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Exploring the Impact of AI on Middle School Mathematics Achievement

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Introduction

Technology is essential for human advancement since it fosters effectiveness, accuracy, and a higher standard of living (Payal & Kanvaria, 2018). Artificial intelligence (AI) has recently revolutionized a wide range of industries, including education. A rising amount of research has been done in recent years to determine how AI affects middle school arithmetic performance. Middle school is a crucial time in a student's academic career since it establishes the groundwork for more complex maths concepts and problem-solving techniques. Researchers and educators are discovering new ways to improve math instruction, student performance, and learning experiences by utilizing AI technologies.

Personalized learning is one key way AI is affecting middle school math achievement. Platforms and tools with AI capabilities may analyze data on individual students, spot knowledge gaps, and modify lessons to suit the needs of each student. This individualized method promotes a deeper comprehension of mathematical ideas by allowing students to advance at their own pace, get tailored interventions, and receive rapid feedback (Tang & Wang, 2018).

AI also provides immersive and interactive learning opportunities. Applications for virtual reality (VR) and augmented reality (AR) give students the chance to simulate abstract mathematical ideas, interact with them in a more understandable way, and visualize them. Math is made more concrete and fun by these immersive technologies, which also aid students in developing their spatial reasoning, critical thinking, and problem-solving abilities (Bacca et al., 2020).

The AI has a lot of potential. Artificial intelligence (AI)-powered personalized learning and immersive technology have the capability to change traditional education, making it more efficient, interesting, and accessible for students. By utilizing AI, educators may help children develop their problem-solving skills and lay a solid foundation for future academic achievement.

Keywords: Achievement, Artificial Intelligence, Technology, Personalised Instruction

About AutoDraw AI Tool

AutoDraw, a dynamic drawing tool developed by Google, revolutionizes the art of illustration. It seamlessly combines cutting-edge machine learning algorithms with a curated repository of artwork contributed by skilled artists. The result? A user-friendly platform that empowers creators to produce captivating drawings swiftly and effortlessly.

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How AutoDraw Works

1. Stroke by Stroke, Insight Emerges: As users sketch their ideas, AutoDraw springs into action. It analyzes each stroke, discerning shapes, and lines with remarkable accuracy.

2. Artistic Suggestions at Fingertips: Leveraging its vast database, AutoDraw offers intelligent recommendations. Users receive a curated selection of complete drawings that align with their initial strokes. These suggestions serve as a creative compass, guiding them toward polished illustrations.

3. Iterative Magic: The more a user engages with AutoDraw, the smarter it becomes. It refines its suggestions based on recognized shapes and lines, adapting to individual artistic styles.

AutoDraw democratizes artistry and unlocks creativity for all. Whether one is an aspiring artist or a casual doodler, this tool bridges the gap. No need to label oneself an artist, AutoDraw ensures that everyone can produce visually stunning creations.

Need for the Study

Interest in determining artificial intelligence's (AI) potential effects on particular disciplines has increased as a result of AI's growing influence in education. Due to the expanding significance of mathematical abilities in contemporary culture and the revolutionary potential AI offers in education, middle school math accomplishment is a vital subject that necessitates investigation.

Learning experiences that are personalized and adaptable are made possible by AI-driven educational systems. AI systems can help students understand difficult mathematical ideas at their own pace by looking at each student's unique learning data and providing individualized feedback and support. A study by D'Mello et al. (2014) highlighted the potential of AI interventions in middle school classrooms by demonstrating how intelligent tutoring systems can improve maths learning outcomes.

