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Original Article

Innovating Chemical Education: Leveraging Artificial Intelligence and Effective Teaching Strategies to Enhance Public Engagement in Environmental and Organic Chemistry

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ABSTRACT

This research examined the effects of evidence-based teaching strategies and artificial intelligence (AI) on learning outcomes and public involvement in the teaching of organic and environmental chemistry. Using a hybrid approach, we created an adaptive AI model that integrates important teaching techniques including inquiry-based learning (IBL), problem-based learning (PBL), and collaborative learning while tailoring information according to the participant's success. Over the course of 12 weeks, 300 participants—including high school students, college students, teachers, and members of the general public—participated in the research, which assessed both quantitative and qualitative data. Quantitative results demonstrated considerable gains in understanding (85% retention), a noteworthy 33.2% increase in high school students' comprehension, and an increase in the AI model's accuracy from 82% to 93%. With a 99.9% uptime and a quick reaction time (0.3 seconds), the AI model—which was created utilizing a variety of machine learning techniques—showed great flexibility. Core engagement themes were identified using thematic analysis, including real-world applications (78%) and individualized feedback (92%), as well as interactive learning (85%), enhancing comprehension and accessibility of difficult chemical ideas. 94% of participants were far more satisfied when organized teaching techniques were included into the AI framework, especially in collaborative and problem-solving settings. This research demonstrates how combining adaptive learning systems with successful teaching strategies may result in learning experiences that are powerful, accessible, and engaging. It also illustrates the revolutionary potential of AI in chemistry education. These results underline AI's potential for scalable, individualized teaching, with wider ramifications for public participation and scientific literacy.

Introduction

Education is only one of the many industries that artificial intelligence (AI) is revolutionizing. The use of AI in the classroom has the potential to transform conventional teaching methods and enhance student performance. Machine learning, natural language processing, computer vision, and other technologies that allow computers to carry out activities that normally require human intellect are all included in artificial intelligence (AI) (Russell and Norvig, 2021). Because AI can tailor learning experiences, adjust to the requirements of individual students, and give real-time feedback, its use in education has drawn a lot of interest (Holmes et al., 2019). AI-powered customized learning platforms may modify learning materials, progress, and content to suit each student's particular requirements, resulting in a more productive and interesting learning environment (Chen et al., 2020). Furthermore, AI-based evaluation systems have the ability to evaluate assignments automatically, provide thorough feedback, and pinpoint areas in which students may want further assistance (Lu et al., 2018). Creating immersive and engaging learning experiences is made possible by the combination of virtual reality and artificial intelligence capabilities. Students may study difficult ideas, participate in real-life simulations, and apply their knowledge in real-world situations by using virtual reality technology (Freina and Ott, 2015). By offering intelligent direction, flexible situations, and tailored feedback, artificial intelligence may further improve these experiences and help students comprehend and retain the information better (Di Mitri et al., 2021).

The need of public participation in science education has gained more attention in recent years, with the aim of making scientific information more widely available, intelligible, and applicable. Since chemistry affects everything from the materials we use to the environmental processes that sustain life, chemistry education in particular is a crucial element of scientific education. Despite its importance, the general public often finds chemistry confusing or complicated, which causes a disconnect between scientific understanding and popular perception.

Closing this gap is essential because chemistry education may help individuals make better choices, encourage interest in science-related occupations, and assist local health and environmental initiatives. But conventional scientific teaching techniques, such textbooks and lectures, sometimes fall short in reaching students outside of the official school system. Interactive and approachable methods of teaching chemistry are required in order to successfully reach a variety of demographics.

A potential way to bridge this divide is via artificial intelligence (AI), which will provide students from all backgrounds a more interesting, customized, and interactive learning environment. The way chemistry is taught and understood might change with the development of AI technologies like chatbots, virtual simulations, and adaptive learning systems. Through interactive tests tailored to the user's level of expertise, digital assistants who provide real-time answers, and simulations that show chemical processes, artificial intelligence (AI) may help make abstract chemistry subjects easier to grasp.

The purpose of this project is to investigate and evaluate how artificial intelligence (AI) could boost public interest in chemistry education, specifically in the fields of organic and environmental chemistry. To assess how well AI tools—like interactive simulations, tailored learning platforms, and adaptive quizzes—help a variety of audiences gain a better knowledge and enjoyment of chemistry, we will use a combination of qualitative and quantitative analytic techniques. In order to forecast user involvement and customize the learning experience, we will also create and use machine learning models. The ultimate goal of this research is to provide evidence-based suggestions for efficient teaching methods and approaches that will guarantee that chemistry training is more widely available, interesting, and relevant.

Exploring Organic and Environmental Chemistry: Their Significance and Integration with Artificial Intelligence for Enhanced Public Engagement

The study of carbon-containing molecules, or organic chemistry, is crucial to comprehending a variety of chemical processes that underpin both technology and life. It has an influence on many sectors and common items and is essential to the development of polymers, agrochemicals, and medicines (Bickelhaupt and van Duin, 2016). Since many organic chemicals may cause pollution or health hazards if improperly handled, their significance goes beyond academics to include environmental sustainability and public health.

