CHAPTER SIX

Artificial Intelligence-Enhanced Work-Integrated Learning in Chemistry Education: Bridging Laboratory Theory and Professional Practice

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Abstract: The integration of artificial intelligence (AI) into higher education is transforming the design and delivery of Work-Integrated Learning (WIL), especially in laboratory-based disciplines such as chemistry. This chapter examines how AI-enhanced WIL can connect theoretical chemistry knowledge with authentic professional experiences, fostering innovation, inclusivity, and skill development in the digital age. Drawing on constructivist and experiential learning theories, the chapter conceptualises AI as both a learning partner and a catalyst for professional competence. It investigates recent advancements in AI-supported feedback, adaptive mentoring, and virtual laboratory simulations to propose a framework for integrating AI-driven tools into chemistry WIL contexts. The chapter illustrates how AI-enabled platforms can facilitate reflective observation, provide real-time feedback, automate assessments, and ensure equitable access to laboratory experiences, all while aligning with emerging principles of authentic assessment and ethical AI use to maintain a human-centred and contextually relevant learning approach. By merging conceptual analysis with a practical implementation model, the chapter underscores the transformative potential of AI in enhancing student readiness, collaboration, and problem-solving within chemistry education. It concludes with recommendations for higher education institutions and industry partners to develop sustainable AI-mediated WIL systems that strengthen laboratory practice, improve employability, and promote inclusive participation in science education across diverse contexts.

Keywords: Artificial intelligence, chemistry education, experiential learning, laboratory innovation, work-integrated learning.

1. Introduction

The rapid advancement of artificial intelligence has begun to reshape higher education in ways that extend far beyond administrative efficiency or automated instruction. Recent developments indicate a shift towards intelligent learning environments that can complement and enhance human teaching, particularly in disciplines where complex problem solving, laboratory practice, and professional competence are central. Chemistry education has witnessed notable advancements in this area, with researchers reporting an increasing utilisation of digital and intelligent tools to support conceptual learning, assessment, and laboratory practice (Ali et al., 2023; Iyamuremye et al., 2024). Studies suggest that artificial intelligence can enhance key components of chemistry instruction, such as formative assessment, feedback quality, and the modelling of multistep problem-solving processes (Ade-Ibijola et al., 2025; Eitemüller et al., 2023). This emerging body of evidence implies that artificial intelligence possesses substantial potential to strengthen learning environments in laboratory-based disciplines where traditional teaching often encounters structural limitations.

A related development is the expanding role of Work-Integrated Learning (WIL) as an educational approach designed to connect theoretical knowledge with practical experience. WIL is recognised across higher education as an effective means of enhancing student employability, professional identity formation, and real-world competence (Curto-Reverte et al., 2025; Ferns et al., 2025). Despite its advantages, traditional models of WIL frequently encounter persistent challenges. These challenges include restricted placement opportunities, variable industry engagement, uneven supervision, and resource constraints that limit meaningful access for many students (Amarathunga, 2024; Cameron et al., 2019). Such challenges are particularly pronounced in chemistry education, where laboratory-based learning is contingent upon specialised infrastructure, safety considerations, and access to equipment. Consequently, students often experience disparities in the quantity and quality of hands-on laboratory practice that universities can provide.

Artificial intelligence has been identified as a potential means of addressing these constraints within laboratory-oriented disciplines. Research on virtual laboratories demonstrates that simulated experimentation can significantly enhance students' academic achievement, conceptual understanding, and confidence when compared with, or used alongside, traditional laboratory experiences (Asare et al., 2023; Bazie et al., 2024). These environments offer safe, scalable, and accessible alternatives for institutions that face infrastructural limitations. Complementary evidence from automated assessment research indicates that artificial intelligence can evaluate chemistry responses with increasing reliability, particularly for objective and structured items, while reducing marking workload and providing timely feedback (Ade-

Ibijola et al., 2025; Yamtinah et al., 2024). Parallel studies on explainable artificial intelligence feedback systems suggest that transparent recommendations improve student understanding and self-regulation, enabling learners to better comprehend the guidance they receive (Afzaal et al., 2024). These developments underscore the potential of artificial intelligence to support essential WIL functions such as supervision, assessment, feedback, and reflective learning.

There is further evidence that the integration of artificial intelligence aligns with contemporary pedagogical theories emphasising active engagement. Research on experiential learning indicates that generative artificial intelligence tools can support authentic tasks, enhance reflective processes, and facilitate deeper engagement in inquiry-based activities (Salinas-Navarro et al., 2024a, 2024b). Studies in related fields also demonstrate that artificial intelligence-supported simulations can foster reflective thinking and structured learning cycles consistent with experiential and constructivist principles (Kim, 2023; Lin et al., 2025). These insights suggest that artificial intelligence is not merely a technical enhancement but can significantly contribute to the theoretical foundations of WIL, provided it is employed within a pedagogically informed framework.