1. Preparing for Future Careers: Proficiency in mathematics is increasingly vital for success in various STEM-related careers. As AI and automation continue to shape the job market, middle school students must possess strong math skills to remain competitive. Understanding the influence of AI on math achievement can guide the development of educational strategies that equip students with essential computational thinking and problem-solving skills. A study conducted by Holmes et al. (2020) underscored the importance of integrating AI into math curricula to prepare students for the demands of the digital era job market
2. Preparing for Future Careers: Proficiency in mathematics is increasingly vital for success in various STEM-related careers. As AI and automation continue to shape the job market, middle school students must possess strong math skills to remain competitive. Understanding the influence of AI on math achievement can guide the development of educational strategies that equip students with essential computational thinking and problem-solving skills. A study conducted by Holmes et al. (2020) underscored the importance of integrating AI into math curricula to prepare students for the demands of the digital era job market.

It is essential to look at how AI affects middle school math performance in order to advance instructional strategies and guarantee children are ready for the future. By investigating the potential advantages of AI-powered interventions, educators can modify instructional strategies, overcome knowledge gaps, and develop students' mathematical proficiency. These studies will help to improve middle school math instruction, leverage the transformative potential of AI in education, and give kids the skills they need to succeed in the digital era.

The Objectives of the Study

- Assess the effectiveness of AI-powered personalized learning interventions on middle school math achievement.
- Explore the impact of AI-driven immersive technologies on middle school students' engagement and understanding of mathematical concepts.

The Hypothesis of the Study

H1: There is no significant difference between Pre and post-test results of the control group.

H2: There is no significant difference in Pre and post-test results of the experimental result.

H3: There is no significant difference in the post-test result of the control and experiment groups.

H4: There is no significant difference in the pre-test result of the control and experiment groups.

Review of Literature

Research on pedagogical content knowledge (PCK), technological pedagogical content knowledge (TPCK), and teachers' resource use has been stimulated by the incorporation of technology in education. In their (2009), article, Angeli and Valanides address the methodological and epistemological issues involved in conceptualizing and evaluating ICT TPCK, emphasising its critical function in successful technology integration. In their (2009) study, Lee, Chang, and Tsai looked at how teaching earth science in middle school affected students' attitudes and academic performance. The study highlights the potential advantages of using technology and subject-specific content together to improve learning results.

Gueudet and Trouche (2009) promote the creation of documentation systems to assist maths teachers in their instructional practices, highlighting the dynamic nature of resource interactions and offering insights into successful maths teaching. Gueudet and Trouche (2012) go into greater detail about the use of resources in professional development, emphasizing the interaction between resource use, expanding knowledge, and pedagogical change.

Pepin, Xu, Trouche, and Wang (2017) investigate the resource systems of Chinese mathematics teachers in an effort to comprehend their knowledge and teaching methods better. The study investigates how teachers use resources including textbooks, technology, and pedagogical tools, providing insightful information about the intricate connection between resource use and teaching proficiency in math education.

In order to provide a theoretical foundation for their application in educational contexts, Wartofsky (1979) investigates the scientific understanding and depiction of models. AMTE

(2006) emphasises the significance of equipping teachers to effectively use technology by advocating for technology integration in maths teacher education. Shulman (1986), and Shulman (1987) place a strong emphasis on knowledge development and the theoretical underpinnings of instruction, emphasising the importance of pedagogical expertise in enabling effective instruction.

The TPCK framework is put forth by Mishra and Koehler (2006), to analyse and enhance teachers' technological literacy. Their strategy places a strong emphasis on the convergence of technical, pedagogical, and subject knowledge, offering a comprehensive framework for improving instructional practices. Cox (2008), explores the theoretical foundations and elements of TPCK while conducting a conceptual analysis of it. In order to construct TPCK, Harris, and Hofer (2009) look into different forms of instructional planning activities. They provide useful advice for creating technology-enhanced learning experiences that are in line with certain content objectives.

Collectively, this research broadens our knowledge of how resources, technology, and instructional expertise interact in education. They offer insightful information on effective teaching methods, teacher professional growth, and the possible effects of using artificial intelligence (AI) on middle school arithmetic achievement. Educators can integrate technology and resources to improve students' maths learning experiences by taking into account these findings and frameworks.

