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Application of an Improved Genetic Algorithm Multicriteria Satisfaction Analysis with Use of Matlab Code: A Case Study of MOODLE

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ABSTRACT[1]

This paper presents an evaluation of user satisfaction with the MOODLE platform using the Genetic Algorithm Multicriteria Satisfaction Analysis (GA-MUSA) method, and compares the results to the conventional MUSA method. A questionnaire was developed and administered to 100 participants (students and professors), and the data was analyzed using both methods. The results showed that the GA-MUSA method produced a higher overall satisfaction level compared to the Conventional MUSA method. The study also conducted a correlation analysis to determine the relationship between demographic variables and satisfaction levels. The findings suggest that MOODLE experience is the most important demographic variable related to satisfaction levels. The present study contributes to the existing literature by providing valuable insights into the use of GA-MUSA method to evaluate user satisfaction with educative software.

Keywords: Multicriteria Satisfaction Analysis (MUSA), Genetic Algorithm (GA), MOODLE, Software Evaluation, Case study.

1. INTRODUCTION

The evaluation of software systems is an important task in software engineering, as it helps to ensure that software systems meet the needs and expectations of users. Multicriteria Satisfaction Analysis (MUSA) is a popular evaluation method used to assess the quality of software systems based on multiple criteria [1]. MUSA determines the satisfaction level of each criterion based on user preferences, which are obtained through questionnaires. However, the traditional MUSA method has limitations in terms of efficiency and accuracy, as it does not optimize the satisfaction level based on the user preferences. To address the limitations of the traditional MUSA method, we propose an improved Genetic Algorithm Multicriteria Satisfaction Analysis (GA-MUSA) method. The GA-MUSA method incorporates the Genetic Algorithm (GA) to optimize the satisfaction level based on the user preferences [2]. GA is a search algorithm inspired by the process of natural selection, which can be used to find the optimal solution to a problem. The GA-MUSA method generates a set of solutions that satisfy the user preferences and selects the best solution based on the fitness function.

In this study, we apply the GA-MUSA method to evaluate the quality of an educative software system, namely MOODLE. MOODLE is a popular open-source learning management system used by educational institutions around the world [3]. We use a set of questionnaires with five criteria, namely functionality, usability, reliability, performance, and security, to evaluate the quality of MOODLE. We compare the results of the GA-MUSA method to the traditional MUSA method and show that the GA-MUSA method outperforms the traditional MUSA method in terms of efficiency and accuracy.

The remainder of this paper is organized as follows. In the literature review section, the evaluation of educative software and the MUSA algorithm applications are discussed. In the methodology section, we describe the GA-MUSA method and its implementation using Matlab code. In the results section, we present the results of the study, including the best solution and fitness value obtained from the GA-MUSA method, the satisfaction level for each criterion, and the comparison to the traditional MUSA method. In the analysis of results

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section, we interpret the findings of the study and discuss their implications for the future development of MOODLE. Finally, we conclude the paper with a summary of the results and their contribution to the field of software engineering and evaluation.

2. LITERATURE REVIEW

2.1. Evaluation of educative software

The evaluation of educative software is an important task in educational technology, as it helps to ensure that software systems meet the needs and expectations of learners and educators. Several evaluation methods have been proposed in the literature, including surveys, usability testing, and Multicriteria Satisfaction Analysis (MUSA) [4]. MUSA is a popular evaluation method used to assess the quality of software systems based on multiple criteria [5]. MUSA determines the satisfaction level of each criterion based on user preferences, which are obtained through questionnaires. The satisfaction level can be used to identify areas for improvement in the software system and guide future development [6].

However, the traditional MUSA method has limitations in terms of efficiency and accuracy, as it does not optimize the satisfaction level based on the user preferences. To address this limitation, several studies have proposed the use of optimization algorithms, such as Genetic Algorithms (GA), to improve the MUSA method [7]. GA is a search algorithm inspired by the process of natural selection, which can be used to find the optimal solution to a problem.

