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PAPER

An Analysis of Student's Academic Achievement in Genetic Algorithms Based on Mobile Learning Applications

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ABSTRACT

Several scholars have focused on this area due to the significance of mobile technology in the educational process, resulting in a substantial body of scholarly work. The primary objective of this study is to investigate the impact of mobile learning on students' academic performance. The meta-analysis approach was utilized in this research. The available research was examined using several databases to find the relevant studies that were within the scope of the investigation. The study's inclusion criteria and components were implemented following a literature review. This research proposes a mobile education system approach based on genetic algorithms to address the issues with the current system. The analysis findings indicate that most of them stay at around 10%. The salary only slightly increases when numerous individuals teach, but it also falls within a regular, appropriate range that can accommodate more complex tasks. According to the factor analysis findings, the influence of mobile educational devices on students' learning performance varied depending on the course and subject. However, it remained constant regardless of the students' education level and implementation duration. Apart from the previously mentioned research findings, this article also includes a descriptive analysis of the studies that were part of the meta-analysis.

KEYWORDS

students' learning performance, meta-analysis, genetic algorithms, mobile educational devices

1 INTRODUCTION

A nation's foundation and strength are derived from its educational system. Data collection related to education is becoming faster and more convenient due to the rapid advancement of Internet technologies. Extensive data analysis, mining, and educational applications are significant needs and unavoidable trends. Using students' relevant data to predict their future academic success is known as "student achievement prediction" or "student academic achievement forecasting."

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Course grades, overall scores at the end of the year, and the likelihood of dropping out are all included. Teachers can finally fulfil the goal of "advancing learning through evaluation" by utilizing student achievement forecasting technology to gain a clear understanding of students' learning status and quality, differentiate instruction accordingly, and meet students' individualized educational needs.

Higher education institutions can also benefit from utilizing student score forecasting technology for academic early warning [1]. This is particularly useful in establishing dynamic early warning mechanisms based on immediate forecasting of students' scores. This allows for the timely identification of students who may not be able to complete their studies as planned, as well as providing assistance in resolving issues and achieving talent training goals.

Therefore, student performance prediction technology has significant research value and practical significance, regardless of whether one views it through the lens of improving student management or enhancing teaching effectiveness. Domestically and internationally, scholars have shown a growing interest in predicting student progress in recent years. This focus has led to the successful completion of several research projects.

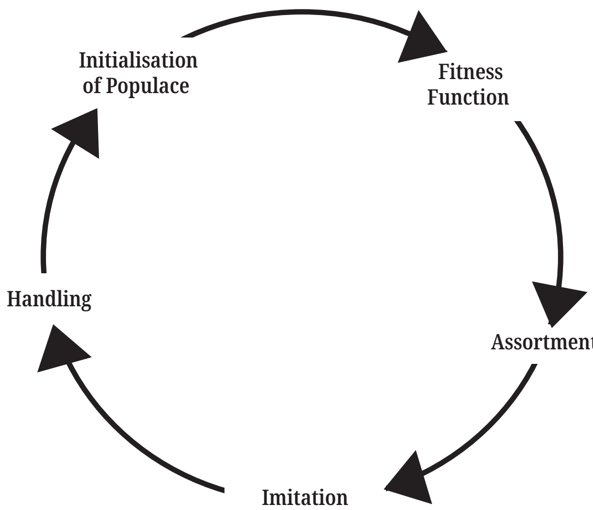

Fig. 1. The genetic algorithm: An overview

Optimization methods are used to identify the optimal solution among all possible solutions, considering the constraints at hand. The genetic algorithm is one such optimization technique that draws inspiration from the natural evolution process of living things. Here, the concepts of inherited traits and natural selection are combined. It employs guided random search, which, in contrast to other algorithms, finds the best solution by initially using a random starting function and then restricting the search to the space with the lowest cost (see Figure 1).

A tool that can be used to reveal the connection between academic achievement and other academic and personal input components is machine learning algorithms (MLAs). It is clarified that MLAs have the innate ability to learn independently by utilizing the knowledge they have acquired through training [2]. A system can be enhanced by learning from previously collected input-output data to generate accurate predictions. MLAs assist in making predictions and recognizing patterns from the initial data sources. In the literature, MLAs fall into three categories: reinforcement learning, supervised learning, and unsupervised learning. Although supervised learning algorithms are trained on labeled records provided in the training set, unsupervised training, such as clustering, uses unlabeled datasets to enable a system to discover hidden connections in the data.