Discussion and Analysis

The examination of quantitative data is crucial for understanding how interventions affect students' learning outcomes in educational research. In this study, a paired t-test was used to examine how an AI application called Auto Draw affected class 6 kids' math achievement scores. The paired t-test is a statistical technique for contrasting the results of two comparable groups assessed at various times, making it appropriate for evaluating the efficacy of interventions using pre- and post-test measures.

Descriptive Statistics of Pre-test Achievement Scores:

Control	Statical Value	Experimental	Statical Value
Mean	17	**Mean**	17.34286
Median	17	**Median**	18
Mode	15	**Mode**	19
Standard Deviation	3.580996	**Standard Deviation**	3.161746
Kurtosis	-0.69928	**Kurtosis**	-0.46949

Skewness	0.41981	**Skewness**	-0.28721

Table 1: Descriptive Statistics of Pre-test Achievement Scores of Experimental and Control

The researcher computed descriptive statistics for the pre-test achievement scores of the experimental and control groups to start the analysis. The experimental group had a mean score of 17.34, which was marginally higher than the control group's mean score of 17. The mean scores for the two groups were nearly equal. Additionally, the median scores were comparable, indicating equivalent pre-intervention performance amongst the groups. The mode values did differ slightly, with the experimental group having a mode of 19 and the control group having a mode of 15. This shows that a somewhat higher proportion of pupils in the experimental group had pre-test results that were better.

Additionally, the standard deviation numbers showed a slight variance in both groups' pre-test results. The experimental group's standard deviation was 3.008 compared to the control group's 3.581, which was somewhat less. These numbers reveal that both groups' score distributions were generally consistent, with the experimental group exhibiting slightly less fluctuation.

Descriptive Statistics of Post-test Achievement Scores:

Control	**Statical Value**	**Experimental**	**Statical Value**
Mean	17.3142857	**Mean**	18.51429
Median	18	**Median**	19
Mode	20	**Mode**	18
Standard Deviation	3.00755352	**Standard Deviation**	2.737232
Kurtosis	-0.904942	**Kurtosis**	-0.53598
Skewness	0.0159896	**Skewness**	-0.29477

Table 2: Descriptive Statistics of Post-test Achievement Scores of Experimental and Control Groups

The researcher then used descriptive statistics to examine the post-test achievement scores for both the experimental and control groups. The findings suggested that the AI tool had a beneficial effect on the achievement scores of the experimental group because the mean score for the experimental group (18.51) was marginally higher than that of the control group (17.31). Similar results were shown in the median scores, where the experimental group outperformed the control group.

Additionally, the experimental group's mode value was 18, while the control group's mode was 20. This suggests that somewhat more students in the control group obtained the top score on the post-test. The post-test results did, however, demonstrate a little amount of fluctuation in both groups' standard deviation values (2.737 for the experimental group and 3.007 for the control group), with the experimental group exhibiting slightly less variation.

Comparing Pre-test Achievement Scores:

Test	Group	No of Student	Mean	Standard Deviation	t' value	Level of Significant
Pre-test Achievement of Experimental and Control Groups	control	35	17.00	3.581	0.46	Significant
	Experimental	35	17.31	3.008		

Table 3: Significance of Mean Scores of Pre-test Achievement of Experimental and Control

The researcher performed a test of significance using the t-value to ascertain the significance of the difference between the mean pre-test scores of the experimental and control groups. According to the research, the derived t-value of 0.46 was not significant at the 0.05 level, proving that there was no appreciable difference between the two groups pre-test results. This result indicates that prior to the intervention, the pre-achievement test scores for mathematics for the experimental and control groups were nearly comparable.

Comparing Post-test Achievement Scores:

Test	Group	No of Student	Mean	Standard Deviation	t' value	Level of Significant
Experimental Group Pre and Post-Test	**Pre**	35	17.00	3.581	-2.39	Significant
	post	**35**	**17.31**	**3.008**		

Table 4: Comparison of Post-test Achievement Scores of Experimental and Control Groups

To compare the post-test results of the experimental and control groups, the researcher performed a test of significance. The estimated t-value of -2.39 was significant at the 0.05 level, demonstrating that the mean scores of the two groups differed significantly from one another. The difference between the mean scores of the experimental and control groups, 18.51 for the experimental group and 17.31 for the control group suggests that the intervention had a favourable effect on the experimental group's performance.