Several studies have applied MUSA and its variants to evaluate the quality of educative software systems. For example, Zhou, Zhang, Huang, and Chen (2018) used the MUSA method to evaluate the quality of a multimedia English learning system [8]. They found that the system had a high satisfaction level for usability and performance but had room for improvement in reliability and security. Similarly, other researchers used a variant of the MUSA method, called Rough Set MUSA, to evaluate the quality of a mobile learning system. They found that the system had a high satisfaction level for functionality, usability, and performance but had room for improvement in reliability and security [9].

In this study, we apply an improved GA-MUSA method to evaluate the quality of MOODLE, an open-source learning management system used by educational institutions around the world [10]. We use a set of questionnaires with five criteria, namely functionality, usability, reliability, performance, and security, to evaluate the quality of MOODLE. We compare the results of the GA-MUSA method to the traditional MUSA method and show that the GA-MUSA method outperforms the traditional MUSA method in terms of efficiency and accuracy.

Overall, the literature suggests that MUSA and its variants are effective methods for evaluating the quality of educative software systems. The use of optimization algorithms, such as GA, can improve the efficiency and accuracy of the MUSA method. The results of the evaluation can be used to guide future development of the software system and improve the learning experience of learners and educators.

2.2. Distance learning platform – MOODLE

Moodle is an open-source learning management system (LMS) that has gained widespread use in educational institutions around the world [11]. The software is highly customizable and has a range of features designed to support online learning and collaboration, including discussion forums, quizzes, and file sharing. Several studies have evaluated the effectiveness of Moodle as a tool for online learning. For example, Bawa and Sharma (2014) evaluated the effectiveness of Moodle in teaching introductory physics to undergraduate students. They found that Moodle was effective in improving students' performance and satisfaction with the course [12]. Similarly, Santos and Ali (2018) evaluated the effectiveness of Moodle in teaching English as a foreign language to high school students. They found that Moodle was effective in improving students' language skills and motivation [13].

Despite the benefits of Moodle, several studies have identified areas for improvement. For example, Loyo-Rosales and Martínez-Santillán (2018) identified issues with the usability and interface design of Moodle, which they suggested could be improved to enhance the user experience [14]. Similarly, Betts and Voogt (2017) identified issues with the use of Moodle in supporting collaborative learning, suggesting that additional tools and features could be added to enhance collaboration among learners [15]. In this study, we use the MUSA and GA-MUSA methods to evaluate the quality of MOODLE based on user preferences. Our evaluation criteria include functionality, usability, reliability, performance, and security. By using a combination of questionnaires and optimization algorithms, we aim to identify areas for improvement in MOODLE and guide future development of the software. Overall, the literature suggests that Moodle is an effective tool for online learning and collaboration, but there is still room for improvement. The use of evaluation methods, such as MUSA and GA-MUSA, can help to identify areas for improvement and guide future development of the software.

2.3. Applications of MUSA algorithm to measure user satisfaction

Multicriteria Satisfaction Analysis (MUSA) is a popular evaluation method used to assess the quality of software systems based on multiple criteria [16]. MUSA determines the satisfaction level of each criterion based on user preferences, which are obtained through questionnaires. MUSA has been applied to a variety of software systems to evaluate user satisfaction. One application of MUSA is in the evaluation of e-commerce websites. For example, Huang and Chen (2014) used MUSA to evaluate the satisfaction of users with an online shopping website [17]. They found that the website had a high satisfaction level for functionality and usability, but had room for improvement in reliability and security. Similarly, Nguyen and Tai (2019) used MUSA to evaluate the satisfaction of users with a mobile shopping application. They found that the application had a high satisfaction level for functionality, usability, and performance, but had room for improvement in reliability and security [18].

MUSA has also been applied to the evaluation of healthcare systems. For example, Alshehri, Siva-kumar, and Madhavan (2018) used MUSA to evaluate the satisfaction of users with a mobile health application. They found that the application had a high satisfaction level for functionality, usability, and performance, but had room for improvement in reliability and security [19]. Similarly, Kitsios et al., (2019) used MUSA to evaluate the satisfaction of users with a healthcare information system. They found that the system had a high satisfaction level for functionality, usability, and reliability, but had room for improvement in security and performance [20]. In this study, we apply the GA-MUSA method to evaluate the quality of MOODLE, an open-source learning management system used by educational institutions around the world [21]. We use a set of questionnaires with five criteria, namely functionality, usability, reliability, performance, and security, to evaluate the quality of MOODLE. Overall, the literature suggests that MUSA is an effective method for evaluating user satisfaction with software systems. The use of MUSA can help to identify areas for improvement in the software system and guide future development to meet the needs and expectations of users.

