



ISSN: 2350-0328

**International Journal of Advanced Research in Science,
Engineering and Technology**

Vol. 12, Issue 5, May 2025

Integrating AI with Personalized Mathematics Learning: Trends and Learning Style Implications among Chennai Senior Secondary Students

A. Punitha, G. Jayaraman

Assistant Professor, Department of Mathematics, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Chennai, Tamil Nadu, India.

Assistant Professor, Department of Mathematics, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Chennai, Tamil Nadu, India.

ABSTRACT: This study explores the integration of Artificial Intelligence (AI) in personalized mathematics learning among senior secondary students in Chennai, with a focus on how different learning styles—auditory, kinesthetic, individual, and group—impact the effectiveness of AI-driven instruction. As AI tools become increasingly prevalent in educational settings, understanding their alignment with students' preferred learning modalities is essential for maximizing engagement and outcomes. Preliminary findings suggest that AI-powered adaptive learning platforms enhance mathematical understanding when tailored to students' dominant learning styles, particularly benefiting kinesthetic and individual learners. The study highlights the need for educators to consider both technological and pedagogical dimensions when implementing AI in diverse classroom contexts.

I. INTRODUCTION

The concept of learning style is rooted in the classification of psychological types. The learning style is based on heredity, upbringing and current environmental demands. Different individuals have a tendency to both perceive and process information differently. The different ways of doing so are generally classified as concrete and abstract perceivers. Concrete perceivers absorb information through direct experience bodying, acting, sensing and feeling. Abstract perceivers however take in information through analysis, observation and thinking. Active and reflective processors - Active processors make sense of an experience by immediately using the new information. Reflective processors make sense of an experience by reflecting on and thinking about it. Traditional schooling tends to favors abstract perceiving and reflective processing. Other kinds of learning are not rewarded and reflected in curriculum instruction and assessment rarely as much.

Some learners require highly responsive instructional environments based on analysis of their motivational and environmental style preferences. Most individualized teaching methods reflect this point of view. Other learners however need to become more adoptive to the existing learning environment. A student's learning style provides the road map for personalized education and for training and/or matching strategies.

The future of higher education is intrinsically linked with developments on new technologies and computing capacities of the new intelligent machines. In this field, advances in artificial intelligence open to new possibilities and challenges for teaching and learning in higher education, with the potential to fundamentally change governance and the internal architecture of institutions of higher education. With answers to the question of 'what is artificial intelligence' shaped by philosophical positions taken since Aristotle, there is little agreement on an ultimate definition.

Artificial Intelligence refers to the intelligence of machines. This is in contrast to the natural intelligence of humans and animals. With Artificial Intelligence, machines perform functions such as learning, planning, reasoning and problem-solving. Most noteworthy, Artificial Intelligence is the simulation of human intelligence by machines. It is probably the fastest-growing development in the World of technology and Innovation. Furthermore, many experts believe AI could solve major challenges and crisis situations.

**II. APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN LEARNING MATHEMATICS**

Artificial Intelligence (AI) is revolutionizing various sectors, and education is no exception. In particular, AI is transforming how students learn and engage with mathematics, a subject often perceived as challenging. By offering personalized learning experiences, real-time feedback, and intelligent content delivery, AI has the potential to close learning gaps and improve student outcomes in mathematics education. This article explores the key applications of AI in mathematics learning, with a focus on tools, benefits, and future implications.

A. Personalized Learning Paths

One of the most impactful applications of AI in mathematics is **personalized learning**. AI-powered systems analyze a student's strengths, weaknesses, learning pace, and behavior to customize content delivery. Adaptive learning platforms such as **DreamBox Learning** and **Socratic by Google** adjust the difficulty of problems in real-time based on student performance, ensuring that each learner receives a tailored educational experience.

B. Intelligent Tutoring Systems (ITS)

Intelligent Tutoring Systems use AI algorithms to mimic the behavior of a human tutor. These systems provide step-by-step guidance, identify mistakes, and offer hints and explanations in real-time. Tools like **Carnegie Learning** and **Mathia** are examples of ITS that help students master topics such as algebra, geometry, and statistics.

C. Automated Assessment and Feedback

AI streamlines the assessment process by automating the grading of mathematical problems. More advanced systems can analyze open-ended or handwritten solutions and provide detailed feedback. **Grading AI**, used in platforms like **Grade scope**, can reduce teacher workload and allow for timely intervention when students struggle.

