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The Bubble and Burner model of AI-infusion: a framework for teaching and learning

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ABSTRACT
This paper proposes a framework for how secondary school teachers might effectively engage with Artificial Intelligence (AI) within the learning process. It contributes to current research by providing teachers with a method for imagining, designing, and enacting AI-supported learning experiences. The two dimensions of the Bubble and Burner Model of AI-infusion emerged through a reflexive iterative cycle of professional practice. They are unified through the metaphor of a Bunsen burner, laboratory flask, and thermometer, which represent the interplay between student learning, teacher roles, and knowledge flow. Together, the dimensions offer a framework for visualizing the integration of AI into classroom practice and clarify the teacher's function within the AI age.

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GAI; generative artificial intelligence; education; teaching; skill acquisition

Introduction

Although artificial intelligence has existed for decades, its definition remains context-dependent (Crawford, 2021). This paper adopts UNESCO's widely accepted definition of Generative AI as technology that "automatically generates content in response to prompts written in natural language conversational interfaces" (Miao & Holmes, 2023, p. 8). It should be noted, however, that others extend this view: Microsoft's AI lead, Mustafa Suleyman, describes AI as "a new digital species" (Suleyman, 2024). This metaphor has a particular resonance in schools where this species now occupies a place in the learning process. Through ubiquitous digital devices, Generative AI (GAI or often simply "AI") – particularly Large Language Models (LLMs) – has become unavoidable in education. Teachers encounter it daily as students, from late primary through university, use it as a form of "easy help" (Molenaar et al., 2025, p. 261).

Despite "significant concerns" (Miranda, 2025, p. 1), AI is widely seen as holding considerable potential for learning. Miranda acknowledges these "vast and continuously expanding" opportunities for leveraging AI's power in education, yet observes that it "cannot fundamentally replace the human role of teachers" (2025, p. 2). Kamalov et al., like Miranda, cautions being seduced by an "alluring picture" of AI (Kamalov et al., 2023, p. 2). With AI now ubiquitous in many schools and universities, educators must reconsider how they teach alongside this "digital species". Miranda observes that while AI has "potential . . . to fundamentally alter the roles of teachers and educational institutions" there remains "a conspicuous lack of comprehensive discussion on how to effectively integrate AI into educational curricula" (2025, p. 2). This view is similar to that of UNESCO who urge for "human-centred" approaches (Miao & Holmes, 2023, para. 1) to AI integration in education whilst teachers grapple with AI's "intricacies" (Miranda, 2025, p. 2). But the need for guidance on how to teach with AI is pressing as teachers are called to help students learn and "thrive in the world" of AI (Pratschke, 2024, p. 13).

This paper responds to that call. Building on the principles articulated in Wall et al. (2025) this paper proposes the Bubble and Burner Model of AI-infusion as a framework for conceptualizing how teachers can regulate, pace, and sequence AI use in schools. It contributes to the current discourse on teaching with AI by creating a framework by which teachers might conceptualize ways of integrating AI integration to enhance learning. It embraces the view of Oakley et al. who argue that by "thoughtfully balancing what our minds

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and machines each do best, we ensure that external innovations enhance rather than diminish our intelligence" (2025, p. 43).

The framework presents a model of two dimensions:

(1) a "Bubble metaphor", describing the sequencing and scaffolding of learning for students in AI-infused classrooms.
(2) a "Burner metaphor", outlining three additional functions for teachers in the AI age – roles specific to guiding learning when AI occupies a space in the classroom.

Together, these dimensions provide a conceptual framework for reimagining learning and teaching in an era where AI has become a ubiquitous "digital species".

Background

Few scholars have systematically examined the impact of generative AI (GAI) on high school pedagogy, and none have focused explicitly on conceptualizing its place within the process of teaching Humanities and Social Science (HASS) subjects – especially History. This paper emerged from a research project, undertaken within the author's dual role as classroom teacher and doctoral researcher, investigating the ethical and effective uses of GAI in the teaching of History at an Australian all-girls Catholic secondary school (UniSQ ethics ETH2023-0794). This context exposed a broad challenge faced by teachers who sought to express a conceptualization of the often highly nuanced position of AI within the teaching and learning processes of their classroom. Thus, although the model proposed in this paper was developed within the context of history teaching, it is not confined to that disciplinary setting. Despite an initial grounding in research related to the historical thinking pedagogy, the Bubble and Burner Model offers a conceptual approach that is adaptable across a broad range of subject areas where AI intersects with classroom practice.

Research on AI in subject-specific methodologies remains limited, with most early work addressing academic integrity, policy, or higher education. While several authors such as Mollick (2023, 2024), Tan and Maravilla (2024), Jackson and Esterman (2024), Duffy and Weil (2023), Furze (2023, 2024, 2025) and Luckin (2018, 2023) have explored AI's educational impacts, it is Mairéad Pratschke (2023, 2024, 2025) who most directly connects AI with epistemology and broader pedagogical frameworks. Her work is therefore particularly influential in this paper.

