JOURNAL OF LEARNING ANALYTICS

SOLAR SOCIETY for LEARNING ANALYTICS RESEARCH

Volume 13(2), 63–86. https://doi.org/10.18608/jla.2026.9145

Applying Generative AI to the Learning Analytics Cycle to Support Competency Development in Health Professions Education

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Abstract

Professional learning environments offer a unique opportunity for exploring professional competencies due to the use of workplace data, which captures important aspects of professional performance. This data is different from that used in formal learning analytics contexts, as it is not collected by systems designed to understand learning. Instead, workplace data represents the digital fingerprint professionals leave behind when interacting with technologies to do their jobs. Harnessing this data to support workplace learning is challenging for a range of reasons, including being able to identify meaningful metrics to identify individual performance and scaffold the use of this data to support professional learning interventions on knowledge and performance. Generative AI (GenAI) has great potential to enhance professional learning analytics by addressing some of the challenges inherent in using workplace data. These challenges include needing to process large amounts of unstructured data to understand individual performance and transform this data into interfaces and interventions that can support learning. In our paper, we modify Clow's learning analytics cycle to inform a modified framework describing the intersection of learning analytics with professional learning. Subsequently, we illustrate the potential power of GenAI for supporting professional learning across the framework through three case studies in health professions education.

Notes for Practice

- Professional learning analytics requires thoughtful design for the workplace. Our research identifies learner control, self-regulated learning, and flexible learning linked to job competencies as particularly important considerations for practitioners designing analytics-supported professional learning.
- Workplace data is not automatically learning data. Unlike in formal contexts, data collected in the workplace was not generated by systems designed to support learning but by ones designed to support individuals undertaking their jobs. Our research identifies this distinct design challenge for professional learning analytics.
- Generative AI (GenAI) provides new ways to support the entire professional learning analytics. Our proposed framework describes the intersection between GenAI and professional learning by defining the key phases (professional, data, analytics, intervention) and summarizing the specific roles of GenAI across these phases.

Keywords

Professional learning analytics, GenAI, healthcare, self-regulated learning, informal learning.

Submitted: 13/06/2025 — **Accepted:** 15/08/2026 — **Published:** 27/08/2026

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1. Introduction

Effective development and assessment of 21st-century professional competencies within workplace learning environments represents a strategic priority for educational institutions and industries seeking an adaptable and future-ready workforce. Healthcare, as a prominent professional field underpinned by mandated continuing professional development (CPD) to maintain registration to practise, provides an ideal yet challenging context for exploring novel methods of competency-based learning analytics (Littlejohn & Margaryan, 2014; Ruiz-Calleja et al., 2021). Despite the abundance of data available through daily practice activities, grounding meaningful professional learning and skill development in healthcare remains problematic. Challenges for realizing the potential of workplace data include the need to repurpose data from systems never designed for understanding or supporting learning (Schofield et al., 2019), as well as the complexities of interpreting fragmented, multimodal, and largely unstructured clinical performance data (Shaw et al., 2019). Generative artificial intelligence (GenAI) has the potential to address these challenges by supporting the interpretation and transformation of the wealth of largely unstructured workplace data in the health sector into meaningful indicators of performance to drive learning interventions. Further, GenAI could enable scaffolded presentation of this data to enable health professionals to reflect on and learn from their performance in a robust way.

Recent advancements in GenAI offer promising opportunities to enhance professional learning analytics by dynamically generating contextually relevant and personalized learning supports from diverse workplace datasets (Yan, Greiff, et al., 2024). GenAI's ability to structure and synthesize potential educational artefacts from unstructured textual and multimodal clinical data can directly address existing gaps in enabling meaningful learning analytics interventions for healthcare professionals (Yan, Martinez-Maldonado, & Gasevic, 2024). However, empirical explorations that explicitly investigate how GenAI-driven workplace analytics can support personalized and adaptive skill development remain scarce, particularly within real-world healthcare learning contexts.

The objective of this paper is to explore the role of GenAI-driven learning analytics in fostering personalized 21st-century competencies for health professionals. It presents a modified version of the learning analytics cycle (Clow, 2012) to demonstrate the distinctive complexities of learning analytics in professional contexts. Subsequently, the power of GenAI for supporting professional learning is illustrated through three novel case studies in the healthcare context. This paper contributes novel insights on employing GenAI-driven learning analytics to foster personalized 21st-century competencies of healthcare practitioners.

2. Background and Related Work

Increasingly, professionals are expected to engage in continuing learning throughout their careers to maintain and grow their competencies and ensure they remain effective at doing their jobs. Much of the learning that professionals engage in occurs in the workplace and is frequently informal, consisting of activities such as incidental conversations and "learning on the job" (Eraut, 2004). One of the distinctive challenges of informal learning is that individuals may not be aware they are engaged in learning activities that are unintended and often opportunistic (Eraut, 2004; Littlejohn & Margaryan, 2014). The digitization of contemporary workplaces is creating a growth in electronic data collection related to individuals' jobs. In parallel, there is an increased interest in the utility of this information for making components of professional learning more "data driven" (Tavares et al., 2024). Despite the emerging opportunity data-driven learning offers in professional contexts, there is insufficient conceptual and empirical understanding to guide the development and use of learning analytics in these settings. Research into elements of learning analytics in formal settings, such as learner characteristics, learning data, and the transformation and use of this data, can provide some insights into the challenges professionals face in harnessing learning analytics.

Professionals have nuanced expectations of learning that make translating existing learning analytics research challenging, such as the emphasis on collaboration, active learning, coaching, and reflection (Cirkony et al., 2024). The nature of the work individuals engage in, even in the same workplace, can be quite different, which is another aspect of professional learners that is distinct from those in formal environments. Furthermore, due to the informal nature of learning in this context, individuals may not even be aware they are engaging in learning activities (Eraut, 2004; Littlejohn & Margaryan, 2014). Motivations for professional learning can also differ from those in formal settings, with professionals often being driven to engage in activities to maintain professional skills and competencies (Kooken et al., 2007), or to meet mandatory requirements to maintain professional registrations (Karas et al., 2020). Finally, professionals have mixed abilities in interpreting data about their performance and using it to support knowledge generation and reflective practice (Dennerlein et al., 2014; Campos et al., 2021; Whitelock-Wainwright et al., 2022). This aligns with the learning analytics literature on supporting teachers to use learner dashboards, which has consistently shown variation in visual literacy skills across the profession (Pozdniakov, Martinez-Maldonado, Tsai, Echeverria, et al., 2023; Pozdniakov, Martinez-Maldonado, Tsai, Srivastava, et al., 2023) and a range of capabilities in interpreting and decision making with data presented using learner dashboards (Campos et al., 2021; Molenaar & Knoop-van Campen, 2019).

Harnessing data and transforming it into meaningful analytics is foundational to learning analytics. Formal learning typically relies on data sources that are specifically designed for learning purposes or that surround individuals when engaging in learning activities. A review of learning analytics in higher education identified a significant amount of heterogeneity in data sources, with many learning analytics interventions drawing on three sources: learning management system (LMS) data, student information system data, and questionnaires (Samuelsen et al., 2019). The data used in professional learning is notably different from that in formal settings, as it is collected from digital technologies designed to support the delivery of various professional services. The utility of workplace data to support self-regulated learning (SRL) (Siadaty et al., 2012), computer-supported reflective learning (Pammer et al., 2017), and social learning (Khousa et al., 2015) has been explored in the learning analytics literature. Despite the potential utility of this data to support learning, analysis to support meaningful professional learning is challenging and has been recognized as an opportunity for further research in learning analytics (Ruiz-Calleja et al., 2021). A major challenge in professional learning analytics is linked to the difficulty of analyzing workplace data to generate learning metrics. Coupled with this, the accuracy of metrics generated from this data for describing an individual's knowledge and performance in practice can be problematic. An attempt to address this problem was the development of *MyExperiences*, an open learner model of the APOSDLE adaptive work-integrated learning system (Brusilovsky & Millán, 2007), designed to visualize underlying data for learners to show them what data was used to generate knowledge indicating events (Kump et al., 2012). Beyond this, there is no best practice on how to present these analytics to professional learners in a way that enables them to reflect on their performance and drive changes in practice. Leveraging insights from the broader learning analytics literature may provide a useful path forward for overcoming this hurdle in the professional space. Techniques like the use of data storytelling can support teachers with varied levels of visual literacy in interpreting and understanding data presented in learning analytics dashboards (Pozdniakov, Martinez-Maldonado, Tsai, Echeverria, et al., 2023).

Measurement, collection, analysis, and reporting of data about learners drives learning analytics interventions (Siemens & Gasevic, 2012), but the informal learning characteristic of professional learning environments (Eraut, 2004) is often supported by generating data and technologies not initially designed for learning, making this challenging. There is a small but growing body of research investigating innovative data-driven interventions that can be used to support learners in the workplace and other professional contexts. An example of this is the SRL tool *Learn-B*, a prototype tool designed to help knowledge workers engage in SRL processes in the workplace by providing scaffolded interventions for learning such as progress-o-meters, sharing of knowledge profiles, and access to motivational messages (Siadaty et al., 2012). The tool has been piloted in several business cases, including in car manufacturing and with teacher professional associates. This work has shown that professionals found *Learn-B* useful for supporting their learning by informing them about the context of their organization in terms of learning objectives, helping contextualize the importance of those objectives for their role, and identifying resources to support them in achieving those learning objectives (Siadaty et al., 2016a, 2016b). Work remains to be done to investigate the extent to which different tools can support SRL processes in the workplace (Siadaty et al., 2016b), as well as the effects of different technological scaffolding approaches on professional learning outcomes (Siadaty et al., 2016a).

