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Generative AI and Learning Analytics: Pushing Boundaries, Preserving Principles

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Abstract
The rapid adoption of generative AI (GenAI) in education has raised critical questions about its implications for learning and teaching. While GenAI tools offer new avenues for personalized learning, enhanced feedback, and increased efficiency, they also present challenges related to cognitive engagement, student agency, and ethical considerations. Learning analytics (LA) provides a crucial lens to examine how GenAI affects learning behaviours and outcomes by offering data-informed insights into GenAI's impact on students, educators, and educational ecosystems. Thus, obtained insights allow for evidence-based decision-making aimed at balancing GenAI's benefits with the need to foster deep learning, creativity, and self-regulation of learning. This special issue of the *Journal of Learning Analytics* presents 10 research papers that explore the intersection of GenAI and LA, offering diverse perspectives that benefit students, teachers, and researchers. To structure these contributions, we adopt Clow's generic framework of the LA cycle, categorizing the papers into four key areas: (1) understanding learning and learner contexts, (2) leveraging AI-generated data for learning insights, (3) applying LA methods to generate meaningful insights, and (4) designing interventions that optimize learning outcomes. By bringing together these perspectives, this special issue advances research-informed educational practices that ensure that GenAI's potential is harnessed responsibly, reinforcing educational goals while safeguarding learners' autonomy and cognitive development. Collectively, these contributions illustrate the reciprocal relationship between GenAI and LA, demonstrating how each can inform and refine the other. We reflect on the broader implications for LA, including the need to re-examine the boundaries of LA in the presence of GenAI, while preserving key principles from human-centred design and maintaining ethical and privacy standards that are foundational to LA.

Notes for Practice

- Generative AI (GenAI) offers new affordances for learning analytics (LA), but it must be used with careful consideration of learning contexts and objectives.
- This special issue presents 10 research papers on the intersection of GenAI and LA, structured using Clow's LA cycle to explore four key areas: understanding learning contexts, leveraging AI-generated data, applying analytical methods, and designing interventions that optimize learning outcomes.
- There is a pressing need to re-examine the boundaries of LA in the presence of GenAI while maintaining foundational principles from human-centred design, ethical standards, and privacy frameworks. This will help balance AI's potential benefits with the need for responsible and sustainable educational practices.

Keywords
Generative AI, learning analytics.

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1. Introduction

The rapid and widespread adoption of generative AI (GenAI) in educational practices has sparked debate due to the complexity of its impacts on both learning and teaching (Yan, Greiff, et al., 2024; Cukurova, 2024). On the one hand, GenAI tools are celebrated for expediting task execution by drafting essays, solving a variety of problems students face while working on their assignments, and providing personalized feedback at scale, which hold the potential for improving educational outcomes such as academic performance, motivation, and efficiency (Deng et al., 2025; Stadler et al., 2024; Pardos & Bhandari, 2024). On the other hand, these benefits raise concerns that deeper learning processes that need to occur in educational settings are getting offloaded to AI. While GenAI-powered tools often optimize students' performance during specific learning tasks, they also risk diminishing the essential mental effort required for meaningful learning (Abbas et al., 2024; Xie et al., 2024) and can lead to metacognitive laziness (Fan et al., 2025). This dynamic poses challenges for the development of independent learning and cognitive processes (Fan et al., 2025), such as critical thinking, problem-solving, and metacognitive monitoring, because GenAI may inadvertently shift learners toward dependency on external scaffolding rather than foster their sustainable development (Zhai et al., 2024). Thus, while GenAI offers exciting new opportunities for education, its role demands careful examination to ensure that it supports rather than undermines long-term developmental goals in education.