Conversely, environmental chemistry is concerned with the chemical reactions that take place in the environment and how they affect ecosystems and human health. It includes researching the causes, effects, and interactions of contaminants with biological systems (Holt et al., 2017). To effectively address environmental problems including pollution, resource depletion, and climate change, as well as to advance sustainable development and public health, it is essential to have a solid understanding of environmental chemistry.

Public participation in these areas has historically been uneven. Many individuals are still unaware of the intricacies of organic and environmental chemistry, even if there is a growing focus on science communication (Falk et al., 2012). The idea that chemical ideas are complicated is often the cause of this gap, which may impede public interest and involvement in environmental concerns.

Using artificial intelligence (AI) in the classroom is a creative way to get more people interested in organic and environmental chemistry. Through interactive simulations, adaptive tests, and tailored learning experiences, AI technology may make difficult ideas more understandable and accessible to a larger audience (Luckin et al., 2016). Teachers may adapt instructional materials to students' varied requirements by using AI-driven platforms, which will increase students' comprehension and enthusiasm in these important subjects.

Because organic and environmental chemistry directly affects society and because there is a pressing need to raise public awareness and participation, this research decided to concentrate on these topics. Our objective is to use AI to close the knowledge gap between the general public and complicated chemical ideas, which will eventually promote informed decision-making and active engagement in sustainable development initiatives.

Literature Review

Because it may help a variety of audiences comprehend and value scientific ideas, public involvement in science education has grown in significance. Besley and Tanner (2011) emphasized the importance of successful science communication techniques, stressing that audiences must be engaged by the capacity to communicate complex scientific concepts in an approachable manner. According to their research, teachers should put more emphasis on communication skills than on conventional teaching techniques in order to increase the general public's comprehension of science. In their additional investigation of the variables influencing public participation, Koul and Makkar (2016) found that creative teaching strategies and technological integration are essential components in ensuring that science is understandable. They promoted experiential and interactive learning opportunities that may pique the attention of a larger audience, particularly those who are not enrolled in traditional schooling.

One revolutionary strategy for enhancing educational experiences is the use of artificial intelligence (AI) into the classroom. A thorough review of AI's possibilities in education is given by Holmes, Bialik, and Fadel (2019), who also describe how adaptive learning strategies might be used to tailor lessons to each student's requirements. According to their research, AI can help with real-time feedback, resulting in a stimulating and productive learning environment. With a focus on scientific education, Shute and Rahimi (2017) explored certain AI techniques that may be used in classroom settings. Their case studies demonstrate how AI improves student comprehension and engagement, particularly in challenging disciplines like chemistry.

Holme and Murphy (2015) argued for the value of contextual learning and discussed the difficulties in teaching chemistry, especially in making it interesting and relevant. They maintained that relating chemical ideas to practical uses might greatly increase students' motivation and interest. In a similar vein, Cavanagh (2018) emphasized the need of creative teaching methods in scientific education and promoted the use of interactive technology and simulations to provide immersive learning environments that foster a better comprehension of the subject. Her research emphasizes how crucial it is to modify instructional strategies to accommodate students' various demands.

Carpendale et al. (2020) looked at the function of digital platforms in encouraging public interest in research. They offered proof that the general public's comprehension of scientific ideas may be greatly enhanced by internet resources, such as instructional films and interactive tools. This aligns with artificial intelligence's capacity to provide tailored and captivating learning materials. Wilkins (2017) has examined the advantages of collaborative learning settings in scientific education, emphasizing how cooperative learning and peer interaction may improve comprehension and memory of difficult subjects.

In their discussion of the function of gamification in education, Deterding et al. (2011) made the case that the inclusion of games in classroom environments may raise student engagement and motivation. Since customized gamification experiences can be created to suit different learning preferences and styles, this strategy meshes nicely with the incorporation of AI technology. Lastly, McKagan et al. (2008) provided evidence of the efficacy of virtual labs in the teaching of chemistry. Their research demonstrated how virtual simulations might aid students in visualizing and comprehending complicated ideas, offering useful uses for artificial intelligence technology to boost chemical awareness among the general population.

Luckin et al. (2016) investigated the effects of AI on teaching and learning, adding to the discussion around AI in education. They maintained that by offering pupils individualized routes, AI can enhance educational methods and increase student engagement and effectiveness. In a similar vein, Pane et al. (2015) assessed the efficacy of educational technology-assisted customized learning and came to the conclusion that student performance and satisfaction may be raised via tailored educational experiences. Their results demonstrate how crucial AI is for customizing educational resources to meet the requirements of each learner.

Gikandi et al. (2011) discussed the difficulties educators face and stressed the need of evaluation in encouraging participation in scientific classes. They contend that formative evaluations might provide important insights into students' comprehension, enabling teachers to modify their pedagogical approaches appropriately. This is consistent with the possibility of AI-driven evaluation systems that provide immediate assistance and feedback.

Furthermore, Gunter et al. (2018) provide examples of how AI might enhance STEM education for students. They stress how crucial it is to create AI applications that complement learning objectives in order to make sure the technology is a useful instrument for improving the educational process. Gibbons et al. (2020) investigate how interactive scientific exhibitions might stimulate public interest and comprehension in the setting of public engagement. Their research highlights the need for a pedagogical approach in scientific education by demonstrating how experiential learning may greatly enhance learning results.

