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Assessment of Organizer Model and Conventional Teaching Method for improved student learning performance: A gamification-based perspective

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Abstract:

Purpose: The main objective of the study is to analyze the effectiveness of the Advance Organizer Model (AOM) versus the Conventional Teaching Method (CTM) in teaching high school math using game-based learning (GBL) for improved student learning performance.

Methodology: Data from 480 students, covering socio-demographics, educational identifiers, and actions, were collected across two semesters. The research analyzed factors like interest, motivation, and problem-solving abilities to assess the impact of teaching methods. A quasi-experimental design, due to non-randomized group selection, was used, mitigating differences via analysis of covariance. Students were split into control and test groups, and test scores before and after administering the treatment were calculated. Hypothesis testing was carried out to find the effectiveness of AOM versus CTM. The sample contains a diverse socio-demographic background and educational setting. 175 students in the sample were female and 305 were male. The sample was made up of 14 nationalities, including Saudi Arabia, Jordan, Peru, Iraq, and Lebanon. Parent participation was also incorporated through parental satisfaction surveys.

Findings: Despite unknown group differences, the study found significant differences in Mean Retention Scores between the AOM and CTM groups. This suggests that AOM has considerable advantages in teaching mathematics over CTM.

Originality: The study of the first kind that explores the effectiveness of different teaching methods based on gamification perspective for improving student performance

Keywords: Advanced organizer model; quasi-experimental; games-based learning strategy; learning outcome; mathematics education

1. Introduction

Children's mathematics education is a major concern of parents worldwide. Both elementary and secondary schools are required to teach mathematics to students, and several governments make significant investments in mathematical education and research [1]. There have been considerable advancements in both mathematics education and the instructional strategies employed. Understanding fundamental concepts should take precedence over memorization of computation in mathematical education [2]. Even though academics are generally interested in modern mathematics, most of the mathematics is utilized in various professional training courses. However, educators' express concerns about how to effectively teach mathematics and struggle to communicate mathematical ideas. It is considered a challenging endeavor since broad principles in modern mathematics are hard to express [3]. Due to these challenges, mathematical education is still in its infancy.

The use of technology in instructional practices has acquired significant traction in education [4]. Among the various technological advancements, Game-Based Learning (GBL) has emerged as a powerful tool to enhance student engagement and facilitate a deeper understanding of complex subjects [5]. GBL [6] entails using game elements in a learning environment to enhance learning effectiveness. This is achieved through GBL with the help of a point system, levels, and other incentives. It includes the use of educational games or simulations whereby the students are allowed to participate in learning activities, be given feedback, and be required to rise to the challenge while learning [7]. It is therefore evident that with the use of GBL motivation can be boosted, students can learn, and achieve such things as problem-solving and collaboration.

In educational psychology, different teaching approaches have been introduced to improve student learning and understanding [8]. Advanced Organizer Model (AOM) and Conventional Teaching Method (CTM) are two such strategies. The AOM [9] is an instructional approach originated by David Ausubel to enhance the efficiency of learning by informing learners in advance of new knowledge. It involves the use of an organizer that can be in the form of an outline, diagram, or analogy which the student uses to develop a mental framework that enables him to relate the new information to the previous knowledge [10]. The ability to present an overview of what is to be taught in the subsequent sections helps the students to understand and memorize what is taught more easily thus improving on understanding and retention. Information technologies and media are also used in current AOM processes to develop an effective and fun learning process [11]. In the process of presenting advanced organizers, educational software, virtual labs, and other online resources are applied [12]. On the other hand, the CTM incorporates traditional forms of teaching practices which are normally associated with direct instruction, memorization, and systematic passing of information [13]. As for CTM, it has been the main approach to education for many years; however, its ability to promote a deep understanding of the subject matter and development of critical thinking skills has recently come into doubt in the context of the new paradigms of education [14].

Additionally, in education, Reinforcement Learning (RL) can be applied to create an intelligent learning environment that can adapt the teaching to the learner's capabilities. RL [15] is a branch of machine learning where an agent learns to make decisions based on the amount of rewards it gets or loses. RL algorithms can be applied to choose the most effective instructional strategies, present content, and pace it according to the learners' needs while accounting for learning disabilities, and enhance educational games by changing their difficulty levels and providing feedback.

This research seeks to fill the existing gap in the literature and practice by examining new approaches to teaching and learning high school mathematics that positively influence students' engagement, motivation, and achievement. The conventional practices do not capture the students' attention or assist them in developing comprehensive knowledge, which necessitates the use of innovative strategies. Therefore, this research aims to determine the extent of the impact of the AOM over the CTM on high school mathematics achievement through GBL. It seeks to determine whether its usage of AOM due to its inherent method of organizing information is more beneficial than that of CTM in engaging students' interest, motivation, and problem-solving abilities. This paper also considers the impact of RL in improving learning results in GBL environments by modifying the level of the game's complexity according to the learner's performance. Additionally, it aims to enhance the reliability and validity of the study by using K-means clustering for the right classification of the students depending on the homogenous level of prior learning and skills. In addition to traditional retention scores, the research assesses the overall effectiveness of AOM and CTM by including such measures of students' interest, motivation, and thinking skills. It also attends to the educational gaps by comparing the efficiency of these methods across different student groups. Furthermore, the study will seek to contribute to the development of educational policy and practice by presenting empirical findings about the comparative efficacy of AOM and CTM, which will help educators and policymakers make the best decisions to enhance the efficacy of teaching approaches and, therefore, students' performance.

The rest of the document is organized as follows: Section 2 offers a thorough analysis of the pertinent literature. Section 3 offers a detailed description of the proposed approach. Section 4 discusses the Results, discussion, and practical implications of the findings in real-world settings. Section 5 provides an overview of the paper's major findings and suggestions for more study.

2. Literature Review

This research literature includes several studies that can be combined to give a general understanding of a wide range of educational approaches and their effects on students' performance specifically in mathematics. Patel et al. [16] conducted a research review on the AOM. Their study, therefore, showed that AOM improves students' learning as compared to the traditional approaches and is applied in a variety of disciplines such as science, social science, mathematics, and English. It fosters students' questioning and analyzing skills by applying the model. Nevertheless, the review has limitations such as a lack of detailed information about the specific studies that were reviewed such as sample size and research design, and more importantly, there is no discussion on the difficulties of implementing AOM. Dimitra et al. [17] conducted a literature review and qualitative content analysis on GBL in education. Their work describes different forms of GBL and gives examples of the application of GBL in Greece, the advantages and disadvantages of GBL are discussed. However, the review is limited because it only superficially examines specific GBL strategies and the effect of GBL on learning outcomes and does not include an international perspective.

Ramli et al. [18] studied GBL and students' motivation in mathematics. The study found GBL positively influences motivation, engagement, and confidence in the learning of mathematics. However, the study recommends that more studies be done on student self-efficacy in learning because motivation, which is a very critical factor in learning, was not given much attention in the study.

Gichohi and John Kihato [19] carried out a quasi-experimental study on the Teams-Games-Tournaments Cooperative Learning Strategy (TGTCLS) and achievement in mathematics, self-concept, and perception of the learning environment. The study affirmed that students in the experimental groups taught with TGTCLS scored higher than the control groups in terms of scores, self-concept and perception of the learning environment. The limitations of the study include the following, the study was done on a particular aspect, Specificity which was Similarity and Enlargement, and the study used quasi-experimental research design which has inherent bias.