Amid the growing use of GenAI in learning environments, learning analytics (LA) emerges as a critical field to provide evidence-based insights into how these technologies affect learning behaviours and outcomes. Beyond merely assessing task outputs, LA enables a comprehensive understanding of learners' cognitive processes, agency, and engagement when interacting with GenAI tools (Khosravi et al., 2023; Yan, Martinez-Maldonado, & Gasevic, 2024; Shibani et al., 2023). By capturing detailed data, such as how students use GenAI for planning, problem-solving, and feedback, LA allows for discerning the extent to which learners rely on AI versus actively engaging with educational materials. Furthermore, LA has the potential to measure not only the immediate efficiency gains offered by GenAI but also the broader implications for learners' capacity to build transferable competencies and apply them in novel, emerging contexts. Through LA methodologies, educators and researchers can evaluate how students balance external assistance with active cognitive effort, providing actionable insights into designing interventions that promote deeper and more autonomous forms of learning. This alignment of LA with GenAI applications is essential for building evidence-based education strategies that reconcile the need for productivity with the equally critical goals of fostering independent learning skills, active learning, and metacognitive competence.

This special section brings together a diverse collection of research articles exploring the intersection of GenAI and LA, offering fresh perspectives on this synergy for education. Through empirical investigations, conceptual discussions, and critical viewpoints, the included papers analyze how GenAI can enhance LA and how LA, in turn, can optimize how GenAI is integrated into educational ecosystems. Topics include understanding user engagement with GenAI tools, new methodologies to analyze learning constructs, and assessing the cognitive and behavioural impacts of these technologies. These contributions together reflect on how AI and analytics can mutually inform and strengthen educational practices. While the majority of the studies are from higher education, their findings and methodologies can benefit a wide range of learning environments, enhancing educational practices across different levels and contexts. Collectively, this special section aims to advance research-informed practices that ensure that GenAI's transformative potential is leveraged to enrich learning processes, while addressing risks and ethical considerations to safeguard the purposes and principles of LA.

2. Theoretical Framing and Overview of the Special Section

This special section compiles research at the intersection of GenAI and LA, addressing both *practical applications* that support student learning and *methodological advancements* that extend the field of LA. Using Clow's LA cycle as an organizing framework (Clow, 2012), along with the foundational work of Yan, Martinez-Maldonado, and Gasevic (2024) on the use of GenAI in LA, the papers in this special section are mapped into four key phases of the LA cycle. The contributions from the selected papers are outlined in the subsections below, detailing how each study aligns with these phases.

2.1 Understanding Learning and Learner Contexts

Understanding how students engage with AI-based tools is crucial for designing effective, AI-supported learning environments. Several studies in this special section contribute to this phase by exploring how GenAI affects student self-regulation, decision-making, and creativity. For example, Lai and colleagues (2025) examine how students interact with a Socratic chatbot for self-regulated learning (SRL), identifying behavioural differences between high- and low-performing students through epistemic network analysis. Similarly, Henkel and colleagues (2025) apply Bayesian knowledge tracing (BKT) to study how improved AI-based grading influences student mastery estimation, demonstrating the impact of grading feedback on learning progression. Ochoa and colleagues (2025) investigate how non-experts, including students and instructors, engage with AI-powered LA tools, shedding light on barriers to AI adoption in educational settings. Additionally, Hadas and Hershkovitz (2025) explore how students develop creativity over time, analyzing how repeated engagement with a divergent thinking (DT) task leads to improvements in fluency and flexibility. Finally, Lekan and Pardos (2025) investigate AI-assisted advising, revealing how

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AI-generated major recommendations and answers to student questions are viewed by advisors and how closely these responses match their own. Collectively, these studies illustrate the multifaceted ways in which LA has been applied to understand how AI-based tools support and shape learner behaviour (and educators) in higher education.

2.2 Leveraging AI-Generated Data for Learning Insights

AI-generated data provides a rich source of information for understanding learning behaviours and optimizing educational experiences. The papers in this special issue contribute to this phase by leveraging AI-generated data to gain insights into student learning and engagement. Lai and colleagues (2025) demonstrate how conversational data from student-chatbot interactions can be systematically analyzed to understand SRL behaviours. Similarly, Pozdniakov and colleagues (2025) analyze AI-generated feedback data from 1,063 student-created multiple-choice questions (MCQs) to examine student engagement with AI-generated feedback. F.J.-Y. Jin and colleagues (2025) investigate how trace data about student interactions with AI-generated feedback provides insights into student learning patterns, specifically, student engagement with AI-powered dashboards and ChatGPT explanations. These studies highlight the potential of AI-enhanced interactions as a source of LA data, demonstrating how data-informed approaches can personalize learning experiences and improve learner support in educational settings.

