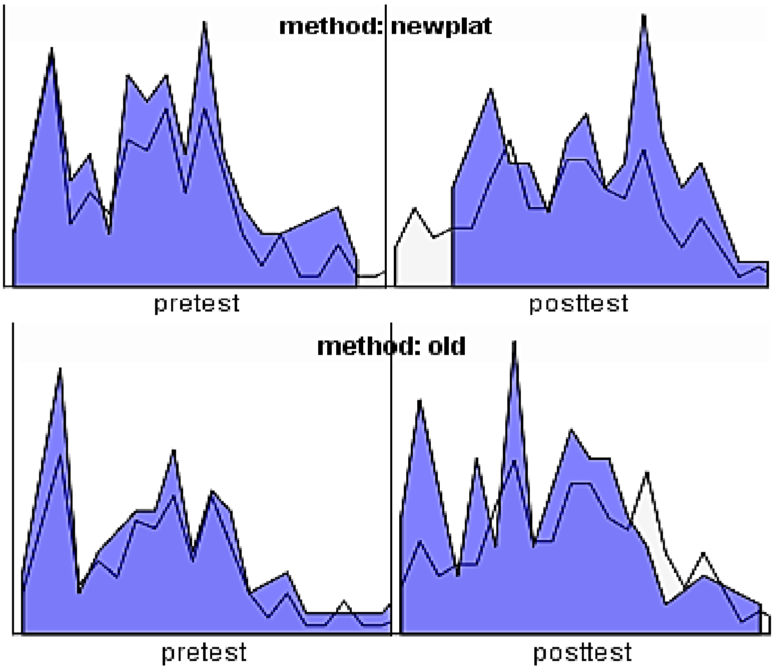

Figure D.2: Shows the assessment of the JSG-Learn online model. The “pretest” charts are before applying the proposed model and the “post-test” charts are associated with the result of applying the proposed model.

D.2 Inferential statistics

To perform statistical tests related to the mean of two or more populations, the statistical distribution of the test is determined by assuming that their variances are the same. In this research, we used univariate analysis. Therefore, before performing mean tests, the equality of variances in communities should be checked with the help of Levene's test.

Table D.1 Shows the Levene's test between variables.

Levene's Test of Equality of Error Variances[a]			
Dependent Variable: posttest			
F	df1	df2	Sig
139	1	150	710

Tests the null hypothesis that the error variance of the dependent variable is equal across groups
a Design: Intercept + method + pretest + method * pretest

The value of Sig, which is the p-value, is greater than the error level of the $\alpha = 0.05$ test, so the assumption of equal variance of the two populations is not rejected, and the results of Levene's test are meaningful here (**Table D.1**).

It can be seen that the mutual effect of the variables on each other in **Table D.2** is equal to method * pretest $= .757$ which is significant because it is greater than 0.05. It means that the interaction between the method and the post-test is significant. In particular, it can be said that it was due to the effect of the teaching method that the scores have changed.

Table D.2 Shows the two-way variance analysis of the variables.

Tests of Between-Subjects Effects								
Dependent Variable: posttest								
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	164.010[a]	3	54.670	10.895	.000	.181	32.686	.999
Intercept	1067.324	1	1067.324	212.709	.000	.590	212.709	1.000
method	7.008	1	7.008	1.397	.239	.009	1.397	.217
pretest	21.825	1	21.825	4.350	.039	.029	4.350	.545
method * pretest	.483	1	.483	.096	.757	.001	.096	.061
Error	742.628	148	5.018					
Total	30335.750	152						
Corrected Total	906.638	151						

Table D.3: Shows the variance analysis of the variables. In this table, one can see whether the independent variables and their interaction are statistically significant or not. This table shows the significant progress of the new method of the JSG-Learn educational model compared to the previous method.

Table D.3 Variance analysis of the variables

Tests of Between-Subjects Effects								
Dependent Variable: posttest								
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	163.527[a]	2	81.764	16.394	.000	.180	32.789	1.000
Intercept	1077.275	1	1077.275	216.003	.000	.592	216.003	1.000
pretest	21.363	1	21.363	4.283	.040	.028	4.283	.538
method	143.791	1	143.791	28.831	.000	.162	28.831	1.000
Error	743.111	149	4.987					
Total	30335.750	152						
Corrected Total	906.638	151						

Also, level of significance in Table D.3 are all smaller than 0.05 and acceptable. It means that there is a meaningful relationship between independent and dependent variables. The table emphasizes the positive effect of the proposed educational method on education.