Technologies and Educational Resources of the Future: Generative AI and Learning Analytics in the Classroom and Beyond

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Abstract

Learning analytics has become an increasingly prominent part of 21st-century educational research and practice. In this article, I will discuss some of the key applications of learning analytics, as well as emerging opportunities to use learning analytics to understand and support learning, engagement, and long-term life success. I will also discuss how recent developments in generative artificial intelligence are impacting learning analytics methods and uses. At the same time, I will discuss the new challenges brought by the growing use of generative AI, and the new opportunities to influence both research and practice.

Introduction: A New Era for Educational Technology

For decades, educational technology has promised to revolutionize learning (Cuban, 1986). To many, generative AI appears to mark a new inflection point in how instruction, assessment, and learning support can be done. As with earlier waves of innovation in educational technology, however, the promise lies in both understanding learning as it occurs and acting on that understanding to improve outcomes (Baker & Siemens, 2022).

There has been a lengthy history of the use of artificial intelligence technologies in education (Doroudi, 2023), dating back to the first intelligent tutoring system in 1970 (Carbonell, 1970) and arguably to some of the teaching machines research earlier (see discussion in Benjamin, 1988). More recently, large language models (LLMs) have rapidly become prominent in formal educational contexts, ranging from student-initiated use of tools like ChatGPT to specialized learning systems that integrate LLMs, perhaps most notably Khanmigo (Yamkovenko, 2025).

In the previous two decades, educational data mining (EDM) and learning analytics (LA) emerged to interpret rich log data from intelligent tutoring systems and other digital learning platforms, and make use of it to better personalize learning and support learners (Baker & Siemens, 2022). So too, GenAI is creating new pathways for representing and processing educational data, and using that information to better respond to and support learners, as well as greatly speeding the process of creating new educational content. The intersection of LA, EDM, and GenAI is rapidly shaping the future trajectory of learning and educational research.

Learning Analytics: Foundations and Frontiers

Generative AI does not emerge into an educational vacuum. Research and practice communities such as EDM, LAK (learning analytics and knowledge), and AIED (artificial intelligence and education) have already achieved a considerable amount by combining AI methods and educational data to improve understanding and support of learning. Applications have ranged from predicting dropout to modeling affect and engagement, employing a wide range of methods, including prediction models, structure discovery, and relationship mining (Baker & Siemens, 2022).

Representative applications include:

- **Knowledge Tracing:** A wide range of intelligent tutoring systems detect whether a student knows a skill, in tasks ranging from mathematics (Corbett & Anderson, 1995) to language learning (Settles & Meeder, 2016)
- **Dropout prediction**: Systems such as Civitas identify students at risk of disengagement or withdrawal and support early intervention, leading to better student success outcomes in both K-12 (Coleman et al., 2019) and higher education (Milliron et al., 2014).
- **Engagement and emotion modeling**: Learner states such as boredom and frustration, and disengaged behaviors such as gaming the system and carelessness can be inferred from interaction logs (Paquette & Baker, 2019; de Morais et al. 2023). In turn, learning systems can respond in ways that improve both engagement and learning (D'Mello et al., 2010; Xia et al., 2020).
- **Meta-cognitive modeling**: Identification and creation of models of behaviors related to help-seeking (Aleven et al., 2006), planning and self-monitoring (Cheng et al., 2025), persistence (Kai et al., 2018), and use of class time (Gurung et al., 2025), and use of these models to support student self-regulation of their learning (Viberg et al., 2020).

Many of these constructs can be modeled with reasonable accuracy using log data alone. While sensor-based approaches can improve detection quality (Bosch et al., 2016), interaction data often provide sufficient resolution for practical application.

Generative AI offers new opportunities to improve detection of constructs such as self-regulated learning and engagement from textual data. For example, Liu and colleagues (2025) used GPT to identify a range of strategic behaviors and disengaged behaviors in students' collaborative observations while participating in astronomy learning activities within Minecraft, Zhang and colleagues (2024) used GPT to identify self-regulated learning strategies within student think-aloud data, and Misiejuk and colleagues (2024) used GPT to identify engagement and conversational strategies within group learning. These applications show how the use of generative AI is emerging from primarily computer-based learning activities to learning activities taking place more in the outside world, such as collaborative learning and classroom discourse.