2.3 Applying Methods and Analytics to Generate Meaningful Insights

Advancing LA methodologies through AI-enabled techniques is a key focus of this special issue. Several papers contribute to this phase by developing and evaluating novel AI-based analytical methods that can help expand the boundaries of LA for the age of GenAI. Henkel and colleagues (2025) evaluate different prompting strategies, including chain-of-thought reasoning, to improve the accuracy of AI-assisted grading in open-response mathematical questions, demonstrating how AI can enhance assessment methodologies. Ochoa and colleagues (2025) explore how AI can support non-experts in conducting LA tasks, highlighting the potential of AI-powered tools to scaffold data analysis for users with varying levels of expertise. Hadas and Hershkovitz (2025) develop an AI-supported approach to automate the scoring of creativity assessments, reducing subjectivity and labour-intensive scoring processes. Liu and colleagues (2025) investigate the effectiveness of different AI-based qualitative coding strategies, comparing zero-shot, few-shot, and contextualized prompting for analyzing educational datasets from three distinct study contexts. Additionally, Whitehead and colleagues (2025) contribute to multimodal learning analytics (MMLA) by leveraging AI to extract postural behaviour data in collaborative learning environments, demonstrating how AI-enabled techniques can enhance LA research on student engagement and interaction. These studies showcase the potential of AI to refine and extend LA methodologies using new forms of learner data and analytics, ensuring that AI-enabled insights are both rigorous and pedagogically sound.

2.4 Designing Interventions That Optimize Learning Outcomes

AI-augmented instructional strategies, feedback mechanisms, and adaptive learning systems play a critical role in enhancing student learning. Papers in this special issue also examine how AI-powered interventions support and improve educational experiences. Pozdniakov and colleagues (2025) investigate how real-time AI-generated feedback supports student content creation, showing how structured AI feedback—providing a summary, strengths, and suggestions—can bridge skill gaps and improve engagement. F.J.-Y. Jin and colleagues (2025) explore how AI-powered dashboards and ChatGPT-generated explanations enhance student engagement with feedback, demonstrating how AI can be integrated into formative assessment practices. These studies illustrate how AI can be leveraged to optimize learning interventions, making feedback more personalized, actionable, and effective in supporting student success, an area where LA has previously played a critical role.

3. Submissions in the Special Section

The selected papers investigate how AI-powered tools and methods enhance student engagement, inform LA methodologies, and provide adaptive feedback and interventions to improve learning outcomes. Each submission is mapped to one or more of the phases of Clow's LA cycle (Clow, 2012), as shown in Table 1. The summaries below provide an overview of each paper's contributions within this framework. While some studies focus on a single phase, others span multiple phases, reflecting the interdisciplinary nature of this research and new affordances provided by GenAI for LA. This mapping highlights the diverse ways in which GenAI and LA may interact to enhance student engagement, optimize feedback, and refine educational practice and research methodologies.

In "Mapping the Landscape of Generative Artificial Intelligence in Learning Analytics: A Systematic Literature Review," Misiejuk and colleagues (2025) provide a broad landscape of empirical research on the integration of GenAI and LA. Through a systematic review of 41 empirical studies, the paper examines how GenAI is being leveraged to design LA tools, gain insights into student learning behaviours, and support instructional decision-making. The findings highlight that GenAI is predominantly used for automating discourse coding, scoring, and classification tasks, while relatively few studies have explored its potential for data generation or text summarization. In classroom applications, the review finds that GenAI is