Pratschke underscores the transformative impact of rapid technological advancements, particularly the explosion of GAI tools that have "burst onto the scene" since November 2023 (Pratschke, 2024, p. 26). These tools expand accessibility, offering multiple entry points for learners while disrupting traditional content transmission models. In ways unimagined in earlier accounts of digital disruption, this reality is stark in 2025: students can now embark on "unmediated intellectual quests" (Kelly, 2013, p. 28) making it essential for educators to reconsider pedagogy. With near-unlimited access to information, students are no longer dependent on teachers for content. Pratschke (2024) extends this point, arguing that AI disrupts "our conception of the agency of the learner" by placing "multiple experts" in every classroom accelerating a shift in the role of teachers from being the "primary source or authority to [a] facilitator [and, hence] challenging the role of the educator as expert" (Pratschke, 2024, p. 82).

DeSilvia has responded with optimism to this challenge. She urges humanities teachers to approach the challenge of this new age "with enthusiasm" (para. 19). She warns against begrudgingly accepting AI-driven change. In this way, she builds upon a particular tradition among humanities educators embracing innovations in technology. Nearly a decade prior to the launch of ChatGPT, Lévesque, for example, urged teachers to embed digital tools, arguing that "rich technological open learning environments" support inquiry through the resources they provide (2014, p. 45). His advice remains relevant: "the question should no longer be about whether to use digital technology but rather how to use it to further the acquisition and development of expertise in domains of knowledge" (Lévesque, 2014, p. 44). Since 2023, GAI has become part of the learning environments that Lévesque referred to. It is noteworthy that the American Historical Association is supportive of this embrace, asserting that "educators have a responsibility to model appropriate engagement with generative AI" (2025, para. 14), even as many are still "seeking guidance on how to responsibly and effectively incorporate generative AI into their teaching practice" (2025, para. 4). This paper seeks to offer one possible answer these calls for guidance.

Theoretical framing

This paper draws upon three complementary theories to develop a Bubble and Burner Model of AI-infusion in learning and teaching – a new model for conceptualizing teaching and learning with AI in schools. The three theories are:

(1) The Five-Stage Model of Adult Skill Acquisition (Dreyfus, 2004, 2009)
(2) Cognitive Load Theory (Sweller et al., 2011)
(3) "Brain-to-LLM findings" (Kosmyna et al., 2025)

Further, this paper is informed by the view that AI is fundamentally a relational technology – a technology that, by its very nature, encourages "symbiotic approach" between learners and AI (Pratschke, 2024, p. 65). This view, called generativism by Pratschke, is "grounded in the principle of learning as a process" (2024, p. 65). She argues that it is "informed by some of the most important and influential learning theories and approaches of our age" (Pratschke, 2024, p. 65) including constructivism, connectivism, and generative learning theory. Pratschke emphasizes the last of these as explaining an important "sense-making process" in learning (2024, p. 65).

Theory 1: the five-stage model of adult skill acquisition

The Dreyfus (2004) model of skill acquisition, first articulated in 1986, offers a valuable framework for guiding the integration of AI into Humanities teaching. It outlines "five stages of skill acquisition" - "novice, advanced beginner, competent, proficient, and expert" (Dreyfus & Dreyfus, 2009, pp. 20, 21). Drawing on research into expertise across various domains, the model challenges the view of skill development as a linear accumulation of facts, instead describing it as a holistic transformation in perception, cognition, and interaction with the environment. Dreyfus' model describes skill acquisition as a "novice-to-expert" process. In essence, "a beginner calculates using rules and facts just like a heuristically programmed computer, but . . . with talent and a great deal of involved experience, the beginner develops into an expert who intuitively sees what to do without recourse to rules" (Dreyfus, 2004, p. 180). Basu similarly notes that "everyone begins as novices" (2020, p. 1), advancing through competence and expertise to become master practitioners This progression depends on experience and "deliberate and graduated challenges and feedbacks" (Basu, 2020, p. 1). Basu points to a process of building mental models – "internal representations" (2020, p. 5) – which "progressively" grow increasingly dense and interconnected through a succession of learner sense-making to experiences (p. 6). Central to this process is the teacher's role in scaffolding, sequencing, monitoring, and guiding student learning. Addressing educators in epidemiology, Basu emphasizes the importance of identifying where students are on their learning journey and tailoring instruction accordingly. Formative assessments, targeted challenges, and teacher feedback are essential to supporting students as they move from novice to expert. Basu also highlights the importance of "fading"- the gradual removal of "training wheels" (2020, p. 10) as leaners' expertise develops. This idea of fading is crucial, yet often overlooked, within Sweller's et al. (2011) Cognitive Load Theory.

Theory 2: cognitive load theory

While the Dreyfus model outlines the learner's developmental trajectory, Sweller's et al. (2011) Cognitive Load Theory (CLT) explains the cognitive mechanics underpinning that progression. CLT is often selectively used by proponents of Explicit Instruction (EI) but, in essence, is a theory centred on learning as a process of altering long-term memory. It is this fuller expression of CLT that informs the Bubble and Burner Model of AI-infusion. CLT's focus on learning and memory is essential in the context of AI-infused classrooms. As Oakley et al. observe, rather than treating memory as "obsolete in the AI era", it must be cultivated as "our personal knowledge bank" (2025, p. 43). CLT offers a complex way of understanding learning that is appropriate to classrooms in which the use of AI has become ubiquitous.