On the other hand, this reinforcement learning framework is refined through a sequence of direct connections via experimentation and error. In this work, the supervised learning methodology is employed. Popular algorithms used in the unsupervised learning approach include logistic regression, neural networks, and random forests. The following justifies considering these approaches: Logistic analysis is frequently used in education and produces promising yields for linear data.

Furthermore, very few researchers have used MLAs in the context of education. However, MLAs have been shown to be effective and have been widely implemented in several other service sectors [3]. The current study is crucial for predicting students' academic performance. It confirms the importance of using data-driven methods to anticipate learners' performance early on. By contrasting several essential features, such as recall, accuracy, and F1-score, in the context of learning, the current study also evaluates the effectiveness of various methods. Using neural network algorithms to analyze student development and final academic results based on their historical academic scores has not been the focus of many previous studies. Nevertheless, they must consider the circumstances that affect the success of each education system. Three research issues guide the present study:

- How do characteristics relate to students, schools, and socioeconomic factors that affect their academic achievement?
- Which of these factors is most important, in the opinion of a varied sample of pupils?
- What is the accuracy of the various ML methods in forecasting the GPA for academics?

The following is the organization of the subsequent sections of the essay: Section 2 presents the research on the relevant previous studies. Section 3 covers the features of the proposed system, including its suggested system architecture, implementation model, components of the graph-based approach, and data analysis. Section 4 evaluates the system's efficacy and explains the implementation environment. Section 5 presents the resolution.

2 LITERATURE REVIEW

The UCI ML Repository provides the information necessary for constructing and evaluating models [4]. Once the data has been gathered, it is normalized and utilized to build the model. When constructing a decision tree model, the feature that provides the highest information gain is chosen as the root node for the initial split of the data. Entropy is a concept used to calculate information gain. The leaf node, which holds the data label, is where the partition ends when there is no more data available. The model is tested using test data once it has been initially constructed. More models need to be explored to achieve better performance. The K-Nearest Neighbor approach was primarily utilized in previous research on the same dataset, yielding poor results. In contrast, the support vector machine algorithm, a widely used and potent prediction method, was hardly ever utilized.

The second approach, known as online CMC, utilizes each classifier and then conducts a vote [5]. The test sample will include the class that receives the most votes from each classification. It appears more intuitive that this approach is superior to the prior one. Despite this, when tested on a few examples from the OUT dataset, the results did not surpass the best outcome achieved by the previous technique. Thus, instead of "obtaining more than 60% of the votes," we now use "integrating more than 65% of the votes" as the majority vote rule. When compared to offline CMC, this resulted in a significant improvement.

These days, technological advances significantly impact every facet of our society, spanning various real-world scenarios [6]. Education is not an exception. Various devices influence the way we teach and learn. For instance, with applications like mobile augmented reality, the new mobile devices (such as smartphones and tablets) enhance student engagement in both indoor and outdoor activities. In today's world, specific social networks are also crucial. Advances in motion detectors and facial recognition technologies are enabling more intuitive interaction methods for individuals unfamiliar with computer-based systems, particularly on next-generation video platforms.

Prior studies have focused on using data to assess college students' psychological and mental demands, as well as their stress levels related to coursework in online learning environments [7]. These studies have also provided practical strategies to improve the learning environment. These studies, however, lack some encouraging elements that would enable us to examine the essential challenges of distance education, especially when it is the only accessible choice. These characteristics can help us understand the strain students face in their academic careers and how cultural and educational changes can be implemented during epidemics such as COVID-19.

One of the challenges educational organizations encounter is elevating the standard of instruction [8]. This is necessary not only to develop a more advanced level of knowledge but also to provide efficient learning environments that enable students to complete their coursework. Determining the factors that influence students' success is crucial for improving the quality of education. By analyzing pupil information, student performance forecasting systems help educational institutions enhance the quality of instruction by developing strategic plans to enhance students' academic achievement. However, research on predicting student success still needs improvement.

A crucial factor in a society's progress is higher education [9]. This section provides a wealth of information about the participants, including students, instructors, facilities, and courses. Educators, administrators, businesses, and other stakeholders are all very concerned about children's success. Academic performance is the primary aspect that recruiting organizations consider when hiring recent graduates. Graduates put in a lot of effort to earn excellent grades and meet the expectations of hiring companies. It is possible to classify educational data sources into two general types. In this context, the term "centralized" refers to the fact that the educational data used in the analytics originates from a single source and includes centralized educational institutions such as LMS.