While research on artificial intelligence in chemistry education is expanding, there remains a notable gap at the intersection of artificial intelligence and Work-Integrated Learning. Existing studies have explored digital technologies in chemistry, the effectiveness of virtual laboratories, and automated assessment and feedback systems. However, there is limited research on how artificial intelligence can be systematically integrated into WIL to support authentic laboratory practice, improve feedback processes, enhance supervision quality, and ensure professional readiness (Ali et al., 2023; Bugaje & Madaki, 2025; Iyamuremye et al., 2024). The issue addressed in this chapter is the lack of a coherent framework that explains how artificial intelligence can strengthen Work-Integrated Learning in chemistry by improving access, enhancing feedback quality, supporting reflective practice, and promoting the human-centred principles necessary for meaningful experiential learning.

2. Conceptual and Theoretical Foundations

The conceptual and theoretical foundations of this chapter are based on established models of learning that advocate for active engagement, reflection, and authentic practice. Constructivist Learning Theory and Experiential Learning Theory serve as the basis for comprehending how learners cultivate deep knowledge through participation in meaningful tasks. These theories are particularly relevant to chemistry education, as laboratory work necessitates active interpretation, practical reasoning, and iterative refinement. Recent studies on artificial intelligence in science and chemistry education illustrate that intelligent tools can effectively align with these pedagogical traditions by reinforcing feedback loops, enhancing inquiry processes, and expanding access to authentic learning activities (Afzaal et al., 2024; Iyamuremye et al., 2024; Salinas-Navarro et al., 2024a). Consequently, this section outlines the two theoretical pillars that inform the analysis and positions artificial intelligence as a learning partner capable of supporting these established educational processes.

In practical terms, conceptualising artificial intelligence as a learning partner entails a structured and deliberate division of roles between technology and human educators. Artificial intelligence assumes responsibility for functions that are challenging to sustain at scale or in real time, including the provision of immediate formative feedback on laboratory tasks, the generation of personalised prompts during simulations, the monitoring of learner engagement through analytics, and the identification of misconceptions that require instructor intervention (Ade-Ibijola et al., 2025; Afzaal et al., 2024). Human educators, in contrast, retain responsibilities that necessitate professional judgement, relational sensitivity, and ethical reasoning — such as the design of learning experiences, the contextualisation of feedback, the moderation of assessment decisions, and the maintenance of supervisory relationships fundamental to Work-Integrated Learning (Ferns et al., 2025; Sharma & Sharma, 2025). Thus, the partnership is structured not as a replacement for human expertise but as an augmentation of educator capacity, enabling instructors to focus on higher-order mentoring and professional development while artificial intelligence manages the operational aspects of learner support. This understanding of the learning partnership ensures that the theoretical frameworks explored in this section are applied in a manner that upholds human-centred pedagogical values (Bugaje & Madaki, 2025; Opesemowo & Adekomaya, 2024).

2.1 Constructivist learning theory

Constructivist Learning Theory posits that knowledge is constructed when learners actively engage with concepts, observe outcomes, test assumptions, and negotiate meaning from their experiences. Learning is shaped by the individual contributions that learners bring to each task and by how they interpret feedback from their environment. This theoretical perspective is reflected in much of chemistry education, where understanding is developed through the interplay of conceptual explanations and laboratory investigations. Research in digital chemistry education confirms that students benefit from opportunities to work through problems in a structured yet exploratory manner. Eitemüller et al. (2023) demonstrated that digitalised multistep chemistry exercises, integrated with automated formative feedback, enable students to construct meaning by visualising errors, revisiting reasoning steps, and refining their approaches through guided practice. Such findings align with core constructivist principles, as they emphasise the value of scaffolded exploration.

Constructivism highlights the cognitive processes through which students derive meaning from laboratory work. In chemistry, learners do not merely observe chemical phenomena; they actively interpret results, reconcile unexpected outcomes with prior knowledge, and revise their conceptual understanding based on new evidence. This internal process of knowledge construction, which is rooted in the learner's interpretation of experience rather than in the cyclical structure of the experience itself, distinguishes constructivist learning from the experiential model discussed in the following section. Bazie et al. (2024) reported that virtual laboratory experiences enhanced students' academic achievement by allowing them to manipulate variables, observe outcomes, and revise their conceptual models in response to evidence. This process is grounded in constructivist meaning-making rather than procedural repetition. These findings illustrate how digitally mediated environments can support the interpretive and conceptual dimensions of laboratory learning that constructivism identifies as central to deep understanding.

Constructivist theory further emphasises the importance of feedback that aids in meaning construction. Afzaal et al. (2024) found that explainable artificial intelligence systems can provide transparent and interpretable feedback, helping students recognise misconceptions and regulate their learning. This aligns with the constructivist focus on learner interpretation of instructional cues. As chemistry learners engage in laboratory-based or simulation-based tasks, they rely on timely feedback to consolidate emerging ideas and establish conceptual coherence. Therefore, artificial intelligence tools can enhance constructivist learning cycles by providing consistent, detailed, and adaptive feedback in situations where human supervision may be limited.

