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Leveraging Artificial Intelligence to Enhance Personalised Learning Experiences in Chemistry Education

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Highlights:

Examines how AI enables personalised learning pathways in chemistry by addressing challenges of abstract concepts, reaction mechanisms, and lab skills.

Identifies key affordances: real-time diagnosis, adaptive sequencing, AI virtual labs, and automated feedback, grounded in constructivist and Vygotsky's ZPD frameworks.

Recommends ethical governance, equitable infrastructure, and teacher PD to ensure AI personalisation improves understanding without deepening inequalities.

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Abstract: This article examines how artificial intelligence (AI) can be leveraged to create personalised learning pathways in chemistry education. Chemistry education, characterised by abstract molecular concepts, intricate reaction mechanisms, and demanding laboratory competencies, presents significant instructional challenges that conventional teaching approaches cannot adequately address. AI technologies, encompassing machine learning, natural language processing, intelligent tutoring systems, and adaptive learning platforms offer transformative possibilities for tailoring instruction to the individual learner. Drawing on constructivist and social constructivist frameworks, the study explores AI's role as a "more knowledgeable other" within Vygotsky's zone of proximal development. Through a systematic review of empirical literature, the article identifies key affordances of AI-enhanced personalisation, including real-time diagnostic assessment, adaptive content sequencing, AI-powered virtual laboratories, and automated feedback. Findings indicate that AI-enhanced personalisation yields measurable improvements in conceptual understanding and learner engagement when implemented with deliberate pedagogical design. It is recommended that AI tools be adopted with strong ethical governance, equitable infrastructure investment, and sustained professional development for educators, to ensure that the benefits of personalised chemistry education are realised without deepening existing inequalities.

Keywords: Artificial Intelligence; Personalised Learning; Adaptive Learning; Intelligent Tutoring Systems

Introduction

Artificial intelligence (AI) is reshaping educational practice across disciplines, and chemistry is no exception. Over the past decade, AI has moved from a niche research tool to a mainstream instructional technology, a shift underscored by its designation among the "Top 10 Emerging Technologies in Chemistry" by IUPAC (2023) and, most recently, by the 2024 Nobel Prize in Chemistry awarded for the AI-driven protein-structure prediction system AlphaFold (The Royal Swedish Academy of Sciences, 2024). These milestones signal not only AI's growing technical sophistication but also its deepening relevance to the knowledge and skills that chemistry students will need to develop. Chemistry is inherently challenging to teach and learn. Its central ideas are invisible, abstract, and multi-representational: students must simultaneously navigate macroscopic laboratory observations, submicroscopic molecular events, and symbolic notation,

while managing a wide range of prior knowledge and cognitive styles (Alasadi & Baiz, 2024). Traditional lecture-based instruction struggles to meet this diversity of need, often leaving some learners disengaged or unable to keep pace (Tassoti, 2024). Personalised learning, an approach that adjusts content, pace, and pedagogical strategy to the individual, offers a promising way forward (Pane et al., 2015). AI makes such personalisation feasible at scale. Machine learning algorithms can build and continuously update learner profiles to optimise content sequencing (Essa et al., 2023); natural language processing enables real-time dialogue and feedback (Lolinco & Holme, 2023); intelligent tutoring systems provide step-by-step adaptive guidance; and AI-supported virtual laboratories make experimental work safer, cheaper, and more repeatable (Chan et al., 2024). Despite these advances, the systematic integration of AI into chemistry education remains nascent, and its pedagogical implications are only beginning to be understood (Yildirim & Akcan, 2024).

This paper looks at AI-supported personalised learning in chemistry education from both theory and evidence. It focuses on four main goals: explaining the theories behind AI-based personalisation, reviewing studies on AI in chemistry, considering the major challenges, and suggesting ways to use these tools responsibly.

Theoretical Framework

This study is grounded in two complementary theoretical traditions: constructivism and social constructivism. These frameworks were selected because they offer the most coherent account of how meaningful learning occurs and, by extension, what AI-enhanced personalisation must achieve to be educationally sound. Constructivism, rooted in Piaget's (1970) work on cognitive development, explains how individual learners actively construct knowledge by assimilating new information into existing mental structures. Social constructivism, advanced by Vygotsky (1978), extends this by emphasising the role of social interaction and guided support in enabling learners to move beyond what they can accomplish alone. Together, these theories provide the conceptual basis for evaluating whether AI systems genuinely facilitate deep, active, and scaffolded learning in chemistry, or merely replicate surface-level content delivery in a digital format. They also supply the criteria by which the affordances and limitations of AI tools are assessed throughout this review.

Constructivism and Active Knowledge Construction

The idea behind personalised learning comes from constructivist theory. Constructivism, first developed by Piaget (1970) and expanded by later scholars, holds that people learn by actively building knowledge from experience and by connecting new ideas to what they already know (Bada & Olusegun, 2015). In chemistry, students understand more deeply when they can handle representations, explore questions, and compare their own ideas with scientific explanations. AI fits well within this approach because it creates active, interactive learning spaces in which adaptive systems can match tasks to a learner's current level and progressively raise the difficulty as competence grows (Strielkowski et al., 2024).