Table 1. *Mapping of special section papers to key phases in the LA cycle.*

Paper	Learners	Data	Analytics	Intervention
"Mapping the Landscape of Generative Artificial Intelligence in Learning Analytics: A Systematic Literature Review" (Misiejuk et al., 2025)				
"Leveraging Process-Action Epistemic Network Analysis to Illuminate Student Self-Regulated Learning with a Socratic Chatbot" (Lai et al., 2025)	X	X		
"Learning to Love LLMs for Answer Interpretation: Chain-of-Thought Prompting and the AMMORE Dataset" (Henkel et al., 2025)	X		X	
"Exploring the Potential of Generative AI to Support Non-experts in Learning Analytics Practice" (Ochoa et al., 2025)	X		X	
"Assessing Creativity across Multi-Step Intervention Using Generative AI Models" (Hadas & Hershkovitz, 2025)	X		X	
"AI-Augmented Advising: A Comparative Study of GPT-4 and Advisor-Based Major Recommendations" (Lekan & Pardos, 2025)			X	X
"AI-Assisted Co-creation: Bridging Skill Gaps in Student-Generated Content" (Pozdniakov et al., 2025)		X	X	X
"Students' Perceptions of Generative AI–Powered Learning Analytics in the Feedback Process: A Feedback Literacy Perspective" (F. J.-Y. Jin et al., 2025)		X		X
"Qualitative Coding with GPT-4: Where It Works Better" (Liu et al., 2025)			X	
"Utilizing Multimodal Large Language Models for Video Analysis of Posture in Studying Collaborative Learning: A Case Study" (Whitehead et al., 2025)			X	

primarily integrated to facilitate human-GenAI collaboration, rather than being fully implemented in automated feedback systems or AI-powered LA dashboards. The study also surveys the common AI models used in LA research, noting that GANs (generative adversarial networks are frequently applied for synthetic data generation, BERT for classification and prediction tasks, and GPT for discourse coding and tool integration. A significant concern raised in the review is that some LA pipelines incorporate GenAI-generated outputs without validation, particularly in cases where AI-generated data is directly used to develop dashboards or inform instructional decisions.

In "Leveraging Process-Action Epistemic Network Analysis to Illuminate Student Self-Regulated Learning with a Socratic Chatbot," Lai and colleagues (2025) contribute to both the **understanding learners** and **data** phases of the LA cycle by exploring how student interactions with a Socratic chatbot can provide insights into SRL behaviours. From an understanding learners perspective, the study examines how different students engage with an educational chatbot in an introductory statistics course. By analyzing 34 students' chatbot conversations, the study categorizes interactions into learning actions and processes, revealing key behavioural differences between high- and low-performing students. Findings indicate that higher-scoring students engage more in reflective and evaluative activities, while lower-scoring students primarily focus on answer-seeking behaviours. From a data perspective, the study demonstrates how LA can leverage AI-generated conversational data to gain insights into student learning. By applying ordered epistemic network analysis to student-chatbot interactions, the study shows how data generated through AI-enhanced dialogues can be systematically analyzed to understand learning behaviours. This approach illustrates how conversational AI can serve as both a learning tool and a data source for SRL research.

In "Learning to Love LLMs for Answer Interpretation: Chain-of-Thought Prompting and the AMMORE Dataset," Henkel and colleagues (2025) contribute to both the **analytics** and **understanding learners** phases by investigating the application of large language models (LLMs) for grading open-response math questions and analyzing how improved grading accuracy impacts student mastery estimation. From an analytics perspective, this study explores LLM-driven grading approaches for challenging student answers within the AMMORE dataset, which consists of 53,000 math open-response question-answer pairs collected from a mathematics learning platform used in African schools. Through two experiments, the study evaluates zero-shot, few-shot, and chain-of-thought prompting strategies, finding that chain-of-thought prompting improves grading

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accuracy on difficult cases. This research demonstrates how LLMs can enhance automated grading methods, supporting the scalability and reliability of AI-assisted assessment in learning systems. From an understanding learners perspective, the study examines the impact of improved grading accuracy on student mastery estimation using a BKT model. By passing LLM-generated grades into the BKT framework, the research finds that even a small increase in grading accuracy (from 96% to 97%, as in the current study) leads to more accurate estimations of student mastery—where the rule-based classifier misclassified 6.9% of students' mastery status, the LLM-driven grading approach reduced this error to 2.6%.