2.2 Experiential learning theory

Experiential Learning Theory, particularly as articulated by Kolb, presents a cyclical model of learning consisting of four interrelated stages: concrete experience, reflective observation, abstract conceptualisation, and active experimentation. This model closely mirrors the structure of chemistry laboratory work, where students design experiments, observe results, analyse data, articulate conclusions, and refine procedures. Research in chemistry and science education indicates that experiential learning fosters deeper conceptual understanding and enhances problem-solving skills. Furthermore, virtual and augmented environments in chemistry have been shown to engage students with the experiential cycle by providing simulated concrete experiences that can be repeated, adjusted, and reflected upon (Asare et al., 2023).

Research on artificial intelligence-mediated experiential learning provides additional insights into how this cycle can be enhanced. Salinas-Navarro et al. (2024b) found that generative artificial intelligence can support reflective observation by prompting students to explain their reasoning, revisit earlier decisions, and consider alternative approaches. Lin et al. (2025) demonstrated that generative artificial intelligence tools can foster reflective thinking in STEM contexts by providing structured prompts that assist students in articulating patterns and connecting experiences to broader principles. These studies highlight how the reflective and conceptual phases of Kolb's cycle can be strengthened through artificial intelligence-guided questioning, personalised feedback, and cognitive scaffolding.

Experiential Learning Theory also emphasises the importance of iterative experimentation. Chemistry education often necessitates that students repeat procedures, adjust parameters, and test new strategies. Virtual laboratories and simulation environments allow students to engage in these cycles without risk, resource limitations, or time constraints. Research by Bazie et al. (2024) provides empirical evidence that virtual laboratories support the experiential cycle by encouraging repeated experimentation and enabling learners to observe chemical processes in controlled, replicable conditions. When combined with artificial intelligence-based assessment or guidance systems, these environments can offer tailored suggestions that facilitate the transition from concrete experience to conceptual understanding. Such alignment strengthens the argument that artificial intelligence can enhance experiential learning structures in ways that support the development of practical and intellectual skills.

2.3 Positioning artificial intelligence as a learning partner

Artificial intelligence can be viewed as a learning partner when considered through the lenses of Constructivist Learning Theory and Experiential Learning Theory. Both theories emphasise active engagement, reflection, and iterative refinement, and emerging literature demonstrates that artificial intelligence systems can effectively support these processes. Constructivist Learning Theory posits that learners construct knowledge through interpretation, exploration, and feedback. Artificial intelligence systems align with these principles by providing continuous formative guidance, identifying misconceptions, and prompting learners to revisit earlier reasoning. Evidence from research on automated assessment indicates that artificial intelligence can deliver consistent and detailed feedback, enabling learners to interpret their performance and adjust their understanding, thereby reflecting the core tenets of constructivist meaning-making (Ade-Ibijola et al., 2025; Yamtinah et al., 2024).

Experiential Learning Theory further elucidates how artificial intelligence can operate within learning cycles. This theory outlines a sequence that includes concrete experience, reflective observation, abstract conceptualisation, and active experimentation. Artificial intelligence tools can facilitate each stage by providing simulated laboratory experiences, reflective prompts, and personalised suggestions that aid in developing conceptual understanding. Research indicates that explainable artificial intelligence systems can enhance reflective observation by assisting students in interpreting their data, understanding errors, and planning subsequent actions (Afzaal et al., 2024). Additionally, studies on generative artificial intelligence for experiential learning suggest that these tools can scaffold authentic tasks, promote engagement with real-world scenarios, and support transitions between reflection, conceptualisation, and experimentation (Salinas-Navarro et al., 2024a, 2024b). Such findings imply that artificial intelligence can play an integral role in the experiential cycle by offering timely input that facilitates repeated practice and informed decision-making.

Furthermore, artificial intelligence can enhance laboratory-based work-integrated learning (WIL) by addressing the supervision and access limitations that often hinder its implementation in chemistry education. Constructivism highlights the importance of guided exploration; however, instructors may not always be available to monitor students' decisions or provide immediate feedback in laboratory environments. AI tools can help bridge this gap by monitoring learner actions, offering context-sensitive guidance, and prompting real-time reflection. Additionally, AI-supported platforms expand the reach of WIL by allowing learners to engage in activities that replicate professional practice, even in the absence of physical placements or laboratory spaces. Studies confirm that such tools can foster the problem-solving, decision-making, and reflective skills that are essential for effective practice in laboratory-based disciplines, particularly when traditional supervision or infrastructure is limited (Ali et al., 2023; Bazie et al., 2024; Eitemüller et al., 2023).

Although constructivist and experiential learning theories provide a supportive foundation for the integration of AI, it is important to acknowledge that this alignment is not without tension. Some scholars caution that AI-mediated feedback may compromise the authenticity that is central to experiential learning, particularly if learners become reliant on algorithmically generated responses rather than engaging critically with the situated and contingent nature of real laboratory problems (Selwyn, 2019; Zawacki-Richter et al., 2019). From a constructivist perspective, concerns have also been raised that AI systems, regardless of their adaptability, cannot fully replicate the dialogic and relational dimensions of human mentoring that facilitate deeper meaning-making (Bayne, 2015). These critiques do not negate the potential of artificial intelligence to support learning; however, they do highlight the importance of designing AI-enhanced environments that preserve opportunities for genuine inquiry, human dialogue, and contextual professional judgement. The framework proposed in this chapter addresses these concerns by positioning artificial intelligence as a supplement to, rather than a substitute for, human-centred learning relationships.