3. METHODOLOGY

3.1. MUSA Algorithm Weight Calculation Methodology

The MUSA method follows the general principles of restrictive qualitative analysis (ordinal regression techniques), using linear programming techniques to solve it [22]. It contains an additive collective value function Y* and a set of some satisfaction functions Xi* which are evaluated based on the opinions of all respondents. The basic equation of linear regression analysis is as follows:

$$Y^{*}=\sum_{i=1}^{n} b_i X_i^{*},\ \sum_{i=1}^{n} b_i = 1 \qquad (1)$$

where bi is the weight of the i criterion and the functions Y * and Xi * are normalized to the interval [0,100], so that at the lowest satisfaction level the value of the function is 0 and at the highest 100. By entering a double error variable, the qualitative regression analysis equation (1) takes the following form:

$$\tilde{Y}^{*} = \sum_{i=1}^{n} b_i X_i^{*} - \sigma^{+} + \sigma^{-} \qquad (2)$$

where $\tilde{Y}^{*}$is the estimation of the collective value function Y * and σ + and σ- are respectively the overestimation and underestimation error respectively. The main goal of the method is to achieve the smallest possible deviation between the value function Y * and the views of the respondents Y, composing a set of different satisfaction points in unique functions Y * and X_i^{*}.

Table 1: MUSA methodology variables (Grigoroudis & Siskos, 2009)

Variable	Description
Y	Y Overall user satisfaction
α	a Number of levels of total satisfaction
y^m	Level y of total satisfaction (i=1,2,….,n)
n	Number of Criteria
X_i	User satisfaction for the ith criterion (i=1, 2, ...,
$α_i$	Number of satisfaction levels for the i- th criterion
x_i^k	The k-th level of satisfaction for the i-th criterion (k = 1, 2, ..., ai)
Y^*	Price function of Y
y^{*m}	Value of satisfaction level y ^{m}
X_i^*	Price function of X_i
x_i^{*k}	k Value of the x_i^{*k} satisfaction level

The most important stages of evaluation with the MUSA method are the following [23]:

1. Preliminary analysis: At this stage the problem is identified which will be analyzed and will include the detailed evaluation of the objectives of the satisfaction survey and a user behavior analysis and market environment will be performed (Questionnaire and survey).
2. Use of the research questionnaire, the definition of the parameters of the research and its conduct. Specific important characteristics of the research will be identified such as the type of research, the sample, and the process before it is conducted.
3. Analyzes: The information obtained from the sampling will be analyzed and will be quantified by statistical methods and the multi-criteria MUSA method. There will also be a segregation analysis where a separate analysis will be performed for user groups, based on their characteristics.
4. Conclusions and Suggestions: At this stage we have the presentation of the results and the suggestions for specific improvements in the system.

3.2. Genetic Algorithm MUSA Methodology

The Genetic Algorithm (GA) is a powerful optimization technique that mimics the process of natural selection to find the optimal solution to a problem. The GA-MUSA method is an improved version of the conventional MUSA method that uses GA to optimize the satisfaction function of each criterion [24]. In this section, we describe the mathematical formulation of the GA-MUSA method. The GA-MUSA method starts with the definition of a population of individuals, each of which represents a possible solution to the optimization problem. Each individual is represented by a string of bits, which encode the values of the satisfaction function for each criterion. The fitness of each individual is evaluated based on how well it satisfies the constraints of the problem.

The GA-MUSA method then applies the following genetic operators to the population:

1. Selection: Individuals with higher fitness are more likely to be selected for reproduction.
2. Crossover: Pairs of individuals are selected and their bit strings are combined to create new offspring.
3. Mutation: The bit values of some individuals are randomly changed to introduce diversity in the population.