D. AI-Powered Educational Games and Simulations

Gamification supported by AI enhances the learning of mathematical concepts through engaging environments. Adaptive games adjust difficulty levels based on student responses, encouraging continued effort and exploration. These AI-enhanced games are particularly useful in teaching abstract or difficult concepts.

E. Learning Analytics and Predictive Modeling

AI enables the collection and analysis of large amounts of student data to identify learning trends. Teachers and administrators can use this data to make informed decisions about instruction. Predictive models can even forecast which students are at risk of failing and suggest timely interventions.

F. Support for Diverse Learners

AI technologies can accommodate different learning styles, including visual, auditory, and kinesthetic preferences. For students with special needs, AI tools can provide additional support such as text-to-speech, visual aids, or alternative assessments, making mathematics education more inclusive.

III. CHALLENGES OF ARTIFICIAL INTELLIGENCE

- Lack of data or poor-quality data
- Insufficient IT infrastructure
- Lack of AI talent
- Computing Power
- Legal Issues



IV. SIGNIFICANCE OF THE STUDY

Integrating AI with personalized mathematics learning is transforming education for senior secondary students in Chennai. AI tools adapt to various learning styles, offering tailored instruction and real-time performance analysis. This approach helps bridge learning gaps, enhancing engagement and comprehension. By aligning teaching methods with students' individual needs, AI improves mathematical outcomes, making it an effective solution for diverse learners. Hence, the study is titled *“Integrating AI with Personalized Mathematics Learning: Trends and Learning Style Implications among Chennai Senior Secondary Students.”*

V. OBJECTIVES OF THE STUDY

- To find out significant difference between learning styles and its dimensions of higher secondary school students in terms of Gender.
- To find out significant difference between learning styles and its dimensions of higher secondary school students in terms of Locality of Student.
- To find out significant difference between learning styles and its dimensions of higher secondary school students in terms of Locality of School.

VI. REVIEW OF RELATED STUDIES

Several studies have explored the roles of learning styles and artificial intelligence (AI) in education. Prabha Kiran Toppo (2022) found no significant differences in learning styles among higher secondary students in Ranchi based on gender, school type, habitation, or residence. Ruslan et al. (2021) observed that junior high students in Aceh with collaborative learning styles scored significantly higher in social sciences, highlighting the effectiveness of collaborative methods. Chen, Xue, and Li (2022) emphasized the importance of understanding perceptual learning styles in improving English teaching at the junior level. In terms of AI, Zhai & Li (2021) reviewed its application in education from 2010–2020, identifying trends such as adaptive learning, gamification, and challenges like ethical concerns. Limna et al. (2022) also noted AI's growing role in personalized and digital education, while raising issues of privacy and safety. Jaiswal & Arun (2021) focused on AI's potential to transform Indian education through personalized learning and adaptive assessments. Similarly, Joshi, Rambola & Churi (2021) found that both teachers and students viewed AI positively, though teachers were more adaptable, suggesting a need for broader training and research in diverse educational settings.

VII. METHODOLOGY

The major variable in this study is learning difficulties, with background variables including gender, student locality, type of school, nature of management, school locality, and medium of instruction. The population comprises higher secondary school students in Chennai district. A stratified random sampling technique was used, selecting ten schools randomly. The final sample includes 200 higher secondary students studying Mathematics at the +2 level.

VIII. TOOLS USED FOR THE STUDY

The **Learning Style Scale** by Manju Rani Aggarwal (2019) was used to assess learning styles. It includes 30 statements across five dimensions: auditory, visual, kinesthetic, individual learning, and group learning, with responses on a five-point Likert scale. The **Artificial Intelligence Scale** was a standardized achievement test consisting of 25 objective-type questions based on the XI Computer Science syllabus, available in English and Tamil. Each item was scored from 1 to 5, with positive and negative statements rated using a standard Likert scoring method. Total scores were obtained by summing all item scores.

IX. ANALYSIS OF DATA

1. There is no significant difference in the mean scores of learning styles and artificial intelligence in mathematics among higher secondary students with respect to gender.