Recognising artificial intelligence as a learning partner also clarifies how the theoretical foundations of this chapter inform the conceptual model developed later. Constructivist Learning Theory elucidates why learners benefit from personalised, interpretive feedback, while Experiential Learning Theory underscores the importance of iterative cycles of action, reflection, and refinement in laboratory practice. Positioning artificial intelligence as a learning partner within these traditions provides the conceptual basis for an AI-enhanced Work-Integrated Learning (WIL) model that is grounded in established principles of knowledge construction and professional competence development.

2.4 Concept of work-integrated learning and artificial intelligence in chemistry education

Work-Integrated Learning (WIL) is widely recognised as an educational approach that intentionally connects academic learning with authentic professional practice. In laboratory-based disciplines such as chemistry, WIL is particularly crucial as professional competence is cultivated through engagement with experimental procedures, instrumentation, safety protocols, and analytical reasoning. Chemistry WIL aims to immerse students in environments where theoretical knowledge is applied to real scientific tasks, thus fostering technical skills, professional judgement, and ethical awareness in line with workplace expectations (Curto-Reverte et al., 2025; Ferns et al., 2025). Through laboratory placements, industry-linked projects, and supervised practical experiences, students encounter the complexity and uncertainty inherent in scientific work, which enhances their readiness for professional roles.

The laboratory is central to WIL in chemistry education, serving as the primary space where abstract concepts are transformed into observable and measurable phenomena. Laboratory-based WIL enables learners to move beyond symbolic representations and engage directly with chemical reactions, data interpretation, and experimental decision-making. Research by Amarathunga (2024) and Ferns et al. (2025) indicates that such engagement enhances procedural fluency and deepens conceptual understanding, particularly when students are required to justify methodological choices and reflect on experimental outcomes. These experiences also contribute to employability by aligning academic learning with industry standards. However, the effectiveness of laboratory-based WIL depends on sustained access to well-structured and adequately supervised practical environments.

Despite its pedagogical value, traditional models of WIL in chemistry face persistent structural challenges. Limited laboratory space, high equipment costs, and strict safety regulations often restrict the frequency and duration of hands-on experimentation, especially in large undergraduate cohorts (Ali et al., 2023). Supervision challenges further compound these limitations. High student-to-instructor ratios can reduce opportunities for personalised feedback and reflective dialogue during laboratory activities, thereby weakening the learning potential of WIL experiences (Cameron et al., 2019). Consequently, some students complete chemistry programmes with uneven exposure to authentic laboratory practice.

Placement inequities also undermine the inclusive goals of WIL. Access to industry laboratories, research facilities, and specialised placements is uneven across institutions and regions. Curto-Reverte et al. (2025) reported that disparities in placement availability often disadvantage students from under-resourced contexts, resulting in unequal skill development and professional confidence. In chemistry education, where laboratory competence is central to professional identity, such inequities raise concerns about fairness and graduate preparedness. These challenges reveal a tension between the aspirational aims of WIL and the practical constraints of its traditional delivery.

In this context, artificial intelligence has emerged as a significant development in chemistry education, offering new ways to support learning and professional preparation. In both teaching and research settings, artificial intelligence assists with molecular modelling, reaction prediction, data analysis, and visualisation, addressing long-standing challenges related to abstraction and delayed feedback (Ali et al., 2023; Iyamuremye et al., 2024). The digital transitions in higher education, accelerated during periods of disruption, have further demonstrated institutional capacity to adopt intelligent learning systems that support flexible and technology-mediated laboratory learning (Opesemowo et al., 2022).

Recent trends indicate a growing utilisation of artificial intelligence-supported virtual laboratories, adaptive feedback systems, mentoring tools, and automated assessment platforms in chemistry education. Virtual laboratories facilitate repeated experimentation and safe exploration of chemical processes, thereby enhancing both conceptual understanding and procedural confidence (Asare et al., 2023; Bazie et al., 2024). Adaptive feedback and automated assessment systems offer timely responses to student work, promote self-regulation, and alleviate the burden of manual marking (Ade-Ibijola et al., 2025; Yamtinah et al., 2024). Furthermore, artificial intelligence-driven mentoring tools provide learners with guidance that emulates supervisory dialogue, particularly in situations where direct instructor support is limited (Afzaal et al., 2024).

While these advancements address challenges related to access, supervision, and scalability, their integration raises significant ethical and pedagogical considerations. Issues such as data privacy, transparency, academic integrity, and equitable access are central to responsible implementation. Research by Bugaje and Madaki (2025) and Opesemowo (2024) underscores the necessity for artificial intelligence in education to preserve learner agency, align with pedagogical intent, and uphold the human-centred values of professional preparation. It is crucial to ensure that artificial intelligence supports, rather than dictates, learning processes to maintain the educational integrity of WIL in chemistry (Opesemowo & Adekomaya, 2024). This integrated perspective positions artificial intelligence as a strategic enhancement of WIL that can strengthen laboratory practice while addressing longstanding structural limitations.