Comparison of Experimental and Control Group Pre and Post-Test:

Test	Group	No of Student	Mean	Standard Deviation	t' value	Level of Significant
Experimental Group Pre and Post-Test	Pre	35	17.34	2.737	1.79851	Significant
	Post Test	35	18.51	3.008	9	

Table 5: Comparison of Experimental and Control Group Pre and Post-Test

The experimental group's pre-and post-test results were the subject of additional analysis. The mean pre-and post-test scores differed significantly, as shown by the estimated t-value of 1.79, which was significant at the 0.05 level. The mean score for the experimental group increased from 17.34 on the pre-test to 18.51 on the post-test, indicating that the intervention had a favourable effect on the student's performance.

Comparison of Control Group Pre and Post-Test:

Test	Group	No of Student	Mean	Standard Deviation	t' value	Level of Significant
Control Group Pre and Post-Test	Pre	35	17.00	3.581	-1.12097	Not Significant
	Post	35	17.31	3.008		

Table 6: Comparison of Control Group Pre and Post-Test

The results of the control group's pre-and post-tests were also compared by the researcher. The pre-and post-test mean scores did not significantly differ, according to the computed t-value of -1.29, which was not significant at the 0.05 level. According to this study, the traditional teaching strategy used in the control group did not result in a material improvement in the student's academic performance.

Discussion:

An efficient statistical technique for examining the paired data in this investigation was the paired t-test. The descriptive statistics, which included measures of central tendency (mean, median, and mode) and dispersion (standard deviation), gave a thorough summary of the pre-and post-test achievement scores. These measures made it possible to analyse the distribution and variance of the data in great detail.

The results of the analysis showed that the experimental group had a somewhat higher pre-and post-test score than the control group, showing that the AI tool had a beneficial effect on mathematical achievement. The experimental group's post-test scores significantly increased,

which shows that the intervention helped students perform better. The control group, on the other hand, had no discernible improvement in achievement, illuminating the possible shortcomings of conventional teaching strategies in raising the level of student learning.

Overall, the study's findings offer insightful information about how well the AI tool Auto Draw works to raise math achievement levels among class 6 children. These findings can help teachers and policymakers understand the advantages of using AI tools in the classroom, highlighting the value of creative strategies for improving student learning outcomes.

Researchers can investigate the effects of interventions on student achievement through the quantitative analysis of data using statistical techniques like the paired t-test. The comparison of experimental and control groups and the study of pre- and post-test results offer important insights into the efficacy of interventions in educational settings. These analytical techniques enable researchers to make well-informed conclusions and suggestions to improve teaching and learning procedures.

Finding from the study

Based on analysis and discussion, the following findings can be identified:

1. Descriptive Statistics of Pre-test Achievement Scores:

- Both the experimental and control groups' mean scores were nearly identical, with the experimental group's mean score of 17.34 being slightly higher than the control group's mean score of 17.
- The groups' median scores were comparable, indicating equivalent performance prior to the intervention.
- There was a minor difference in the mode values, with the experimental group having a mode of 19 and the control group having a mode of 15.
- The pre-test scores showed some modest variance, with the experimental group displaying slightly less variation (3.008) than the control group (3.581), as indicated by the standard deviation values.

2. Comparing Pre-test Achievement Scores:

1. The calculated t-value of 0.46 was not significant at the 0.05 level, according to the t-value test of significance, indicating that there was no appreciable difference in pre-test scores between the experimental and control groups.

3. Descriptive Statistics of Post-test Achievement Scores:

- The mean score for the experimental group was slightly higher (18.51) than that of the control group (17.31), suggesting a positive impact of the AI tool on the achievement scores of the experimental group.
- The median scores also indicated a similar pattern, with the experimental group outperforming the control group.
- The mode values showed that a slightly higher number of students in the control group achieved the highest score in the post-test.