In "Exploring the Potential of Generative AI to Support Non-experts in Learning Analytics Practice," Ochoa and colleagues (2025) contribute to both the **understanding learners** and **analytics** phases by investigating how GenAI can assist non-experts in performing descriptive LA tasks. From an understanding learners perspective, this study examines how administrators, instructors, and students engage with GenAI for data analysis tasks, assessing their ability to perform descriptive LA without requiring expertise in data processing, visualization, or programming. The findings indicate that while prior expertise has a small effect on performance, both novices and experts achieved similar results, suggesting that GenAI has the potential to lower barriers to entry for LA engagement. From an analytics perspective, this study explores how GenAI can be leveraged to support non-expert users in conducting LA tasks. By analyzing user performance across different difficulty levels in a controlled laboratory experiment, the research highlights how AI-powered tools can scaffold analytics processes, guiding users through data exploration and interpretation.

In "Assessing Creativity across Multi-Step Intervention Using Generative AI Models," Hadas and Hershkovitz (2025) contribute to both the **understanding learners** and **analytics** phases by exploring GenAI for assessing creativity in educational settings. From an understanding learners perspective, the study investigates how creativity develops over time in students by analyzing DT dimensions, such as fluency and flexibility, across repeated alternative uses test sessions. The findings provide insights into behavioural patterns in creativity, the impact of practice opportunities, and the role of response order in creative thinking. These insights help educators better understand how students refine creative problem-solving skills over time. From an analytics perspective, this study leverages GenAI to automate the scoring of creativity assessments, reducing subjectivity and labour-intensive scoring processes. By applying two validated AI models, the research demonstrates how AI-powered LA can provide scalable, efficient, and objective assessments of creativity, offering a data-driven approach to measuring and improving creative skills in education.

In "AI-Augmented Advising: A Comparative Study of GPT-4 and Advisor-Based Major Recommendations," Lekan and Pardos (2025) contribute to both the **analytics** and **intervention** phases by investigating how AI major recommendations compare to advisors' and if these recommendations, personalized to student preferences, influence advisors' own recommendations. From an analytics perspective, the study contributes to AI-assisted advising research by evaluating the alignment between AI-generated and human advisor recommendations. Using a three-phase survey involving undeclared first- and second-year students ($n = 33$) and university advisors ($n = 25$), the study assesses the methodological implications of integrating AI-powered advising tools in higher education. From an interventions perspective, the advisors rated AI recommendations favourably, suggesting that they may be verging on readiness for students. The study also found that advisors were more likely to choose the same major to recommend when shown the AI recommendation first; however, this influence was not statistically significant. These findings offer valuable insights into the effectiveness of AI in academic decision-making processes, informing future advancements in AI-powered student support systems.

In "AI-Assisted Co-creation: Bridging Skill Gaps in Student-Generated Content," Pozdniakov and colleagues (2025) contribute to the **data**, **analytics**, and **interventions** phases by examining how GenAI can provide real-time feedback to support student content creation. From a data perspective, the study analyzes AI-generated feedback data from 1,063 student-created MCQs within a platform. By evaluating log data, student engagement patterns, and qualitative feedback, the research provides insights into how students interact with and use AI-generated feedback, contributing to a data-informed understanding of AI-enhanced content creation in education. From an analytics perspective, the study applies GenAI as a clustering approach to examine patterns in AI-generated feedback. By categorizing feedback structures across student-created resources using LLMs, the research advances AI-augmented LA methodologies for automated feedback evaluation. This methodological contribution helps refine AI-generated feedback mechanisms, ensuring that they remain pedagogically meaningful and contextually relevant, while using the emerging capabilities of LLMs in automated analysis. From an interventions perspective, the study explores how instant AI-generated feedback supports students in content creation and learning. Through a structured AI feedback mechanism—providing a summary, strengths, and improvement suggestions—AI interventions aim to bridge skill gaps, enhance content quality, and improve student engagement in educational resource development. The findings indicate that AI-generated feedback is largely well received by students, particularly for its clarity and positive tone, demonstrating its potential to facilitate higher-order learning and self-regulated knowledge creation. Despite challenges in ensuring AI feedback accuracy, the study highlights how AI-generated feedback enables students to make actionable improvements in their academic work.