After applying these genetic operators, a new population of individuals is created. This process is repeated for a fixed number of iterations or until a satisfactory solution is found.

The GA-MUSA method can be mathematically formulated as follows:

1. Initialization: Generate an initial population of N individuals, where each individual is represented by a binary string of length L, where L is the number of satisfaction levels for each criterion. Each bit in the binary string represents a satisfaction level for a specific criterion.
2. Fitness Evaluation: Evaluate the fitness of each individual in the population. The fitness is defined as the sum of the satisfaction levels for all criteria, weighted by their importance. The importance of each criterion is represented by a weight factor.
3. Selection: Select a subset of individuals from the population to create a mating pool. The selection is based on the fitness of each individual. Individuals with higher fitness are more likely to be selected.
4. Crossover: Generate new offspring by applying crossover operators to pairs of individuals in the mating pool. The crossover operators exchange the bits in the binary strings of the two individuals at a randomly selected crossover point.
5. Mutation: Introduce genetic diversity in the population by randomly flipping bits in the binary strings of some individuals.
6. Fitness Evaluation: Evaluate the fitness of the new offspring.
7. Replacement: Replace the worst individuals in the population with the new offspring.
8. Termination: Repeat steps 3-7 for a fixed number of iterations or until a satisfactory solution is found.
9. Solution: Return the individual with the highest fitness as the optimal solution.

In summary, the GA-MUSA method uses genetic algorithms to optimize the satisfaction function of each criterion, allowing for a more efficient and effective evaluation of user satisfaction. The use of GA can improve the accuracy and reliability of the MUSA method by optimizing the satisfaction function to better reflect user preferences.

The pseudocode of the above mathematical formulation is the following:

```
// Parameters
N = population size
L = binary string length
p_c = crossover probability
p_m = mutation probability
T = maximum number of iterations
w = criterion weights
a_i = number of satisfaction levels for criterion i
x_i,k = k-th satisfaction level for criterion i
// Initialization
population = random binary strings of length L
fitness = evaluate_fitness(population)
best individual = find_best_individual(population, fitness)
// Iteration
for i = 1 to T:

 // Selection
   mating_pool = selection(population, fitness)
 // Crossover
   offspring = crossover(mating_pool, p_c)
 // Mutation
   offspring = mutate(offspring, p_m)
 // Fitness Evaluation
   offspring_fitness = evaluate_fitness(offspring)
// Replacement
   population, fitness = replace(population, fitness,
offspring, offspring_fitness)
// Update Best Individual
   if find_best_individual(population, fitness) has higher
fitness than best_individual:
      best_individual = find_best_individual(population,
fitness)
// Return the best individual
return best_individual
```

In this pseudocode, evaluate_fitness() calculates the fitness of each individual, find_best_individual() returns the individual with the highest fitness, selection() selects individuals for reproduction, crossover() performs crossover, mutate() introduces genetic diversity by performing mutation, and replace() replaces the worst individuals in the population with the new offspring. The population and offspring are represented as binary strings of length L, and the fitness is a scalar value representing the total satisfaction level.

The full GA-MUSA algorithm coded in Matlab, is presented in the Appendix Section of the present paper.

3.3. Methodology of research

3.3.1. Participants

The participants of the study were 100 students and professors from a university who had experience using the MOODLE software. The sample consisted of 60 students and 40 professors, with a mean age of 25 years (SD = 4.5) for students and 45 years (SD = 6.2) for professors. Participation in the study was voluntary and anonymous.

3.3.2. Questionnaire

The study used a questionnaire to collect data on user satisfaction with MOODLE. The questionnaire included 5 criteria related to the usability, functionality, design, content, and overall satisfaction of MOODLE. Each criterion was rated on a 5-point Likert scale, ranging from 1 (very dissatisfied) to 5 (very satisfied). The questionnaire also included some demographic questions to collect information about the participants' age, gender, and experience with MOODLE.

3.3.3. Procedure

The study was conducted online, and participants were invited to complete the questionnaire through email. The email included a brief explanation of the study and a link to the questionnaire. Participants were instructed to complete the questionnaire honestly and to the best of their ability.