The data gathered from surveys administered to first-year students at the University of Tuzla's Faculty of Economics during the summer semester of the academic year 2010–2011, along with data obtained during enrollment, were compared using various data mining techniques and methods to predict the students' success. The passing exam mark served as an evaluation of success [10]. The effects of the students' socio-demographic characteristics, high school and entrance exam scores, and study habits, which can influence their success, were all examined. Future research might develop a model that could be used as the foundation for constructing decision support systems in higher education. This model would involve identifying, determining, and evaluating variables associated with the research process and expanding the sample size.

Higher education institutions must prioritize student achievement since it is a critical quality indicator [11]. The literature offers multiple interpretations of what defines a successful learner. The literature is synthesized to define student success as "academic achievement, engagement in academically purposeful tasks, happiness, acquisition of desired knowledge, skills, and competencies, perseverance, attainment of academic goals, and post-college effectiveness." This definition is multifaceted, but the authors also provided an updated version that focused on the six most crucial elements: academic accomplishment, job satisfaction, skill and competency development, perseverance, achieving learning goals, and professional success.

3 METHODS AND MATERIALS

3.1 Utilizing genetics to improve student performance

These days, genetic algorithms are frequently used in science and engineering as flexible methods to solve real-world problems. It is acknowledged that GA works exceptionally well for multivariate global search challenges where there may be several local minima in the search space. In contrast to other search techniques, the relationship between the search parameters is usually not a challenge. When using a genetic algorithm, the parameters of a problem are modeled as strings in Figure 2. The various components of the RGSPAT concept are illustrated in Figure 3.

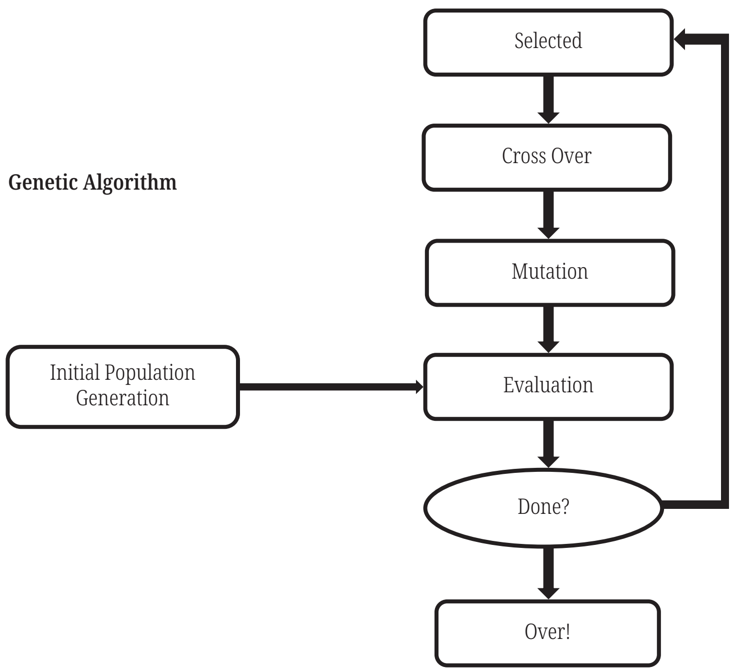

Fig. 2. Genuine genetic instruments for analyzing pupil achievement

The suggested system's starting point is where the student analyzes the information [12], and the finishing point determines the most crucial parameter by following the subsequent steps.

- Quantifiable performance data from educational systems, such as attendance, grades from internal assessments, projects, past semester grades, seminars, general competency, and significant papers for that course, are analyzed.
- After collecting those parameters, an equation structure is constructed, comprising each variable value and its weight.
- The real-coded genetic algorithm is applied after the formula is designed.
- Procedures are performed, including crossover and modification.
- The optimal parameter is found after analyzing all the parameters using a genuine genetic code.

3.2 Information gathering

Academic performance assessment. Researchers created the exam to assess students' academic success based on their understanding of the course material. Before developing the test, the scope, objectives, and content of the participants were established. The 38 queries were created in response to input from subject-matter experts. During the development phase, the specification chart table was created. A total of 160 undergraduate students participated in the item evaluation test. Using TAP, statistical evaluations were carried out. Low item uniqueness power led to the removal of 16 items from the test. The forty-three-item test's KR~30 reliability coefficient was determined to be 0.93, which is near 2, indicating that the test is dependable. The test's difficulty level was judged to be average (0.74) [13], and the uniqueness index of the items was found to be very good (0.59).