3. AI-Enhanced Work Integrated Learning: Conceptual Integration Framework

The AI-Enhanced Work-Integrated Learning (WIL) Conceptual Integration Framework (Figure 1) presented in this chapter synthesises insights from research in chemistry education, Work-Integrated Learning, and artificial intelligence. It illustrates how technology-mediated systems can enhance the connection between theoretical knowledge and professional laboratory practice. Grounded in constructivist and experiential learning theories, the framework positions artificial intelligence as a learning partner that fosters authentic engagement, reflection, and skill development within chemistry-based WIL contexts. It addresses documented challenges in traditional laboratory instruction, such as limited supervision, unequal access to placements, and constraints on practical exposure (Ali et al., 2023; Curto-Reverte et al., 2025; Ferns et al., 2025).

At the centre of the framework are the chemistry learners, whose development is shaped through iterative engagement with learning activities. Surrounding the learner are interconnected components mediated by artificial intelligence that support progression through Work-Integrated Learning activities. The first component, AI-supported feedback and reflective observation, draws on studies demonstrating the value of automated and adaptive feedback in promoting self-regulation and conceptual understanding. Research indicates that artificial intelligence systems can provide timely, consistent, and task-specific feedback, helping learners evaluate experimental outcomes and identify misconceptions. This feedback is essential for reflective learning in laboratory contexts (Ade-Ibijola et al., 2025; Afzaal et al., 2024; Yamtinah et al., 2024). This component aligns with experiential learning principles by strengthening the transition from concrete experience to reflective observation.

Linked to feedback is adaptive mentoring and personalised learning, which reflects evidence that artificial intelligence can guide learners through complex tasks when direct supervision is limited. Studies on explainable artificial intelligence and generative systems suggest that these tools can provide prompts, explanations, and recommendations that aid decision-making and scaffold learner progression (Afzaal et al., 2024; Salinas-Navarro et al., 2024a). In the context of chemistry WIL, adaptive mentoring supports constructivist learning by enabling learners to actively interpret guidance, test ideas, and refine their understanding during laboratory activities, rather than relying solely on prescriptive instruction.

The framework also incorporates virtual laboratory simulations and remote experimentation, supported by a growing body of research that highlights their role in expanding access to practical chemistry experiences. Virtual laboratories allow learners to conduct experiments, manipulate variables, and observe outcomes repeatedly in safe and controlled environments, addressing the infrastructural and safety constraints associated with physical laboratories (Asare et al., 2023; Bazie et al., 2024). These environments support experiential learning by enabling learners to engage in cycles of experimentation and revision, while also reducing inequities linked to limited laboratory space and placement availability (Curto-Reverte et al., 2025).

Another key element of the framework is the use of automated assessment and learning analytics for performance tracking. Artificial intelligence-based assessment systems have demonstrated their ability to evaluate conceptual understanding, problem-solving processes, and laboratory reports with consistency and efficiency (Ade-Ibijola et al., 2025; Eitemüller et al., 2023). The learning analytics generated by these systems allow educators to monitor learner progression, identify support needs, and assess the effectiveness of WIL activities at scale. This component reinforces authentic assessment practices while addressing the scalability challenges that are often encountered in chemistry education.

At the core of these components is a commitment to equitable access and inclusion, reflecting concerns raised in the literature about disparities in laboratory exposure, feedback quality, and placement opportunities. Artificial intelligence-mediated tools can promote inclusive participation by facilitating remote engagement, providing adaptive support, and offering flexible access to learning resources, particularly for students in under-resourced settings (Bugaje & Madaki, 2025; Opesemowo, 2024; Opesemowo & Adekomaya, 2024). Ethical considerations related to transparency, data privacy, and human oversight inform the design and implementation of the AI-enhanced WIL framework, guiding the selection, deployment, and evaluation of artificial intelligence tools within chemistry education contexts to ensure a human-centred approach to professional preparation (Bugaje & Madaki, 2025; Opesemowo, 2024).

Figure 1 illustrates the dynamic interaction among these components, demonstrating how artificial intelligence-mediated processes collectively support learner development within Work-Integrated Learning. The framework provides a theory-informed and evidence-based foundation for designing AI-enhanced WIL models that strengthen laboratory practice, improve feedback and assessment, and promote inclusive participation in chemistry education.

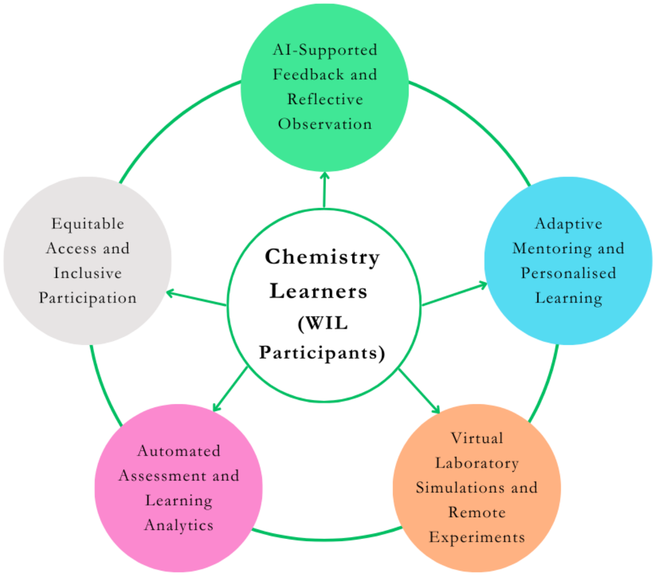

Figure 1. *AI-enhanced work-integrated learning framework for chemistry education*