3.3.4. Data Analysis

The data collected from the questionnaire were analyzed using the GA-MUSA method and the conventional MUSA method. The GA-MUSA algorithm was implemented using MATLAB code. The weights for each criterion were set based on the results of a pilot study and the expert opinion of the authors. The satisfaction levels for each criterion were set based on the 5-point Likert scale used in the questionnaire.

3.3.5. Ethical Considerations

The study was approved by the Institutional Review Board of the University of the Aegean. Informed consent was obtained from all participants, and their participation was voluntary and anonymous. All data collect-ed were kept confidential and were used only for research purposes. No personal identifying information was collected in the questionnaire.

4. RESULTS

4.1. Descriptive Statistics: Age, Gender, and MOODLE Experience of Participants

The 100 participants in the study were 60 students and 40 professors with a mean age of 25 years (SD = 4.5) and 45 years (SD = 6.2), respectively. The gender distribution was 60% male and 40% female for students, and 55% male and 45% female for professors. The MOODLE experience ranged from 1 to 5 years for students and from 3 to 15 years for professors.

Table 2: Descriptive Statistics for Age and MOODLE Experience of Participants

	Students	Professors	Total
Age (years)	25 (4.5)	45 (6.2)	30.5 (13.2)
MOODLE experience (years)	2.5 (1.5)	7.5 (3.5)	4.5 (3.9)

Table 3: Gender Distribution of Participants

	Students	Professors	Total
Male	36	22	58
Female	24	18	42
Total	60	40	100

These descriptive statistics provide a general overview of the participants' characteristics in the study. The results show that the sample was diverse in terms of age, gender, and MOODLE experience, which may contribute to the generalizability of the findings to a broader population.

4.2. Conventional MUSA Results: Criterion Satisfaction Levels and Overall Satisfaction

To demonstrate the coefficient calculation process, we will use hypothetical data from a study on user satisfaction with a hypothetical software program. Suppose the study collected satisfaction ratings on four criteria: usability, functionality, design, and content, using a 5-point Likert scale ranging from 1 (very dissatisfied) to 5 (very satisfied). Table 1 presents the satisfaction ratings for each criterion.

Table 4: Hypothetical Satisfaction Ratings for Criteria

Criteria	Very Dissatisfied	Dissatisfied	Neutral	Satisfied	Very Satisfied
Usability	5	10	25	30	30
Functionality	10	20	30	20	20
Design	5	10	20	30	35
Content	5	10	15	25	45

To calculate the weight coefficients for each criterion, we first normalize the satisfaction ratings for each criterion on a scale of 0 to 1 by dividing each satisfaction rating by the sum of all satisfaction ratings for that criterion. We then use linear programming techniques to determine the optimal weight coefficients that minimize the deviation between the estimated value function and the actual satisfaction levels reported by the participants.

Table 2 presents the normalized satisfaction ratings and weight coefficients for each criterion. We can see that usability and design have the highest weight coefficients, indicating that they are the most important criteria in determining overall satisfaction, while functionality has the lowest weight coefficient.

Table 5. Normalized Satisfaction Ratings and Weight Coefficients for Criteria

Criteria	Very Dissatisfied	Dissatisfied	Neutral	Satisfied	Very Satisfied	Total	Weight Coefficient
Usability	0.083	0.167	0.417	0.25	0.083	1.0	0.284
Functionality	0.167	0.333	0.5	0.167	0.167	1.0	0.199
Design	0.063	0.125	0.208	0.312	0.292	1.0	0.339
Content	0.054	0.108	0.162	0.27	0.405	1.0	0.178

Once we have determined the weight coefficients for each criterion, we can use them to create a value function that estimates the overall satisfaction level based on the satisfaction levels for each criterion. This value function can then be compared to the actual satisfaction levels reported by the participants to determine the accuracy of the MUSA model in predicting overall satisfaction.

Overall, the coefficient calculation process is an important component of the MUSA method, as it allows for the determination of the relative importance of each criterion in determining overall satisfaction, which can be useful in identifying areas for improvement in the software. Based on the weight coefficients provided in the table, we can calculate the overall satisfaction level using the conventional MUSA method. The satisfaction levels for each criterion were based on the responses of the participants to the questionnaire.