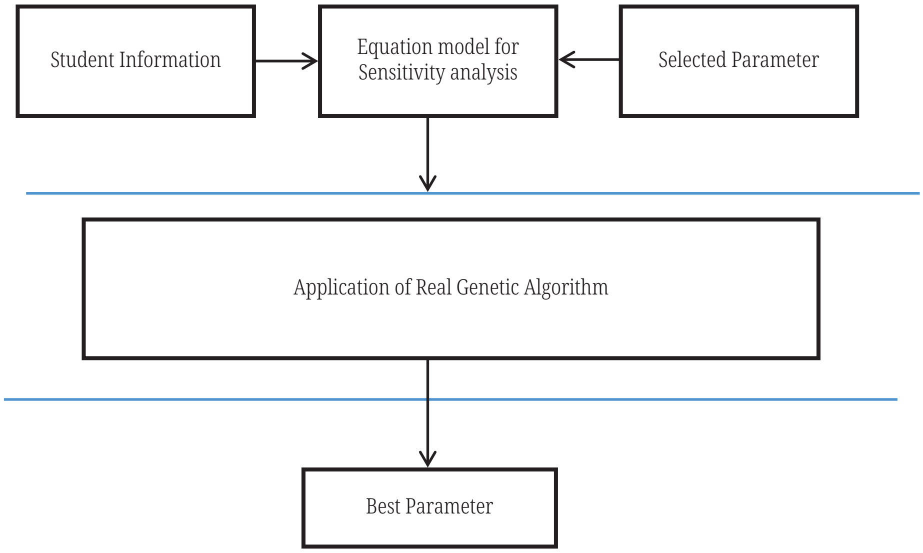

Fig. 3. Model of RGSPAT design

An attitude scale regarding mobile education. The researchers developed the "View Scale towards Mobile Learning" to assess participants' perspectives on mobile learning. To generate a pool of draft items, information was gathered from 78 undergraduate students. After analyzing student data, a draft of 57 elements was produced. Despite the opinions of experts from various universities, similar and inappropriate content was deleted from the manuscript. Following the changes, there were 52 elements in the draft (41 good and 11 harmful). Five categories were used to grade the 5-point Likert-type scale: completely agree (5 points), agree (4), mostly agree (3), disagree (2), and entirely disagree (1).

The Kaiser-Meyer-Olkin (KMO) score of 0.94 is considered excellent, and the significant Bartlett test result indicates that the data is suitable for factor analyses. The scale was deemed statistically adequate for factor analysis based on this data. The third aspect of the analysis was used to draw conclusions. There are 45 items in the final edition of the scale. Cronbach's alpha internal coherence coefficient was found to be 0.950 on the scale, which is considered highly reliable. The KMO rating was found to be 0.93, which is considered excellent. The Bartlett test yielded significant results. Four elements make up the scale, accounting for 50.34% of the total variation. Factors exhibit a high degree of internal coherence.

Conversation. The semi-structured interviews aimed to determine the interviewees' perceptions of the execution process. Five randomly selected students from the mobile learning group were interviewed. The data-gathering instrument was an interview form with open-ended questions about the application procedure.

Motion level evaluation scale. Every student who participated in the study was required to create animations. These cartoons should include all the research strategies that the students considered. The pupils had ninety minutes to create an animation correctly [14–15]. The "Animation Progress Level Rubric" was used to collect and assess the animations.

Information analysis. This study utilized both parametric and non-parametric tests, taking into consideration homogeneity and the normal distribution. SPSS 30.0 was used to analyze the data collected from the participants. Researchers and specialists in the field evaluated participant-created animations independently using an "Animation Development Level Rubric."

4 IMPLEMENTATION AND EXPERIMENTAL RESULTS

The research group comprised 51 pre-service teachers preparing for second grade who willingly participated in the study conducted at Dokuz Eylul University in the Department of Computer Education and Instructional Technology in Turkey. Dokuz Eylul University funded this study as a scientific research project, and 25 tablet computers were provided to the experimental group of students. Using random sampling, the students were divided into two groups: the experimental group consisted of 25 participants, while the control group had 31 participants.