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Thus, in a study by Arbitron et al., [20] the researchers aimed to identify the effect of the Advance Organizer on students' mathematics achievement in public secondary schools in the post-test-only quasi-experimental design. They noted that the Advance Organizer improved students' understanding and mastery of mathematics to a much higher level than the other two strategies. However, the study has some limitations as follows: small sample, no follow-up on the consequences of the interventions, and inadequate information on how the interventions were conducted. Singla et al. [21] presented a systematic review of RL in education and learning, and its prospects and challenges. They discussed RL's opportunities in individual approach, learning technologies, and learning games, but also pointed out its weaknesses, such as the conclusions made based on the specific group of participants of the workshops, and the lack of research on long-term effects of RL. Umar et al. [22] examined the use of the Van Hiele Instructional Model for teaching mensuration in mathematics with conventional teaching approaches. They discovered that students taught using the Van Hiele model scored better than their counterparts who were taught using conventional methods. The study's main drawbacks include its short-term perspective and lack of information on the traditional approaches and potential teacher biases. Al-Fahad Mon et al. [23] conducted a systematic review of RL in education where they looked at different RL policies and uses. They discovered that RL allows for an individualized and dynamic approach to learning that is likely to increase the student's interest. The review is quite general and may overlook specific techniques; the paper also lacks sufficient empirical support, and more longitudinal studies are needed to confirm the conclusions. Ruan et al. [24] employed deep RL to design an adaptive pedagogical support system for teaching volume concepts. This was particularly effective for lower-achieving students at the beginning of the year and the results showed relative homogeneity across the different groups. However, the study was carried out only on a single mathematical concept and no information was given on its long-term impact. Pögelt et al. [25] proposed an RL-based recommendation system to suggest mathematical tasks according to ILOs. They discovered that this RL-based system was much better than a random baseline in terms of recommendation and learning personalization. However, the study's evaluation was limited to 129 tasks, and the applicability of other subjects or larger datasets cannot be guaranteed. Additionally, the accuracy of measuring student progress was not fully addressed. The summary of the literature review is presented in Table 1.

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Table 1: Summary of Literature Review (Authors' own creation)

Ref.	Methodology	Main Findings	Limitations
[16]	Review, Advance Organizer Model (AOM)	Enhancing student learning, critical thinking	Specific studies, implementation challenges
[17]	Literature review, qualitative content analysis	Types of GBL, Greece, benefits and drawbacks	GBL types, effectiveness, Greece perspective
[18]	Game-based learning, challenge, curiosity, fantasy	Motivation, engagement, and confidence in learning	Self-efficacy, student motivation
[19]	Quasi-experimental, MAT, MSCQ, MLEQ	TGTCLS, achievement, self-concept, learning environment	Specific topic, quasi-experimental biases, external variables
[20]	Quasi-experimental, post-test, TMAT	Advance organizer, understanding, academic achievement	Small sample size, short-term, implementation details
[21]	Survey, RL4ED workshop	Personalized education, intelligent tutoring systems	Workshop participants, longitudinal studies
[22]	Quasi-experimental, MAT	Van Hiele model, achievement, no gender difference	Short-term, conventional methods, teacher bias
[23]	The systematic review, RL	Personalized learning, motivation, best practices	Broad focus, empirical evidence, longitudinal studies
[24]	Deep RL, adaptive pedagogical support	Adaptive support, lower-performing students, different populations	Specific concept, long-term effects
[25]	RL-based recommendation, ILOs, Anderson and Krathwohl	Personalizing task recommendations, achieving ILOs	Specific tasks, progress measurement, generalization

2.1. Research Gaps

This study seeks to fill the research gap born from the limited degree of comparison between the two approaches, presenting a multifaceted examination of the comparative efficacy of AOM and CTM that is so far missing from the pre-existing literature. Prior studies have failed to satisfactorily compare CTM and AOM methodologies, either lacking explanations as to how the interventions were carried out, the long-term effects of AOM, and in-depth analysis of mathematical learning from a multi-faceted approach.

Additionally, this research seeks to apply RL techniques to create a dynamic gamified mathematical environment that can continuously challenge students learning mathematics.

3. Methodology

This section summarizes the study's methodological approach, including the research design, participant selection, K-means clustering participant grouping, data collection, equipment, and data analysis processes.

3.1 Research Design

The researchers employed a quasi-experimental research approach, as in [26], which comprised non-control groups before and following the exam. No one was arbitrarily placed in the experimental or control groups. Because the pre- and post-test nonequivalent groups were unable to conduct an actual experiment owing to several limitations, our study employed a quasi-experimental design.

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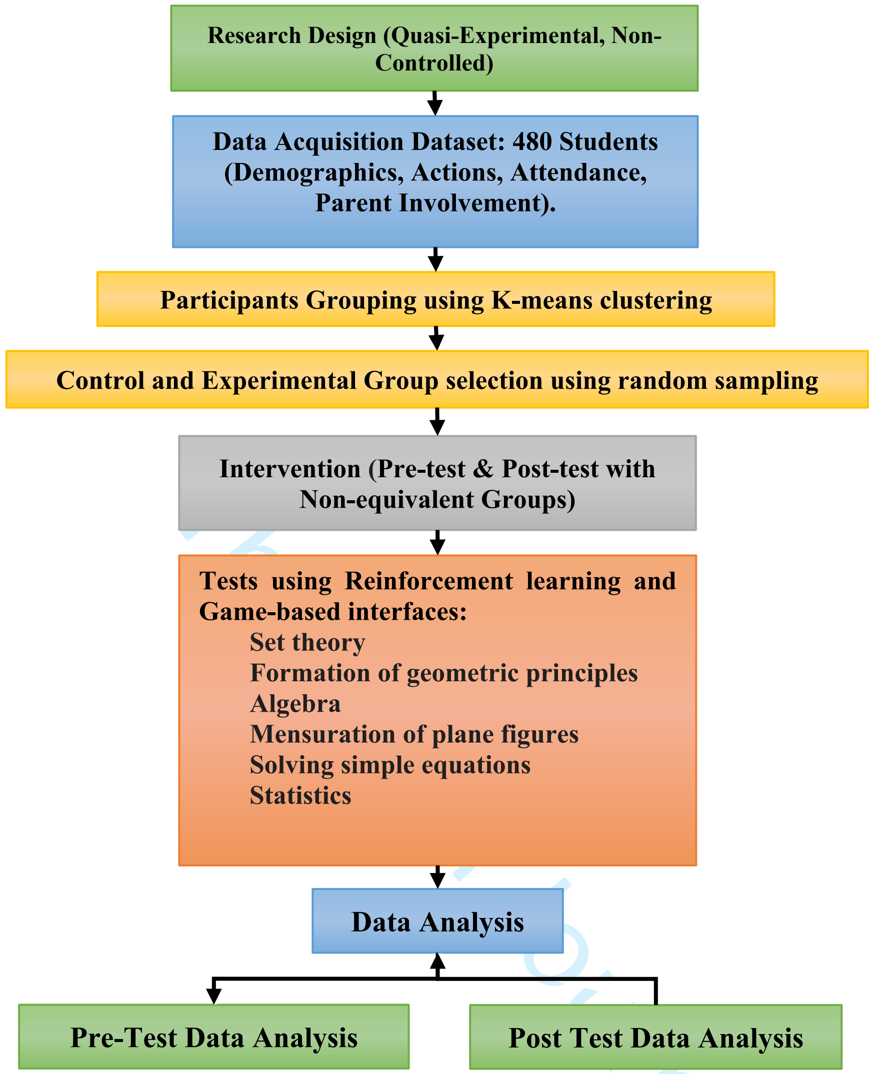

Figure 1 Block Diagram of Proposed Work (Authors' own creation)

This study employs a quasi-experimental design, which lacks full control over variables typically seen in true experimental designs as shown in Figure 1. This design is chosen to investigate an educational intervention without using a specific control group, aligning with its non-controlled aspect. Data acquisition involves collecting information from a dataset of 480 students, encompassing demographics, actions, attendance, and parent involvement. The students are then grouped using K-means clustering, a machine-learning technique that helps create distinct participant groups for the intervention. The intervention includes both pre-test and post-test phases with non-equivalent groups, focusing on educational activities such as teaching geometric principles, solving algebraic problems, and understanding the mensuration of plane figures, all facilitated through reinforcement learning and game-based interfaces. Following the intervention, statistical analysis is conducted. Pre-test data analysis involves examining data collected before the intervention to establish baseline knowledge and skills. Post-test data analysis evaluates the data collected after the intervention to measure its impact and effectiveness.