The placement of the chemistry learner at the centre of Figure 1 is not merely structural but holds significant conceptual importance. Instead of interacting with each surrounding component in a fixed, linear sequence, the learner engages iteratively and concurrently across all four domains. This process involves receiving AI-generated feedback that encourages reflection, accessing adaptive mentoring when decision-making encounters obstacles, rehearsing procedures through virtual simulations, and having their progression monitored through learning analytics that identify areas necessitating instructor or teacher attention. This multi-directional connectivity ensures that each component reinforces the others: simulations generate the experiential data that feedback systems interpret; analytics reveal patterns that adaptive mentoring addresses; and the cumulative effect results in a coherent, learner-centred WIL environment. This design directly supports the central argument of the study that artificial intelligence, when positioned in relation to the learner rather than as a standalone tool, can address the structural limitations of traditional chemistry WIL while preserving the human-centred values of authentic professional preparation.

3.1 Sequencing and interaction of framework components in a typical WIL cycle

Although the components of the AI-enhanced WIL framework are described individually above, their pedagogical value lies in their dynamic interactions throughout a coherent learning sequence. The framework is not designed as a linear progression but as an iterative cycle, where each component activates and reinforces the others in response to the evolving needs of the learner. Understanding how these components interact in practice is essential for educators seeking to implement the framework within chemistry WIL.

In a typical AI-enhanced WIL sequence, students may begin with virtual laboratory simulations (component 3) to rehearse experimental procedures, manipulate variables, and build procedural confidence before engaging with physical or industry-linked laboratory settings. As they progress through simulated tasks, adaptive mentoring (component 2) provides scaffolded guidance, offering prompts that challenge assumptions, suggest alternative interpretations, and support informed decision-making in real time. Simultaneously, AI-supported feedback (component 1) analyses student responses to experimental outcomes, prompting reflection on observed data and facilitating the transition from concrete experience to conceptual understanding, in alignment with the reflective observation stage of Kolb's experiential learning cycle. Throughout this process, learning analytics (component 4) track performance patterns across all activities, identify students who may require targeted support, and generate evidence that enables educators to make timely and informed interventions. The interaction among these components is therefore neither linear nor autonomous, but a pedagogically structured cycle in which artificial intelligence augments and extends what human educators can offer, while human judgement provides the interpretive and ethical framework within which all AI tools operate.

3.2 Implementation and implications of AI-enhanced WIL framework

The implementation of an AI-enhanced Work-Integrated Learning framework in chemistry education necessitates deliberate institutional planning that aligns policy, curriculum, and digital infrastructure. At the policy level, higher education institutions must establish clear guidelines governing the ethical use of artificial intelligence, data protection, and academic integrity to ensure responsible adoption (Bugaje & Madaki, 2025; Opesemowo, 2024). These policies should explicitly recognise artificial intelligence as a pedagogical support rather than a substitute for human instruction. Curriculum redesign is equally critical, as chemistry programmes need to intentionally incorporate AI-mediated WIL activities within laboratory courses, industrial attachments, and capstone projects. Such integration ensures that artificial intelligence tools support defined learning outcomes related to professional competence, reflective practice, and problem-solving. Concurrently, investments in digital infrastructure, such as learning management systems, secure data platforms, and virtual laboratory technologies, are necessary to ensure scalable and reliable implementation (Ali et al., 2023; Iyamuremye et al., 2024).

Effective implementation also relies on strong collaboration between universities and industry partners. AI-enhanced WIL creates opportunities for shared supervision models, in which academic staff and industry professionals jointly support students through digitally mediated environments. For instance, virtual internships backed by artificial intelligence can allow students to engage with authentic industrial datasets, simulated laboratory workflows, or remote experimentation under the oversight of both academic and industry personnel (Ferns et al., 2025). Similarly, AI-based laboratory simulation platforms can be co-developed with industry to reflect current professional practices, equipment standards, and safety protocols, thereby enhancing the relevance of university training to workforce needs (Curto-Reverte et al., 2025). These collaborative models help bridge traditional gaps between theory and practice while expanding placement capacity beyond physical constraints.

Evidence of AI-enhanced WIL in practice is already emerging across higher education contexts. Institutions have begun integrating virtual simulations and AI-supported feedback into undergraduate programmes, enabling students to rehearse laboratory procedures and receive guided formative assessments beyond scheduled contact hours (Asare et al., 2023; Bazie et al., 2024). In some cases, artificial intelligence has been used to support virtual internships by monitoring task progression, offering prompts, and facilitating reflective reporting where direct supervision is limited (Afzaal et al., 2024). These emerging applications demonstrate that AI-enhanced WIL is not merely theoretical; it is a practical and scalable response to the structural constraints that have long limited the depth and equity of chemistry WIL experiences.