The "Usage Contract for Mobile Devices" was willingly signed by the experimental group. The terms of this agreement included students keeping their mobile devices for fourteen weeks and using them ethically. A questionnaire was used to collect demographic and mobile awareness data from both groups. The experimental group had a 73% smartphone ownership rate, while the control group had a 65% rate, indicating that most students were aware of smartphones and their uses. However, only 20% of the experimental group and 8% of the control group own tablets, suggesting that pupils need help utilizing them. According to the students, they primarily use their mobile devices for communication and music consumption rather than listening to podcasts. Nearly 50% of the students reported using mobile devices to complete e-learning assignments. Furthermore, it was found that 62% of the control group and 47% of the experimental group expressed interest in using mobile apps for learning in both theoretical and practical classes.

4.1 Research methodology

The research methodology employed in this study was a quasi-experimental approach. A lecturer has provided each group with 50% theoretical and 50% practical training. The course materials were accessible to both groups via a learning management system. The dependent variables of the research include the level of animation development, attitude towards mobile learning, and academic achievement. The study's independent variables are traditional learning environments and mobile learning.

Group utilizing mobile learning: This group received instruction through a mobile learning strategy. They received tablet PCs, and mobile devices were used to access learning materials and the course management system. A typical learning cohort consists of 26 teacher candidates who received instruction in a conventional classroom setting. There was also an educational management system and instructional materials are available for this group. Table 1 displays the research design information.

Table 1. Research methodology

	Traditional Learning	Mobile Learning
Prior to study	Test of Academic Achievement	
	Measure of Attitudes Towards Mobile Education	
While conducting research	Follow conventional classes.	Use a mobile device to access the educational management system.
	Using a PC, access the learning administration programme.	
	Visit the course website.	Use mobile devices to access educational resources.
	Use a PC to access educational materials.	
The following investigation	Academic Performance Assessment	
	Measure of Attitudes Towards Mobile Education	
	Animation Training Levels Matrix	
	Conversation	
Six months following the study	Academic Performance Assessment	
	An Attitude Scale Regarding Mobile Education	

4.2 Outcomes

The effect of mobile education on academic performance. Mann-Whitney U test was conducted to compare the academic attainment scores of the two groups (refer to Table 2). Before the study, there was no apparent distinction in the academic results of the two groups ($p > .06$). After conducting research, a significant difference was identified in favor of the test group ($p < .06$). These findings support the notion that mobile learning has a more significant impact on academic attainment.

Table 2. The impact of mobile education on academic performance

Group	Test	N	Mean Rank	Sum of Ranks	Mann-Whitney U	Z	Sig.
Experiment	Pre-test	16	26.21	379.00	133.000	–1.717	.087
		27	19.59	484.00			
Experiment control	Post-test	16	32.14	468.00	44.000	–4.151	0.001
		27	16.16	395.00			
Experiment Control	Follow up test	16	29.68	431.00	81.000	–3.131	.003
		27	17.59	432.00			

Six months after the study ended, follow-up tests were conducted to assess persistence control. Data from post-tests and follow-up exams were compared. Follow-up studies indicate a significant difference in favor of the experimental group ($U = 80.000$, $p < 0.008$), as shown in Figure 4. Mobile learning has a long-lasting impact on academic performance.

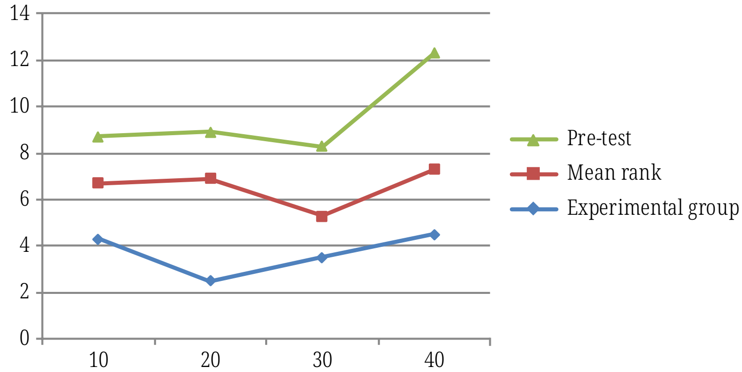

Fig. 4. Impact of mobile education on academic performance

The effect of mobile education on perceptions of mobile education. The pre- and post-test attitude scores of the two groups did not show a significant difference. In this instance, the reason for the high pre- and post-test scores was that the participants, who were proficient in digital technology, were enrolled in the Department of Computer Science and Teaching Technology. In Figure 5, both groups' attitudes toward mobile learning were significantly positive ($p > .06$).