A rich understanding of CLT moves beyond simplistic EI articulations of learning. A frequent limitation in arguments which seek to promote EI is the way in which teachers' ways of working must evolve and change as learning progresses. CLT indicates the EI is *highly* effective for novices but CLT also warns that, as expertise grows, it is important for teacher guidance to fade to avoid the expertise reversal effect. CLT does not propose a simple replication of the rote teaching methodologies of previous eras. Such characterizations of Sweller's work are flawed and selective readings of his important research findings are unhelpful. Certainly, while for a novice (and at times, others) the "sage-on-the stage" is invaluable, it's clear that a teacher acting in the modality of a "guide-on-the-side" or as a "meddler-in-the-middle" can also be crucial (McWilliam, 2009, p. 288). In classrooms where AI can be used flexibly by students, the challenge for teachers is to find a model that is adaptive to different situations and responsive to student and student needs; a model that has a broad application across contexts – one that maintains a level of cognitive friction; that strikes a "balance" in which student use of AI extends rather than supplants student thinking (Oakley et al., 2025, p. 42). Such a balance can be struck through with reference to the ideas of cognitive architecture discussed by Sweller et al. (2011). Of particular relevance to this paper are the CLT-related concepts of "expertise reversal effect" and the "guidance fading effect" (Sweller et al., 2011, p. 155).

In CLT, learning involves the construction and automation of complex knowledge structures called "schemas". A schema is a cognitive construct – a mental model – that integrates multiple pieces of information into a single unit, allowing it to be processed as one element in working memory. Grounded in human cognitive architecture, CLT rests on two core principles: the brain's limited capacity for processing novel information and its virtually unlimited capacity for accessing stored knowledge. Sweller et al. (2011) found that reducing teacher support in line with "increasing levels of learner expertise" (2011, p. 175) significantly enhances learning. This is referred to by Sweller et al. (2011, p. 155) as guidance fading. Related to this is the expertise reversal effect. Sweller et al. (2011, p. 155) argue that an expertise reversal effect "occurs when information beneficial to novice learners becomes redundant to those more knowledgeable". In essence, they found that as learners gain expertise, strategies effective for novices – such as worked examples – can not only lose their value but become counterproductive. Consequently, "instructional methods including the amount of instructional guidance provided to learners should be dynamically tailored to changing levels of learner expertise in a particular area or domain" (Sweller et al., 2011, p. 171). This insight directly aligns with the Dreyfus model, reinforcing its inclusion in the Bubble and Burner framework for guiding AI integration in K-12 classrooms.

CLT reveals that while EI is essential for novices, the gradual fading of guidance is equally critical – the "sequencing of learning tasks with decreased guidance as expertise increases is important" (Sweller et al., 2011, p. 174). Likewise, when students are novices, their use of Large Language Models (LLMs) should be constrained and closely supported. As their expertise grows, teacher guidance should fade, allowing for broader and more autonomous engagement with AI tools. "Instructional formats that provide reduced guidance or minimal support, such as problem-solving practice or exploratory learning environments" are often more "cognitively efficient" as expertise increases (Sweller et al., 2011, p. 171). Close guidance and supervision, valuable at the novice stage, "may become redundant and so increase extraneous cognitive load as levels of expertise increase" (Sweller et al., 2011, p. 171). These ideas also resonate with findings from the MIT Media Lab and Kosmyna et al. (2025). They are incorporated into the Bubble and Burner Model of AI-Infusion.

Theory 3: "Brain-to-LLM"

As noted earlier, Kosmyna et al.'s influential 2025 MIT study stressed the need for teachers to use AI tools with intentionality. While AI offers students "immediate convenience", it also poses "potential cognitive costs" (Kosmyna et al., 2025, para. 1). The authors emphasized the need for "very careful consideration and continued research" into how AI is integrated into student learning (Kosmyna et al., 2025, p. 142). Due to frequent misrepresentation of the study appearing in new literature, it is worth clarifying key aspects here.

Participants were divided into three groups: those using a large language model (LLM), those using a search engine, and those working unaided. Brain activity was monitored via EEG to track cognitive engagement, while essays were scored by both human and AI markers. Participants were also interviewed after each task. The results revealed significant differences in neural connectivity and recall. Brain-only participants demonstrated the strongest cognitive integration, while those using LLMs retained less. As Pratschke summarized: "Unsurprisingly, those who used an LLM to generate essays recalled nothing, while those who used a web search did a bit better, and those who wrote their own work recalled a lot (2025, p. 8). Kosmyna et al. (2025) also identified a "critical" concern: "over-reliance on AI can erode critical thinking and problem-solving skills" (2025, p. 112).

The sequencing of LLM use significantly influenced learning outcomes. Participants who began with LLMs (the LLM-to-Brain group) showed weak neural connectivity, poor recall, and an inability to quote from their own essays – evidence of "shallow encoding" due to "outsourced cognitive processing" (Kosmyna et al., 2025, p. 140). In contrast, the Brain-to-LLM group – those who began unaided and later used AI support – showed the strongest results: better recall, higher quoting accuracy, and re-engaged neural networks, particularly those tied to memory and integration (Kosmyna et al., 2025, p. 140).