- The standard deviation values for both groups indicated mild variation in the post-test scores, with the experimental group showing slightly less variation (2.737) compared to the control group (3.007).

4. Comparing Post-test Achievement Scores:

   - The estimated t-value of -2.39 was significant at the 0.05 level according to the t-value test of significance, demonstrating a significant difference between the mean scores of the experimental and control groups. The experimental group had a higher mean score, indicating that the intervention had a positive effect on their performance.

   Comparison of Experimental Group Pre and Post-Test:

   - The estimated t-value of 1.79 was significant at the 0.05 level according to the t-value test of significance, demonstrating a significant difference between the mean pre- and post-test scores within the experimental group. The mean score increased as a result of the intervention, rising from 17.34 in the pre-test to 18.51 in the post-test.

5. Comparison of Control Group Pre and Post-Test:

   - The estimated t-value of -1.29 was not significant at the 0.05 level, according to the t-value test of significance, indicating that there was no discernible difference in the mean scores between the pre- and post-tests within the control group. The students' achievement levels did not significantly change as a result of using conventional instructional techniques.

Overall, the results point to a beneficial effect of the AI tool Auto Draw on class 6 kids' mathematical achievement scores. In both the pre- and post-tests, the experimental group outperformed the control group in terms of mean scores, and the intervention significantly raised the experimental group's performance. However, there was no discernible difference in accomplishment levels between the experimental group and the control group, which used conventional teaching techniques. These results emphasise the limitations of conventional approaches to improving student learning outcomes as well as the potential advantages of integrating AI tools in teaching practises.

Conclusion

In conclusion, this study looked at how middle school arithmetic achievement was affected by an AI application called Auto Draw. Important information about the intervention's efficacy was gleaned from the study of quantitative data.

According to the results, the experimental group, which used the AI tool, showed a modest edge over the control group, which used conventional teaching techniques. According to the descriptive statistics of the pre-test results, neither group performed significantly better than the other. However, a marginally greater proportion of pupils in the experimental group got better grades.

The experimental group performed better on the post-test than the control group in terms of mean and median scores, indicating that the AI tool had a beneficial effect on math

achievement. The mode values showed some diversity in student performance, with more students in the control group scoring highly.

The statistical analysis supported the intervention's success by confirming the significant difference between the experimental and control groups' mean post-test scores. The experimental group's mean scores significantly increased from the pre-test to the post-test, demonstrating the AI tool's beneficial effects on student accomplishment.

These results offer insightful information on the potential of AI tools to improve middle school math instruction. The study emphasises the value of creative strategies for enhancing student learning outcomes. These findings can be useful for educators and policymakers as they think about incorporating AI capabilities into instructional strategies to improve student progress.

It's crucial to remember that the focus of this study was solely on how Auto Draw affected maths achievement. The long-term effects and potential limitations of AI tools in different subject areas and educational situations require further study. However, this study adds to the expanding body of information on the advantages of AI in education and highlights the necessity for ongoing research and application of technological interventions to improve.

Recommendations

1. Use AI-based tutoring services for maths to deliver individualised education and support.
2. Integrate AI tools for formative assessment to efficiently monitor each student's progress.
3. Provide teachers with professional development opportunities to improve their understanding of and proficiency using AI tools.
4. To create cutting-edge methods for teaching maths, promote collaboration between educators and AI specialists.
5. Investigate AI-powered virtual reality simulations to improve students' comprehension of challenging mathematical ideas.
6. Give users access to online tools and materials that make use of AI algorithms to practise and reinforce maths skills.
7. To determine the long-term effects of AI treatments on maths achievement, conduct more research.
8. Encourage students to participate in multidisciplinary projects that integrate maths and AI to solve real-world issues.
9. Encourage the integration of AI literacy into math curricula to better prepare students for the workforce of the future.

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