3.2 Participant Selection

A total of 480 students participated in the study, drawn from diverse socio-demographic backgrounds and educational settings across two academic semesters. 480 students from a range of backgrounds participated in this study; 175 of them were female and 305 of them were male as shown in Figure 2. Figure 3 presents the nationality distribution. 179 Saudi Arabians, 172 Jordanians, 28 Peruvians, 22 Iraqis, 17 Lebanese, 12 Tunisian students, 11 Kuwaiti students, 9 Egyptians, 7 Syrians, 6 US students, 4 Libyans, 1 Venezuelan, and 11 students from Iran and Kuwait. Sixteen distinct student characteristics are included in the dataset, broadly classified as follows: Some examples of socio-demographic factors include (1) nationality, age, and racial/ethnic background. (2) educational identifiers such as year in school, grade, and course level. (3) student actions, such as contributions to class discussions, use of course materials, parental survey completion, and overall happiness with the school. As seen in Figure 4, which records students' absences from class, 191 students have missed more than 7 days of school and 289 have missed less than 7. Parental participation in the classroom is now a part of the dataset. The parent involvement aspect consists of the parent satisfaction survey and the responses from parents. Just under half of the 270 parents who filled out the poll were satisfied with their child's school; the other half were either very happy or very dissatisfied. The sample size was determined using a combination of random and purposeful sampling procedures. In other words, all students in a single mathematics class were given a pretest in a game-based learning approach to the subject. Factors that can impact the outcomes of this study, such as prior student performance and motivation, are isolated through purposeful sampling which separates students into different groups based on their performance on the administered pre-test. This ensures that the real effect of the intervention is isolated.

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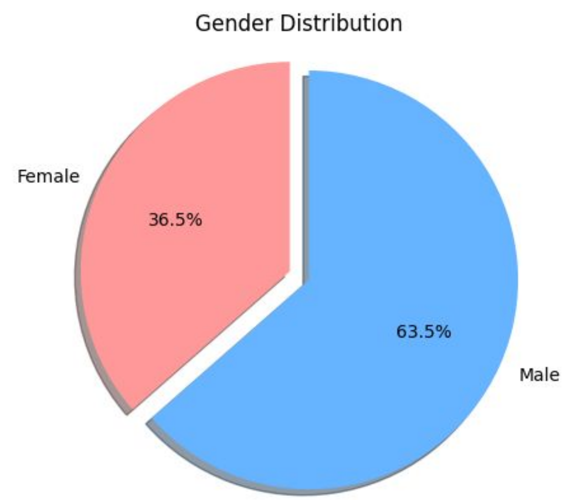

Figure 2: Gender Distribution of the participants (Authors' own creation)

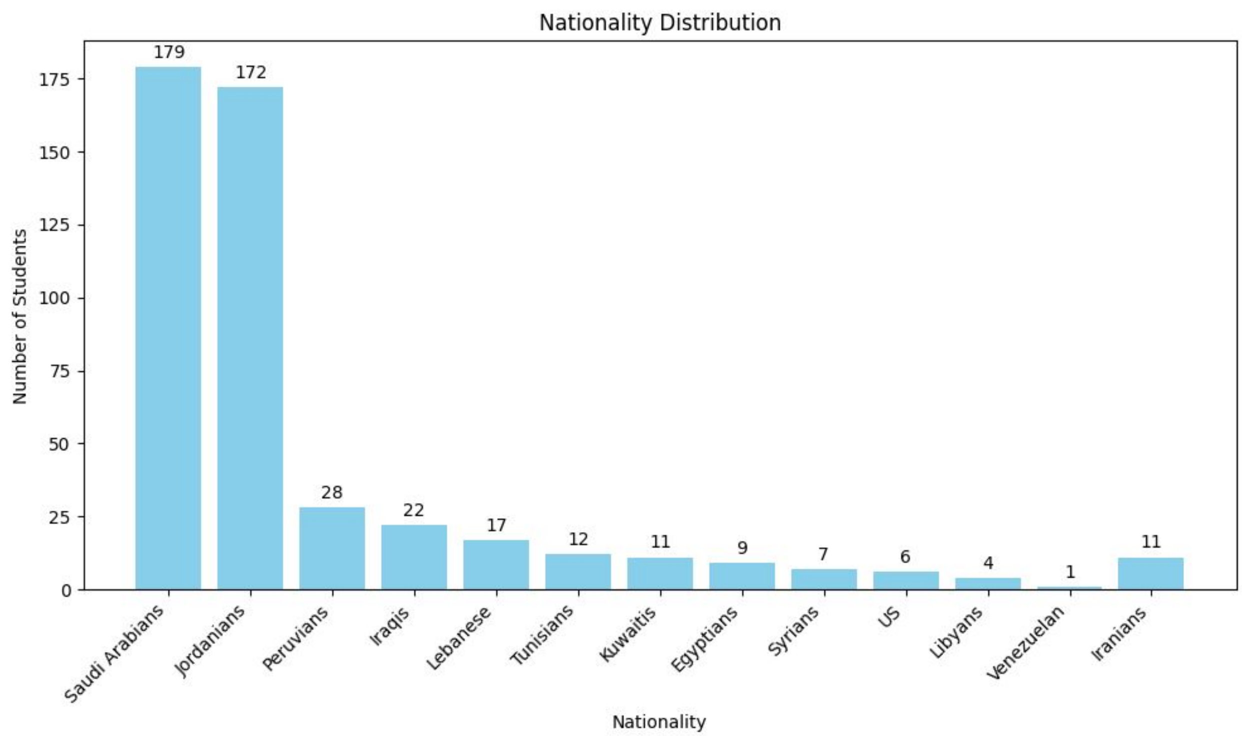

Figure 3: Nationality distribution of the participants (Authors' own creation)

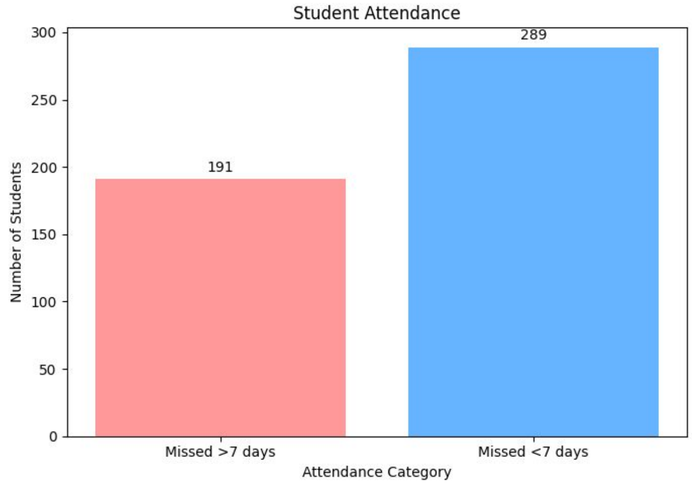

Figure 4: Student attendance of the participants (Authors' own creation)

3.3 Participants grouping using K-means Clustering

In this study, K-means clustering was utilized to group participants based on their pre-test results to ensure homogeneity within each group. The primary goal of this grouping method was to create clusters of students who shared similar levels of initial knowledge and skills, thereby facilitating a more accurate assessment of the intervention's impact on student performance.

K-means clustering [27] is an example of an unsupervised machine learning algorithm that aims to categorize a given dataset into K different clusters that are disjointed from each other. Every cluster is described by a centroid which is a mean position of all the points belonging to the cluster in a multi-dimensional space. The reason for selecting K-means clustering in this study was based on its efficiency in the analysis of a large population and its ability to reduce the within-cluster variation which would mean students in each cluster had similar background characteristics.

Before the K-means algorithm was applied the test data was pre-processed to prepare it for clustering. Data cleaning included missing data treatment and outliers where numerical data were treated with mean imputation for continuous variables and categorical data with mode imputation for categorical variables and outliers treated with the interquartile range method. Normalization was carried out using z-score normalization to make sure that each feature contributed equally to the distance computations. For clustering and data dimensionality reduction, Principal Component Analysis (PCA) [28] was used where only the principal components accounting for most variance was kept. According to the Elbow Method and Silhouette Analysis, the correct number of clusters was identified to be five. The K-means algorithm was then conducted with the process of randomly choosing the K number of centroids, then allocating the data points nearest to these centroids, and repeating this process until the centroids were optimized. Variance in the pre-test score was also computed after the process of clustering to ensure that each cluster was indeed homogeneous and descriptive statistics of each cluster were also calculated.

3.4 Data Collection

Data collection for this study was carefully and systematically carried out to ensure that all the essential information concerning the student's performance and other variables was captured adequately. The process embraced several steps that helped to efficiently collect quantitative as well as qualitative data.