Ensuring a human-centred and ethical deployment remains a central consideration throughout the implementation process. Institutions must prioritise transparency regarding how artificial intelligence systems function, maintain human oversight in assessment and mentoring processes, and address equity issues in access to digital resources (Opesemowo & Adekomaya, 2024). When these conditions are met, the implications of the framework are substantial. Students benefit from enhanced professional competence, confidence, and employability derived from authentic, supported practice. Educators experience evolving roles as facilitators, mentors, and designers of learning experiences supported by artificial intelligence. For institutions and industry partners, AI-enhanced WIL strengthens collaboration, supports workforce relevance, and reinforces shared responsibility for ethical data use and professional preparation in chemistry education.

A further implementation consideration is how to assess AI-enhanced WIL activities and how they align with accreditation requirements for chemistry programmes. Professional bodies, such as the Royal Society of Chemistry (RSC) in the United Kingdom, the American Chemical Society (ACS), and equivalent national organisations, typically specify competency benchmarks that graduating chemists must demonstrate. These include laboratory skills, safety awareness, and professional conduct. Therefore, institutions adopting AI-enhanced WIL must ensure that AI-mediated experiences, such as virtual laboratory simulations and automated assessment tasks, are validated against these requirements, particularly when they are intended to fulfil mandated laboratory hours or practical competency standards. This may involve institutional review processes, formal engagement with accreditation bodies to clarify the standing of AI-mediated activities, and the development of equivalency frameworks that document how virtual and AI-supported experiences meet professional standards. Failing to address these accreditation dimensions risks a decline in institutional recognition of AI-enhanced WIL and may limit the transferability of students' credentials across professional and national contexts (Ferns et al., 2025).

3.3 Challenges and ethical considerations for implementation of AI-enhanced WIL

The implementation of AI-enhanced Work-Integrated Learning (WIL) in higher education presents significant pedagogical benefits; however, it is accompanied by structural and ethical challenges that require careful consideration. A primary concern relates to digital equity and infrastructural disparities across institutions and regions. Although artificial intelligence can enhance access to learning resources, virtual laboratories, and personalised support, its effectiveness is contingent upon the availability of reliable digital infrastructure. Research on technology integration in chemistry education indicates that limited access to laboratory facilities, digital tools, and technical support already constrains practical learning in numerous institutions (Ali et al., 2023; Mahbub et al., 2024). Nwakocha et al. (2025) emphasise that, while AI-driven systems possess the capacity to promote inclusive learning and employability, unequal access risks reinforcing existing educational inequalities. In AI-enhanced WIL contexts, students in under-resourced settings may, therefore, experience reduced exposure to simulations, adaptive mentoring, and analytics-driven feedback, thereby undermining the equity goals central to WIL (Curto-Reverte et al., 2025).

Closely linked to access is the challenge of safeguarding data privacy and academic integrity. AI-enhanced WIL environments depend on continuous data collection from student interactions with virtual laboratories, assessment platforms, and feedback systems. While such data facilitate adaptive learning and performance tracking, they also raise concerns regarding surveillance, data security, and potential misuse. Huang (2023) highlights that the widespread adoption of AI in education has intensified ethical risks related to student data privacy, particularly in systems that collect sensitive personal and academic information. Within chemistry education, automated assessment and AI-supported feedback systems have demonstrated efficiency and consistency (Ade-Ibijola et al., 2025; Yamtinah et al., 2024); however, their deployment must be accompanied by transparent governance structures. Bugaje and Madaki (2025) emphasise that ethical AI use in education necessitates clarity concerning data ownership, informed consent, and accountability to preserve trust and uphold academic integrity.

Another critical concern is the risk of over-automation, which may undermine the human-centred foundations of Work-Integrated Learning. WIL is inherently relational, relying on supervision, mentoring, and professional judgement to support learner development. While AI-driven mentoring and feedback tools can supplement instructional support, excessive reliance on automation may diminish opportunities for reflective dialogue and contextual guidance. Afzaal et al. (2024) demonstrate that explainable AI can support self-regulation; however, they also stress the importance of human interpretation in learning processes. Sharma and Sharma (2025) similarly caution that generative AI tools, if uncritically adopted, may displace meaningful educator involvement in WIL programmes. In chemistry education, where professional responsibility and ethical reasoning are cultivated through guided practice, the risk of over-automation extends beyond pedagogy into the domain of safety (Ferns et al., 2025).

Beyond the general ethical concerns surrounding AI in education, chemistry education presents discipline-specific ethical considerations that require explicit attention. A particularly significant issue pertains to the role of AI in safety training. Laboratory safety in chemistry relies not only on procedural knowledge but on embodied competence: the ability to identify hazards through sensory experience, respond appropriately under pressure, and cultivate a professional culture of caution and responsibility (Cameron et al., 2019). Although AI simulations can model safety protocols and present hazard scenarios in controlled virtual environments, they cannot fully replicate the physical, sensory, and affective dimensions of real laboratory risk management. Institutions must therefore ensure that AI-mediated safety training is deliberately supplemented with supervised hands-on experience, rather than being treated as a substitute.