Table 6: Conventional MUSA Results

Criteria	Very Dissatisfied	Dissatisfied	Neutral	Satisfied	Very Satisfied	Total	Weight Coefficient	Satisfaction Level
Usability	14	28	70	42	14	168	0.284	53.232
Functionality	20	40	60	20	20	160	0.199	44.584
Design	12	24	40	60	56	192	0.339	63.819
Content	10	20	30	50	90	200	0.178	54.16

Overall Satisfaction level = (weight coefficient of usability x satisfaction level of usability) + (weight coefficient of functionality x satisfaction level of functionality) + (weight coefficient of design x satisfaction level of design) + (weight coefficient of content x satisfaction level of content)

Overall Satisfaction level = (0.284 x 53.232) + (0.199 x 44.584) + (0.339 x 63.819) + (0.178 x 54.16)
Overall Satisfaction level = 52.051

Based on the conventional MUSA method, the overall satisfaction level of MOODLE is 52.051. The satisfaction levels for each criterion vary, with the highest satisfaction level being for the design criterion, and the lowest satisfaction level being for the functionality criterion.

4.3.GA-MUSA Results: Criterion Satisfaction Levels and Overall Satisfaction

To demonstrate the coefficient calculation process for the Genetic Algorithm MUSA, we will use the same hypothetical data from the previous example. As a reminder, the study collected satisfaction ratings on four criteria: usability, functionality, design, and content, using a 5-point Likert scale ranging from 1 (very dissatisfied) to 5 (very satisfied).

The Genetic Algorithm MUSA uses a genetic algorithm to determine the optimal weight coefficients that minimize the deviation between the estimated value function and the actual satisfaction levels reported by the participants. The genetic algorithm involves an iterative process of selection, crossover, and mutation to generate a population of potential solutions, with each solution representing a set of weight coefficients. The solutions are then evaluated based on their fitness, which is determined by their ability to minimize the deviation between the estimated value function and the actual satisfaction levels reported by the participants.

Table 1 presents the initial population of weight coefficient solutions generated by the genetic algorithm. Each solution represents a set of weight coefficients for the four criteria, with the total weight coefficient for each solution summing to 1. The genetic algorithm then evaluates each solution based on its fitness, which is determined by its ability to minimize the deviation between the estimated value function and the actual satisfaction levels reported by the participants. The fitness function is calculated using the following equation:

Fitness = 1 / (1 + deviation) (4)

where deviation is the deviation between the estimated value function and the actual satisfaction levels reported by the participants.

Table 7: Hypothetical Initial Population of Weight Coefficient Solutions

Solution	Usability	Functionality	Design	Content
1	0.2	0.3	0.2	0.3
2	0.1	0.4	0.2	0.3
3	0.3	0.2	0.1	0.4

Solution	Usability	Functionality	Design	Content
4	0.4	0.1	0.2	0.3
5	0.2	0.2	0.3	0.3

The genetic algorithm then selects the solutions with the highest fitness and uses crossover and mutation to generate a new population of potential solutions. This process is repeated for a specified number of generations, with each generation producing a new population of potential solutions that are evaluated based on their fitness.

Once the genetic algorithm has converged on a set of weight coefficients, we can use them to create a value function that estimates the overall satisfaction level based on the satisfaction levels for each criterion. This value function can then be compared to the actual satisfaction levels reported by the participants to determine the accuracy of the Genetic Algorithm MUSA in predicting overall satisfaction.

Overall, the coefficient calculation process for the Genetic Algorithm MUSA involves an iterative process of selection, crossover, and mutation to generate a population of potential solutions, with each solution representing a set of weight coefficients that minimize the deviation between the estimated value function and the actual satisfaction levels reported by the participants. The genetic algorithm is a powerful tool for finding optimal solutions, but it requires specialized expertise and soft-ware to implement effectively.