3.4.1 Instrumentation

Lesson Plans

In line with the lessons developed for the experimental group, the lessons followed the AOM learning cycle which comprises of presenting the advance organizer, presenting the learning task and organizing the cognition. For the control group, lessons were based on the traditional teaching model, emphasizing teacher control and student observation.

AOM is used to create the lesson plan for the test group. The three stages of this paradigm are as follows: (1) introducing the advance organizer, (2) presenting the learning task or content, and (3) enhancing cognitive organization. Those schools in the sampled nations often use CTM, which is how the lesson for the control group was produced (students have different origins). Introductory, presentational, stabilizing, and evaluative stages compose this lesson's four stages of instruction. In classrooms when the instructor has complete control and the students are only observers, instructors often resort to this strategy.

Achievement Tests

Pre-tests and post-tests were conducted to measure students' understanding of mathematical concepts. The tests covered set theory, geometric principles, algebra, mensuration of plane figures, solving simple equations, and statistics. Table 2 indicates six tests taken during the pretest and posttest.

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Table 2: Test I to VI in pre and post-test (Authors' own creation)

Test I	Test II	Test III	Test IV	Test V	Test VI
Set theory	Formation of geometric principles	Algebra	Mensuration of plane figures	Solving simple equations	Statistics

"Conceptual structure," "meaningful absorption of material," "a habit of exact thinking," and "an Interest in inquiry" are just a few of the numerous student attributes that are assessed in these exams. This Test covers the assessment of the experimental data as well as a broad overview of the data interpretation and techniques. In addition, this Test discusses the analysis of the experimental data.

3.4.2 Game-Based Learning for Mathematics

Game-based learning for mathematics [29] involves integrating interactive, game-like elements into educational content to enhance student engagement and improve learning outcomes. This approach leverages the motivational aspects of games to create a dynamic and immersive learning experience that facilitates the acquisition and reinforcement of mathematical concepts.

As shown in Figure 5(a), the game incorporates AI to adapt to the difficulty of mathematical problems based on the student's performance. This personalized approach ensures that the level of challenge adjusts dynamically, maintaining an optimal balance between difficulty and skill level. The AI-driven game provides immediate feedback and progressively more complex problems as the student demonstrates mastery of earlier content, thereby fostering a tailored learning environment. As shown in Figure 5(b), the focus shifts to applying the concepts learned in Stage 1 through more complex and integrated mathematical tasks. The game presents scenarios that require students to use their knowledge in practical, problem-solving contexts. This stage emphasizes the application of learned skills in varied situations, reinforcing comprehension through practice and contextual understanding.

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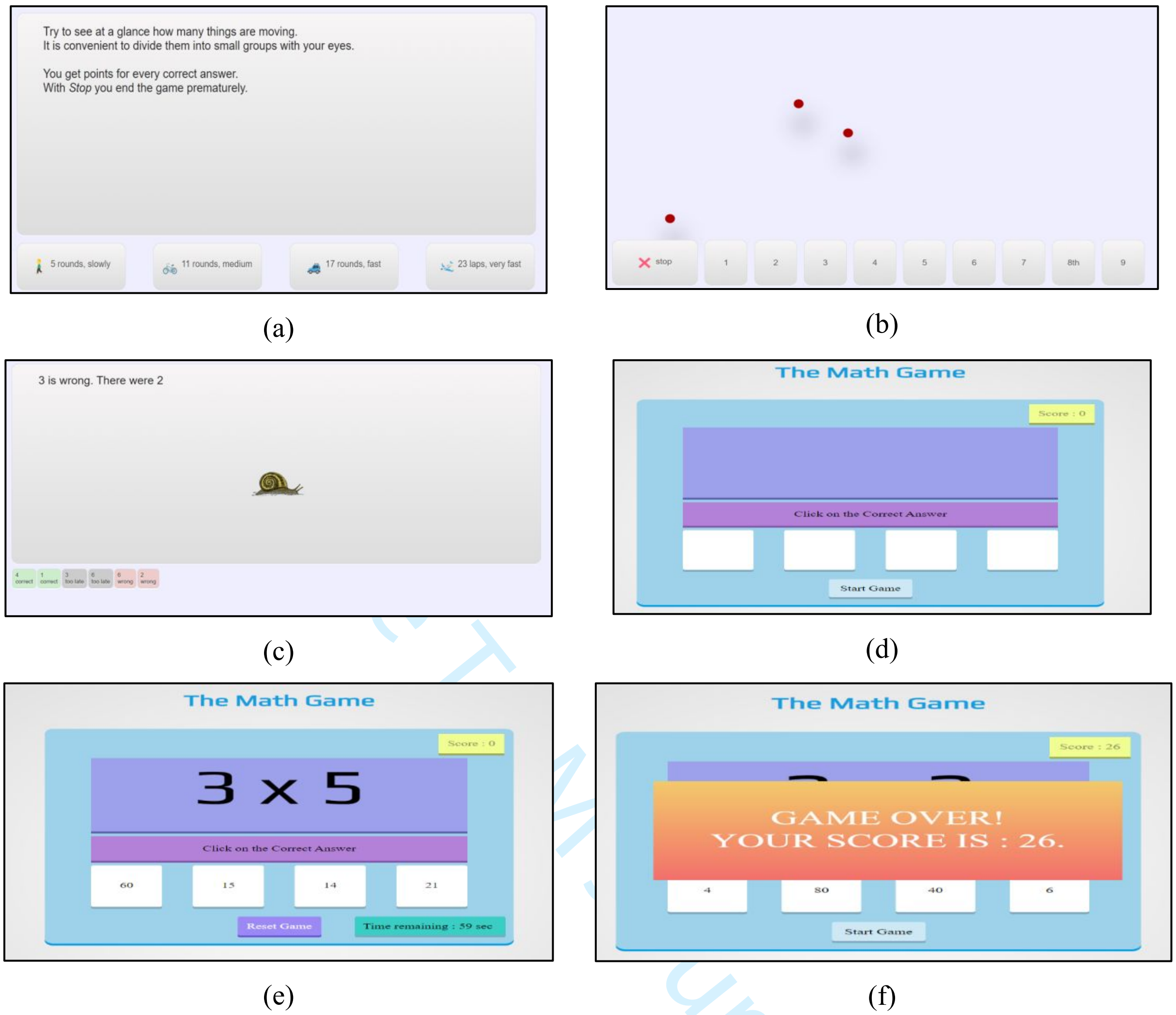

Figure 5: (a) Maths Game with AI at Stage 1; (b) Maths game at Stage 2; (c) Maths game at Stage 3; (d) Maths Game Sample 2; (e) Math Game sample 2 stage 2; (f) Math's Game sample 2 stage 3; (Authors' own creation)

As shown in Figure 5(c), Stage 3 of the game introduces advanced mathematical problems that challenge students to synthesize and apply their knowledge in innovative ways. This stage is designed to test higher-order thinking skills such as analysis and evaluation. By engaging with complex scenarios and solving intricate problems, students are encouraged to integrate and apply their mathematical understanding in new contexts, preparing them for real-world applications. Figure 5(d) presents a sample of another game designed for teaching mathematics. This game incorporates various mathematical concepts into engaging challenges, aiming to enhance students' problem-solving abilities and conceptual understanding. The graphics and the activities incorporated in the game are designed to keep the student engaged and motivated while at the same time being able to impart knowledge and skills.

In Figure 5(e) Math Game Sample 2 is at Stage 2, more challenging problems which are based on the previous level are introduced to the students. This stage entails the elaboration of mathematics knowledge and skills by students through game-like activities, which enrich their learning through practical manipulations and problem-solving exercises. As illustrated in Figure 5(f), Math Game Sample 2 is at Stage 3 with the more complex problems that allow the students to prove their full understanding of the mathematical concepts. This stage of the game involves testing the students' knowledge of higher-order thinking and problem-solving skills in line with the intended learning outcomes.