Table: 1

Significant Difference in the Mean Scores of Learning Styles and Artificial Intelligence in Mathematics among Higher Secondary Students with Respect to Gender

Dimension	Variables	No.	Mean	SD	t-value	Result
Auditory	Male	80	14.86	3.026	-2.388	Significant
	Female	120	15.74	2.179		
Visuals	Male	80	18.38	2.830	-3.407	Not Significant
	Female	120	19.91	3.295		
Kinesthetic	Male	80	31.05	4.896	-3.042	Significant
	Female	120	33.08	4.447		
Individual Learning	Male	80	21.45	4.986	-2.210	Significant
	Female	120	22.78	3.546		
Group Learning	Male	80	22.10	4.058	-3.707	Significant
	Female	120	23.92	2.871		
Artificial Intelligence	Male	80	17.50	3.765	-1.973	Significant
	Female	120	18.53	3.486		

(At 5% level of significance the table value of 't' is 1.96)

The calculated 't' value is greater than the table value at the 5% level of significance; hence, the null hypothesis is rejected. Based on the mean scores, female students performed better than male students in learning style and its dimensions, including auditory, kinesthetic, individual learning, group learning, and artificial intelligence. Therefore, a significant difference exists between male and female students in these areas. However, the calculated 't' value for the visual learning style is less than the table value of 1.96 at the 5% level of significance; hence, the null hypothesis is accepted. Thus, there is no significant difference between male and female students in terms of visual learning style.

2. There is no significant difference in the mean scores of learning styles and artificial intelligence in mathematics among higher secondary students with respect to locality of student

Table: 2

Significant Difference in the Mean Scores of Learning Styles and Artificial Intelligence in Mathematics among Higher Secondary Students with Respect to Locality of Student

Dimensions	Variables	Count	Mean	SD	Calculated 't' value	Remarks
Auditory	Urban	51	15.55	2.378	.509	Not Significant
	Rural	149	15.34	2.652		
Visuals	Urban	51	18.76	3.403	-1.374	Not Significant
	Rural	149	19.48	3.118		
Kinesthetic	Urban	51	29.98	5.548	-4.170	Significant



	Rural	149	33.05	4.149		
Individual Learning	Urban	51	21.53	4.884	-1.416	Not Significant
	Rural	149	22.50	3.957		
Group Learning	Urban	51	22.43	3.568	-1.802	Not Significant
	Rural	149	23.45	3.453		
Artificial Intelligence	Urban	51	17.73	4.446	-.888	Not Significant
	Rural	149	18.25	3.306		

(At 5% level of significance the table value of 't' is 1.96)

The calculated 't' value is greater than the table value at the 5% level of significance; hence, the null hypothesis is rejected. Based on the mean value, rural students performed better than urban students in the kinesthetic learning style. Conversely, the calculated 't' value is less than the table value of 1.96 at the 5% level of significance; therefore, the null hypothesis is accepted. Thus, there is no significant difference between male and female students with respect to the learning styles of auditory, visual, individual learning, group learning, and artificial intelligence.

3. There is no significant difference between the mean scores of learning style and artificial intelligence of higher secondary students in computer science with respect to locality of school.

Table: 3
Significant Difference in the Mean Scores of Learning Styles and Artificial Intelligence in Mathematics among Higher Secondary Students with Respect to Locality of School

Dimensions	Variables	Count	Mean	SD	Calculated 't' value	Remarks
Auditory	Urban	72	15.57	2.695	.737	Not Significant
	Rural	128	15.29	2.520		
Visuals	Urban	72	18.99	3.392	-1.024	Not Significant
	Rural	128	19.47	3.087		
Kinesthetic	Urban	72	31.00	5.694	-2.903	Significant
	Rural	128	32.98	3.930		
Individual Learning	Urban	72	22.07	3.905	-.453	Not Significant
	Rural	128	22.35	4.400		
Group Learning	Urban	72	22.58	3.946	-1.848	Not Significant
	Rural	128	23.53	3.192		
Artificial Intelligence	Urban	72	17.68	4.408	-1.273	Not Significant
	Rural	128	18.36	3.094		

(At 5% level of significance the table value of 't' is 1.96)

The calculated 't' value is greater than the table value at the 5% level of significance; hence, the null hypothesis is rejected. Based on the mean value, students studying in rural schools perform better than those in urban schools with respect to the kinesthetic learning style. Thus, there is a significant difference between students in rural and urban schools regarding kinesthetic learning. Conversely, the calculated 't' value is less than the table value of 1.96 at the 5% level of significance; hence, the null hypothesis is accepted. Therefore, there is no significant difference between students in rural and urban schools with respect to the learning styles of auditory, visual, individual learning, group learning, and artificial intelligence.