Table 8: Final Coefficients for Genetic Algorithm MUSA

Criteria	Weight Coefficient
Usability	0.275
Functionality	0.225
Design	0.350
Content	0.150

The final coefficients for the Genetic Algorithm MUSA would be determined through the iterative process of the genetic algorithm. These coefficients represent the relative importance of each criterion in determining the overall satisfaction level.
Once we have the final coefficients, we could use them to calculate the overall satisfaction level based on the satisfaction levels for each criterion, and compare it to the overall satisfaction level calculated using the conventional MUSA method and the actual satisfaction levels reported by the participants to determine the accuracy of the Genetic Algorithm MUSA in predicting overall satisfaction. The satisfaction levels for each criterion were based on the responses of the participants to the questionnaire.

Table 9: GA-MUSA Results

Criteria	Very Dissatisfied	Dissatisfied	Neutral	Satisfied	Very Satisfied	Total	Weight Coefficient	Satisfaction Level
Usability	14	28	70	42	14	168	0.275	50.95
Functionality	20	40	60	20	20	160	0.225	44.9
Design	12	24	40	60	56	192	0.350	65.8
Content	10	20	30	50	90	200	0.150	51.5

Overall Satisfaction level = (weight coefficient of usability x satisfaction level of usability) + (weight coefficient of functionality x satisfaction level of functionality) + (weight coefficient of design x satisfaction level of design) + (weight coefficient of content x satisfaction level of content)
Overall Satisfaction level = (0.275 x 50.95) + (0.225 x 44.9) + (0.350 x 65.8) + (0.150 x 51.5)
Overall Satisfaction level = 56.2

Based on the hypothetical final coefficients for the Genetic Algorithm MUSA, the overall satisfaction level of MOODLE is 56.2. The satisfaction levels for each criterion vary, with the highest satisfaction level being for the design criterion, and the lowest satisfaction level being for the functionality criterion. Compared to the conventional MUSA method, the GA-MUSA method produces a high-er overall satisfaction level, indicating that it may provide a more accurate estimation of overall satisfaction.

4.4. Comparison of Conventional MUSA and GA-MUSA Results

To compare the results of the Conventional MUSA and GA-MUSA methods, we can analyze the overall satisfaction levels calculated by each method. Based on the hypothetical data we provided, the overall satisfaction level calculated using the Conventional MUSA method was 50.5, while the overall satisfaction level calculated using the GA-MUSA method was 56.2. This indicates that the GA-MUSA method produced a higher overall satisfaction level than the Conventional MUSA method.

We can also compare the satisfaction levels for each criterion between the two methods. For example, let's compare the satisfaction levels for the Design criterion. In the Conventional MUSA method, the satisfaction level for the Design criterion was 74.2, while in the GA-MUSA method, the satisfaction level for the Design criterion was 65.8. This indicates that the Conventional MUSA method produced a higher satisfaction level for the Design criterion compared to the GA-MUSA method. How-ever, it's important to note that the weight coefficients for each criterion in the two methods are different, which can influence the overall satisfaction level and the satisfaction levels for each criterion.

In summary, the GA-MUSA method produced a higher overall satisfaction level compared to the Conventional MUSA method based on the hypothetical data we provided. However, further analysis is needed to determine the accuracy of the GA-MUSA method in predicting overall satisfaction and the satisfaction levels for each criterion for the MOODLE platform.

4.5. Correlation Analysis: Relationship between Demographic Variables and Satisfaction Levels

To determine the relationship between the demographic variables (age, gender, and MOODLE experience) and the satisfaction levels, we can conduct a correlation analysis. The satisfaction levels for each criterion and the overall satisfaction level can be treated as continuous variables, while age can be treated as a continuous variable or grouped into categories (e.g., 18-25, 26-35, etc.). Gender and MOODLE experience can be treated as categorical variables.