One promising mechanism to enhance professional learning analytics is through utilizing GenAI. GenAI provides opportunities and challenges across the learning analytics pipeline (Yan, Martinez-Maldonado, & Gasevic, 2024). A recent review of the literature has begun to investigate the practical implementations of GenAI in learning analytics, mapping examples of how the technology had been integrated in practice (Misiejuk et al., 2025). This review identified examples of GenAI being used across a spectrum of learning analytics contexts, but noted a lack of robust evidence on the effectiveness of these tools to justify ongoing investment (Misiejuk et al., 2025). Supporting learners with different GenAI literacy levels can be challenging when using these tools to support competency development, with early evidence suggesting learners with higher GenAI literacy engage in more complex cognitive activities when using GenAI tools for learning (Jin, Yang, et al., 2025). Identifying reliable approaches for coding textual data used by GenAI (Misiejuk et al., 2025) and ensuring the accuracy of AI-generated feedback (Pozdniakov et al., 2025) are both unresolved issues. There is also a recognized need to better understand human–GenAI interaction and establish methods for classifying these interactions (Misiejuk et al., 2025). GenAI has the ability to generate meaningful insights from the data by structuring and synthesizing (Yan, Martinez-Maldonado, & Gasevic, 2024) the plethora of unstructured information collected in workplace systems. Despite the potential of these technologies, there is a recognized gap in the literature when it comes to applying them to healthcare learning contexts, and many of the gaps in knowledge in the use of GenAI in formal learning contexts align with those in professional learning.

3. Framework

3.1 General Comparison: Clow's Learning Analytics Cycle and Professional Learning Analytics

In this section we explore the theoretical context that has informed the development of the *GenAI-enhanced professional learning analytics framework* (Figure 1). We subsequently reflect on the proposed framework and how it contrasts with existing learning analytics theoretical models.

Clow's learning analytics cycle (Clow, 2012), encompassing learners, data, analytics, and interventions, provides a foundational framework broadly used to examine data-driven interventions in educational contexts, as well as enabling contributions to learning analytics research and practice to be positioned and compared. Although insightful, Clow's cycle primarily considers formal education scenarios involving structured courses and dedicated educational technologies, where learner engagement and generation of relevant data often occur within explicitly educational activities or environments. In contrast, professional learning, particularly within healthcare, diverges from such structured educational contexts (Cole, 2000; DunnGalvin et al., 2019). Health professionals typically interact with clinical and administrative systems designed to support care delivery, along with metrics presented in government and organizational reporting rather than for learning (Dowding et al., 2015; Khairat et al., 2018). Unlike students whose primary aim is acquiring knowledge explicitly through deliberately structured learning activities, health professionals typically engage in ongoing learning activities that are informal, incidental, and of secondary priority to the core responsibilities of their jobs (Van De Wiel et al., 2011; Joynes et al., 2017). Consequently, data generated in these settings rarely explicitly targets educational purposes (Tavares et al., 2024); analytics mainly aim to reflect and diagnose performance quality rather than directly measure learning process or outcomes (Singer et al., 2015; Wiljer et al., 2023). Learning in this context shifts from using structured instructional tools toward using highly communicative interfaces designed to scaffold reflective practices, naturally supported through advanced technologies like GenAI.

We base our framework on Clow's learning analytics cycle as it remains a relevant and appropriate starting point for modelling analytics in healthcare professions education. The learning analytics cycle aligns with the plan-do-study-act (PDSA) cycle that is the basis for quality improvement in healthcare (Lang et al., 2022; Moen & Norman, 2010). Despite the emergence of a more sophisticated LA framework (van Leeuwen et al., 2021; Sailer et al., 2024), Clow's emphasis on linking data to analytics, analytics to interventions, and interventions to learner action provides a conceptual simplicity that maps well onto the lived reality of professional learning and development, where practitioners continually generate data through practice, interpret feedback, and adjust behaviours as part of lifelong learning (Cole, 2000; DunnGalvin et al., 2019).

We outline below how each stage of Clow's learning analytics cycle maps to the GenAI-enhanced professional learning analytics framework in the context of healthcare professions education (Figure 1). In many formal education contexts, analytics increasingly support teachers' decision-making as well as learners' SRL, and these developments offer useful conceptual parallels. However, in healthcare, and professional learning more broadly, the role of "teacher" does not map cleanly onto any single stakeholder. While clinicians may have supervision and teaching duties, clinicians are not primarily educators, but rather they are reflective practitioners who learn continuously through their own workplace activities. CPD requirements and the norms of clinical practice call on clinicians to be self-directed lifelong learners, responsible for monitoring and improving their own performance. As such, the professional learner in our framework is not a teacher analyzing others' learning but a practitioner engaging in reflective practice to support their own competency development.

3.2 Learner/Professional Phase: Healthcare Professionals as Non-traditional Learners

Clow's original conception of learners refers predominantly to students engaging explicitly and intentionally within structured educational activities that take place either face to face or online, typically as part of formal educational courses. In contrast, health professionals differ considerably, as they function primarily as practitioners who learn through authentic, ongoing clinical duties and professional experiences rather than structured educational curricula (Ryan et al., 2007). Learning constitutes a secondary goal to the primary activity of patient care. Professionals may engage in formal learning activities, such as CPD, to maintain their registration to practise, but more frequently they engage in informal and often incidental learning during their clinical practice (Chaiyachati et al., 2019; Westbrook et al., 2008). Consequently, their engagement with learning interventions and their motivational orientations toward participating in these activities can vary (Sargeant et al., 2013; Allen et al., 2024). This variation necessitates the use of distinct analytics methods and intervention designs specifically suited to these unique professional learning objectives and conditions.

3.3 Data Phase: Distinct Nature and Sources in Professional Contexts

In traditional educational settings captured by Clow's model, data typically originate from structured interactions within educational environments, such as LMSs, assessments, peer discussions, and other explicit pedagogical activities (Lang et al., 2022; Samuelsen et al., 2019). By contrast, as illustrated in our model, data used in health professions learning primarily emerges indirectly from workplace practices. This data encompasses complex, multimodal, and often unstructured data such as discharge summaries, clinical notes, and patient incident reports (Janssen, Donnelly, & Shaw, 2024). Explicit learning activities, such as participating in clinical simulations or case-based learning aligned with specific clinical practice points, generate specific learning data but are infrequent, and their occurrence is relatively limited compared to regular clinical practice activities (Yan et al., 2023; Yan, Echeverria, et al., 2024; Robinson et al., 2017; Moore et al., 2022; Womack-Adams et al., 2025). Moreover, professional learning analytics data commonly extends over prolonged timelines, spanning weeks, months, or even entire career phases, considerably longer than the timescale conventionally considered by Clow's learning analytics cycle.

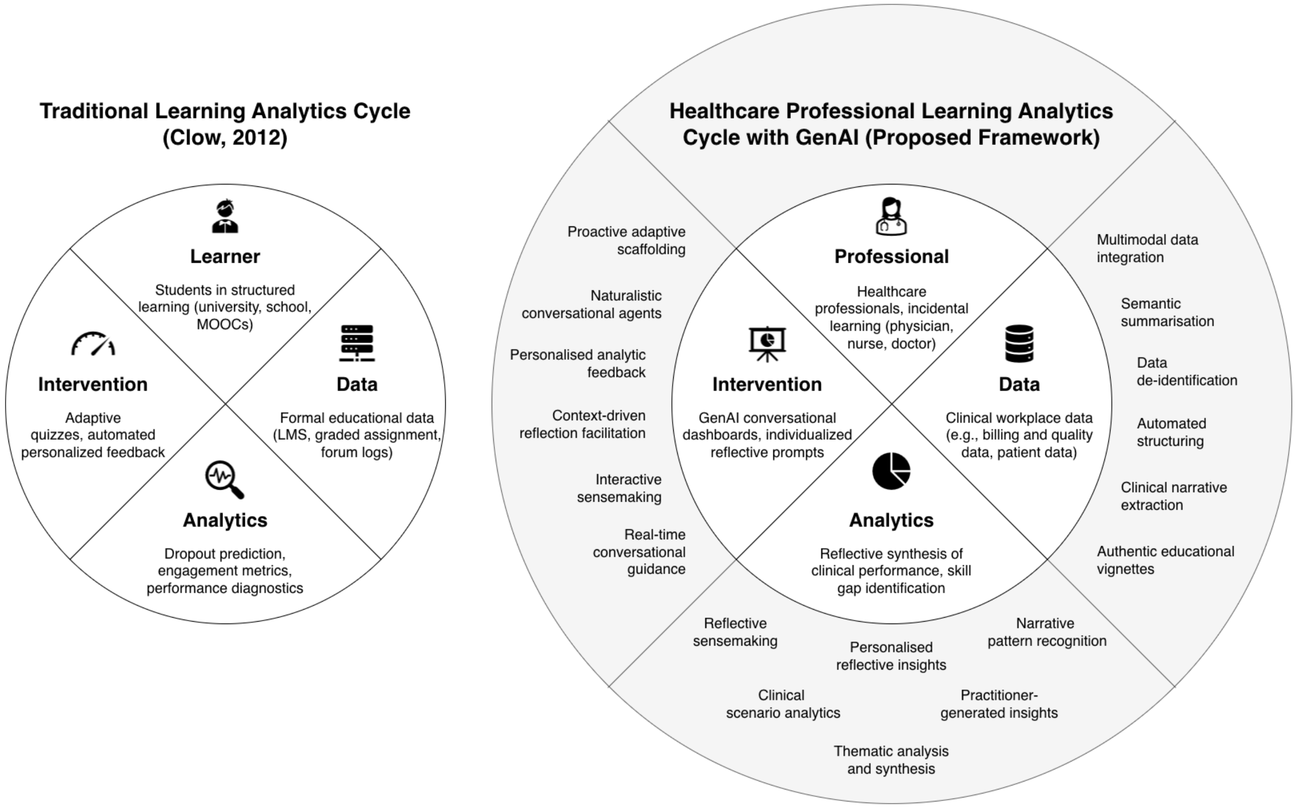

Figure 1. Contrasting Clow's (2012) original learning analytics cycle (left) with the proposed GenAI-enhanced professional learning analytics framework. The proposed framework (right) revises Clow's original cycle for healthcare. The inner circle defines each key phase (professional, data, analytics, intervention). The outer layer summarizes the specific roles and benefits provided by GenAI across these phases.