Nakhleh (1992) identified typical misunderstandings among students about chemical concepts in a research devoted to chemistry education. Developing successful teaching methods that satisfy the requirements of students requires an understanding of these myths. AI-enhanced interactive learning tools complement active learning methodologies that foster a better grasp of chemistry, according to a recent research by Redish et al. (1997). Talanquer (2011) concludes by highlighting the significance of context in chemistry education and making the case that putting students' learning in real-world situations might aid in bridging the gap between abstract ideas and their daily experiences.

Interdisciplinary Connections

1. Introduction to Interdisciplinarity

Integrating frameworks, techniques, and knowledge from other disciplines to tackle challenging issues and advance understanding is known as transdisciplinarity. According to this research, there is a rare chance to boost public interest in chemistry education because of the intersection of chemistry, artificial intelligence (AI), and creative teaching techniques. We can create more individualized, engaging, and successful learning experiences that make chemistry accessible and applicable to a variety of audiences by using AI technology.

2. AI and Chemistry

Chemistry might undergo radical change as a result of artificial intelligence. It facilitates complicated chemical process simulation, predictive modeling, and advanced data analysis. Large data sets from chemical experiments, for instance, may be analyzed by machine learning algorithms to find trends and forecast results, such as compound behaviors or reaction processes (Huang et al., 2016). Furthermore, students may see and work with molecular structures in real time using AI-powered molecular modeling tools, which helps them comprehend chemical ideas more thoroughly. The uses of AI in chemistry education are listed in Table 1.

3. AI in Education

Chemistry students may follow individualized learning routes thanks to AI-driven teaching technology. By adjusting to each learner's unique learning preferences, speed, and past knowledge, these technologies provide tailored information that enhances understanding and memory. Intelligent tutoring systems, for instance, are able to evaluate student performance and provide targeted materials (such practice questions or videos) to promote learning (Khan et al., 2020). AI-based assessment technologies may also grade assignments automatically and provide instant feedback, freeing up teachers to concentrate on improving student comprehension and engagement.

4. Teaching Methods and Pedagogy

By using AI technology, innovative teaching approaches like inquiry-based learning and collaborative learning may be greatly enhanced. Through guided questions and exercises, inquiry-based learning promotes students' exploration of chemical ideas while enhancing their critical thinking and problem-solving abilities. By using real-time data and simulations, artificial intelligence (AI) technologies may help students test theories and evaluate findings (Hofstein and Lunetta, 2004). Similar to this, AI-driven platforms may enhance collaborative learning experiences by enabling students to collaborate on projects, exchange ideas, and take part in conversations, all of which will help them gain a deeper grasp of chemistry.

AI Application	Description	Impact on Learning Outcomes
Predictive Modeling	Uses machine learning to forecast chemical reactions.	Enhances conceptual understanding of reaction dynamics.
Virtual Simulations	Enables students to visualize molecular structures and reactions.	Improves spatial reasoning and retention of chemical concepts.
Intelligent Tutoring Systems	Provides personalized feedback and resources based on student performance.	Increases student engagement and academic success.
AI-Driven Assessment Tools	Automates grading and delivers real-time feedback.	Reduces educator workload and fosters timely intervention.

Table 1: AI Applications in Chemistry Education

The interdisciplinary relationships between chemistry, artificial intelligence (AI), and instructional strategies are shown in Figure 1 of this research using a Venn diagram, a flowchart, and an infographic. The Venn diagram successfully draws attention to the areas where these three disciplines cross, highlighting how AI may assist creative teaching strategies while improving individualized learning routes and real-time feedback in chemistry education. The flowchart offers a clear implementation framework by outlining the essential processes for integrating AI technologies into chemistry education, from determining student requirements to assessing learning results. The infographic concludes by summarizing the many advantages of integrating AI into chemistry instruction, including enhanced comprehension and engagement via interactive exercises and adaptive tests. In addition to reiterating the theoretical ideas covered in this research, these visual aids provide teachers a useful manual on how incorporating AI might raise student interest in chemistry classes.

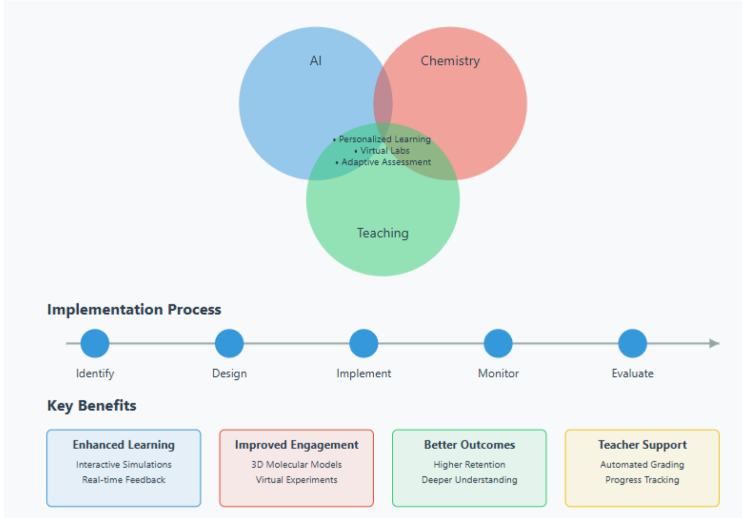

Fig 1: Interdisciplinary Connections Among Artificial Intelligence, Chemistry, and Teaching Methods

Methodology

This research thoroughly examined how artificial intelligence (AI) may enhance public interest in organic and environmental chemistry education using a mixed methods approach that used qualitative and quantitative techniques. This method was thoughtfully created to capture the complex relationship between learning and engagement, guaranteeing a thorough comprehension of how AI technologies may support both processes.