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3.4.3 Reinforcement Learning Integration

RL [30] was used to make the level of maths games variable in a way that adapts to the child's learning progress. The RL model always adjusted the difficulty level based on the student's performance to ensure they remain challenged but not overwhelmed. An appropriate RL algorithm was selected for this task based on the complexity and flexibility of the algorithm. Model-free RL algorithm Q-learning was chosen because of its suitability for problems with a discrete number of actions, which is the case with changing game difficulty levels. The Q-learning algorithm was applied using a dataset of students' interactions with the math games, where the state was the student's performance level, the action was the change in the difficulty level of the game, and the reward was determined by the student's subsequent performance and activity level.

The state space of the RL model included a number of the performance parameters that characterize the student behaviour, including the correctness of the answers, the time needed to solve the problems, the frequency and intensity of hints or help requests, and overall activity level expressed in terms of the number and length of interactions. The reward function was carefully crafted to ensure that short-term performance and learning goals were met; positive rewards were given to correct answers and to increase performance while negative rewards were given to wrong answers and over-dependence on hints. The reward function also included engagement metrics, which received higher rewards for continued playtime with the game. The RL model of the game assessed the student's state at each step and used it to determine the difficulty of the subsequent math problems during the gameplay. Algebraic and geometric problems were also given and the degree of difficulty of the problems given at the start was determined by the student's performance in a pre-test. When the students were playing the game, the RL model adapted the level of difficulty in real-time and made the difficulty higher after a correct answer was given and lower if the answer was incorrect. The RL model was learning throughout the entire study and updating its knowledge base with each student's interaction data to improve the difficulty adjustment strategy. This continuous learning ensured that the model was able to adjust to the rate and method of learning of the students thus individualizing the learning process. The performance feedback loop helped the model to correct its predictions for the subsequent problems, while the re-evaluation periodically checked the overall efficiency of the proposed difficulty adjustment strategy. The RL system was incorporated into the game-based learning platform in such a way that the game interface and the RL model exchanged data in real-time for immediate adjustment of the game's difficulty level. The game interface gave simple and understandable feedback to the students while the back-end computation catered for a large amount of data and real-time computation. To evaluate the RL integration's effectiveness, metrics such as changes in student engagement, pre- and post-test performance improvements, and qualitative feedback from students were analyzed.

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3.5 Data Analysis

In terms of data analysis, there was pre- and post-test data standardization and preparation, descriptive statistics and hypothesis testing to ascertain the efficacy of the AOM and CTM and the influence of RL, and a thorough assessment of the performance and comprehension of the students.

3.5.1 Pre-test Analysis (Stage 1)

The pre-test gathered data were compared to the post-intervention data to ensure that the experimental and control groups were similar. To compare the prior knowledge and other factors that could be controlled, significance tests and correlation analyses were conducted.

In the pre-test analysis phase, all the data gathered before the intervention was implemented were scrutinized to determine the groups' similarity before the commencement of the actual experiment. This examination included several stages. First, the data collected from the pre-tests were pre-processed to handle missing or inconsistent data entries. The data were then normalized to keep the consistency of the data collected from different student records. Subsequently, the mean, standard deviations, and range were calculated to get the general performance and dispersion of each group. Mann-Whitney U or t-tests were employed to assess how comparable the experimental and control groups were. These tests compared the means of scores on variables of interest to determine that the pre-intervention knowledge and skills of the groups were equivalent. Moreover, correlation analyses were conducted to reveal if there is a connection between pre-test scores and other demographic or educational factors; this would help to define if external factors could affect the results. The equal distribution of subjects in the groups was further confirmed using Levene's test to check the equality of variance to ensure that the two groups had similar prior knowledge.

3.5.2 Post-test Analysis (Stage 2)

After the intervention, post-test scores were computed to determine the effectiveness of AOM and CTM on students' achievement. The analysis involved hypothesis testing concerning the mean achievement scores, group and between-group comparisons, and the efficiency of RL-enhanced game-based learning.

The impact of the AOM and the CTM on students' performance was evaluated by post-intervention post-test analysis. As with the collection and processing of the pre-test data, the production of the post-test data marked the beginning of the analytical process. This meant that the data was cleaned and standardized to remove or minimize errors and to make it easy to compare across the variables. The post-test results were then descriptively examined to ascertain the students' performance and to compare the means of the experimental and control groups' pre- and post-test scores.

Since the aim of the study was to assess the impact of the intervention, hypothesis testing was used with tools like ANCOVA. To control for any initial differences between the groups, ANCOVA was used, which gave a precise comparison of the mean achievement scores of the AOM and CTM groups. A comparison of post-test scores was made between the experimental and control groups as well as within the groups to gain a deeper understanding of the outcomes and to ascertain how well the AOM and CTM improved the performance of the students.

The performance of RL within the game-based learning framework was also evaluated. This entailed studying how the variation in the level of difficulty affected the students' interest and achievement levels, with the performance levels being compared before and after the manipulation. Furthermore, the synthesis approach was also used to evaluate the extent of knowledge gained together with the relations made between ideas within the content area; in this way, the effects of the teaching strategies on the students' math mastery were determined.

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4. Results and Discussion

This section examines the suitability of the AOM and CTM in educating high school mathematics using GBL and RL technologies.

4.1 K-Means Clustering Results

The use of K-means clustering in this study provided meaningful and statistically significant outcomes that improved the research study's general credibility and dependability. The pre-test score data of the 480 students was grouped into five clusters by applying the K-means clustering algorithm. The distribution of students across these clusters is summarized in Table 3 as well as visually presented in Figure 6.

Table 3: Distribution of Students Across Clusters (Authors' own creation)

Cluster	**Number of Students**	**Percentage of Total**
1	96	20%
2	102	21.25%
3	89	18.54%
4	97	20.21%
5	96	20%
Total	**480**	**100%**

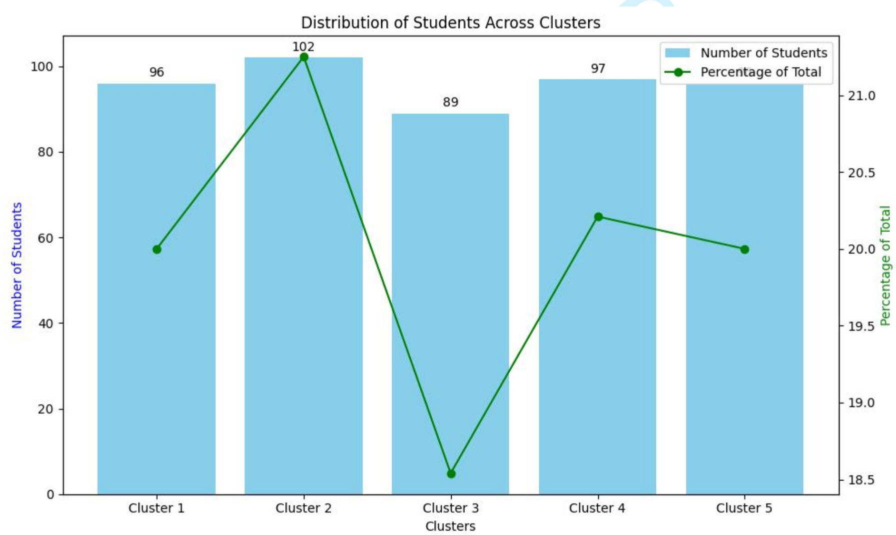

Figure 6: Distribution of Students Across Clusters (Authors' own creation)

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The mean pre-test scores and the standard deviations are presented in Table 4, which reveals the differences in the student's academic performance at the pre-test stage in each of the clusters. The mean of the pre-test for the clusters is as follows; Cluster 1 is 58.7 with an average deviation of 4.3, which is a mediocre performance and fluctuation between this group of people. Cluster 2 received the highest mean score of 72.1 and standard deviation of 5.2 which indicates higher initial KV and a bit higher variability of scores. Cluster 3, the mean score was 48.9 and a standard deviation of 3.9, depicts the group with the lowest level of performance at the beginning of the study. As for Cluster 4, the mean score is equal to 65. The means of the positive and negative feedback are equal to 4 and the standard deviations are also equal to 4.8, which means that the first performance is rather strong, and the variability is moderate. The mean for Cluster 5 is 53.2 and the standard deviation is equal to 4.1, meaning they start with lower scores and have moderate score variability.