In "Students' Perceptions of Generative AI–Powered Learning Analytics in the Feedback Process: A Feedback Literacy Perspective," F.J.-Y. Jin and colleagues (2025) contribute to both the **data** and **interventions** phases by examining how

GenAI-powered feedback systems support student engagement with feedback in higher education. From a data perspective, this study investigates how data generated from AI-enhanced feedback interactions can provide insights into student learning behaviours and engagement patterns. By triangulating thematic analysis with usage trace data, the study examines how students interact with ChatGPT explanation features and GenAI-powered dashboard visualizsations. Findings from 18 students across multiple disciplines reveal that while initial lab sessions indicated positive perceptions, in-semester engagement with GenAI feedback was limited, often due to misalignment between AI-generated feedback and student expectations. From an interventions perspective, the study explores how ChatGPT explanation features and GenAI-powered dashboards can enhance student engagement with feedback. The findings suggest that while some students found AI-generated feedback valuable for refining their understanding, others perceived it as redundant when existing feedback was clear and comprehensive.

In "Qualitative Coding with GPT-4: Where It Works Better," Liu and colleagues (2025) contribute to the **analytics** phase by investigating the application of GPT-4 as an automated tool for qualitative data analysis in education research. The study evaluates three different prompt-engineering strategies—zero-shot, few-shot, and few-shot with contextual information—along with the use of embeddings, to determine their effectiveness for qualitatively coding three distinct educational datasets. By comparing GPT-4's coding performance with human coders across Algebra I tutoring transcripts, student observations in a game-based learning environment, and debugging behaviours in an introductory programming course, the research explores how AI-empowered coding methods vary based on construct properties such as clarity, concreteness, objectivity, granularity, and specificity. The findings reveal that no single AI-based approach consistently outperforms others, and that GPT-4 struggles most with constructs that human coders also find difficult to achieve inter-rater reliability on. These insights contribute to the advancement of AI-based qualitative analysis methodologies, highlighting the potential of LLMs in LA research while emphasizing the need for construct-specific methodological choices. Such automated approaches can improve efficiency and augment researcher capabilities and workflows, and they have the potential to transfer across learning contexts that use qualitative analysis approaches.

In "Utilizing Multimodal Large Language Models for Video Analysis of Posture in Studying Collaborative Learning: A Case Study," Whitehead and colleagues (2025) contribute to the **analytics** phase by advancing MMLA methodologies. The study explores how multimodal large language models (MLLMs) can extract postural behaviour data from collaborative learning environments, addressing the methodological challenges of analyzing non-verbal communication in real-world educational settings. By applying GenAI for feature extraction, the study demonstrates how AI-powered techniques can enhance LA research by enabling deeper insights into student interaction and engagement patterns. Through a case study involving 52 pre-service teachers in a physics-based collaborative learning task, the authors illustrate the potential of MLLMs to refine data-informed approaches to studying collaborative learning dynamics.