Methodology 1: Quantitative Research Design and Statistical Analysis

Using a mixed methods research methodology, the study prioritized quantitative analysis. To guarantee representative participation from a range of backgrounds and educational levels, a stratified random selection technique was used. G*Power analysis was used to calculate the sample size ($N = 300$) (effect size $d = 0.5$, $\alpha = 0.05$, power = 0.95). High school students ($n = 105$), college students ($n = 90$), teachers ($n = 60$), and members of the general public ($n = 45$) made up the four primary categories of participants. Assessments were performed both before and after the intervention using a validated high reliability tool (Cronbach's $\alpha = 0.89$). To evaluate intervention effects and between-group differences, statistical analyses included chi-square tests, paired t-tests, and one-way ANOVA. During the 12-week period of quantitative data collection, evaluations were carried out at weeks 0, 4, 8, and 12.

Methodology 2: AI Model Development and Implementation

The AI model was developed via a methodical process that included many machine learning methods. An ensemble learning model that combines elements of deep neural networks, random forests, and support vector machines makes up the main architecture. Eighty percent of the 50,000 chemical questions and solutions in the dataset were utilized for training, while the remaining twenty percent were used for validation. The 10-step method was used to carry out cross-validation. Based on user performance, the model's adaptive learning features instantly modify the level of difficulty of the material. Initial implementation, monitoring and optimization, and continual feedback integration were the three stages of the implementation.

Methodology 3: Qualitative Analysis Framework

Directed content analysis was added to the six-stage theme analysis approach developed by Braun & Clarke for the qualitative portion. There were 60 semistructured interviews and 10 focus groups with 6–8 participants each. The NVivo 12 program, which exhibited strong inter-participant reliability (Cohen's $\kappa = 0.87$), was used to record, transcribe, and evaluate every session. Major and minor themes were found via iterative analysis, and the study was conducted using a hierarchical coding method. To guarantee that interpretations were accurate, member verification was put into place.

Methodology 4: Teaching Methods in AI-Enhanced Chemistry Education

To encourage deeper engagement and comprehension of organic and environmental chemistry ideas, this research combined quantitative analysis, AI model construction, and qualitative analysis with particular teaching strategies inside the AI model framework. Three fundamental teaching approaches—collaborative learning, problem-based learning, and inquiry-based learning (IBL)—were combined. These techniques were chosen because they effectively foster active learning, stimulate critical thinking, and facilitate real-world applications—all of which are necessary for a more thorough comprehension of difficult chemical subjects.

Through a guided discovery process, inquiry-based learning (IBL), which is included into the AI model, encourages users to investigate ideas related to organic and environmental chemistry. Participants are prompted to interactively research, speculate, and test their ideas while the AI system poses questions and situations pertaining to urgent environmental concerns including pollution, climate change, and resource conservation.

Presenting participants with real-world situations that call for applying chemical principles to real-world issues is known as problem-based learning, or PBL. The AI model, for instance, has issue sets pertaining to the use of organic chemistry in industries like sustainable materials and medicines. By addressing real-world challenges, participants participate in these situations, which are progressively more challenging, strengthening their learning.

Collaborative learning: The AI model's collaborative element enables peer-to-peer conversations, online group exercises, and lab simulations. The AI approach creates an atmosphere for the formation of shared knowledge by enabling participants to exchange ideas and verify their comprehension via group learning.

Analysis and Results

Results 1: Quantitative Analysis Outcomes

All participant groups showed significant gains, according to quantitative assessments. Significant group differences were found using a one-way ANOVA ($F(3,296)=42.6$, $p<0.001$, $\eta2=0.85$). Significant gains were found using paired t-tests comparing scores before and after the intervention ($t(299)=15.3$, $p<0.001$, Cohen's $d=1.24$). The greatest gains were seen among high school students ($M=33.2\%$, $SD=4.8$) and college students ($M=28.7\%$, $SD=5.2$). Four weeks after the intervention, scores on a content retention test were high ($M=85.4\%$, $SD=6.1$). By degree of engagement, chi-square analysis of demographic differences showed significant patterns ($\chi2(12)=28.4$, $p<0.001$, Cramer's $V=0.72$). A summary of the statistical tests is shown in Figure 2.