This temporal difference implies the necessity for longitudinal, aggregated analytics, which present challenges regarding data volume, interpretation complexity, ethical considerations, and privacy assurance.

As illustrated in the outer layer of our model, in the data phase, GenAI methods provide substantial benefits for addressing inherent challenges at this data phase, extending traditional analytics capabilities. First, advanced generative tools can automate semantic interpretation, structuring, and summarization of large-scale unstructured textual data such as clinical notes, reflective narratives, and discharge summaries (Chua et al., 2024). Second, generative language models enable effective integration of multimodal data sources (e.g., text, audio logs, imaging data), supporting comprehensive and nuanced analytics that reflect complex healthcare realities (AlSaad et al., 2024). Third, GenAI tools offer sophisticated means for automated data anonymization and de-identification, thus promoting adherence to confidentiality, privacy standards, and ethical norms governing healthcare data reuse (Yoon et al., 2020). Moreover, GenAI contributes innovative ways to repurpose clinical data into meaningful educational experiences (Preiksaitis & Rose, 2023). Since clinical documentation typically lacks structured educational intents, GenAI can transform contextually authentic and clinically rich textual records into structured educational artefacts, such as simulated scenarios and vignettes, to facilitate targeted professional learning activities (e.g., elaborated in Case 1). Thus, through GenAI-driven extraction and transformation of relevant clinical scenarios from routine clinical data, healthcare professionals gain access to highly realistic, contextually relevant learning materials grounded directly in their actual workplace experiences.

3.4 Analytics Phase: Reflective Performance Metrics for Professional Sensemaking

Traditional learning analytics, as captured by Clow, focus predominantly on metrics measuring learner interactions, the effectiveness of educational interventions, and predictive or diagnostic analytics aimed at supporting educational achievement or understanding learning processes. As shown in our model, professional learning analytics contrasts with this, especially within healthcare, due to the emphasis on reflective and performance-oriented analytics intended to drive practice changes and performance improvements (Rashid, 2016; Dickerson, 2023). Rather than directly analyzing learning outcomes, these analytics prioritize an accurate reflection of clinical performance and interdisciplinary professional activities. Analytics thus become descriptive and exploratory, enabling learners to reflect on past practice, recognize professional strengths, identify potential areas for growth, and support informed strategic decisions aimed at continuous improvement (Rashid, 2016; Dickerson, 2023).

Moving to the outer layer of our model, GenAI technologies can substantially enhance analytics in professional contexts by enabling more sophisticated, personalized, and reflective interpretation of clinical practice data (Bragazzi & Garbarino, 2024). Through powerful generative language models, GenAI systems synthesize and structure complex, multimodal clinical data, converting it into intuitive visualizations and meaningful narrative insights that directly support professionals' reflective sensemaking practices (e.g., elaborated further in Case 2). Specifically, GenAI-driven analytics can identify practitioner-generated constructs and perceptions underpinning their understanding of clinical performance data, facilitating deeper personal reflection and clearer connections between clinical outcomes and professional decision-making (Whitelock-Wainwright et al., 2024). Additionally, generative AI–driven analytics support formative processes such as scenario-based analyses, adaptive interpretations of clinical events, identification of thematic patterns within clinical experiences, and personalized, contextually enriched insights (Biswas & Talukdar, 2024). Professionals thereby gain enhanced opportunities to critically engage with reflective performance analytics, diagnose individual growth areas, and strategically shape potential future trajectories of professional skill enhancement and development.

3.5 Intervention Phase: Communication and Scaffolding via GenAI-Enabled Interventions

Whereas conventional learning analytics interventions in educational contexts commonly adopt structured instructional approaches (Verbert et al., 2020), such as personalized recommendations, timely notifications, and detailed guidance to support improvement, professional healthcare contexts require interventions explicitly designed to facilitate reflective practices (Chan et al., 2019). Health professionals typically manage busy workloads within their primary roles and are therefore likely to interact with analytics interfaces only intermittently (Cordero-Guevara et al., 2022). Consequently, abstract analytics insights without appropriate scaffolding or design clarity may fail to gain attention or meaningful engagement (Jivet et al., 2018). Effective healthcare analytics interfaces must therefore prioritize ease of learning and rapid use (Pusic et al., 2023), enabling users to quickly derive benefit without significant training or, alternatively, provide clear scaffolding that gradually supports deeper exploration and reflection. The effectiveness of reflection and practice improvement within healthcare settings thus critically depends upon interface design and the manner in which analytics insights are communicated to time-constrained professionals.

The outer setting of our model shows how GenAI technology, particularly generative conversational agents and dashboards, can enhance professional learning interventions at the interface level. These advanced interactive solutions offer scalable, naturalistic conversational interactions that effectively bridge the gap between complex analytics and healthcare professionals' individual reflective practices (Yan, Zhao, et al., 2024; Khosravi et al., 2025). Specifically, proactive GenAI approaches embedded within interactive dashboards can dynamically respond to user interactions, adaptively scaffolding professionals through insightful reflective prompts, structured questioning, and conversational guidance (Yan et al., 2025). These intervention approaches help healthcare professionals derive clearer, context-relevant insights from clinical dashboards, improving sensemaking, reflective practice, and clinical decision-making based on analytic insights (e.g., elaborated further in Case 3). In this way, GenAI-driven communicative interfaces have unique capabilities for converting complex data views and performance indicators into meaningful, personalized feedback experiences. Consequently, interventions transition from purely informational to genuinely reflective, adaptive, conversationally engaging, and contextually relevant, effectively supporting ongoing professional development and promoting authentic improvements in clinical practice.

3.6 Closing the Loop: Continuous Feedback and Professional Improvement

The professional learning analytics framework presented here modifies Clow's original framework to illustrate the iterative, continuous feedback cycle that occurs in professional learning contexts rather than isolated or short-term learning interventions that learning analytics research and practice informed by Clow's framework have led to. This focus on short-term learning interventions is increasingly being recognized as a problem in learning analytics (Dawson, 2020). Healthcare professionals continuously engage with real clinical activities, generating a continuous stream of high-quality, diverse multimodal data that feeds into sophisticated and increasingly GenAI-driven reflective analytics. Communicated through interactive, adaptive conversational experiences, these analytics can facilitate critical professional reflection and inform actionable professional improvement plans (Cohen et al., 2023; Almansour & Alfhaid, 2024). The continuous cycle supports iterative, long-term professional development, building on authentic clinical experiences, supported by rich data analytics, and scaffolded via high-quality communicative interfaces provided by GenAI, thus enabling transformative opportunities in health professions education.

4. Case Studies

Many professional domains could utilize workplace data to generate performance insights and drive data-driven learning interventions, particularly those industries that have formal CPD processes, such as architecture, law, and engineering.

Healthcare is a particularly useful sector for exploring professional learning analytics due to the convergence of large workplace data sets (Pusic et al., 2023; Janssen et al., 2022), an established culture of both formal and informal learning coupled with a workforce interested in harnessing workplace data to support learning (Shaw et al., 2019), and regulation increasingly driving health professionals to engage with their data for reflection and learning (Medical Board of Australia, 2019). There is also already a small but growing amount of research focused on healthcare in the professional learning analytics field (Ruiz-Calleja et al., 2021). Foundational workplace data sources in healthcare include clinical information systems such as patient administrative systems (PASs), electronic medical records (EMRs), and electronic health records (EHRs), which collect data about aspects of care delivery (Janssen, Donnelly, Murphy, et al., 2024).

In this section, we present three case studies exploring the application of GenAI in the context of health professions learning. Each case study is illustrative of aspects of our proposed professional learning analytics framework, which modifies Clow's learning analytics framework to highlight the aspects of learning analytics that are distinct in the professional domain. Refer to Figure 2 to see a visualization of the intersection between the framework and each case study presented in this section. These case studies are at different points in their implementation, with the first two being proposals for future applications of GenAI and the third describing a mature piece of work undertaken with health professions students that is proposed for translation into the professional context. These cases have been chosen to illustrate the potential roles for GenAI in professional learning.

In our first case study, we propose and empirically examine how generative language models (e.g., large language models (LLMs) or transformer-based methods) can repurpose unstructured clinical records into educationally relevant, authentic, and context-specific learning scenarios without compromising data privacy. By generating realistic vignettes and adaptive simulations from existing clinical text data, healthcare professionals can engage in effective skill-building exercises, promoting personalized and situated competency enhancement. In the second case study, we illustrate theoretical and exploratory empirical work applying GenAI to facilitate healthcare professionals' sensemaking and reflective practices. Our research prototype, the Construct Elicitation Rating Activities (CERA) tool, utilizes advanced GenAI techniques to provide intuitive, automated scaffolds supporting professionals' interpretation of their own complex performance data. Preliminary qualitative evidence indicates that these dynamic, AI-generated narratives can enhance deeper critical reflections and self-assessment processes crucial for professionals to make sense of the data about their practice. In third and final case study, we present practical examples of using interactive, GenAI-enhanced dashboard solutions to translate clinical performance indicators into insightful, personalized feedback for healthcare learners. Initial qualitative assessments suggest that medical professionals report increased agency, reduced cognitive burden, and greater motivation when interacting with these contextually enriched dashboards.