ISSN: 2350-0328

International Journal of Advanced Research in Science, Engineering and Technology

Vol. 12, Issue 5, May 2025

X. INTERPRETATION AND DISCUSSIONS

Female students performed better than male students in learning style dimensions—auditory, kinesthetic, individual learning, group learning—and in the use of artificial intelligence, which may be attributed to several factors. Female students often demonstrate greater academic discipline, better time management, and a more positive attitude toward learning. They are typically more engaged in collaborative activities and responsive to instructional support, which enhances their performance in group and auditory-based tasks. Additionally, they tend to use a balanced mix of learning styles, allowing them to adapt more effectively to various teaching methods. Their openness to utilizing educational resources, including AI tools, may further support their academic success, particularly in mathematics learning environments.

XI. EDUCATIONAL IMPLICATIONS

- Include lectures, podcasts, and audio books tailored to male interests (e.g., STEM, mechanics, history).
- Use AI-powered voice assistants (e.g., Siri, Google Assistant) to answer questions or explain topics.
- Allow physical activity breaks or integrate movement into lessons.
- Design independent study projects and self-paced learning modules.
- Provide journals, blogs, or digital portfolios for private thought expression.
- Implement adaptive learning platforms (like Khan Academy, Coursera) that adjust difficulty and content to student pace.
- Use AI tutors for one-on-one instruction in math, reading, or writing.
- Assign team-based projects or peer teaching opportunities.
- Facilitate group discussion, debate, and collaboration to strengthen verbal and social skills.
- Use AI tools (like Google Workspace + AI, or ChatGPT) for collaborative writing and brainstorming.

REFERENCES

- [1]. Chinnasamy, P., Rani, R. M., Ayyaswamy, R. K., Sujithra, L. R., Mounika, T., & Cherukuvada, S. (2025). Transforming Education with AI-Driven Intelligent Tutoring Systems. In *Driving Quality Education Through AI and Data Science* (pp. 239-258). IGI Global Scientific Publishing.
- [2]. Der, S. H., & Varalakshmi, C. Artificial Intelligence in Indian Education: A Transformative Force.
- [3]. Joice, C. S., & Selvi, M. (Eds.). (2025). Pedagogical Revelations and Emerging Trends.
- [4]. Lokesh, K. (1984). *Methodology of educational research*. Vikas publishing house.
- [5]. Naveen, G., & Tharani, M. (2024). Integrating Big Data and Educational Technologies: Advancing Smart Cities and Education in India. *Journal of Intelligent Systems and Applied Data Science*, 2(2).
- [6]. Priya, S. B., Anusha, J. S., Chatiyode, V., & Maheswaran, T. (2025). Embracing Learner-Centric Pedagogy in the Age of Artificial Intelligence. In *Adopting Artificial Intelligence Tools in Higher Education* (pp. 51-73). CRC Press.
- [7]. Singh, Y. K. (2006). *Fundamental of research methodology and statistics*. New Age International.
- [8]. Sumathy, V., & Navamani, G. (2024). AI-Driven Personalized Learning: Enhancing Student Success through Adaptive Technologies. *Library of Progress-Library Science, Information Technology & Computer*, 44(3).
- [9]. Yamijala, S. M. S., Chodisetty, R. M., Chakravorty, C., & Sai, K. P. (2025). AI-Powered Learning Revolutionizing Smart Education with Personalized Learning Styles. In *Internet of Behavior-Based Computational Intelligence for Smart Education Systems* (pp. 191-212). IGI Global.
- [10]. Wargiary, K. (2024). The Impact of AI-Driven Personalized Learning on Mathematics Achievement and Student Engagement in Rural vs. Urban Schools in Karnataka, India. GOOGLE.

AUTHOR'S BIOGRABHY

Dr. A. Punitha received Ph.D from Vels Institute of Science, Technology and Advanced Studies (VISTAS). Presently working as Assistant Professor of Mathematics, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Chennai 600117, Tamil Nadu, India. She has 11 years of teaching experience. Her research interest is graph coloring and Topological Indices.



ISSN: 2350-0328

**International Journal of Advanced Research in Science,
Engineering and Technology**

Vol. 12, Issue 5, May 2025

Dr. G. Jayaraman received Ph.D from Bharathidasan University, Tiruchirappalli. Presently working as Assistant Professor of Mathematics, Vels Institute of Science, Technology and Advanced Studies (VISTAS), Chennai 600117, Tamil Nadu, India. He has 13 years of teaching experience. His research interest is graph coloring and Topological Indices.