Social Constructivism and the Zone of Proximal Development

Vygotsky's (1978) zone of proximal development (ZPD) describes the gap between what a learner can do alone and

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what the learner can achieve with guidance from a more experienced other. Guided support is therefore central to effective learning. Guo et al. (2024) demonstrate that generative AI can serve as that more knowledgeable guide within a social constructivist framework. AI chatbots and tutoring systems can explain ideas, offer hints, and correct errors in ways that are calibrated to each learner's current level, effectively extending the ZPD through patient and immediate support, while complementing rather than replacing the human teacher (Stojanov, 2024).

AI Technologies for Personalised Chemistry Education

Machine Learning and Adaptive Content Delivery

Machine learning (ML) is the engine behind many adaptive learning systems. By studying learner data such as accuracy, response time, navigation patterns, and engagement, ML algorithms build and update a model of what each student knows and where they struggle (Essa et al., 2023). Supervised methods can predict performance and spot students who may be at risk, unsupervised methods can reveal hidden learner patterns, and reinforcement learning can improve content delivery over time based on results (Almasri, 2024; Sharif & Uckelmann, 2024).

In chemistry, ML-based systems can adjust topics like stoichiometry, chemical equilibrium, and organic reaction mechanisms so that the level of explanation and the form of representation match the learner's ability. Studies show that students using these systems often work more efficiently, understand concepts better, and feel more satisfied than students using non-adaptive systems (Atmosukarto et al., 2021).

Natural Language Processing and Conversational Agents

Natural language processing (NLP) underpins a growing range of educational tools, including chatbots, conversational agents, and AI-powered virtual tutors capable of engaging students in real-time dialogue, answering questions, and generating targeted explanations (Lolinco & Holme, 2023). The advent of large language models such as GPT-4 has substantially raised the ceiling of what these tools can do: they can now produce context-sensitive explanations of reaction mechanisms, generate exam-style questions, and adapt their responses to individual learners (Fernandez et al., 2024). In the author's view, this capacity for dynamic, personalised interaction represents a significant advance over static instructional materials. NLP-based tools can also calibrate the linguistic complexity of their output, pose Socratic guiding questions, and detect conceptual misconceptions from students' written responses (Reddy et al., 2024). That said, the problem of "hallucination" where an AI produces a fluent but factually incorrect answerremains a concern that neither developers nor educators can afford to ignore. Watts et al. (2023) demonstrated that chatbot responses to organic chemistry tasks were largely accurate but not without error, a finding that reinforces the importance of treating AI output as a resource to be evaluated critically rather than a source of final authority (Yik & Dood, 2024).

Intelligent Tutoring Systems

Intelligent tutoring systems (ITS) are among the most established forms of AI in education. They usually include a domain model, a learner model, a tutor model, and a user interface (Chan et al., 2024). In chemistry, these systems can support topics

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such as stoichiometry, bonding, laboratory safety, and experimental design by giving step-by-step help and selecting practice questions based on the learner's progress.

Studies show that well-designed ITS can lead to strong learning gains. Chan et al. (2024) reported a 40% drop in laboratory accidents and a 20% rise in conceptual understanding when students used an AI-guided virtual experiment system with real-time feedback. These gains come mainly from immediate, personalised support and pacing that keeps learners working within their ZPD, although building high-quality ITS still requires a lot of time and resources.

AI-Powered Virtual Laboratories and Simulations

Laboratory work is a key part of chemistry education, but not every school has a well-equipped lab. Cost, safety concerns, and sustainability issues have also increased interest in virtual alternatives. AI-powered virtual laboratories use simulation engines, real-time feedback, and adaptive support to create learning spaces where students can change variables, watch reactions, and study results without needing physical lab equipment (Akbar & Manado, 2024).

These virtual labs bring several benefits. The AI can watch each learner's choices, spot mistakes as they happen, and give targeted hints. Students can repeat experiments as often as needed, which supports the kind of trial-and-error learning that constructivism encourages. When augmented reality and virtual reality are added, students can also interact with three-dimensional molecular models and explore reaction pathways in more immersive ways (Lee et al., 2024).

Automated Assessment and Feedback Generation

Timely feedback is one of the strongest supports for learning, but teachers often do not have enough time to give detailed formative assessment in large classes. AI helps by automating much of this work. Machine learning scoring systems can judge student answers to open-ended chemistry tasks, including spectrum interpretation, molecular drawings, and reaction mechanism explanations, with accuracy close to human experts (Fernandez et al., 2024). NLP-based tools can also review written responses, identify misconceptions, and generate feedback for individual learners.