4.1 Case 1: Applying LLMs to Generate Clinically Authentic Scenarios to Support Professional Learning

4.1.1 Study Overview

Our first case study explores the potential application of LLMs to more efficiently develop clinical vignettes to support medical practitioners' workplace learning. This case study explores the potential role of LLMs in the *data phase* described in our model (Figure 1). The data being captured is multimodal data from an EMR combining both structured data such as test results with unstructured textual data such as clinical notes. Notably, the data being extracted describes single instances of patient care, rather than more longitudinal information about quality of care provided by the health professional.

Preliminary work in this space investigated the use of workplace data extracted from EMRs to understand the types of clinical encounters medical practitioners were engaged in as part of their jobs. These data were then used to trigger delivery of an adaptive microlearning program aligned with each medical practitioner's individual practice. EMRs collected a variety of structured data, including patient presentations, test results, and medication lists, as well as unstructured data such as clinical notes and discharge summaries (Pethani et al., 2025). Preliminary work to develop the adaptive microlearning program extracted structured data from the EMR for specific types of patient presentations and used it to personalize the delivery of content in the program. Microlearning is a relatively new learning approach that usually involves the delivery of small bundles of learning content over a short period, usually delivered online or using a digital intervention (Monib et al., 2025). In our work, the microlearning platform delivered learners' questions consisting of a clinical vignette, multiple-choice responses, and detailed feedback once a response had been selected on best practice management of the clinical vignette (Phillips et al., 2019). Questions were delivered adaptively based on the clinical encounters each EMR report indicated that a learner had experienced since the last reporting period.

Although the program was well received (Janssen et al., 2025; Janssen, Donnelly, Murphy, et al., 2024), the reliance on structured data limited how closely the content of the microlearning program could be aligned with the clinical practice of an individual medical practitioner. The preliminary work demonstrated that it was possible to improve the efficiency of workplace learning for medical practitioners by using EMR data to only deliver clinical vignettes relevant to their clinical practice (Janssen et al., 2025). However, this approach limited the perception that data was linked to individual performance and provided fewer opportunities for reflective practice. Furthermore, the use of structured data limited the scalability of the intervention. Relying on structured data made it difficult to use the intervention with medical practitioners in specialties that relied more heavily on clinical notes and had less structured data.

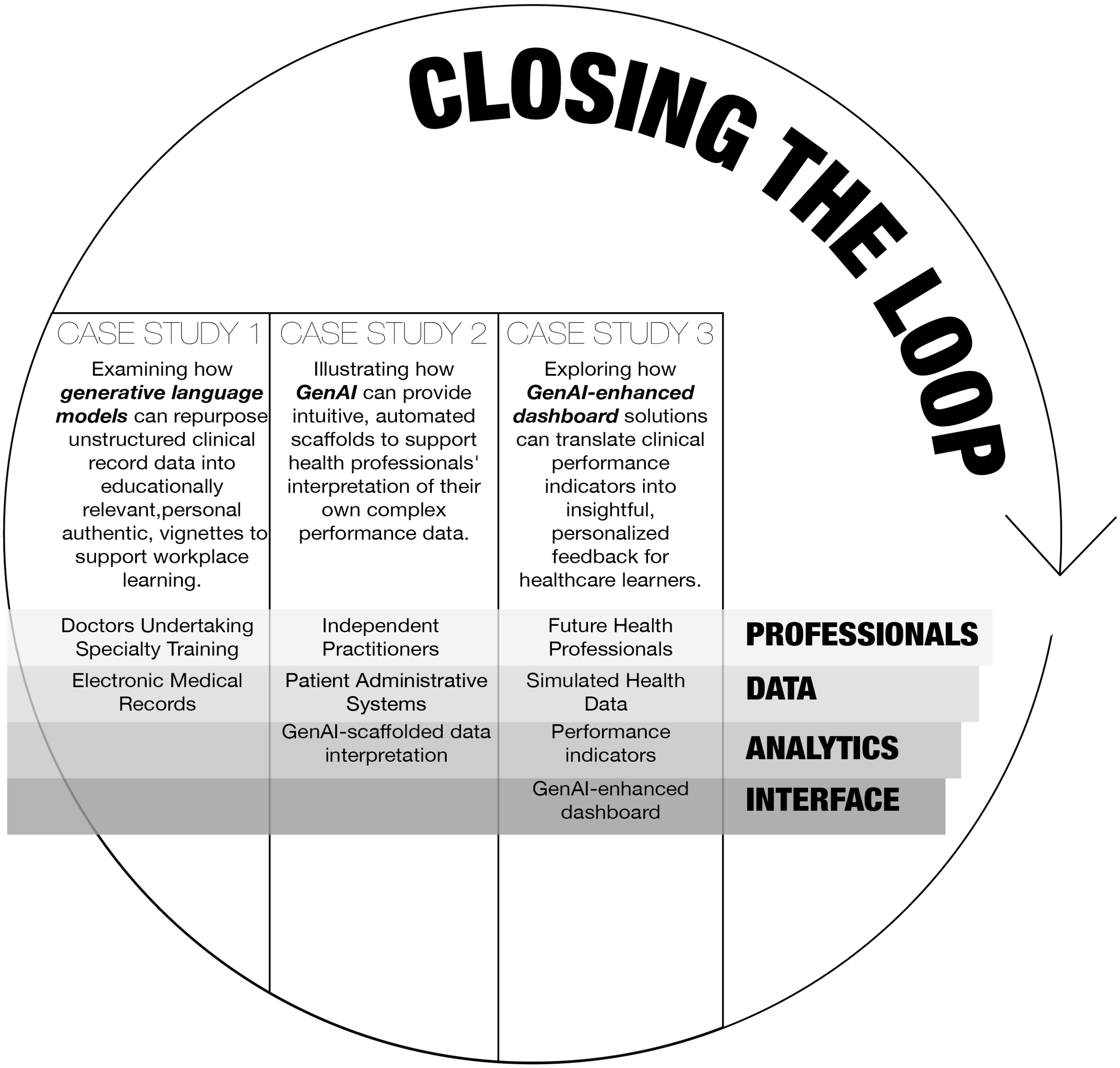

Figure 2. Illustration of the intersection between domains of the learning analytics cycle with the three professional learning analytics case studies presented in this section.

The proposed extension to this work involved using LLMs to synthesize and structure free-text EMR data, such as clinical notes, to automatically create authentic clinical vignettes for delivery via a microlearning platform. The intention was to pilot this extension work with early-career doctors working in oncology. Early-career doctors are still undergoing training to become independent practitioners, so they have a significant appetite for engaging in learning activities due to the need to build skills and capabilities. Despite the need to engage in professional learning activities, they are notably time poor (Chaiyachati et al., 2019), so efficient workplace interventions that can integrate into workflows have the potential for high engagement. Compared to other clinical areas, oncology relies heavily on recording patient care in free-text clinical notes rather than structured fields, making it a particularly good use case for applying LLMs. Unstructured data is widely collected in healthcare workplaces (Wang et al., 2021; Gu et al., 2025), so this intervention could be scaled to many other medical specialties and health professions (Figure 3).

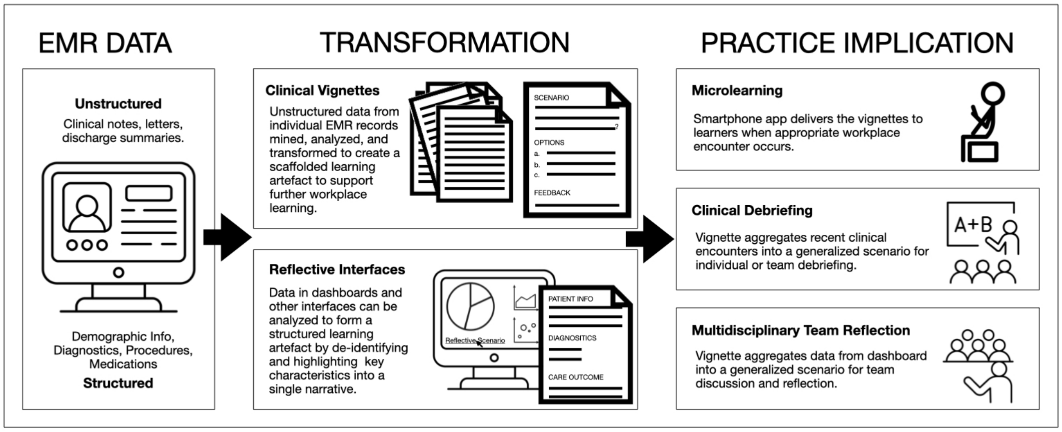

Figure 3. Illustration of the flow of data in this case study, the ways in which it can be transformed, and some potential applications in practice as professional learning interventions.

4.1.2 Data Transformation and Analysis

To generate the vignettes, a retrospective set of clinical notes would be extracted from the EMR and cleaned and categorized into clusters by presentation type. The cleaned EMR extract would be synthesized using LLMs to generate a suite of vignettes indicative of real-world clinical scenarios but wholly de-identified. A structured approach for generating the vignettes would be used to define the final structure of the cases to ensure content was presented in a way to maximize opportunities for learning and reflective practice. One approach to creating this structure would be to train the LLM to apply the collaborative, authentic, succinct, embedding (CASE) methodology to structure clinical scenarios (Shaw et al., 2018). The CASE methodology is an evidence-based framework to guide humans in developing authentic clinical scenarios that are succinct and aligned with best practice. Initially, generated content would need to be reviewed by domain experts to ensure its clinical authenticity and accuracy to support learning, but as LLMs become more sophisticated, this human-checking may no longer be required. Similar methodologies are currently being used to distill unstructured clinical data to generate insights to support care delivery (Pethani et al., 2025), but the value of LLMs and GenAI for synthesizing professional learning artefacts remains unexplored.