In their preliminary findings, Kosmyna et al. (2025, p. 141) identified a "concerning" pattern among participants in the Brain-to-LLM group. These students "repeatedly focused on a narrower set of ideas . . . [and] may not have engaged deeply with the topics or critically examined the material provided by the LLM" (Kosmyna et al., 2025, p. 141). The researchers linked this to the accumulation of cognitive debt: a reliance on external supports that displace "the effortful cognitive processes required for independent thinking" (Kosmyna et al., 2025, p. 141). Cognitive debt postpones mental effort in the short term but incurs "long-term costs" including weakened critical inquiry, increased "vulnerability to manipulation", and reduced creativity. When participants reproduce AI-generated content without scrutiny, they risk forfeiting both ownership of their ideas but their capacity for deeper learning (Kosmyna et al., 2025, p. 141). Interviews revealed stronger metacognitive engagement among participants in the Brain-to-LLM group. Collectively, the findings "support an educational model that delays AI integration until learners have engaged in sufficient self-driven cognitive effort" (Kosmyna et al., 2025, p. 141). For teachers, these findings indicate that students benefit most when AI use is sequenced and scaffolded in ways that complement, support and extend – rather than replace – students' own cognitive effort.

A theoretical synthesis

These three theories converge in ways that are both instructive and actionable for teachers. If a learner's progression from novice to expert depends on experience and "deliberate and graduated challenges and feedbacks" (Basu, 2020, p. 1) then AI must be integrated in ways that reinforce – rather than disrupt – this process of constructing internal, connected representations. Basu highlights the teacher's role in adjusting learning experiences through formative assessment, guidance, and feedback. Crucially, this "sense-making" process includes the gradual removal of "training wheels" (Basu, 2020, p. 10), a principle that aligns with Sweller's concept of fading in Cognitive Load Theory.

Sweller and his colleagues' work provides a key insight: in CLT, "experts possess a large number of domain-specific schemes" while novices benefit from "instructional guidance", which can become "disadvantageous for more expert learners" (Kalyuga et al., 2003, p. 24). His early work (e.g., Sweller, 1988) stressed that learning required matching the proficiency of a learner with the mental effort required of them. As he later noted, "[a] combination of the intensity of mental effort being expended by learners and the level of performance attained by the learners, constitutes the best estimator of instructional efficiency" (Sweller et al., 1998, p. 266). These findings suggest that as students develop greater knowledge and skill, they are increasingly capable of using AI for more complex or autonomous tasks.

Taken together, these three theoretical models underscore the need to align instructional support with learners' expertise, especially when introducing technologies like LLMs. Novices should engage with LLMs only with close teacher guidance and scaffolding. As their knowledge and skills grow, guidance should gradually fade, allowing for greater autonomy and complexity in AI use. As Sweller (2024, p. 5) notes, "a person with knowledge of a particular historical epoch or the science associated with energy production is in a vastly better position to think critically" than someone without such long-term knowledge. Similarly, learners with established frameworks can "use their knowledge base to guide" their use of AI, requiring less "external guidance" and benefiting more from "minimally guided instruction" (Sweller et al., 2011, p. 176).

Kosmyna et al.'s (2025) MIT study offers valuable insight into integrating LLMs in ways that balance "immediate convenience and long-term skill development" (2025, p. 116). They recommend "hybrid strategies" where AI support is used selectively, sequenced, and scaffolded (Kosmyna et al., 2025, p. 116). Their findings further suggest that "educational interventions should consider combining AI tool assistance with tools-free learning phases to optimise both immediate skill transfer and long-term neural development", noting the "dynamic interplay between cognitive scaffolding and neural engagement in AI-supported learning contexts" (Kosmyna et al., 2025, p. 139). They stress it is "crucial" to investigate the "full spectrum of cognitive consequences associated with LLM integration" (Kosmyna et al., 2025, p. 142).

While LLMs present unprecedented opportunities, their effects "on cognitive development, critical thinking, and intellectual independence" demand ongoing scrutiny (Kosmyna et al., 2025, p. 142). Alongside Dreyfus (2004, 2009) and Sweller et al. (2011), this work underscores the central role of teachers in guiding AI-supported learning and provides the theoretical foundation for the Bubble and Burner Model of AI-infusion, which balances intelligent tools with pedagogical expertise to foster deep, independent learning.

The Bubble and Burner model of AI-infusion

The Bubble and Burner Model has been created from three influential strands of research: the Dreyfus (2004, 2009) model of skill acquisition, Sweller's Cognitive Load Theory (Sweller et al., 2011), and recent findings from Kosmyna et al. (2025) at MIT. Together, these highlight a central truth for teachers: the journey from novice to expert requires sequenced challenges, formative feedback, and the gradual fading of support. AI, like any educational tool, must be integrated in ways that strengthen rather than undermine this process. Sweller et al. (2011) shows that novices benefit from guidance while experts require greater independence, and the research of Kosmyna et al. (2025) sharpens this further: students who begin unaided and later incorporate AI demonstrate stronger recall, deeper engagement, and greater ownership than those who rely on AI from the outset. These findings reinforce the need for careful sequencing, scaffolding, and fading so learners first build their own frameworks before extending them with AI.

The Bubble and Burner Model of AI-infusion translates these insights into a clear way for teachers to conceptualize their work as it incorporates the relational technology that is generative AI. *The Bubble* (Figure 1) represents the learning process itself, with AI used in different ways as learners move from novice to expert. *The Burner* (Figure 2) represents the teacher's role as regulator – adjusting support, checking for understanding, and ensuring that AI is used safely and ethically. The model highlights both the promise of AI to support learning and the teacher's responsibility to ensure that long-term skill acquisition and independence are not compromised.