AI assessment does more than score answers. It can also generate questions that fit a learner's strengths and weaknesses. Adaptive testing systems adjust difficulty in real time based on previous responses, making tests more efficient and more informative than fixed exams. In chemistry, where later understanding depends heavily on earlier foundations, this kind of precise diagnosis is especially useful for finding and fixing knowledge gaps (Ariely et al., 2024).

Empirical Evidence and Emerging Trends

More and more research shows that AI-supported personalised learning works well in chemistry. Systematic reviews show a sharp increase in studies from 2021 onward, especially after generative AI tools became widely available in late 2022 (Ozkaya et al., 2025). Even so, the field would benefit from more randomised controlled trials carried out in real classroom settings.

Across studies, AI-based adaptive systems have been linked to better conceptual understanding, stronger procedural skill, and improved problem

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solving in chemistry (Almasri, 2024). Students using AI-powered virtual laboratories often make especially large gains in understanding, particularly when they begin with lower prior knowledge (Atmosukarto et al., 2021). Engagement is usually highest when the material matches the student's current level and preferred way of learning.

Researchers are also paying more attention to emotional and motivational outcomes. AI-based learning environments are often associated with higher self-confidence, stronger motivation, and more positive attitudes toward chemistry (Jere & Mpeta, 2024). Many students find AI tutors helpful because they do not judge, which makes it easier to ask questions and make mistakes without embarrassment. Even so, there is still limited evidence about long-term retention and transfer, so more longitudinal research is needed (Roll et al., 2023).

Challenges and Critical Considerations

Algorithmic Bias and Equity

AI systems trained on data that do not represent all learners can produce models that work better for some groups than for others (Baker & Hawn, 2022). In chemistry, where gaps by gender, race, and socioeconomic background are already a concern, biased systems may deepen existing inequalities. To avoid this, developers need diverse training data, clear and reviewable decision processes, and the involvement of a broad range of stakeholders during design and testing.

Data Privacy and Ethical Governance

AI personalisation depends on collecting a great deal of learner data, which raises serious privacy concerns, especially for minors (Berendt et al., 2020). Responsible use requires strong data protection measures, clear policies about how data will be used, informed consent, and real control for learners and families.

Teacher Agency and Professional Development

Introducing AI also changes the teacher's role, so it must be done in a way that protects teacher agency. AI works best when it supports teachers rather than replaces them, taking over routine tasks so that teachers can spend more time mentoring students, leading discussion, and helping them think scientifically (Polak et al., 2022). To make this work, educators need professional development that builds both technical confidence and the ability to judge whether AI output is pedagogically sound (Yildirim & Akcan, 2024).

Scalability and Infrastructure Constraints

Advanced AI systems need cloud services and strong internet connections, and these are not available everywhere, especially in low-resource settings (Khanal & Pokhrel, 2024). Lightweight tools and open-source systems can help, but infrastructure investment is still necessary if AI is to reach more students rather than widen the digital divide.

Accuracy and the Hallucination Problem

The problem of "hallucination," where generative AI produces a convincing but incorrect answer, is especially risky in chemistry because errors can affect safety as well as understanding. Yik and Dood (2024) showed that ChatGPT could give polished but slightly wrong explanations of organic reaction mechanisms. This means AI content should be treated as a starting point

for discussion and checking, not as a final authority.

Recommendations

The following recommendations are offered for educators, curriculum developers, and policymakers.

1. AI-based learning tools should be guided by educational theory, especially constructivism and social constructivism, rather than by technology alone. These tools should be used to support active learning, knowledge building, and reflection.

2. Teacher professional development should be funded alongside infrastructure. Teachers need both technical skills for using AI tools and the judgement to decide when and how those tools are appropriate.

3. Equity and inclusion must stay central to any AI strategy. Diverse learners should help shape the tools, training data should be checked for bias, and infrastructure investment should aim to reduce, not increase, the digital divide.

4. Strong data governance is essential. Learner privacy must be protected, educational data must be used in line with legal and ethical standards, and users should be given clear information and real choices about consent and control.

5. Researchers should carry out more rigorous long-term studies, including randomised controlled trials in real learning environments, to test how AI affects retention, higher-order thinking, and scientific reasoning over time.

Conclusion(s)

Artificial intelligence holds genuine promise for transforming chemistry education by making learning more responsive, flexible, and personal. Machine learning, NLP, intelligent tutoring systems, virtual laboratories, and automated assessment together constitute a powerful toolkit for personalised instruction grounded in constructivist principles. At the same time, challenges such as algorithmic bias, data privacy concerns, unequal infrastructure, the risk of teacher marginalisation, and the ever-present danger of AI-generated errors must be addressed with equal seriousness. AI should augment skilled human teaching, not supplant it, because teachers provide the relationships, professional judgement, and ethical sensitivity that no technology can replicate. The future of chemistry education will ultimately depend not on the sophistication of the tools themselves, but on the wisdom, fairness, and intentionality with which they are designed, implemented, and evaluated.

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