If this process turns out to be feasible, it could potentially be applied to an individual medical practitioner's own patient presentations to generate de-identified vignettes that closely mirror their individual clinical practice. A sufficiently sophisticated model integrated into the EMR could silently monitor the EMR data for significant performance deviation and harness structured and unstructured data as required to push microlearning to medical practitioners when variation was identified. The EMR data could also be leveraged to automatically generate clinical vignettes for those medical practitioners simulating the patient presentations that would provide the most impact on learning opportunities.

Our exploratory work on the automated use of LLMs to support professional learning integrated into workflows is, at present, only conceptually feasible. Foundational challenges relate to the collection, governance, and accessibility of electronic health data for professional learning purposes, which remains constrained by privacy regulations, organizational policies, and fragmented data infrastructures (Pizzuti, 2024; Roberts et al., 2025). Beyond data availability, GenAI technologies introduce additional risks. Current LLMs still exhibit well-documented limitations in generating accurate, consistent, and clinically valid content (Xu & Wang, 2024), raising concerns about the potential for hallucination, misrepresentation, or subtle factual errors in automatically generated vignettes (Wornow et al., 2023). Such risks call for robust human oversight, particularly in safety-critical domains such as healthcare (Meskó & Topol, 2023). Furthermore, the successful adoption of LLM-generated learning artefacts relies heavily on practitioner trust (Hough et al., 2025). Early evidence suggests that users may question the legitimacy, reliability, or educational value of AI-produced content (Choudhury & Shamszare, 2023). These considerations highlight the fact that, while promising, the integration of LLM-driven vignette generation into real clinical workflows requires careful evaluation, transparent safeguards, and staged implementation.

4.1.3 Implications for Practice: Efficient, Authentic Workplace Learning Artefacts Aligned with Clinical Practice

The major implication of using LLMs in the manner described in this case study is their ability to process EMR data to enable the generation of authentic simulated clinical vignettes delivered adaptively to align with a medical practitioner's performance. The current process for generating effective clinical vignettes for use in the workplace is a time-consuming process when best-practice methods are being used (Shaw et al., 2018). Application of LLMs to support the generation of clinical vignette content could offer significant efficiency benefits, as well as enhancing the perceived alignment of content in the vignettes with an individual medical practitioner's clinical presentations.

LLM-generated vignettes could also be applied more broadly to support professional learning than just as part of an adaptive microlearning intervention. There are many situations in which medical practitioners draw on clinical vignettes to support practice reflection and learning. Being able to generate robust clinical narratives that feel authentic, but are de-identified, has potential benefits for professional learning in many of these situations. One example of this is to support medical practitioners reviewing data in clinical dashboards as part of multidisciplinary team meetings. These vignettes could distill data in the dashboard to create a scaffolded scenario for team discussion and group learning to make it easier for medical practitioners, who can have varied levels of data literacy (Janssen & Shaw, 2022), to understand key insights in their data and engage in reflection on their practice. This approach may be useful for balancing the need for medical professionals to review patient cases as a group to support learning, with patient uncertainty about their data being reviewed by teams of medical practitioners who may not have been directly involved in their care (Janssen, Shah, et al., 2024). This application could also allow streamlining of clinical narratives by focusing on aspects of data known to prompt reflection, while removing details that add distraction. A second potential application is to generate authentic scenarios to support clinical debriefing (Coggins et al., 2021). Clinical debriefing is an important process during which early-career doctors reflect on patient scenarios and the approach to managing them to support their learning. Simulated scenarios are currently used, but generating these scenarios from EMR data aligned with the patient encounters junior doctors had during their training could enhance the authenticity of the scenarios used in these debriefing sessions.

4.2 Case 2: GenAI to Facilitate Healthcare Professionals' Sensemaking and Reflective Practices

4.2.1 Study Overview

In this case study, we introduce the CERA tool mentioned above to explore medical practitioners' sensemaking. There is a lack of understanding of how practitioners "make sense" of routinely collected hospital data that could support reflective practice (Whitelock-Wainwright et al., 2022). Addressing these barriers can enable practitioners to identify actionable insights from their practice data, and understanding such processes can inform the design of interfaces that support meaningful reflection (Whitelock-Wainwright et al., 2024; Bucalon et al., 2022, 2025). Our study had two objectives: (1) to explore the sensemaking processes of medical practitioners and (2) to evaluate the effectiveness of the CERA tool. Early work presented in this case study lays the foundations for a GenAI-powered tool to provide intuitive, automated scaffolds to support health professionals' interpretation of their complex performance data (Case Study 2 in Figure 2). Such a tool would align with the *analytics phase* of our proposed framework (Figure 1), as it leverages GenAI's advanced text and data analytics to support meaningful reflection on clinical data about their practice.

We designed the CERA tool, pronounced "Syrah," by adapting the traditional repertory grid technique (Bourne & Jankowicz, 2017; Hadley & Grogan, 2022). The repertory grid technique is an established interview technique that enables respondents to articulate their experience in the way they see the world, according to their own personal constructs. It is an idiographic, mixed-methods technique, with multiple stages (Saqr & López-Pernas, 2021). Idiographic methods, in contrast to monothetic methods, focus on understanding the individual at the centre of a highly personal phenomenon (García-Mieres et al., 2019; Fransella et al., 2004; Leach et al., 2001). Rather than gathering limited data from large populations, they collect extensive data about a single person (Beltz et al., 2016). Although not intended for population-level generalization, idiographic approaches provide rich insights essential for designing data-driven tools. They enable a deeper understanding of the end-user, including their specialty, clinical practice, learning needs, professional development, and individual sensemaking processes (Whitelock-Wainwright et al., 2022, 2024).

In the repertory grid, the interviewer guides the respondent to explore a "topic," which is made of different "elements" that are linked by "constructs." The technique is used in clinical psychology, education, and human–computer interaction studies and requires a trained therapist or interviewer (Leach et al., 2001; Rozenszajn et al., 2021; Doyle et al., 2021). This is not feasible for many researchers, and many health professionals are too time poor to commit to an in-depth interview, so we designed a novel adaptation of the technique that participants can complete online, in their own time, and alone. Given that our study was grounded in an idiographic approach, which seeks to understand phenomena at the level of the individual, a single participant was sufficient for our analysis.

The online study was delivered through Qualtrics. After the respondent confirmed their consent to participate, they completed a pre-study questionnaire and a short tutorial on the different stages of the tool (. We presented respondents with a predetermined list of "elements," extracted from a hospital-standardized minimum reporting dataset in Australia (Australian Government Department of Health, Disability, and Ageing, 2025). The clinical indicators included average length of stay, hospital-acquired complications, mortality, patient-reported outcome measures, readmissions within 28 days, unplanned returns to theatre, and intensive care unit (ICU) days. These indicators were selected as they are not specialty specific, are routinely collected in hospitals, and would be relevant to a broad range of medical practitioners (Aghaei Hashjin et al., 2014). In the first stage (construct elicitation), the respondent is randomly presented with three of the seven clinical indicators. They are asked to group two indicators that are similar and one indicator that is different. They are also asked to explain why they are similar and different. This task is repeated for all unique combinations of three indicators. In the second stage (rating activities), their previous explanations for the similarities and differences are used as polar ends of a five-point bipolar construct. For instance, the left side of the construct might say "Within my control" and the right side might say "Outside of my control." The respondent is asked to rate each clinical indicator (element) against each five-point scale (construct). Therefore, starting with seven elements and presenting them in unique combinations of three elicits 35 constructs.

This idiographic process generates a wealth of data from one medical practitioner: each of the seven elements was rated against the 35 different constructs, which generated 245 quantitative data points (35 multiplied by 7). We analyzed the construct text and rating values using the *OpenRepGrid* R package. The construct data was thematically analyzed. The constructs and rating values were also visualized in a *bertin plot* and a *biplot*. Researcher reflexivity was used to evaluate the effectiveness and feasibility of the tool.

4.2.2 Exploring Medical Practitioners' Sensemaking

We use a biplot visualization in Figure 4 to present the elements and constructs provided by the medical practitioner from the CERA tool. The biplot plots elements and constructs in two-dimensional space and visually presents the relationships between them. Constructs and elements that are plotted close together have a greater affiliation than those further away.

The practitioner made limited connections between the indicators and their clinical performance, suggesting that effective reflection requires indicators that clearly link to clinical practice (Schon, 1992; DunnGalvin et al., 2019). Outcome measures such as morbidity, mortality, or pain may feel less meaningful because the practitioner can no longer influence the patient concerned. More actionable reflection may arise from process, structural, or patient-reported measures (Bucalon et al., 2022), which clinicians feel able to improve for future patients. Routine, day-to-day indicators may therefore offer more immediate and impactful opportunities for learning. The analysis also shows that negatively framed or uncontrollable outcomes can evoke affect, which shapes sensemaking and may hinder reflective engagement (Whitelock-Wainwright et al., 2022). If data appears misaligned with a practitioner's expectations or past experiences, they may dismiss it as uninformative, consistent with sensemaking theory (Weick et al., 2005). Such data is still valuable but requires careful scaffolding to support constructive interpretation rather than defensive or avoidant responses.