Beyond its metaphors, the model provides a shared professional language for navigating the use of AI in the classroom. By making visible both the learning dimension (*the Bubble* - Figure 1) and the teaching dimension (*the Burner* - Figure 3), it helps educators plan when and how AI should be introduced and to articulate the relationship between early over-reliance on AI and risks of shallow encoding and cognitive debt. In this way, the model supports teachers to design experiences wherein students establish strong foundational understandings built upon a cognitive friction – with minimal AI support – before they engage more extensively with the AI tools available to them.

The model also clarifies the teacher's role in AI-rich classrooms. Teachers are conceptualized in this model, not as passive overseers but, as active regulators, adjusting the "heat" - the "cognitive friction" of challenge (Pratschke, 2025, p. 1) – and monitoring progress through checks for understanding. This role underscores teachers' responsibility to integrate AI safely, ethically, and with deliberate attention to deep learning. The model demonstrates that while novices may need high levels of teacher guidance to prevent cognitive overload or offloading, more expert learners may be granted greater freedom to use AI as a partner in the learning process.

At its core, the Bubble and Burner Model conceptualizes a means by which teachers and students can engage with AI so as to enriches rather than diminish the classroom experience. It positions the teacher's role as key to orchestrating the timing and scale of AI use so that learning is deepened. By drawing on the work of Dreyfus (2004), Sweller et al. (2011), and Kosmyna et al. (2025), the model becomes a practical tool

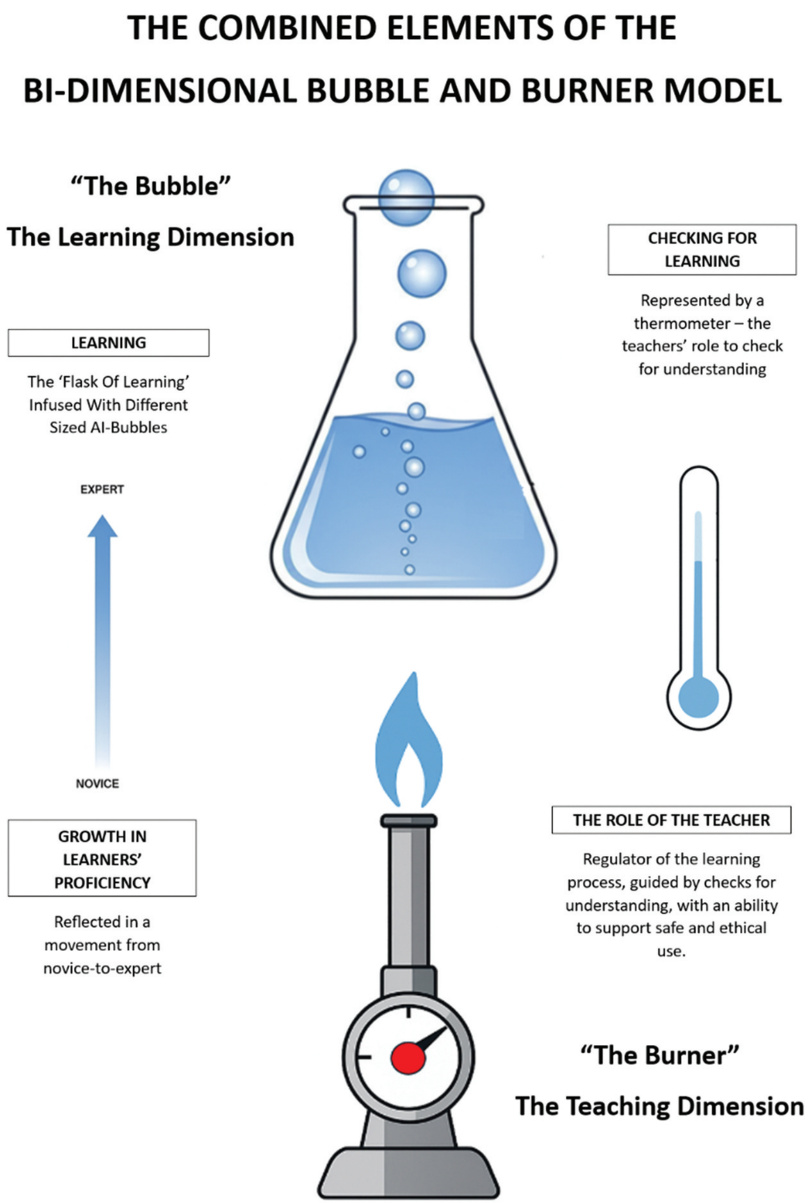

Figure 1. The Bubble and Burner Metaphor as a conceptualisation of teaching and learning in an AI age.

for shaping classroom practice. Its central principle is clear: students learn best when AI supports the scaffolded journey from novice to expert.

Dimension 1: the Bubble dimension – conceptualizing learning

The Bubble Dimension frames learning with AI as a journey from novice to expert, marked by students' capacity to engage with increasingly complex or larger "bubbles" of AI use. At the novice stage, learners sit at the base of the model with limited, fragile knowledge. Here, small, low-level bubbles of AI use are most appropriate – supporting tasks such as defining terms, generating outlines, or clarifying requirements. These uses build understanding while preserving the friction of effortful thinking needed for durable learning. The guiding principle for learning is clear: Students must *think first* before turning to AI. As proficiency develops, learners engage with larger, more complex bubbles. At this stage, AI can serve as a devil's advocate, provide detailed feedback, or simulate alternative scenarios. These higher-level use cases create a more dynamic partnership between learner and AI, where external support is integrated into existing mental frameworks rather than replacing them. Such uses provide a foundation for memory