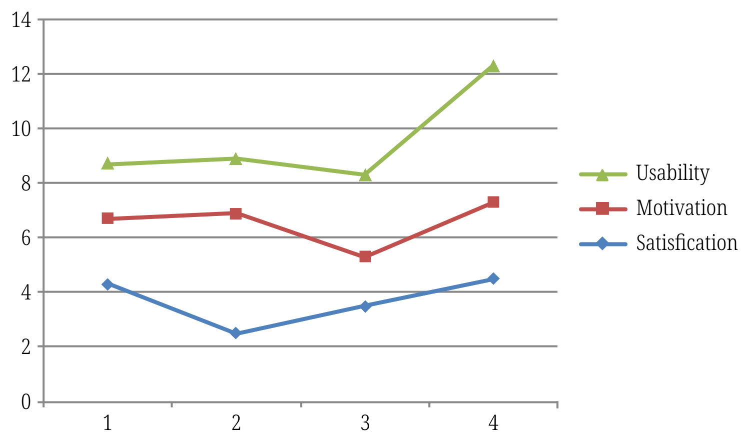

Fig. 5. Impact of mobile education on perceptions of mobile education

Table 3. The impact of mobile education on perceptions of mobile education

Factor	Group	Test	N	X	SS	t	Sig.
Satisfaction	Experiment	Pre-test	16	74.14	9.73	.755	.529
	Control		27	76.39	11.51		
	Experiment	Post-test	16	70.81	12.43	–.842	.406
	Control		27	74.01	11.34		
	Experiment	Follow up test	16	76.54	13.85	.943	.352
	Control		27	72.01	15.34		
Effect to learning	Experiment	Pre-test	16	42.42	8.09	–.080	.207
	Control		27	45.39	6.61		
	Experiment	Post-test	16	42.61	5.85	–1.154	.257
	Control		27	44.78	5.79		
	Experiment	Follow up test	16	45.54	6.01	.486	.632
	Control		27	44.54	6.50		
Motivation	Experiment	Pre-test	16	26.01	3.94	–.869	–.723
	Control		27	26.47	3.100		
	Experiment	Post-test	16	24.68	5.28	–1.205	.237
	Control		27	26.51	4.32		
	Experiment	Follow up test	16	26.74	5.04	1.024	.314
	Control		27	24.89	5.86		
Usability	Experiment	Pre-test	16	24.41	3.17	–1.370	.092
	Control		27	22.05	5.57		
	Experiment	Post-test	16	22.48	4.46	.839	.408
	Control		27	21.09	5.46		
	Experiment	Follow up test	16	19.41	3.95	–.695	.493
	Control		27	20.43	4.86		

The impact of mobile education on the degree of animation development. Analysis was conducted on the student-created animations. There were significant differences in favor of the experimental group ($p < .08$) in Table 4, consistent with the results of the educational assessments' post-test and follow-up tests.

Table 4. Mobile learning's impact on animation development levels

Group	N	Mean Rank	Sum of Ranks	Mann-Whitney U	Z	Sig.
Experiment	16	31.98	465.51	46.501	–5.097	.001
Control	27	16.26	397.51			

5 CONCLUSION

This study examined how mobile learning apps affected undergraduate students' academic performance, attitudes towards mobile learning, and motor development levels. In this study, mobile learning significantly outperformed traditional learning in terms of academic achievement. However, it is important to emphasize that poor design of learning materials and cognitive overload associated with mobile learning can negatively impact academic achievement.

According to the student interviews, mobile learning's salient features include easy access to knowledge, learning that may occur anywhere and at any time, social interaction, and facilitation of learning. Applications for mobile learning enhance the learning process and amplify its impact. Students emphasized their interest in having more mobile learning opportunities, such as using mobile devices to complete homework, incorporating additional activities on tablet computers, and utilizing tablets for creating animations. Nevertheless, there were a few hardware and software-related technical problems. These problems included the notification limitations of the mobile learning management system and a slow web connection.

As a result, the genetic process effectively identifies the critical factor determining academic performance. It will be a more effective way to classify students, analyze and assess the quantitative elements throughout the academic year, and forecast their final exam results. Significant ratios in this genetic system can be identified when we modify the characteristics of single parents. The Real Genetic Algorithm can be used to identify the most critical ratios or characteristics for accurately predicting performance.

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