Because reflecting on repurposed data is a new concept for many clinicians, practitioners require support to interpret indicators constructively. Such scaffolding can shape sensemaking in ways that promote reflection, learning, and professional development. Although support needs will vary across individuals, encouraging curiosity, questioning, and positive engagement with data can help build data maturity and strengthen cultures of data sharing (Whitelock-Wainwright et al., 2022, 2024; Bucalon et al., 2023). Even imperfect data can offer valuable insights if approached with openness (Whitelock-Wainwright et al., 2024; Bucalon et al., 2025). The practitioner's difficulty linking indicators to their performance may stem from unfamiliarity with practice analytics and existing assumptions shaped by audit-focused or punitive experiences (Whitelock-Wainwright et al., 2024). While practice analytics aim to empower clinicians to generate their own interpretations, general indicators used for quality improvement or research may not intuitively support reflection. As sensemaking draws on past experiences, clearer communication and contextualization are needed to help practitioners recognize how such indicators relate to their own practice.

4.2.3 Implications for Practice: Health Professionals, Designers, and Policy Makers

The key contribution of our study is the demonstration of the potential for a tool to explore medical practitioners' sensemaking. For individual practitioners, reflecting on the data visualizations generated by the tool may be insightful to reflect on and provide actionable insights related to their practice. The insights from the reports could also support mentoring and coaching discussions by structuring conversations around clinical performance, particularly between administrators and individual clinicians. For designers and data providers such as healthcare organizations and CPD platforms, while the results cannot be applied generically to all practitioners, they may highlight where practitioners require personalization and flexibility. For medical regulators and policy makers, the tool could be configured to explore other topics, such as how practitioners "make sense" of professional competencies, e.g., communication, leadership, and ethics.

Researcher reflexivity on the effectiveness and feasibility identified opportunities to enhance the CERA's usability with

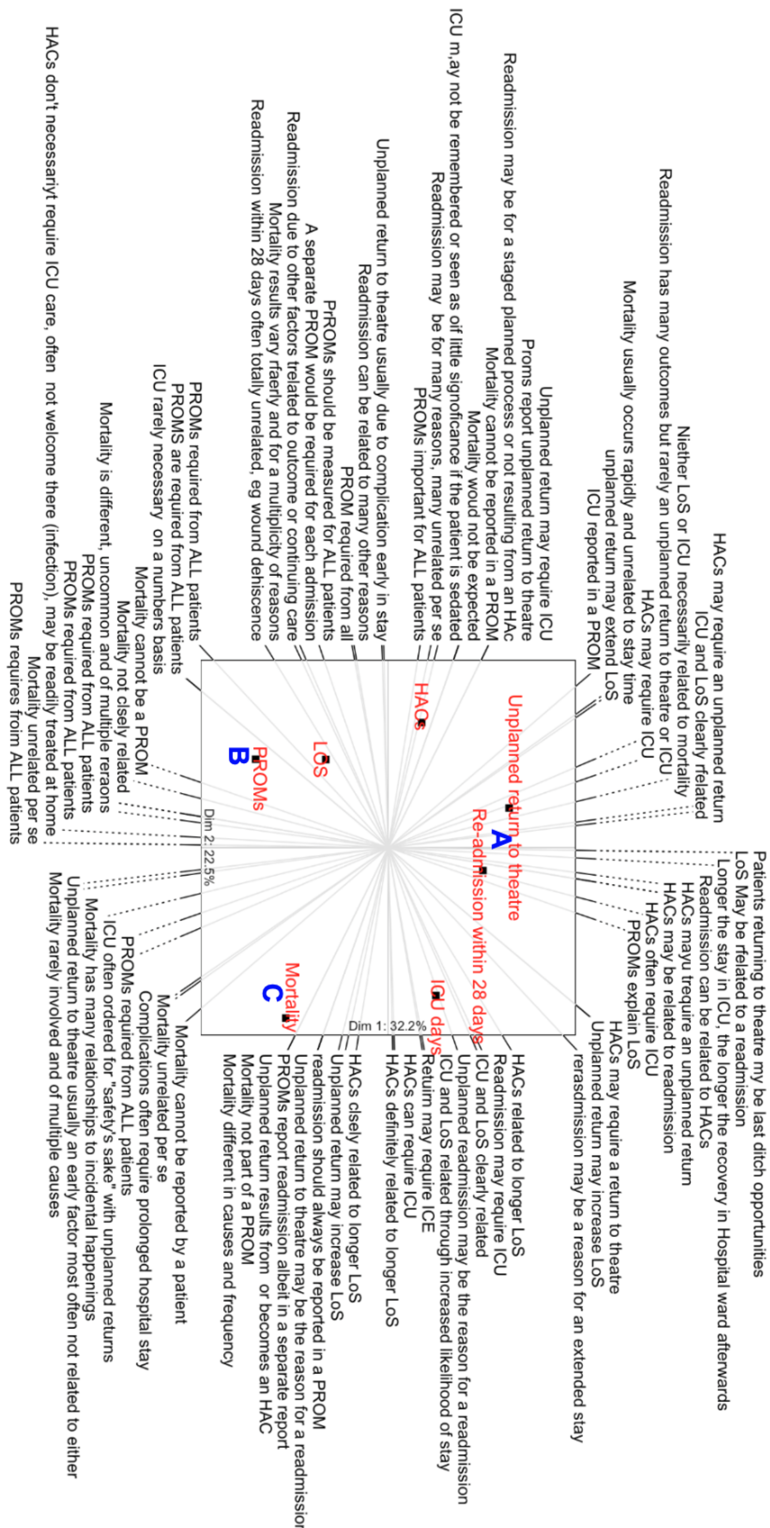

Figure 4. Biplot visualization of the practitioner's sensemaking—indicators related to unplanned or adverse events cluster tightly together (A), contrasting with patient-reported outcome measures associated with more positive care sentiments (B). Time-based indicators also form a distinct grouping, reflecting the practitioner's focus on duration of care. Mortality appears as a singular outlier (C), perceived as rare and largely unrelated to day-to-day clinical performance. This pattern illustrates how the practitioner differentiated between routine, actionable aspects of care and outcomes viewed as externally driven or beyond their control.

a GenAI. We envision that the CERA tool could be enhanced with GenAI by supporting the respondent in generating and identifying relevant elements, asking the respondent clarifying questions when they provide broad or repeated constructs, and suggesting concise alternatives to the respondent's verbose constructs. These improvements relate to the intervention phase (Section 3.5) of our proposed framework. GenAI's advanced interactive interface provides naturalistic conversational interactions that have the potential to replicate and enhance the traditional in-person repertory grid interview technique. In this way, CERA would scaffold practitioners through reflective prompts and structured questioning to uncover new insights about their practice, in their own time and without the need for a trained interviewer. Such interventions powered by GenAI could foster meaningful, reflective, contextually relevant, and conversationally engaging activities for health professionals (Cohen et al., 2023; Almansour & Alfhaid, 2024), which would contribute to their professional learning and development.

Our case study on exploring health professionals' sensemaking processes demonstrates the *analytics phase* of our proposed framework (Section 3.4). The CERA tool enables health professionals to formatively reflect on different aspects of their clinical practice—in our example, we focused on routinely collected clinical indicators related to their clinical performance. This type of data-driven reflective practice and sensemaking is integral to the ongoing professional development of practitioners, as they are required to continually self-assess areas for their development throughout their careers. The CERA tool, powered by GenAI-driven analytics, has the potential to identify practitioner-generated constructs, fostering deeper reflection on constructs and elements related to practice, and identify themes or patterns in practice leading to actionable insights.

4.3 Case 3: GenAI-Enhanced Dashboards for Personalized Clinical Feedback

4.3.1 Study Overview

In this case study, we investigated how GenAI could support clinical professional practice by dynamically providing personalized feedback through GenAI-enhanced dashboards (Yan et al., 2025). The case study illustrates the *intervention phase* of our proposed framework (Section 3.5). Our investigation focused explicitly on evaluating proactive versus passive GenAI-enhanced interventions to scaffolding sensemaking and reflective practices among healthcare students using complex clinical visual learning analytics (VLA). This study employed a randomized controlled trial design to rigorously examine the effectiveness of these AI-scaffolding features in enabling healthcare learners to accurately and efficiently interpret multimodal clinical visualizations in a simulated patient-care scenario (Figure 5). This case serves as an illustrative example of how microlearning activities in authentic workplace contexts could be effectively supported by GenAI-enhanced interventions, acknowledging that conducting this initial evaluation with student cohorts represents a pragmatic step before deploying similar interventions with professional clinical practitioners.

Participants were 117 higher education students enrolled in health, medical, or nursing programs who interacted with visual analytic dashboards derived from authentic healthcare simulations. Recruitment occurred via Prolific and compensated £8 per hour, with eligibility restricted to individuals fluent in English and using a laptop or desktop device. The sample was geographically diverse, including participants from North or Central America (51), Europe (28), Africa (25), Australia (5), South America (4), and other regions (4). The cohort comprised 68 female, 48 male, and 1 non-binary participants. Educational backgrounds spanned undergraduate (77), graduate (21), vocational (13), and doctoral (6) levels. Participants also varied in analytic proficiency: most reported intermediate data analysis experience (50), followed by beginners (36), advanced users (17), those with no experience (12), and experts (2). GenAI familiarity showed a similar distribution, with most identifying as intermediate (63), alongside beginners (34), advanced users (15), experts (4), and one participant with no prior exposure.

We conducted a randomized controlled mixed-design (3 × 3) experiment, using both within-subject and between-subject comparisons to evaluate the effectiveness of data storytelling, passive GenAI agents, and proactive GenAI agents in enhancing insight extraction from VLA, employing a structured, standardized procedure across all conditions with four main stages. First, participants were introduced to the study and completed demographic and background questions. Second, they completed 12 items from the mini visualisation literacy assessment test (mini VLAT) (Pandey & Ottley, 2023). Third, participants moved to our custom platform to undertake three analytical writing tasks, each followed by six evaluation questions in Qualtrics to assess their understanding of the VLA. Finally, they completed a feedback questionnaire about their experience with the assigned intervention. Our study collected quantitative metrics on effectiveness (number of accurately extracted insights from dashboards) and efficiency (time taken per correctly extracted insight). Participants also took pre- and post-intervention assessments to measure persistence and potential improvements in clinical analytic comprehension without continued intervention support.