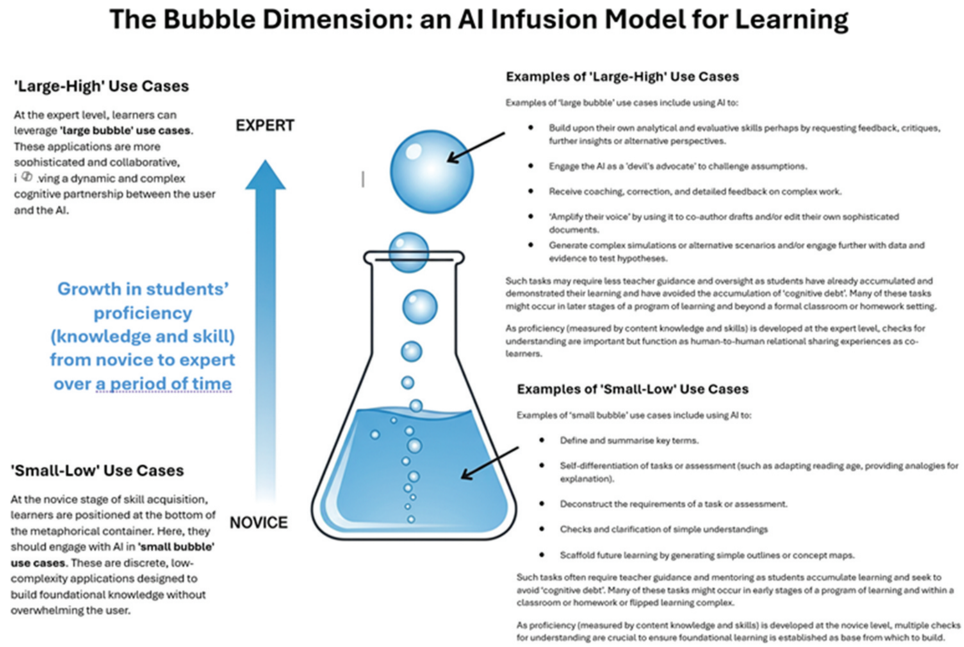

Figure 2. The Bubble Dimension of the Bubble and Burner Framerwork.

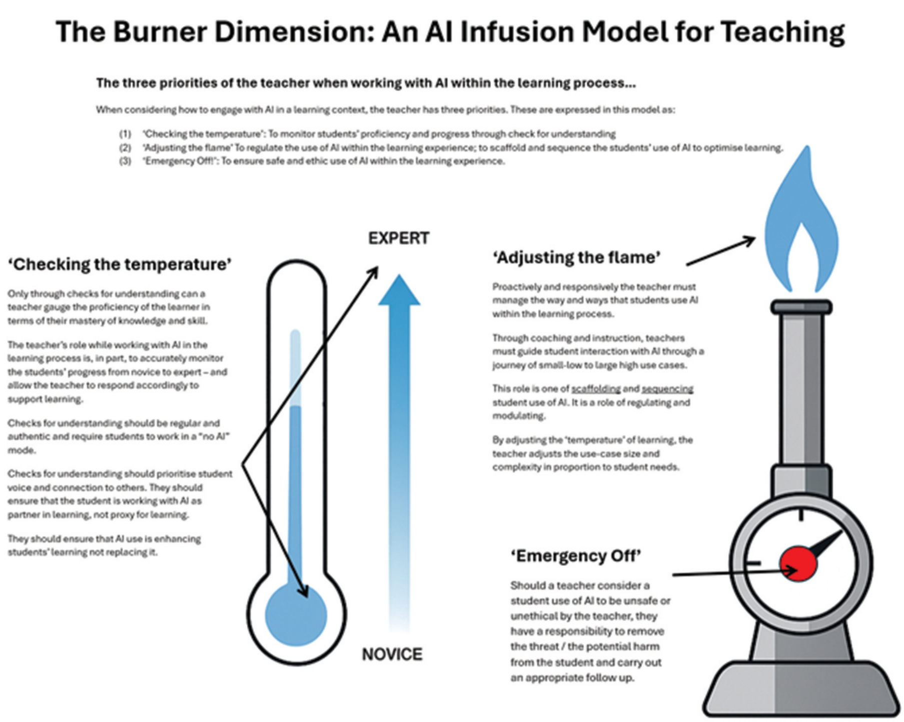

Figure 3. The Burner Dimension of the Bubble and Burner Framework.

formation, while maintaining the friction of effortful thinking that is necessary to build durable neural pathways. At this stage, the guiding principle is clear: learners must "Think First" before drawing upon AI support. As proficiency develops, learners progress "upward" from novice to expert. As their proficiency grows, they are more able to engage with more expansive and complex bubbles of AI use.

The sequence of moving from small-low to large-high bubbles is central to the model. As Pratschke (2025, p. 1) notes, "learning requires specific sequences: declarative memory (effortful thinking) must precede procedural memory (automatic skill). Using AI to bypass cognitive friction accumulates 'cognitive debt', undermining the neural pathway formation essential for learning" (Pratschke, 2025, p. 1). The Bubble Model cautions against leaping into complex AI tasks without first experiencing the friction of cognitive effort. It is this expense of effort that encodes durable knowledge, enabling later AI use to enrich rather than replace thinking. Both small-low and large-high "bubbles" are essential, but their value depends on alignment with the learner's stage of development. Small-low bubbles can protect novices from both overload and offloading while building foundational knowledge, while large-high bubbles can support higher-order analysis and creativity once learners have the established the structures required to think critically. Neither is more important; their power lies in careful sequencing across the journey from novice to expert.