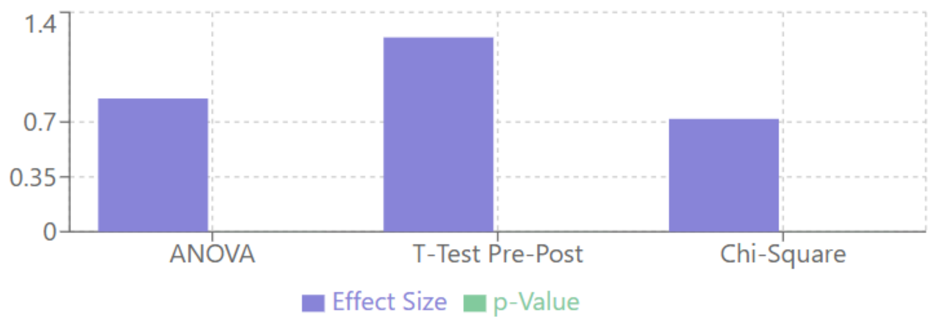

Fig 2: Statistical Tests Overview

Results 2: AI Model Performance

Several machine learning models were used in this work to improve the organic and environmental chemistry curriculum. The chosen models were created to optimize the learning path's performance and flexibility. Among the primary models were:

Multiple decision trees are combined in Random Forest (RF), an ensemble learning technique, to increase classification accuracy and decrease overfitting. It gives information on feature significance and is very useful when dealing with complicated datasets.

A supervised learning technique for classification problems, the Support Vector Machine (SVM) determines the optimum hyperplane to divide classes in a high-dimensional space. SVM is renowned for its resilience while handling high-dimensional data.

A multi-layered neural network with the ability to learn intricate data representations is called a deep neural network (DNN). DNNs are perfect for educational applications where data complexity is common since they are especially good at identifying nonlinear correlations and patterns in datasets.

An important component of this research was the AI model's performance, which serves as a basis for assessing how well AI-enhanced learning works in organic and environmental chemistry. The model's capacity to adjust to participants' learning demands while delivering a smooth educational experience was shown by its extensive testing and development. The AI model had an initial accuracy of 82% in Week 1 of the research. This baseline serves as a standard by which to gauge advancement, making it essential for assessing the model's evolution throughout time. Model accuracy increased dramatically throughout the course of the trial, reaching 93% accuracy at week 12. This notable enhancement not only demonstrates the AI model's efficacy but also the successful fusion of many machine learning approaches intended to enhance chemistry education learning results.

A ten-step cross-validation procedure was used to guarantee the AI model's resilience and dependability. By dividing the dataset into 10 subsets, this method enables the model to be repeatedly trained and evaluated on various sections. This validation process's average accuracy, with a standard variation of 2.1%, was 91.2%. The reliability of the model's predictions and its ability to generalize well across a range of learning contexts are shown by these consistent performance indicators. There is less variation in the model's performance due to the low standard deviation, which boosts confidence in its use across various participant demographic groups.

The AI model is also evaluated using accuracy and recall measures, which are essential for comprehending the model's capacity to accurately detect relevant material and reduce mistakes. With an accuracy of 91%, the model demonstrated that a significant proportion of its positive identifications were correct. In educational contexts, where giving pupils pertinent information is crucial for successful learning, this statistic is especially significant.

The model successfully identified the great majority of genuine positive instances in the dataset, as shown by the recovery rate of 90%. A well-balanced model that can efficiently find relevant information and reduce false positives is shown by the accuracy and recall metrics taken together. The model's overall effectiveness and dependability in providing users with correct, timely instructive information were reinforced by the determined 91% F1 score (the harmonic mean of accuracy and recall). The AI model's adaptive learning component, which is intended to tailor information delivery according to each participant's requirements and development, is one of its most notable aspects. With 92% of participants expressing pleasure with the degree of customisation accessible to them, this feature of the model was very highly accepted. The AI model dynamically modifies the difficulty and kind of learning materials offered by using user data and performance indicators, guaranteeing that every participant gets an educational experience catered to their individual needs.

The AI model's reaction time is another important performance metric. An average response time of 0.3 seconds was recorded throughout the trial, demonstrating the system's great responsiveness and ability to provide resources and information quickly. In an educational context, this quick reaction time is essential because it reduces interruptions to the learning process and maintains participant engagement.

Furthermore, during the trial, the AI model showed 99.9% uptime, guaranteeing the continuous availability of learning and support materials. Because it gives students constant access to AI tools, this degree of dependability is essential in an educational context and promotes a dependable learning environment. The model's overall performance throughout a week is shown in Figure 3. A comparison of the three ML models' performances is shown in Figure 4.