The simulations presented challenging clinical tasks involving simultaneous patient care, communication complexities, stress management, and prioritization skills. The dashboards featured sophisticated multimodal analytics, including bar charts illustrating task prioritization, social network visualizations representing communication patterns, and integrated spatial-physiological heat maps showing student positioning, verbal communication intensity, and peak heart-rate locations (Yan, Echeverria, et al., 2024). Participants were randomly assigned to one of three dashboard intervention conditions to evaluate effectiveness and efficiency differences: (1) static dashboards employing conventional data storytelling methods, (2) passive GenAI dashboards that reactively responded to learner queries about visualizations, and (3) proactive GenAI-assisted dashboards, providing structured and adaptive scaffolding explicitly designed to guide learners toward critical reflective insights and meaningful interpretations of clinical data.

4.3.2 Demonstrating the Effectiveness of GenAI Dashboards

Results clearly demonstrated the advantages provided by GenAI interventions, particularly the proactive GenAI dashboards. Compared to passive GenAI and traditional static data storytelling dashboards, proactive GenAI dashboards significantly improved participants' effectiveness in extracting accurate insights from clinical performance visualizations during the intervention and, crucially, after the intervention's removal. Specifically, the proactive GenAI-supported dashboard condition demonstrated a significant increase in participant performance scores (median gain from pre- to post-intervention), indicating not merely temporary improvements but sustained learning enhancements even without continued AI support. Notably, proactive dashboards offered substantial scaffolding through targeted reflection prompts and structured questioning adapted in real time to participant responses (e.g., asking learners,"How did communication patterns differ between team members and the patient under high-stress periods?"). By dynamically addressing participants' specific comprehension gaps or misinterpretations, proactive GenAI dashboards played an important role in enhancing participants' ability to accurately derive clinical insights from complex multimodal visualization displays. In contrast, passive GenAI dashboards, while offering useful reactive support to queries, did not provide proactive guidance. Participants receiving passive GenAI support exhibited improved effectiveness during the intervention, yet these gains largely mirrored those observed in the traditional static annotation condition and did not match the enduring gains observed in proactive conditions. This suggests that proactive adaptive scaffolding, rather than merely responsive information retrieval, holds the real value in enhancing clinical analytical effectiveness and supporting genuine learning.

4.3.3 Impact on Efficiency of Clinical Analytics Interpretation

Regarding participants' efficiency (as measured by time per correctly identified insight) in interpreting clinical VLA, all three interventions (data storytelling, passive, and proactive GenAI support) reduced the time required to achieve accurate interpretations compared to baseline. However, there were no significant differences observed among the interventions themselves. This reflects a consistent efficiency enhancement provided by advanced analytic dashboards, yet importantly underscores that the distinguishing strength of proactive GenAI-driven dashboards lies primarily in effectiveness and sustained comprehension improvements, not merely in speeding comprehension.

4.3.4 Implications for Practice: Closing the Loop from Analytics to Action

This case study offers a practical demonstration of how GenAI-enhanced dashboards uniquely contribute toward closing the analytics-to-practice gap often reported in learning analytics research. While traditional dashboard designs often rely solely on visually descriptive analytics (leaving users responsible for deriving actionable interpretations), our proactive GenAI-enhanced dashboards extend analytics to effective implementation by explicitly scaffolding user reflection and sensemaking in real time. By interacting conversationally with learners, proactively scaffolding interpretation, and facilitating extraction of meaningful insights, these agent-enhanced dashboards move beyond simply informative displays. Rather, they actively foster deeper reflective inquiry that directly translates complex analytics into personal learning outcomes, meaningful professional considerations, and decisions relevant to clinical practice improvements (Verbert et al., 2020; Li et al., 2024; Yan, Zhao, et al., 2024). This aligns closely with established theories related to educational scaffolding, particularly Vygotsky's zone of proximal development, which emphasizes the importance of targeted, responsive support (scaffolding) in helping learners achieve insights and competencies slightly beyond their current independent capabilities (Kim et al., 2018; Gibbons, 2002). Thus, our proactive GenAI-enhanced dashboards leverage these concepts effectively, aligning analytic insights with robust education-supported implementation exercises that directly support professional reflection and facilitate clinical sensemaking.

In summary, this case study explicitly illustrates the potential and demonstrated effectiveness of proactive, GenAI-enhanced dashboard solutions in translating sophisticated clinical performance indicators into meaningful, personalized reflective practices. More broadly, this work exemplifies learning analytics' potential when paired strategically with GenAI approaches, unveiling new opportunities to meaningfully close the learning analytics loop, thus actively contributing to fostering enhanced professional competency and informed clinical decision-making.

5. Discussion

Our paper aimed to explore the role of GenAI-driven learning analytics in fostering personalized 21st-century competencies for health professionals. We have used a revised version of Clow's learning analytics cycle tailored to support professional learning analytics in the age of GenAI. Subsequently, we illustrated using three case studies the potential of GenAI to transform the ways healthcare professionals interpret, reflect upon, and ultimately utilize complex multimodal workplace data for personalized competency growth. Our work builds on the broader literature, which has made refinements to Clow's original model. In our context these refinements include applying Clow's learning analytics model to the domain of healthcare. This context is particularly novel as it requires leveraging and transforming data sets routinely collected by workplace technologies to support

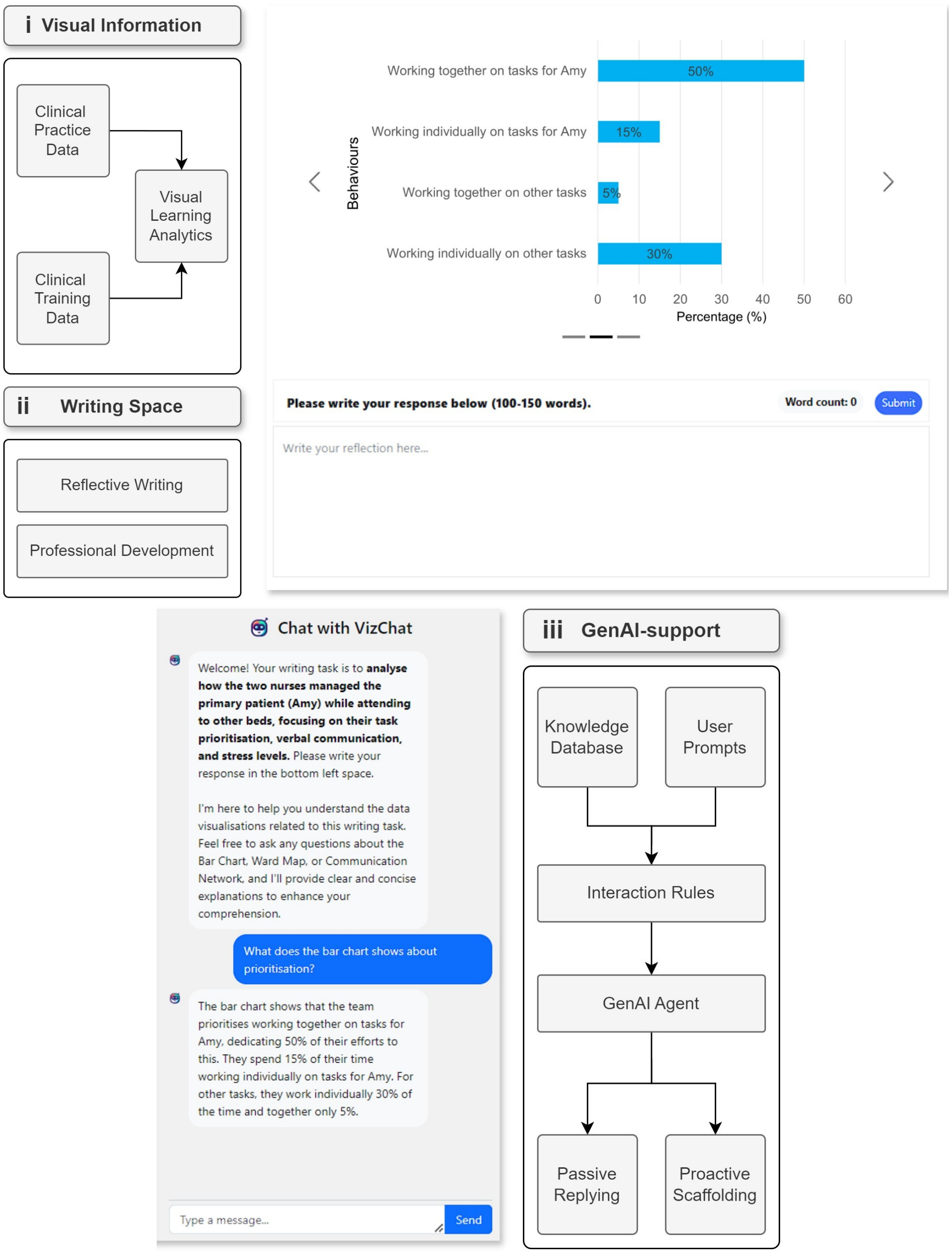

Figure 5. Example of integrating a GenAI chatbot to support reflective writing for healthcare professions development: (i) VLA derived from clinical practice or training data, (ii) writing space dedicated to reflective practice and professional development activities, and (iii) GenAI chatbot capable of proactively scaffolding reflection or passively responding to practitioners' reflective experiences as guided by VLA.

professional learning, which is distinct from the educational data more typically used in the context of learning analytics. A recent refinement of Clow's learning analytics cycle used it to inform the development of a closed-loop learning analytics framework that emphasized data collection and transformation to support adaptive and personalized learning approaches (Sailer et al., 2024). Other researchers have reframed the learning analytics cycle to de-emphasize the learner and focus more heavily on content creation (Bojic et al., 2023). Yan and colleagues (2024) applied Clow's LA cycle to contextualize opportunities and challenges for harnessing GenAI in learning analytics.