The Bubble Dimension provides a visualization of how memory, friction, and sequencing can interact in an AI-rich environment. It provides space to design appropriate use cases across subject areas while anchoring itself in the mantra of *Think First*. By tying increasingly complex forms of AI engagement to the learner's development in proficiency, the model positions AI not as a shortcut but as a supplement to thinking – one that strengthens independence, critical inquiry, and long-term mastery.

Dimension 2: the Burner dimension – conceptualizing teaching

The Burner Dimension of the Bubble and Burner Model for AI-Infusion positions the teacher as the regulator of the learning process. In this metaphor, the teacher controls the "flame" that determines the pace, sequence, and scaffolding of learning. Just as the Bubble Dimension reflects the scale of student engagement with AI, the Burner represents the teacher's responsibility for how, when, and to what extent AI is used. The teacher's task is not to abdicate responsibility to the technology, but to regulate its integration so that learning remains intentional, sequenced, and aligned to the learner's stage of development. A central element of this regulation is "checking the temperature". Only through regular and authentic checks for understanding can teachers gauge where learners are on the novice-expert pathway. As Sweller et al. (2011, p. 177) note, "evaluation of levels of expertise" is essential if fading and adaptive guidance are to be effective (2011, p. 177). They argue:

> The quality of adaptive fading procedures is likely to depend significantly on the accuracy of information about current levels of learner knowledge and skills. Knowing when to fade guidance depends on accurate information concerning learner knowledge levels. (Sweller et al., 2011, p. 177)

Traditional tests may not provide sufficiently precise or timely information, but dynamic formative practices allow teachers to diagnose progress in real time. In this way, the teacher remains the human in the loop, ensuring AI supports rather than replaces students' thinking.

A second function of teachers within the Burner Dimension is "adjusting the flame". Here, teachers proactively adjust and manage the size and complexity of students' AI use based upon "temperature checks". This is an active and ongoing role applying the work of Sweller et al. (2011) to the place of AI in the learning process. The expertise reversal effect underscores the need for AI scaffolding and sequencing. Just as novices benefit from structured supports around AI use, advanced learners may require reduced guidance and greater independence. As Sweller et al. (2011) observe, "instructional techniques effective for novices may actually inhibit learning for more experienced learners" (2011, p. 169). Within this model's metaphor, "heat" represents the intensity of the learning experience – the friction of cognitive effort, the pace, sequence, and scaffolding provided. Adjusting the flame means modulating challenge and AI use so that it aligns with the learner's stage of development, neither overwhelming nor under-stimulating them. In the Burner Dimension, the teacher adjusts the "heat" of the learning experience to support students as they move from small-low to large-high bubbles of AI use. Teachers must use their expertise to carefully calibrate the level of cognitive demand experienced by students and the ways in which AI is used in the face of that demand.

A third function for teachers in the Burner Dimension is the model's "emergency off" metaphor. Teachers retain ultimate responsibility for ensuring that AI use in classrooms is safe, ethical, and compliant with institutional and legal frameworks. Teachers retain ultimate responsibility for ensuring that AI use is safe, ethical, and compliant with institutional and legal frameworks. If students engage with AI in ways that risk harm, compromise integrity, or undermine authentic learning, teachers must step in to curtail its use. This role recognizes that AI is not neutral and that its use requires the same professional care as any other learning resource. Teachers are thus regulators of cognitive load, guardians of ethical boundaries, and the responsible "grown-up in the loop".

Taken together, the Burner Dimension provides a shared language and visualization of teachers' responsibilities in AI-rich classrooms. It highlights three interwoven priorities: checking the temperature through formative assessment, adjusting the flame to match challenges with student development, and activating the emergency off to protect safety and integrity. Framing their role in this way enables teachers to ensure AI scaffolds deeper learning rather than substitutes for it, supporting students on their journey from novice to expert.

Conclusion: implications and future research

This paper has presented the Bubble and Burner Model of AI-infusion as a conceptual tool for integrating AI into teaching and learning. The model underscores the importance of sequencing, scaffolding, and teacher-led design to ensure AI enriches rather than diminishes cognitive effort. By focusing on both the learner's journey from novice to expert and the teacher's role as regulator – checking for understanding, adjusting the cognitive friction, and safeguarding the learner – it situates AI use within pedagogy rather than as a technological novelty.

The model suggests that there can be no one-size-fits-all approach to AI in education. Effective integration requires calibration: small-low use cases for novices, large-high use cases for experts, and teacher regulation of pace and ethical boundaries. In this way, the Bubble and Burner Model aligns with recent empirical findings (such as those of Kosmyna et al., 2025) which emphasize sequencing AI use and delaying its introduction until learners have engaged in sufficient cognitive effort.

The Bubble and Burner Model of AI-infusion is offered as a flexible heuristic, not a prescriptive formula. Its features provide a device for visualizing the place of AI within the teaching and learning process. Its principles provide a way of conceptualizing AI not simply as a tool to be integrated, but as a relational presence within the teaching and learning process. In contrast to the proliferation of implementation frameworks, rubrics, and competency scales that position AI primarily in terms of productivity, assessment, compliance, efficiency, or technical adoption, this model foregrounds the pedagogical dynamics through which learning unfolds. It directs attention to sequencing, cognitive demand, and teacher mediation, enabling educators to consider how AI may reshape – but does not replace – the relational interplay between the teacher, the learner, and subject-area knowledge.