Another chemistry-specific concern pertains to the use of AI-generated data in experimental contexts. Students who rely on AI-produced outputs, such as simulated spectra, predicted reaction yields, or algorithmically generated datasets, may develop an inaccurate understanding of experimental variability, measurement uncertainty, and the reproducibility challenges inherent in authentic laboratory science. Educators and curriculum designers must explicitly address this risk, ensuring that learners understand the limitations of AI-generated data and can critically evaluate its relationship to real experimental practice.

Together, these challenges underscore the need for a balanced and principled approach to implementing AI-enhanced WIL. Addressing infrastructural inequities, protecting data privacy, and avoiding over-automation are not peripheral concerns but core conditions for ethical and effective practice. By embedding artificial intelligence within robust pedagogical frameworks and maintaining human-centred supervision, higher education institutions can harness AI to strengthen, rather than compromise, the educational and professional aims of Work-Integrated Learning.

4. Conclusion and Recommendations

This chapter examines the integration of AI into WIL within chemistry education as a strategic response to ongoing challenges in laboratory-based instruction. Drawing on constructivist and experiential learning theories, the discussion establishes that AI can serve as a learning partner, enhancing access to authentic practice, supporting reflective learning, and strengthening the connection between theoretical knowledge and professional laboratory competence. Evidence from the literature indicates that AI-supported virtual laboratories, adaptive mentoring systems, automated assessments, and analytics-driven feedback can alleviate constraints related to limited infrastructure, uneven supervision, and inequitable placement opportunities. When thoughtfully implemented, these tools facilitate repeated experimentation, timely feedback, and personalised guidance, all of which are central to effective experiential learning and professional preparation in chemistry.

The chapter also proposes an AI-enhanced WIL conceptual framework that integrates feedback, simulation, mentoring, and assessment within a human-centred pedagogical structure. This framework illustrates how AI can reinforce experiential learning cycles while maintaining the supervisory and reflective dimensions essential to WIL. However, the analysis highlights that the educational value of AI is contingent upon ethical implementation, transparency, and sustained human oversight. Issues of data privacy, digital equity, and over-automation remain critical considerations, particularly in laboratory-based disciplines where professional judgement, safety awareness, and ethical reasoning are developed through guided practice. Therefore, the discussion positions AI as a transformative yet complementary tool, capable of enhancing laboratory learning and employability when aligned with sound pedagogical principles.

Several key recommendations emerge from this analysis. First, higher education institutions should develop clear policies regulating the ethical use of AI, focusing on data privacy, transparency, and academic integrity in WIL. Second, chemistry curricula should be intentionally redesigned to incorporate AI-supported simulations, feedback, and assessment activities that align with defined professional and laboratory learning outcomes. Third, universities should strengthen collaboration with industry partners to co-design AI-enhanced WIL experiences that reflect authentic workplace practices and shared supervision models. Fourth, targeted professional development should be provided for both educators and students to build the digital, pedagogical, and critical skills necessary for the effective and responsible use of AI in WIL settings. Lastly, sustained interdisciplinary research should be encouraged to evaluate the long-term pedagogical, ethical, and employability impacts of AI-enhanced WIL in chemistry education, with findings used to refine and adapt emerging frameworks as the technology continues to evolve.

4.1 Limitations of the study

It is crucial to recognise the limitations inherent in this conceptual analysis. The framework presented in this chapter has not undergone empirical validation; rather, it is based on a synthesis of existing literature and theoretical considerations, rather than primary data derived from chemistry WIL programmes. Consequently, the proposed model necessitates validation through pilot studies, case studies, and longitudinal research conducted across a range of institutional contexts and national environments. Furthermore, the analysis is specifically centred on chemistry education; while many of the principles discussed may hold relevance in other laboratory-based disciplines, caution should be exercised in generalising the framework beyond its intended scope. Another limitation pertains to the rapid pace of AI development: specific tools, platforms, and applications referenced in this chapter may evolve considerably in the near term, potentially altering the landscape of AI-enhanced WIL in ways that the present analysis cannot fully anticipate. The framework has been designed with this consideration in mind; its principles are intended to be adaptable rather than tool-specific, but ongoing review and revision will be necessary as the evidence base matures.

5. Declarations

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Use of Artificial Intelligence: During the preparation of this manuscript, the authors utilised AI-assisted writing tools, specifically Claude AI (Anthropic) and ChatGPT (OpenAI), solely for the purposes of language construction, sentence coherence, and editorial clarity. These tools were not employed to generate ideas, produce original arguments, conduct literature searches, or draw conclusions. All conceptual content, theoretical analysis, framework development, and scholarly interpretation are entirely the work of the authors. Following the use of these tools, the authors carefully reviewed and edited all AI-assisted passages to ensure that the resulting text accurately reflects their original meaning and intended scholarly contribution. The authors take full responsibility for the integrity, accuracy, and originality of the content of this publication.

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