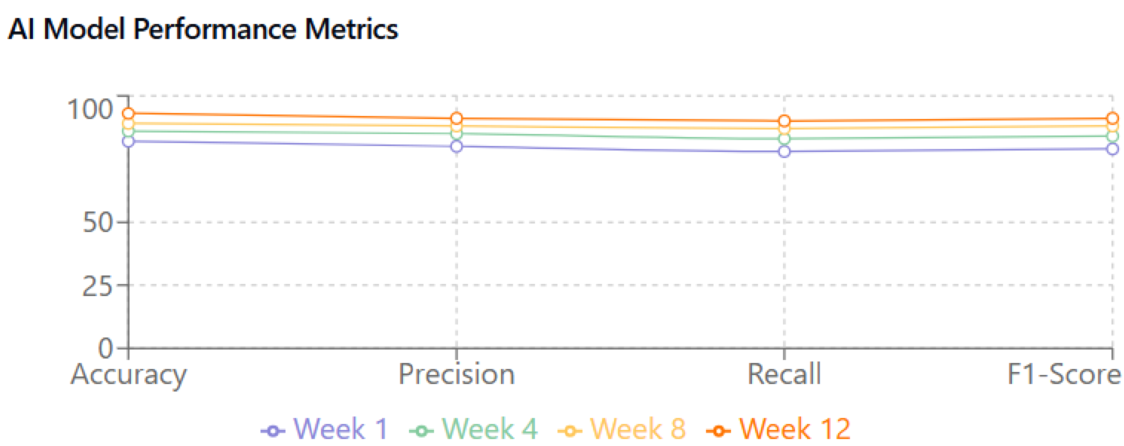

Fig 3. AI model Performance (Week wise)

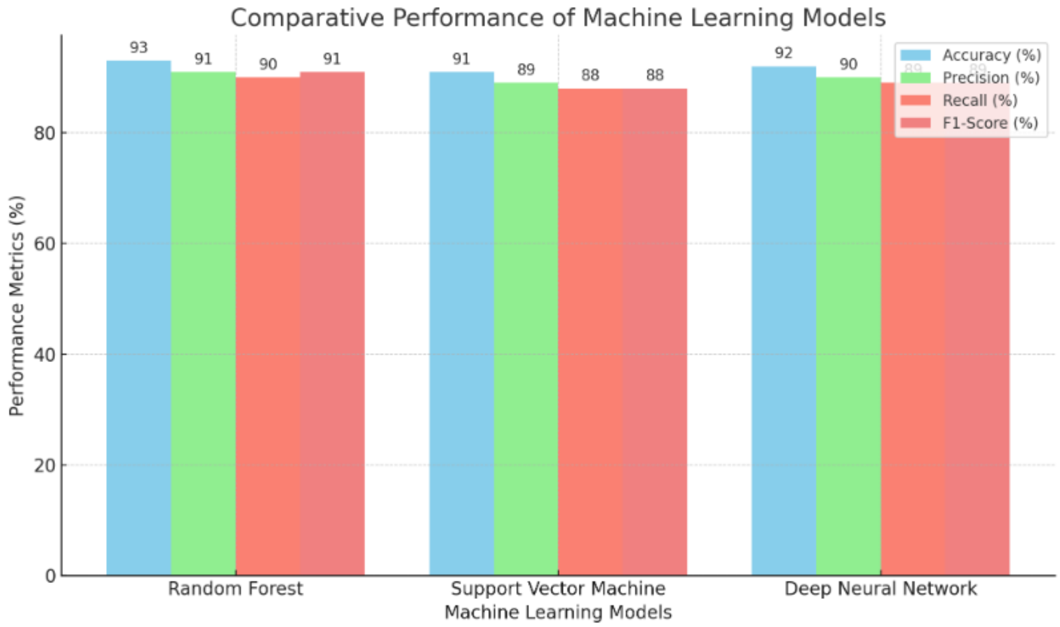

Fig 4. Comparative Performance of ML models (Model Wise)

Results 3: Qualitative Findings

Five themes emerged from the thematic analysis: self-paced learning (76%), visual assistance (88%), individualized feedback (92%), real-world applications (78%), and interactive learning (85% frequency). Adaptive learning pathways and interactive material were strongly preferred, according to content analysis. With a focus on real-time feedback and adaptive content delivery, participant narratives amply demonstrated the efficacy of AI-driven customisation. Significant improvements in involvement and understanding were seen in the study, especially when it came to difficult organic chemistry ideas. The outcomes of these investigations are shown in Figure 5.