Table 4: Pre-test Score Statistics for Each Cluster (Authors' own creation)

Cluster	Mean Pre-test Score	Standard Deviation
1	58.7	4.3
2	72.1	5.2
3	48.9	3.9
4	65.4	4.8
5	53.2	4.1

Table 5 gives an enhanced insight about the pre-test score distribution and basic demographic characteristics in each cluster. The first cluster with a score between 55 and 62 includes mainly urban students with an almost equal ratio of male and female students. The scores of the students in Cluster 2 are between 68 and 76; most of the students are male with high parental involvement, which suggests that the home environment may be more supportive and hence the good performance. Cluster 3 students have a score range of 45 to 52, they have high truancy rates and mixed ethnicity which imply difficulties in attendance and cultural differences. Cluster 4 has scores ranging from 61 to 69; there is an equal number of boys and girls; students have a good previous academic record, so their experience is quite stable. The last cluster has scores between 50 and 57; it is also a female-dominant group with moderate parental participation, which does not mean a very supportive home environment.

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Table 5: Detailed Cluster Profiles (Authors' own creation)

Cluster	Pre-test Score Range	Key Demographic Attributes
1	55 - 62	Majority from urban areas, mixed gender
2	68 - 76	Predominantly male, high parental involvement
3	45 - 52	High absenteeism, diverse ethnic backgrounds
4	61 - 69	Balanced gender ratio, strong prior academic performance
5	50 - 57	Predominantly female, with moderate parental involvement

4.2 Pretest and posttest results of the experimental and control groups

The statistical analysis of the intelligence scores for the two student groups is shown in Table 6, which also looks at the importance of the difference between the mean values. Group 1 consists of 32 students with a mean intelligence score of 29.56 and a standard deviation of 9.46, indicating some variation in the scores within this group. With 32 students in Group 2 and a mean score of 29.50 with a standard deviation of 9.50, the amount of variance is comparable to that of Group 1. The statistical significance of the difference between the means of the two groups is ascertained using the critical ratio, which stands at 0.01. The relatively modest crucial ratio suggests that there is no statistically significant difference between the mean scores of the two groups.

Table 6: Significance of the Difference between the Means of Intelligence Score of students in the two groups (Authors' own creation)

Group	No. of students	Mean	Standard deviation	Critical Ratio
Group 1	32	29.56	9.46	0.01
Group II	32	29.50	9.50	

Table 7 provides the statistical analysis of the general mathematics proficiency scores for two groups of students, assessing the significance of the difference between their mean scores. Group 1, which consists of 32 students, shows variation in its results in mathematical competency, with a mean score of 21.81 and a standard deviation of 7.95. The critical ratio, which measures the statistical significance of the difference between the means of the two groups, is 0.241. The low

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critical ratio suggests that there is no statistically significant difference between the mean scores of the two groups.

Table 7: Significance of the Difference between the Means of General Mathematics Proficiency Score of Students in the Two Groups (Authors' own creation)

Group	No. of students	Mean	Standard deviation	Critical Ratio
Group 1	32	21.81	7.95	0.241
Group II	32	21.34	7.64	

Table 8 presents the statistical analysis of pre-requisite scores for students in two groups, focusing on the significance of the differences between their mean scores across various tests. The results of every test indicate that there are no appreciable variations in the prerequisite scores between the two groups, indicating that before the intervention, both groups' baseline knowledge and abilities were comparable.

Table 8: Significance of the Difference between the Mean of Pre-Requisite Scores for the students in the two groups (Authors' own creation)

Pre-requisite Scores	Group	No. of students	Mean	Standard deviation	Critical Ratio
Test I	Group 1	32	15.19	3.57	0.210
	Group II	32	15.38	3.56	
Test II	Group 1	32	14.97	3.55	0.310
	Group II	32	15.25	3.71	
Test III	Group 1	32	15.03	3.53	0.582
	Group II	32	14.50	3.77	
Test IV	Group 1	32	15.25	3.65	0.35
	Group II	32	15.22	3.50	
Test V	Group 1	32	15.00	3.92	0.93
	Group II	32	14.91	4.13	

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Test VI	Group 1	32	15.03	3.59	0.473
	Group II	32	15.47	3.80	

Table 9: The statistical significance of the difference in post-experiment test scores between the experimental and control groups, both overall and for the six tests at issue (Authors' own creation)

Post-test Scores	Group	No. of Students	Mean	Standard deviation	r	Critical Ratio
Whole test	Control	32	73.34	13.21	0.67	6.77**
	Experimental	32	98.38	24.83		
Test I	Control	32	12.63	2.61	0.74	6.22**
	Experimental	32	15.97	3.73		
Test II	Control	32	12.38	2.34	0.70	6.57**
	Experimental	32	16.16	3.94		
Test III	Control	32	13.41	2.71	0.73	4.98**
	Experimental	32	16.41	4.15		
Test IV	Control	32	12.16	2.49	0.65	6.24**
	Experimental	32	16.47	4.49		
Test V	Control	32	11.59	1.72	0.57	7.67**
	Experimental	32	16.78	4.31		
Test VI	Control	32	11.19	2.07	0.57	7.54**
	Experimental	32	16.59	4.48		

To shed light on the effectiveness of the intervention, Table 9 presents the statistical significance of the variations in post-experiment test scores between the experimental and control groups. The experimental group's mean post-test score is 98.38 with a standard deviation of 24.83, whereas the control group is 73.34 with a standard deviation of 13.21. The very significant difference indicated by the critical ratio of 6.77** suggests that generally, the experimental group outperformed the control group.

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Table 10: The statistical significance of the two groups' mean results on mathematics achievement tests administered to students of varying IQs (Authors' own creation)

Levels of Intelligence	Group	No. of Students	Mean	Standard deviation	r	CR
Low Intelligence	Control	11	59.91	8.55	0.65	4.24**
	Experimental	11	74.00	11.76		
Average Intelligence	Control	11	76.64	5.55	0.28	6.98**
	Experimental	12	107.92	15.12		
High Intelligence	Control	10	84.50	10.64	0.58	4.24**
	Experimental	9	115.44	24.92		

Table 10 shows the probability value for the inter-group difference in the mathematics achievement test score with intelligence as the independent variable and control and experimental groups as the dependent variable. But in the control group having low intelligence the mean score was 59 only. 91 with a standard deviation of 8.55 and the experimental group got 74 as the mean score. 00 with a standard deviation of 11.76. The critical ratio is defined to be 4.24** shows a difference in favour of the experimental group and it also depicts that the intervention made a good impact on the mathematics achievement of students with low intelligence. The average intelligence students who make up the control group scored a mean of 76 on the test. 64 and the standard deviation of the same was 5. With a standard deviation of 15, the experimental group's average was 107.92, whereas the control group's was 55. This critical ratio stands at 6. 98 depicts a considerable difference, suggesting that the experimental group's performance was much better than the control group implying that the intervention was good for the students with average intelligence as well. High-intelligent students in the control group scored a mean of 84. 50 +/-10. Of the two groups, the control group got a mean of 64 while the experimental group got a mean of 115.44 with an SD of 24.92. Here, the crucial ratio of 4.24** indicates a difference of 13.46% in favour of the experimental group, suggesting that the intervention improved the high-IQ students' understanding of mathematics.

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Table 11: The statistical significance of the two groups' mean post-test results on mathematics achievement, broken down by students' IQ (Authors' own creation)

Group	**Levels of Intelligence**	**No. of Students**	**Mean**	**Standard deviation**	**r**	**Critical Ratio**
Experimental	Low	11	74.00	11.76	0.89	11.23**
	Average	12	107.92	15.12		
Experimental	Low	11	74.00	11.76	0.89	10.17**
	High	09	115.44	24.92		
Experimental	Average	12	107.92	15.12	0.53	0.95
	High	09	115.44	24.92		
Control	Low	11	59.91	8.55	0.92	14.16**
	Average	11	76.64	5.55		
Control	Low	11	59.91	8.55	0.93	15.30**
	High	10	84.50	10.64		
Control	Average	11	76.64	5.55	0.73	2.04.
	High	10	84.50	10.64		

The examination of the mathematical achievement post-test results between the experimental and control groups, divided into IQ-based groups, is presented in Table 11. As a result, the experimental group's mean score for students who were not very brilliant was 74. The control group had a mean score of 59.91 with an SD of 8.55, whereas the experimental group had a score of 11.76. The critical ratios for the experimental group are significantly high, which are 11.23** and 10.17**, which shows significant differences in the experimental group's favour. This implies that the intervention made a significant improvement in the mathematics performance of the students with low intelligence. For the average intelligence, the experimental group scored a mean of 107.92 in the experiment, with a standard deviation of 15.12. The control group on the other hand had a mean score of 76.64 with a standard deviation of 5.55. As a result, in this comparison, the crucial ratio is 0. The achieved score of 95 for this IQ category indicates that there is no statistically significant difference between the groups. This means that the intervention did not demonstrate a higher level of effectiveness than the control group in enhancing the mathematics learning outcomes for the average intelligence students.