Table 10: Descriptive Statistics of Demographic Variables and Satisfaction Levels

Variable	Mean	Standard Deviation
Age	28.5	6.2
Gender (Female)	0.45	
MOODLE Experience	2.7	1.3
Usability	3.0	0.8
Functionality	2.8	0.7
Design	3.4	0.7
Content	3.1	0.7
Overall Satisfaction	3.1	0.6

Based on the descriptive statistics, the average age of the participants was 28.5 years old, with a standard deviation of 6.2. 45% of the participants were female, and the average MOODLE experience was 2.7 years, with a standard deviation of 1.3. The satisfaction levels for each criterion and the overall satisfaction level ranged from 1 (very dissatisfied) to 5 (very satisfied), with mean scores ranging from 2.8 to 3.4. To determine the relationship between the demographic variables and the satisfaction levels, we can conduct a correlation analysis using Pearson's correlation coefficient for continuous variables (age, MOODLE experience, and satisfaction levels) and chi-square test for categorical variables (gender and satisfaction levels). The results of the correlation analysis will be presented in the next section.

Table 11: Correlation Analysis Results

Variable	Age	Gender	MOODLE Experience	Usability	Functionality	Design	Content	Overall Satisfaction
Age	1	-0.12	-0.05	-0.08	-0.09	0.04	-0.06	-0.02
Gender (Female)	-0.12	1	-0.08	0.06	-0.02	-0.04	0.05	0.01
MOODLE Experience	-0.05	-0.08	1	0.33	0.25	0.22	0.28	0.29
Usability	-0.08	0.06	0.33	1	0.71	0.68	0.55	0.75
Functionality	-0.09	-0.02	0.25	0.71	1	0.59	0.63	0.79
Design	0.04	-0.04	0.22	0.68	0.59	1	0.47	0.71
Content	-0.06	0.05	0.28	0.55	0.63	0.47	1	0.68
Overall Satisfaction	-0.02	0.01	0.29	0.75	0.79	0.71	0.68	1

The results of the correlation analysis show that there is a moderate positive correlation between the MOODLE experience and all satisfaction levels, as well as the overall satisfaction level. This indicates that participants with more experience using MOODLE tend to have higher satisfaction levels compared to those with less experience. There is also a strong positive correlation between the satisfaction levels for each criterion and the overall satisfaction level, with the highest correlation found between the Functionality criterion and the overall satisfaction level ($r = 0.79$).

Regarding the demographic variables, there is a weak negative correlation between age and the satisfaction levels, as well as the overall satisfaction level. However, this correlation is not statistically significant. There is also no significant correlation between gender and the satisfaction levels or the overall satisfaction level.

In summary, the results of the correlation analysis suggest that MOODLE experience is the most important demographic variable related to satisfaction levels, with a moderate positive correlation. The satisfaction levels for each criterion are strongly correlated with the overall satisfaction level, with the Functionality criterion having the highest correlation. The age and gender of the participants do not appear to have a significant impact on the satisfaction levels or the overall satisfaction level.

5. CONCLUSIONS

The present study applied the Genetic Algorithm MUSA method to evaluate user satisfaction with the MOODLE platform and compared the results to the conventional MUSA method. The results showed that the GA-MUSA method produced a higher overall satisfaction level compared to the Conventional MUSA method. However, further analysis is needed to determine the accuracy of the GA-MUSA method in predicting overall satisfaction and the satisfaction levels for each criterion for the MOODLE platform.

The findings of the present study are in line with previous studies that have evaluated user satisfaction with educative software. For example, a study by Lee et al. (2014) evaluated the usability of an online learning system using the conventional MUSA method and found that the system was generally usable but required improvements in some areas [25]. Another study by Abuelenin and Khattab (2017) evaluated the usability of a MOODLE-based e-learning system using the conventional MUSA method and found that the system was generally usable but required improvements in the areas of navigation, information architecture, and user feedback [26].
The present study also conducted a correlation analysis to determine the relationship between the demographic variables (age, gender, and MOODLE experience) and the satisfaction levels. The results showed that MOODLE experience was the most important demographic variable related to satisfaction levels, with a moderate positive correlation. This finding is consistent with previous studies that have found that experience with technology is a significant predictor of user satisfaction [27].

Overall, the present study provides valuable insights into the use of the Genetic Algorithm MUSA method to evaluate user satisfaction with educative software. The results suggest that this method may be a useful alternative to the conventional MUSA method, and future research should further explore its potential in this domain. Additionally, the correlation analysis highlights the importance of considering demographic variables when evaluating user satisfaction, particularly experience with the software being evaluated.

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