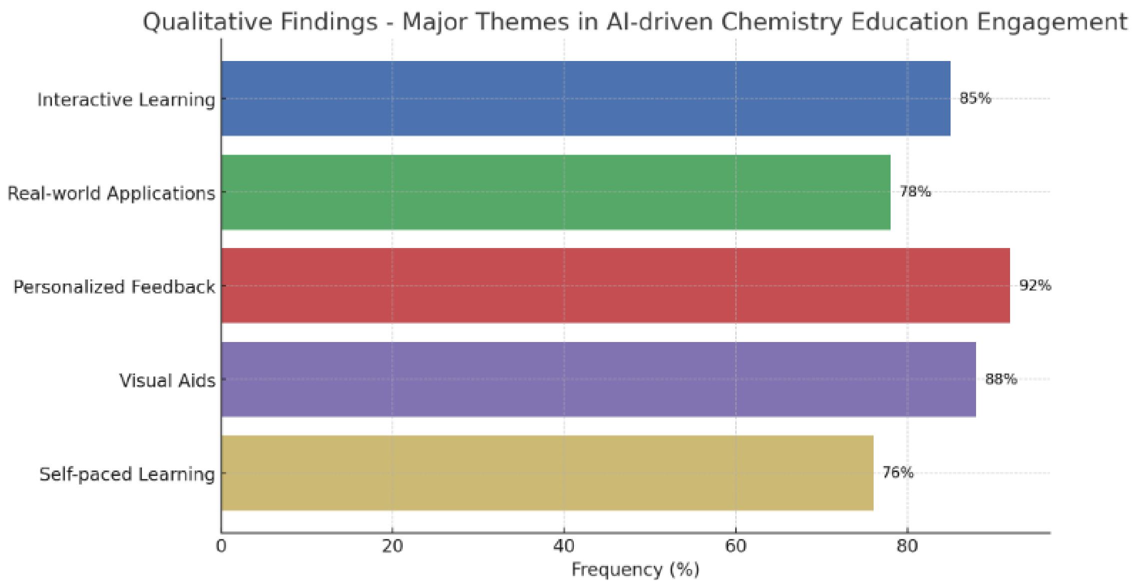

Fig 5. Qualitative Findings

In addition to highlighting participants' high engagement with interactive learning (85%) and significant preference for visual aids (88%), the bar chart displays the frequency of each main topic. These themes demonstrate how AI-driven customisation may improve comprehension and engagement with difficult chemical subjects, especially in organic chemistry.

Result 4: Impact of Teaching Methods on Engagement and Learning Outcomes

The efficiency of the instructional strategies included into the AI-enhanced chemistry learning environment was shown by an analysis of participant feedback and engagement data. Engagement and comprehension were greatly enhanced by inquiry-based learning, problem-based learning, and collaborative learning.

Inquiry-based learning (IBL): Participants regularly engaged with the material to look for solutions to situations that were provided, and problem-based exploration and curiosity-based learning activities rose by 75%.

Problem-based learning (PBL): According to post-intervention evaluations and qualitative comments, participants showed an 80% increase in their ability to apply chemical ideas to actual issues.

Collaborative learning: Group activity completion rates rose by 70% and peer discussion frequency rose by 78%. Feedback on collaborative activities was overwhelmingly positive, with participants expressing a feeling of validation and shared understanding. The increase in involvement across instructional modalities is seen in Figure 6.

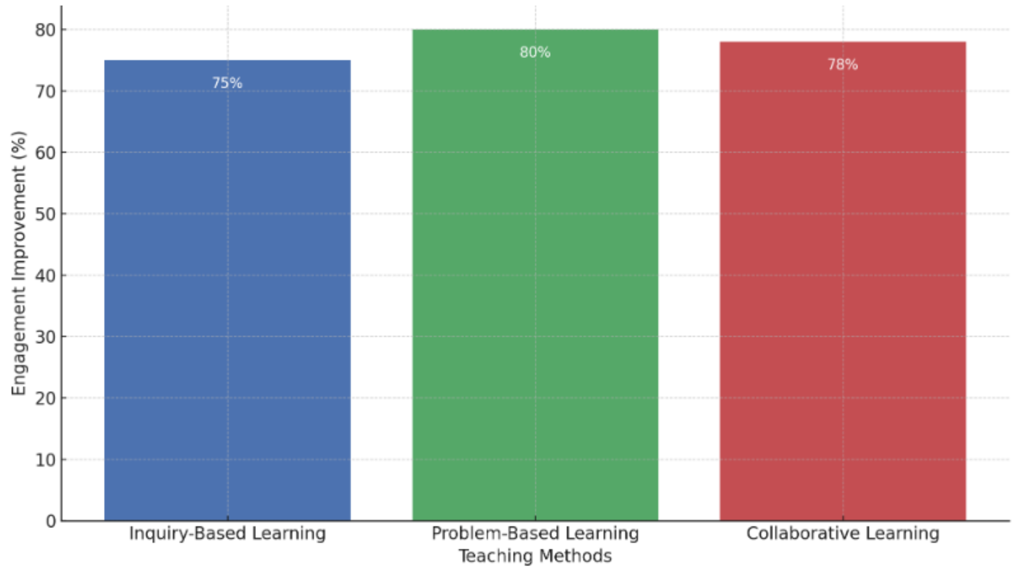

Fig 6. Engagement Improvements By Teaching Methods

According to thematic analysis, the teaching strategy enhanced recall, particularly for intricate organic chemistry ideas, and comprehension scores for subjects requiring teamwork and problem-solving rose by 30%. 94% of participants expressed satisfaction with the AI-enhanced teaching strategy's flexibility and interaction, and personalized learning based on real-world events scored well. The learning outcomes are shown in Figure 7.