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4.3 Results of Mathematics Achievement Post-Test

Table 12 displays the post-test results of the learning objectives for both the experimental and control groups, demonstrating notable variations in their respective performances. Based on the survey findings, every assessed domain showed that the experimental group scored higher than the control group. As for the Knowledge objective, the experimental group achieved a higher mean of 17.91 compared to 16.88 in the control group, and the CR was significant at 3.85** which shows that there is improved recall and understanding. Additionally, there was a substantial increase in Understanding for the experimental group (mean of 21.06 against 16.66 for the control group; CR = 6.36**), suggesting that the control group understood more. In Application, the experimental group got a total score of 18.31 compared to 13.09 in the control group (CR = 5.67**), which pointed to the enhanced capacity of the students to apply concepts. Likewise, for Analysis, Synthesis, and Evaluation, the experimental group obtained higher scores with CR values of 6.66**, 5.89**, and 5.23**, respectively, which means that they are more skilled in these areas. The experimental group also excelled in Skill Level, scoring 14.19 compared to 9.88 in the control group (CR = 6.01**).

Table 12: Significance of the Disparity in Mean Scores of Items according to Primary Learning Objectives of Students in the Experimental and Control Group Post-Test (Authors' own creation)

Instructional objective	**Group**	**No.of Students**	**Mean**	**Standard deviation**	**r**	**CR**
Knowledge	Control	32	16.88	1.72	0.67	3.85**
	Experimental	32	17.91	1.09		
Understanding	Control	32	16.66	3.14	0.65	6.36**
	Experimental	32	21.06	4.10		
Application	Control	32	13.09	2.97	0.62	5.67**
	Experimental	32	18.31	5.90		
Analysis	Control	32	7.72	1.75	0.57	6.66**
	Experimental	32	11.56	3.56		
Synthesis	Control	32	5.50	2.14	0.65	5.89**

	Experimental	32	8.78	3.56		
Evaluation	Control	32	3.63	1.70	0.62	5.23**
	Experimental	32	6.56	3.69		
Skill Level	Control	32	9.88	2.35	0.60	6.01**
	Experimental	32	14.19	4.50		

Table 13: Statistical significance of the difference between the experimental and control groups' mean scores on the Mathematics Achievement Test, which was administered to all students just after the experiment was completed, on questions based on the key teaching goals (Authors' own creation)

Instructional Objective	**Group**	**No. of Students**	**Mean**	**SD**	**r**	**CR**
Knowledge	Control	11	15.09	1.87	0.79	4.42**
	Experimental	11	16.91	1.22		
Understanding	Control	11	13.45	1.44	0.40	3.56**
	Experimental	11	16.73	3.00		
Application	Control	11	10.27	1.68	0.52	2.96**
	Experimental	11	12.82	2.89		
Analysis	Control	11	7.09	1.58	0.62	2.53**
	Experimental	11	8.36	1.43		
Synthesis	Control	11	4.09	1.51	0.55	2.93**
	Experimental	11	5.73	1.62		
Evaluation	Control	11	2.09	1.30	0.41	2.56**
	Experimental	11	3.45	2.02		
Skill Level	Control	11	7.82	1.78	0.57	2.78**
	Experimental	11	10.00	2.61		

A comparative examination of post-experiment mathematics achievement is shown in Table 13. Exam results comparing the experimental and control groups, emphasizing important learning goals. In every goal, the experimental group continuously outperformed the control group. The experimental group performed significantly better on knowledge recall and understanding, with a mean score of 16.91 with a standard deviation of 1.22 compared to a mean score of 15.09 with a standard deviation of 1.87 for the control group. This resulted in a critical ratio (CR) of 4.42**. In the Understanding category, the experimental group had a mean of 16.73 with a standard deviation of 3. 00, compared to 13.45 with a standard deviation of 1.44 in the control group (CR = 3.56**), which might be due to refined comprehension abilities.

Table 14 presents the findings of the t-test analysis of the variations in the mean scores of the experimental and control groups' answers to questions on the objectives of the Mathematics Achievement exam that was administered just after the experiment. The findings show that, as compared to the control group, the experimental group's scores in all instructional objectives increased significantly. The experimental group had a mean score of 18.42 with a standard deviation of 0.51 for the Knowledge goal, whereas the control group received a mean score of 17.82 with a standard deviation of 0.40. A critical ratio (CR) of 3. 35** indicates that the experimental group's performance in terms of remembering and applying information has improved. The experimental group outperformed the control group with a mean score of 23 in the Understanding category. 08 with a standard deviation of 2.39 and a mean of 17.82 with a standard deviation of 1.99 for the control group. The experimental group has significantly improved in terms of knowledge comprehensiveness, as evidenced by the CR of 5.94**. The experimental group's mean result for Application was 20.92 with a standard deviation of 4.32, whereas the control group's mean result was 13.91 with a standard deviation of 2.07. The CR of 5.36** shows a marked increase in the student’s capacity to use mathematics in novel problems. The experimental group's mean score in Analysis was 12.58 with a 2.47 standard deviation, whereas the control group's score was 7.09 with a 1.14 standard deviation. The CR of 7.31** indicates a significant improvement in analytical abilities. The control group had a mean score of 5.45 with a standard deviation of 0.93 for Synthesis, whereas the experimental group received a mean score of 9.67 with a standard deviation of 2.27. The CR of 5.99** reflects a significant improvement in the ability to integrate and combine information.

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Table 14: The statistical significance of the difference between the experimental and control groups' mean scores on questions based on the key instructional goals of the Mathematics Achievement exam taken as a whole and administered immediately after the experiment (Authors' own creation)

Instructional objective	Group	No. of Students	Mean	Standard deviation	r	Critical Ratio (CR)
Knowledge	Control	11	17.82	0.40	0.37	3.35**
	Experimental	12	18.42	0.51		
Understanding	Control	11	17.82	1.99	0.24	5.94**
	Experimental	12	23.08	2.39		
Application	Control	11	13.91	2.07	0.34	5.36**
	Experimental	12	20.92	4.32		
Analysis	Control	11	7.09	1.14	0.31	7.31**
	Experimental	12	12.58	2.47		
Synthesis	Control	11	5.45	0.93	0.17	5.99**
	Experimental	12	9.67	2.27		
Evaluation	Control	11	4.18	1.08	0.02	5.24**
	Experimental	12	7.50	1.88		
Skill Level	Control	11	10.36	136	0.34	5.77**
	Experimental	12	15.75	3.14		

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Table 15: The statistical significance of the difference in mean scores between the experimental and control groups on questions based on the major instructional goals from the post-experiment mathematics achievement exam (Authors' own creation)

Instructional objective	Group	No. of Students	Mean	Standard deviation	r	Critical Ratio
Knowledge	Control	10	17.80	0.42	0.43	3.24**
	Experimental	9	18.44	0.53		
Understanding	Control	10	18.90	2.73	0.54	4.73**

	Experimental	9	23.67	2.50		
Application	Control	10	15.30	2.54	0.55	3.51**
	Experimental	9	21.56	5.96		
Analysis	Control	10	9.10	1.79	0.51	4.13**
	Experimental	9	14.11	3.89		
Synthesis	Control	10	7.10	2.64	0.71	3.69**
	Experimental	9	11.33	4.18		
Evaluation	Control	10	11.60	2.17	0.37	3.83**
	Experimental	9	17.22	4.27		
Skill Level	Control	10	11.60	2.17	0.37	3.83**
	Experimental	9	17.22	4.27		

Table 15 shows that on the post-experiment mathematics achievement assessment, the experimental group considerably outperformed the control group across all main teaching objectives. Specifically, the experimental group showed substantial improvements in Knowledge, Understanding, Application, Analysis, Synthesis, Evaluation, and Skill Level. The experimental group's higher mean scores, coupled with lower standard deviations, and significant critical ratios (ranging from 3.24 to 4.73) indicate a notable advantage in recalling information, comprehending concepts, applying mathematical skills, analyzing data, synthesizing ideas, and evaluating information.