Although there are parallels between formal and professional learning contexts, this framework captures important aspects of the nature of learning analytics in professional contexts. This contrasts Clow's (2012) framework and builds on it to show the potential roles of GenAI in the professional setting. The learners themselves have a difference in agency levels and priorities from those in formal settings. Drivers for knowledge acquisition can include both individual desires to develop workplace skills (Ruiz-Calleja et al., 2021) and external drivers such as requirements to maintain qualifications to practise (Janssen et al., 2021). Learning is also often informal, and learners may not even be aware they are engaged in it (Eraut, 2004). Workplace data is also notably different from that in formal settings (Samuelsen et al., 2019). It is not generated by systems explicitly created to support learning, but by systems designed to support work processes. The questions asked of workplace data are also very different from the ones asked of data in formal contexts, requiring unique analytics approaches.

GenAI has the ability to address some of the challenges in professional learning analytics. Nonetheless, significant challenges persist, including best-practice approaches for developing systematic educational design frameworks for GenAI-supported interventions, addressing ethical concerns around data privacy and equity, ensuring the explainability and trustworthiness of GenAI-generated scaffolds, and evaluating their impact on learning and professional outcomes over extended periods in authentic workplace environments. Many of these challenges align with those identified in the broader learning analytics literature on barriers to applying GenAI in practice to support learners (Misiejuk et al., 2025). Furthermore, extensive dialogues and empirical investigations into ethical and equity considerations surrounding GenAI-informed learning analytics implementation remain critical for scaling these innovative applications responsibly (Yan, Martinez-Maldonado, & Gasevic, 2024).

5.1 Implications for Research and Practice

The GenAI-enhanced professional learning analytics framework (Figure 1) provides a structured lens for practitioners, researchers, and organizations developing data-driven professional learning initiatives in healthcare. By articulating how GenAI can augment the learner, data, analytics, and intervention phases of Clow's learning analytics cycle, our proposed framework maps specific design considerations for transforming workplace data into meaningful learning opportunities. We demonstrate the value of the proposed framework through three case studies and present our insights to guide organizations to create new professional learning analytics systems that integrate GenAI.

5.1.1 Generating Clinically Authentic Scenarios to Support Clinical Debriefing and multidisciplinary Team Reflection

Our first case study presented exploratory work into the application of LLMs to process EMR data to enable the generation of authentic simulated clinical vignettes delivered adaptively to align with a medical practitioner's performance. Yanagita and colleagues (2025) demonstrated the benefits of AI-generated vignettes in a quality evaluation of Japanese-language physician–patient dialogues produced by GPT-4o, focusing on their medical accuracy and overall appropriateness as medical interviews. They showed that it is feasible to efficiently create AI-generated educational materials for medical education that overcome the limitations of traditional clinical vignettes. Similarly, Arain and colleagues (2025) evaluated the Gemini Advanced model for creating aligned problem-based learning (PBL) materials. The LLM enhanced alignment with learning goals by restructuring the tutor guide and adding thought-provoking questions, producing a well-organized and informative resource, although the original vignette was viewed as more appropriate for the learners' educational level. Further research could explore broader applications of LLM-generated vignettes across diverse professional learning contexts beyond adaptive microlearning (Hoagland, 2025). One promising direction is the integration of LLM-generated scenarios into clinical debriefing, where junior doctors reflect on real or simulated cases (Hong et al., 2025). Additionally, LLM-supported vignette generation could be examined as a mechanism for translating complex dashboard data into accessible narratives for multidisciplinary team meetings, enabling shared interpretation and collaborative reflection (Yan, Zhao, et al., 2024). Together, these potential research directions highlight the potential for LLMs to generate authentic clinical vignettes for health professions education.

5.1.2 Exploring Healthcare Professionals' Sensemaking to Align Repurposed Workplace Data for Reflective Practice

In our second case study, we described the development and evaluation of the CERA tool to explore medical practitioners' sensemaking. Multiple factors, such as data accuracy, validity, infrastructure, and organizational culture, shape how medical practitioners make sense of their performance data and influence how it informs future practice (Whitelock-Wainwright et al., 2022). These influences are especially important to consider when data is intended to support reflective practice and professional development. Whitelock-Wainwright and colleagues (2024) conducted a mixed-methods study into how specialist clinicians interact with routinely collected clinical indicators to inform their professional learning and development. They found human-centred considerations such as the use of "frames of reference," presentation of "cases of interest" to support reflective discussions, significance of data attribution, and factors that impact sensemaking (i.e., affect and prior experiences) to be critical in designing interventions that align workplace-generated data meaningfully to clinical practice. However, decisions about whether repurposed performance data, extracted from secondary data sources, e.g., billing and administration systems, are suitable for learning depend on perceptions of their purpose, meaning, and use. These may align, overlap, or conflict depending on context. Building trust, fostering team-based approaches, and involving key stakeholders such as data specialists and organizational leaders can strengthen the effectiveness and uptake of data-informed professional development (Wiljer et al., 2023). Future research should examine how individual practitioners, clinical teams, and hospital administrators make sense of this data for learning, how these interpretations differ among users, and what system-level conditions are required to create alignment that supports meaningful learning (Tavares et al., 2024).

5.1.3 Proactive GenAI-Enhanced Dashboards to Foster Deeper Reflective Inquiry

In our third case study, we presented the results from an empirical study of how GenAI-enhanced dashboards uniquely contribute toward closing the analytics-to-practice gap often reported in learning analytics research. Studies on learning analytics dashboards have reported negligible or small effects on learner outcomes, with few well-powered controlled experiments demonstrating meaningful impact (Kaliisa et al., 2024). Evidence for improvements in motivation or attitudes is similarly limited, suggesting traditional dashboards alone are insufficient to support deeper learning or behavioural change. These limitations are especially pronounced in clinical contexts, where integrating dashboards into day-to-day workflows remains challenging due to information overload, data quality, and clinicians' difficulty interpreting complex visualizations or identifying actionable insights (Khairat et al., 2018; Xie et al., 2022). The findings from this case study indicate that conversational AI interfaces powered by GenAI can address some of these challenges by providing proactive, contextually relevant scaffolding that facilitates clinicians' reflection on practice. Such agents can support the interpretation and sensemaking of data and encourage deeper inquiry into practice (Jin, Yang, et al., 2025; Xie et al., 2022). Future research directions should investigate how medical practitioner GenAI literacy impacts the effectiveness of GenAI-enhanced dashboards (Jin, Martinez-Maldonado, et al., 2025) and more importantly the risks to safety and quality of care in GenAI implementation within healthcare contexts (Scott et al., 2025).

5.2 Limitations

A notable limitation of this work is that it presents case studies of proposed applications of GenAI for professional learners, but these are yet to be tested in real-world workplaces. A further limitation is that one of the case studies focuses on development of a tool for health professionals in training, not those in the workplace. Although this work is yet to be translated to the professional context, piloting learning innovations with health professionals is challenging as they are time poor and difficult to recruit for real-world testing. Initial testing of innovations with future health professionals can be a pragmatic solution for iterating on ideas prior to real-world testing with professionals. A further opportunity for future research would be to explore the utility of this data for use by patients, an area that has been relatively underexplored to date.

6. Conclusion

This research advances understanding of professional learning analytics for healthcare by articulating a framework that maps how GenAI can meaningfully augment each phase of Clow's learning analytics cycle: learner, data, analytics, and intervention. In the *learner/professional* phase, the framework reframes clinicians as lifelong learners who engage in informal, incidental, and self-directed professional development embedded within everyday clinical practice, requiring analytics and interventions that align with their unique learning needs, motivations, and work constraints. In the *data* phase, the framework clarifies how GenAI can transform the unstructured and multimodal workplace data typical of healthcare, such as clinical notes, discharge summaries, and incident reports, into structured, educationally meaningful artefacts that practitioners can use for learning. In the *analytics* phase, it identifies how GenAI can support reflective, practice-oriented sensemaking by helping clinicians interpret longitudinal performance data, recognize patterns in their own clinical activity, and explore potential areas for improvement in ways that align with their scope of practice. Finally, in the *intervention* phase, the framework explains how GenAI-enabled conversational scaffolding can enhance the accessibility and usefulness of analytics by supporting brief, meaningful engagement with data; prompting reflection; and guiding practitioners through interpretive tasks that might otherwise be overlooked in busy clinical workflows. Through three detailed case studies, we demonstrate how these design principles can be operationalized and the types of learning challenges they address.

This special issue provides clearer guidance for researchers and practitioners seeking to integrate GenAI in learning analytics systems in healthcare and contributes foundational insights into how GenAI can support competency development in real-world clinical contexts.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The publication of this article received financial support from the Digital Health CRC Limited (DHCRC), funded under the Commonwealth's Cooperative Research Centres (CRC) Program. Authors BB and LY were undertaking postdoctoral research fellowships funded by DHCRC.

Acknowledgements

The authors wish to acknowledge that this work is part of a major collaborative research program that brings together researchers and health sector partners to undertake a range of projects on the role of health data to support health professions education and reflective practice. Work presented in this article builds on and extends that being undertaken as part of the existing collaboration.

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