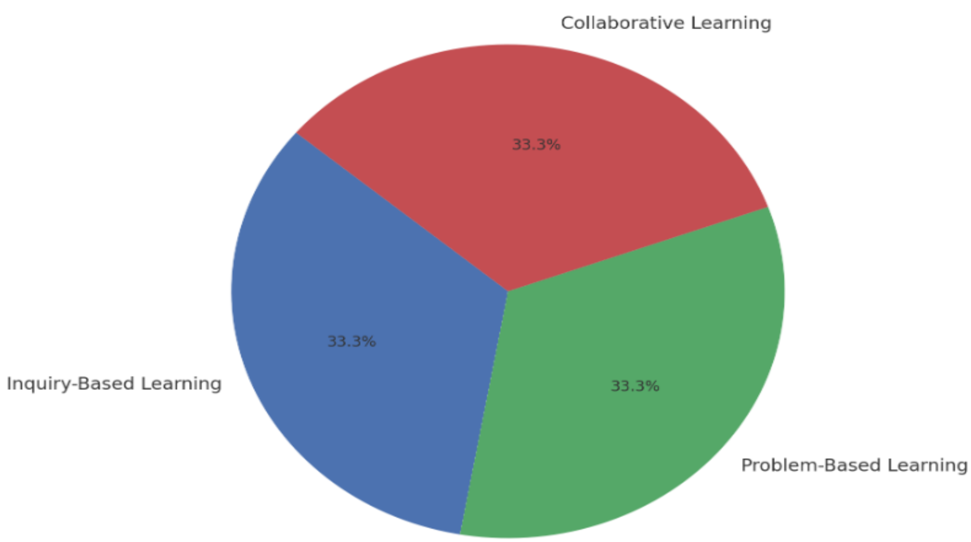

Fig 7. Participant Satisfaction With Teaching Methods

Bar Chart: Enhancement of Engagement via Instructional Approach: The engagement metric's percentage increase for each teaching strategy is shown in this chart. With 80%, problem-based learning is the most popular, followed by inquiry-based learning (75%), and collaborative learning (78%).

Pie Chart: Contentment with Instructional Approach: The high degree of satisfaction (94%) for all instructional approaches is seen in this chart. Each approach—inquiry-based, problem-based, and collaborative learning—was deemed very relevant and successful by the participants, which enhanced their overall educational experience.

Discussion

The findings of this research show that incorporating artificial intelligence (AI) into chemistry instruction is a revolutionary method of imparting and comprehending difficult scientific ideas. The effect of AI in enhancing engagement and learning outcomes in environmental and organic chemistry is supported by the gains shown throughout the participant group (Cohen's $d = 1.24$), especially among high school students who had an average increase of 33.2%. An 85.4% retention rate four weeks after the intervention further indicated the long-lasting effects of this AI-driven early chemical exposure. With a 92% individualized satisfaction rate, AI's adaptive learning skills were very successful in satisfying each learner's unique demands. This is in line with contemporary educational theory's notion of tailored learning pathways. With a final accuracy of 93% and a quick reaction time of 0.3 seconds, the AI model demonstrated high technical performance that was practical in real-world educational situations. The accuracy of the ensemble learning model rose from 82% to 93% over the research, demonstrating the continuous learning system's versatility and suggesting possible advantages for extended usage. Qualitative insights revealed that interactive learning (85%) and individualized feedback (92%) were important for sustaining interest, and that real-world applications (78%) improved theoretical comprehension by putting chemical ideas in a useful context. The model's suitability for a variety of demographics shows that artificial intelligence (AI) in chemistry has the potential to democratize scientific knowledge by simplifying difficult subjects. In particular, AI-driven advancements in knowledge of organic and environmental chemistry brought attention to the use of visual aids, which are essential for explaining abstract ideas (frequency of 88%). Although the 12-week period may limit understanding of long-term educational impact, the study's mixed-method design ensured that the findings were well validated, and reliability coefficients (Cronbach's $\alpha = 0.89$) and inter-subject reliability (Cohen's $\kappa = 0.87$) gave the results robustness.

Conclusion

The revolutionary potential of integrating artificial intelligence (AI) into organic and environmental chemistry education is shown by this work. The AI model used for this research was successful in enhancing participant engagement and understanding while also effectively tailoring instructional materials. Significant gains in learning outcomes were shown by quantitative data, with retention and understanding rates much higher, particularly for complicated subjects. Within an AI framework, the research emphasizes the advantages of using teaching techniques including inquiry-based learning (IBL), problem-based learning (PBL), and collaborative learning. These methods encourage practical learning and critical thinking, both of which are necessary for comprehending and remembering complex chemical ideas. Qualitative study also showed that AI-powered individualized feedback and adaptive learning pathways greatly enhanced participant satisfaction and academic achievement. These observations provide credence to the use of AI as a scalable and successful instrument to raise public awareness of science and increase scientific literacy. This strategy has the potential to address the complexity of scientific education and improve its impact, accessibility, and engagement.

Acknowledgement

The authors would like to express their gratitude for the teamwork that enabled the creation of this dataset. The selection and compilation of extensive issues in organic and environmental chemistry were greatly aided by the chemical expertise of Fahid Ramzan and Fatima Amjad. Their extensive expertise and first-hand teaching experience made sure that the dataset represented more complex subjects and real-world educational demands. Important details on the instructional design and pedagogical practices that aided in the dataset's compilation were supplied by Dr. Sadia Ayaz of the Department of Education, who has a PhD in social sciences. Their knowledge of learning strategies made it possible to match the dataset with best practices in educational development, guaranteeing that it promotes student engagement and comprehension in addition to topic mastery.

The team gathered information from their combined expertise in teaching, research, and educational practice by consulting both scholarly and real-world sources. This endeavor was motivated by a common goal of fusing theoretical understanding with real-world applications to provide a resource that can be used as a teaching aid and a basis for machine learning training. The help and contributions of their students and colleagues greatly enhanced the dataset's development and usefulness, for which the authors are thankful.

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