4.4 Comparative Analysis

Table 16 provides a comparative analysis between the CTM and the AOM. CTM is a form of didactic method of teaching with low prior categorization of content and depends mostly on conventional teaching methodologies without a proper mode of pre-classification. It usually entails a structured style of teaching where the teacher is the main figure, there is little to no collaborative learning, is centered on presenting content without much prior planning, and offers little to no chance for students to engage actively in their learning, and the main form of assessment is through tests and quizzes. On the other hand, AOM lays much stress on a method that is structured to have frameworks or outlines that help pre-arrange the content so that there is enhanced understanding. This model incorporates interactive and game-based learning techniques to boost student engagement, encourages active participation through discussions and activities, and considers

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holistic understanding and connections in its evaluation. AOM allows greater flexibility to accommodate diverse learning styles and individual needs, with the educator's role shifting towards facilitating content organization and comprehension rather than solely delivering information.

Table 16: Comparative analysis of CTM and AOM (Authors' own creation)

Aspect	Conventional Teaching Method (CTM)	Advance Organizer Model (AOM)
Teaching Approach	Traditional lecture-based approach with limited pre-organization of content.	Structured method emphasizing content organization using frameworks or outlines before instruction.
Methodological Focus	Relies on established teaching methods and materials without a specific pre-structuring model.	Prioritizes organizing information to create meaningful connections and enhance comprehension.
Engagement Strategy	Typically involves teacher-led instruction with limited interactive elements.	Incorporates game-based learning techniques to enhance student engagement and interactivity.
Preparation Emphasis	Focuses on delivering curriculum content without extensive pre-organization or structuring.	Emphasizes the creation of mental frameworks or organizers before teaching to aid comprehension.
Student Interaction	Limited opportunities for active participation, often restricted to Q&A sessions.	Encourages student engagement through interactive activities and discussions, promoting active learning.
Outcome Evaluation	Evaluation is based on traditional metrics like test scores and standard assessments.	Evaluation often considers holistic understanding and connections made within the subject matter.
Flexibility in Teaching	Limited adaptability to diverse learning styles or individual student needs.	Allows for flexibility and adaptability to cater to various learning styles and student needs.
Educator's Role	Primarily focuses on content delivery and explanation.	Emphasizes content organization, connections, and facilitation of deeper comprehension.

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4.5 Discussion

Based on results of the ANCOVA testing of significance, the use of gamified teaching strategies in teaching mathematics has a significant and positive impact on students' understanding of geometric principles, algebraic problem-solving, and mensuration of geometrical shapes.

The findings of this study are in line with prior research. The effectiveness of gamification in improving student test scores as compared to traditional instructional methods supports the research carried out in [5]. AOM has likely shown greater improvements in test scores as compared to CTM due to the differences in methodologies. While CTM focuses more on working through the curriculum without the need for extensive background knowledge, AOM's focus on building connections with prior concepts and improving student comprehension likely contributes to improved student performance in tests [4].

AOM's greater performance in improving student test scores can also perhaps be traced back to its base theories. AOM is based on constructivist theories of education [4]. Constructivism is an activity-based teaching methodology that can improve student appreciation of core mathematical reasoning [7]. As per the existing research, mathematical reasoning taught by linking old ideas to form new ideas, as opposed to the traditional methods of memorizing a series of ideas which may conflict with one another, results in more robust understanding [7]. Furthermore, AOM organizes the lessons in such a manner to make the connections between old and new ideas much clearer, which can be beneficial for students studying outside the classroom, enabling more effective self-studying [8].

Additionally, the usage of Reinforcement Learning in improving the performance of the gamification model should not be underestimated. As shown in [31], Reinforcement Learning-based difficulty adjustment can present effective methods to balance the reward function with the difficulty of the game, allowing for the gamified lessons to maintain engagement by modifying the difficulty of the base game according to the student's skill level.

The results of this study are of significant importance to a number of stakeholders. For parents who seek to improve their children's academic performance, the proposed AOM method provides a more effective alternative to mainstream teaching methods. Additionally, AOM highlights a teaching methodology that parents can adopt themselves when teaching their children at home.

For educational institutions, this research highlights the weaknesses of CTM in student learning. Educational institutions wishing to maintain their competitiveness will need to adopt the AOM in their teaching moving towards the future. For institutions struggling with low student motivation, the gamification strategy provides an effective means to address this problem.

Finally, for teachers, the advantages of AOM over CTM highlights the need for a shift in the way that mathematics is taught. The failings of the traditional methods in imparting long-lasting mathematical knowledge in students has been a factor of much concern. While traditional methods can be effective with some students, in students with low motivation or interest in mathematics alternative methods must be found. AOM meets these needs and has proven effective in improving the retention and scoring of even otherwise low-scoring students.

5. Conclusion

The research findings present important information regarding the effectiveness of the AOM over the CTM in improving learners' performance in mathematics. The K-means clustering analysis revealed that students' characteristics are heterogeneous and are distributed into five clusters with different baseline academic achievements and demographics. These clusters gave a rich picture of the differences in the baseline and conditions of students' learning achievements. The results of comparing the experimental and control groups' pre- and post-test results demonstrate the substantial impact of the AOM intervention. The study's conclusions showed that the experimental group did better than the control group even though the two groups' demographic information and pre-test results were comparable. The experimental group that applied the AOM scored significantly higher in all the instructional objectives of Knowledge, Understanding, Application, Analysis, Synthesis, Evaluation, and skill level. This was illustrated by an increase in the mean scores and a decrease in the standard deviations of the post-test scores with the critical ratios indicating extremely high significance for all the aspects that were tested. Additionally, the statistical study of the math proficiency of kids with varying IQs shows that the AOM intervention was successful in all cases. Particularly among low and ordinary-intelligence students, the experimental group outperformed the control group in terms of scores; however, the difference was negligible in high-intelligence students. As highlighted in the comparison between the CTM and AOM methodologies, the AOM had more advantages as compared to the former. In contrast to the CTM approach that focuses on the teacher's lecture and limited preparation as well as low levels of interaction between the teacher and learners, the AOM encourages organization and

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structure, which leads to increased student engagement and meaningful mathematical learning. The experimental group's improved academic performance suggests that the active learning environment and the organized layout of the AOM during the pre-organization phase are key components in producing improved results.

5.1 Limitations and Future Directions

Although the study on high school math education utilizing game-based learning offers vital insights into the AOM and the CTM, there are significant research gaps that need to be filled. The research mainly uses Mean Retention Scores as its end measure, ignoring more generalized components of learning including the ability to think critically, solve problems effectively, and apply what one has learned in the actual world. Furthermore, concerns about the long-term impacts and durability of information gained from both methods of instruction are raised by the study's short duration, which only lasts two semesters. Without delving into student preferences and engagement levels, the inquiry misses out on important learner-centric insights into the success of each strategy. The effect of contextual factors on the effectiveness of AOM and CTM as well as the potential influence of teacher training and characteristics on the implementation of the above models is beyond the scope of the research. This could be achieved through employing qualitative research approaches, which might give further details beyond what the quantitative measures show on the learning and teaching processes. To enhance the quality of the study, researchers should examine how specific approaches to teaching are used across the disciplines and how technology is incorporated into game-based learning. As we know that in the process of teaching high school mathematics the utilization of AOM and CTM are widely used, it becomes imperative to fill up these gaps of knowledge for a more comprehensive understanding of the two approaches.

Additionally, future research can examine the relative effectiveness of AOM and CTM based on prior performance. This can be done by using clustering to cluster together samples into groups with similar traits, of which representatives can be selected and tested, as based on methodologies such as [32] and [33]. In the context of the research methodology outlined, clustering can also be used to compare the performance with respect to other metrics such as prior performance, grouping together individuals based on prior scores, and then carrying out hypothesis testing to compare their gains in performance after the intervention is administered.

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