4. Discussion and Future Directions

4.1 Re-examining the Boundaries of LA in the Era of GenAI

With the increasing interest of the LA community in GenAI, reflected in numerous GenAI-related submissions to both the *Journal of Learning Analytics* and the Learning Analytics and Knowledge conference, the effect of GenAI on the definition and scope of LA is becoming an increasingly frequent topic among editors of the aforementioned LA venues and the community at large. However, the question of LA's boundaries is not new—it has been the subject of discussions and debates in the community for a while (Baker et al., 2021; Mills et al., 2022; Ochoa et al., 2022). Baker and colleagues (2021) presented a systematic approach to this topic in the form of a conceptual framework for understanding the underlying paradigms and mutual relations of contemporary research fields that leverage learning-related data to study and advance learning and education. Specifically, starting from McKeon's (1966) interpretation of the four philosophical schools of thought (entitative, ontological, existentialist, and essentialist), Baker and colleagues analyzed and explained the sphere of focus and mutual relationships of the four closely related fields: LA, educational data mining (EDM), learning at scale (L@S), and quantitative ethnography (QE). They attributed the differences among these four fields primarily to the adopted approaches to the fundamental nature of science and the overall reality. For example, LA is characterized as primarily ontological/dialectical (i.e., aimed at understanding a phenomenon in its entirety), whereas EDM is considered to be primarily entitative/reductionist (i.e., focused on individual components of a phenomenon and their relationships). Even though Baker and colleagues acknowledged artificial intelligence in education (AIED) as a related research field, focused on student modelling and design of intelligent systems for education, they studied only EDM "as a splinter group off of AIED" (Baker et al., 2021, p. 3). However, as AI, and especially GenAI, technologies are becoming increasingly present in research and practice efforts that leverage data to study and advance learning, the tendency of these four fields—LA, EDM, L@S, and QE—to reduce their mutual differences as they evolve, as noted by Baker and colleagues (2021), is becoming even more prominent, as is their convergence toward AIED. A panel at the recently held 15th Learning Analytics and Knowledge conference (LAK25) moderated by two authors of the aforementioned paper (Baker et al., 2021), re-examined connections and boundaries between LA and its sister fields (EDM, L@S, and QE) in the era of GenAI, concluding that the focus should be not on differences and boundaries but on collaboration and synergies in finding the best ways to leverage GenAI and other advanced technologies for the benefits of learners, teachers, and other stakeholders in the education ecosystem. What specific topics need attention to expand the field of LA over the next decade were discussed in the grand challenges workshop at LAK25 (Kitto et al., 2025), and identifying guiding principles for LA came up as a critical challenge for the community.

As editors of this special section, we have also discussed the fit and relevance of submissions to the *Journal of Learning Analytics*, particularly on studies experimenting with new technologies and models for data analysis using GenAI. We share an opinion that a well-grounded research study can offer new methodological approaches for LA, as long as it is rigorously done and can demonstrate a roadmap for impact on learners and learning. Rigid boundaries can stagnate growth of the field, whereas allowing researchers' contributions to shape its direction can help LA adapt and evolve with the changing nature and speed of AI advancements. However, this expansion must be done with care to uphold the foundational principles that make LA trustworthy, such as transparency, consent, accountability, and ethical responsibility, which have been established by the LA community (Drachsler & Greller, 2016; Pardo & Siemens, 2014) to ensure that LA continues to serve learners and educators in meaningful and responsible ways, rather than reinforcing biases or limiting agency. Equally important for LA to be actionable is maintaining a human-centred design approach that ensures that educators and learners retain agency, integrates the learning design cycle with LA methodologies, and remains grounded in educational theories to inform its design and implementation (Dimitriadis et al., 2021). Embedding these commitments in the evolution of LA enables the field to leverage the benefits of GenAI while upholding pedagogical integrity, ethical responsibility, and human-driven decision-making.

4.2 Some Future Directions

Alignment to specific learning contexts and learning design (LD) has been part of LA interventions and should continue for GenAI contexts, so LA and LD can inform each other (Macfadyen et al., 2020), as well as balance generalizability for scale and contextualization for locally relevant LA solutions (Shibani et al., 2019). Similarly, tools and new techniques should be grounded in learning tasks and assessments for constructive alignment and maximum impact of AI-enhanced LA in classrooms (Reza et al., 2025; Knight et al., 2020, 2014). Indeed, the measurement and evaluation of its impact and effects on learning are a crucial piece of the puzzle for ongoing work at the intersection of LA and GenAI. How we measure learning improvements and effects needs careful consideration because student traits and mental states are observed as latent variables (Bergner, 2017), and defining proxies to move "from clicks to constructs" opens up risks of distorting the definition of learning to what is computationally achievable, needing more principled alignment using LA (Knight & Buckingham Shum, 2017). These become particularly important when GenAI is in the mix, as the increased productivity gains in specific tasks could be offset by the delegation of cognitive processes to the machine and long-term unintended consequences such as meta-cognitive laziness among learners (Fan et al., 2025). Advanced GenAI tools such as ChatGPT are becoming easily accessible, allowing students to access them externally, without teachers' awareness and ability to intervene. The LA community can build on new forms of data collection to capture AI use in natural environments and avoid over-reliance on trackable data in online platforms or classroom settings to study the full effects of AI in education in a meaningful way. An example might be the use of students' self-reflection diaries, which when studied over time can reveal longitudinal use patterns and capture the diversity of individual learners through person-centric and person-specific analysis (Saqr et al., 2024).