Crucially, the model does not purport to be a pedagogical "silver bullet" that resolves tensions between technology and instruction. Rather, it requires ongoing professional judgement by teachers. By positioning the teacher as a regulator, a calibrator, and an ethical boundary-setter, the Bubble and Burner conceptualization invites educators to reimagine their role within AI-infused classrooms – not as facilitators of technological access, but as mediators of cognitive friction. In doing so, the model places the teacher-learner relationship at the centre of AI integration, ensuring that decisions about AI use remain anchored in pedagogical purpose rather than technological novelty.

Further, the model provides a way of conceptualizing AI use in K-12 classrooms across multiple levels of educational decision-making. At a macro level, the model offers school leaders, curriculum planners, and policy-makers a lens through which to consider how AI intersects with the broader architecture of learning within school systems – including questions of sequencing, assessment design, cognitive development, and ethical governance. Rather than reducing AI to an issue of access or regulation alone, the model invites system-level actors to reflect on how generative technologies alter the conditions under which knowledge is constructed and disciplinary expertise is cultivated.

At both school and system levels, the model counters both "blanket ban" approaches towards the use of AI in schools and uncritical adoption of AI. It frames AI integration as a question of developmental alignment and pedagogical purpose. Embedding the model into professional dialogue may enable consistent communication of teacher expectations around the use of AI across subjects area specialization while also respecting the important place of teacher professional judgement. Policies shaped by the model may clarify teachers' role in maintaining safe, ethical boundaries, supporting student well-being and compliance with legal frameworks. Further research should focus on this potential.

For policymakers, the Bubble and Burner Model offers language to move beyond "techno-solutionism" towards frameworks that foreground teacher expertise and student agency. It encourages system-level initiatives that build teacher capacity and balance innovation with accountability. It reinforces the centrality of formative assessment and professional discernment in classroom AI use.

At a micro level, the model serves classroom practitioners by offering a shared language for thinking about pacing, cognitive demand, and the graduated release of AI assistance. It enables teachers to visualize when AI access might be withheld, moderated, or extended, in alignment with learner readiness and instructional purpose. In this way, the Bubble and Burner conceptualization bridges systemic planning and everyday classroom practice, ensuring coherence between institutional policy and classroom activities while preserving the centrality of teacher judgement.

For classroom practitioners, the place of AI within their practice is a core concern. The Bubble and Burner Model provides a way to visualize sequencing and scaffolding, with a shared language for discussing cognitive load, fading, and metacognition through the metacognitive principle of *Think First*. Through use of the model, educators can map curriculum sequences against the bubble scale, designing unit plans that shift from small-low to large-high use cases. Likewise, professional learning within schools can use the model to guide the integration of LLMs, aligning cognitive demand with learner readiness.

The Bubble and Burner Model of AI-infusion, however, remains exploratory. Its strength lies in metaphorical clarity and theoretical grounding, but it requires empirical validation across diverse contexts. Current limitations include the early stage of research into AI's long-term cognitive effects and a narrow evidence base from specific subjects and age groups. The rise of agentic AI systems and corporate educational platforms – some of which misapply the core principles of CLT or Explicit Instruction – raises questions about teachers' ability to "adjust the heat" of learning experiences.

Future research should examine how teachers "adjust the flame" in different contexts, how scaffolding, sequencing, and "bubble size" vary across learning areas, and the most effective ways for checking student understanding and evidence of learning in AI-infused classrooms. Comparative studies could test whether the model's emphasis on sequencing and scaffolding holds across subject area disciplines. Research into teacher professional learning should explore how best to build teacher capacity for work in schools that will continue to be shaped by increasingly powerful AI.

Importantly, the Bubble and Burner Model of AI-infusion underscores that the teacher remains central to effective AI integration in classrooms. It resists reductive narratives that cast AI as a replacement for professional expertise or student thought. Instead, it highlights how teachers – by regulating intensity, and with careful scaffolding and sequencing – might design AI-infused learning experiences that strengthen critical thinking, creativity, and ethical practice.

By offering a shared language and a visual conceptualization of teaching and learning with AI, the Bubble and Burner Model of AI-infusion invites educators, leaders, and policymakers to engage with this new technology in ways not motivated by fear or hype, but with a sense of careful pedagogical design. It provides a foundation upon which educators can build that is developmentally grounded, ethically aware, and professionally sustaining. In this way, the Bubble and Burner Model positions AI not as a threat to human learning but as a catalyst for reimagining it.

Declaration of use of generative AI in the writing process

The author has made use of GenAI tools for some ideation and in some passages of draft text creation. These sections of text were then substantially revised within the editing and revision process as the manuscript was produced. Further, GenAI tools were used to create the images within diagrams of the Bubble and Burner Model. The tools used were OpenAI's ChatGPT (GPT-5.2) and Google Gemini (2.5 Pro). These tools were chosen primarily for their ability to provide sophisticated outputs. AI was used selectively as a means of supporting, not replacing, core author responsibilities. The author has reviewed, edited, and takes responsibility for all outputs of the tools used.

Author contributions

CRediT: **Vince Wall:** Writing – original draft.

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