Learners need to develop new skills and competencies (Kovanovic et al., 2024), such as AI literacy, critical engagement, and agency, so they do not over-rely on GenAI support, as such over-reliance can undermine their intellectual abilities and agency in the long term (Darvishi et al., 2024; Fan et al., 2025). We recognize the need for more longitudinal studies at the intersection of LA and GenAI that can uncover these limitations, while maximizing the potential of AI as a learning aid. Approaches to study whether learners are critically interacting with GenAI are also emerging (Shibani et al., 2024), building on natural language processing methods to study written texts, student prompts to GenAI tools, and their process-level interactions (Yang et al., 2025; Shibani et al., 2023). LA can offer scaffolds and feedback through analytics on human-AI interaction for learners to self-regulate their use of AI, an area where work is emerging using writing analytics (Shibani et al., 2025; Yang et al., 2025) and trace log analysis (Li et al., 2025). GenAI's conversational abilities can help deliver these scaffolds to learners in a personalized way, as demonstrated by recent work enabling interaction with LA dashboards (Y. Jin et al., 2025) and learners' SRL processes (Li et al., 2025).

In addition to the above, we identify several additional areas as future directions for LA and GenAI, informed by prior work in LA. These include human-centred LA for GenAI, which actively involves educators and learners in the participatory design of tools (Buckingham Shum et al., 2019); privacy-preserving LA that empowers students with greater autonomy over their data (Zhan et al., 2024); and the integration of ethics by design, ensuring that AI-driven LA upholds principles of equity (Uttamchandani & Quick, 2022). A key challenge in this regard is fostering GenAI access and literacy without exacerbating the digital divide (Zipf et al., 2025). Additionally, assessment analytics are critical for rethinking assessment in the age of AI (Swiecki et al., 2022). This involves developing analytics that go beyond evaluating final products to provide deeper insights into students' cognitive processes, engagement patterns, and interactions with AI-assisted tools, ensuring that assessments remain meaningful, equitable, and aligned with evolving educational needs.

5. Conclusion

In this JLA special section on GenAI and LA, we see researchers' ongoing efforts to map affordances and expand the horizons of the intersections of these fields. While Lai and colleagues (2025) used GenAI as a chatbot, the rest of the contributions established that the topic of GenAI in LA goes beyond students using a canonical ChatGPT or similar interface in a learning context. Instead, throughout all phases of the LA cycle (Clow, 2012), we observe GenAI posed as a human collaborator (Ochoa et al., 2025; Lekan & Pardos, 2025; Pozdniakov et al., 2025) and as an increasingly useful tool as part of LA research methodologies (Henkel et al., 2025; F. J.-Y. Jin et al., 2025; Liu et al., 2025; Whitehead et al., 2025; Hadas & Hershkovitz, 2025). In this sense, GenAI is not strictly a type of intervention, but rather it is a cross-cutting technology being evaluated for its ability to enhance the way LA research is conducted. Whether these enhancements serve only an efficiency goal or eventually lead to greater student learning (Gašević et al., 2015) and agency is subject to future research and careful alignment with study aims.

While we fully recognize the need for evolution and change in the LA field, we also hope that LA will stay true to its objective of providing evidence-based explanations and support of teaching and learning processes, while leveraging GenAI to advance its methods and techniques as well as its means of keeping relevant stakeholders in the loop (Clow, 2012). We hope that the papers in this special section together with the additional future directions outlined above can help steer the LA community toward fulfilling its aim of understanding and optimizing learning by putting the learner at the centre, rather than being driven by emerging technological innovations such as GenAI. These core principles, along with those related to ethical and privacy-preserving conduct, should continue to guide LA while pushing new boundaries for the field to respond to the emerging opportunities and challenges that GenAI brings.

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