GenAI Shifts the Data Itself

Generative AI now functions not only as a tool for detecting aspects of a learner's behavior and experience, but actually changes the data itself. The most obvious way this happens is when learning environments are built around generative AI, using generative AI to create text-based learning experiences such as chatbots (Levonian & Henkel, 2024; Yamkovenko, 2025), discussion forum partners (Baker et al., in press), or sources of feedback (Pankiewicz & Baker, 2023; Koutcheme et al., 2024; Phung et al., 2024). The ways that students interact with generative AI may differ meaningfully from previous generations of learning technologies, in ways that we may not even be fully aware of yet.

Even beyond this, the presence and existence of generative AI may influence and impact student experience and interaction within learning environments that do not use generative AI at all. Students are increasingly using GenAI tools such as ChatGPT for drafting essays, debugging code, exploring concepts, getting explanations, obtaining the answers to exercises, and conceptual exploration (Abdeljaleel et al., 2024). If a correct student submission may have been generated by a model rather than the student, then the interpretation of performance signals becomes more uncertain. Established models developed with human-generated data may behave inconsistently in such settings. If students use ChatGPT inconsistently, they may appear to frequently guess or make slips (Corbett & Anderson, 1995) to an existing model inferring student knowledge. If students use ChatGPT constantly, then it will be ChatGPT's knowledge and problem-solving skill that are evaluated. While the detection of the use of ChatGPT remains imperfect (Dik et al., 2025), inference about whether a model is evaluating a human, an LLM, or a human and LLM working together may become increasingly essential for automated assessment models. In time, even human-human learning and classroom learning will be influenced heavily by generative AI, as teachers use LLMs to create course resources, and LLM coaches advise students in real time.

Nonetheless, GenAI also creates the potential to create new contexts that can facilitate assessing aspects of the student that were previously difficult to assess, by creating new interactions. This is especially salient in conversational assessment, an area where automation has previously proven difficult to scale.

Facilitating Assessment with Generative AI

Conversational assessment—dialogue-based interactions where student reasoning is elicited and evaluated—has long been posited as a rich source of evidence for learning (McKnight et al., 2023). However, while specific success cases had been developed with high effort (McKnight et al., 2023), and some simplified approaches were developed to improve scalability (Hu et al., 2009), broader utilization was long constrained by resource limitations. GenAI offers a means to sustain adaptive and context-sensitive dialogue for both assessment and learning at scale. In recent years, conversational assessments based on GenAI have been used to assess learners in domains ranging from medicine (Johri et al., 2023) to artificial intelligence (Bergerhoff et al., 2024).

Generative AI has also been used to facilitate assessment in non-conversational contexts – for instance, on assignment drafts. For example, JeepyTA, a GPT-based virtual teaching assistant, has been used to provide rapid formative feedback on student assignments based on past semesters' feedback, supporting students in understanding the limitations of their project work relative to the instructor's criteria, and leading to better final work (Baker et al., in press). Another example, RunCode, delivers immediate feedback on programming exercises in introductory computer science (Pankiewicz & Baker, 2023). In two randomized controlled trials, students who received RunCode's GenAI feedback showed performance improvements both while they were receiving feedback and later, even after the GenAI feedback had been turned off. This indicates that the feedback was not simply a scaffold—learners actually learned from it across use.

Equity Considerations

The integration of GenAI into educational practice introduces questions related to equity. On the one hand, generative AI has rapidly become available to learners worldwide, with free ChatGPT accounts and access to LLM Chatbots (such as Meta AI) becoming available even through WhatsApp and to learners with highly limited bandwidth. In addition, high-quality learning environments based on generative AI have become widely available to learners in the Global South (Levonian & Henkel, 2024; Sun et al., 2024). These trends suggest that GenAI may help to level the playing field educationally, creating greater opportunities for historically underserved populations of learners. On the other hand, wealthier schools may have more resources to integrate generative AI into curricula thoughtfully and more bandwidth for heavier usage of multimodal LLMs and multimodal learning analytics. The first prototypes of what can be done with truly multimodal learning support for learners and teachers (Martinez-Maldonado et al., 2013; Holstein et al., 2018) are highly impressive and well beyond what might be possible in less well-resourced contexts. Similarly, full integration of GenAI into a broad range of classroom and learning activities will involve costs that are likely infeasible for less well-resourced schools and families.

These challenges and opportunities mirror previous challenges and opportunities coming from the prior generation of learning analytics and the learning systems it enabled; they were highly beneficial for historically underserved students (Koedinger et al., 1997), and helped to close gaps between historically better-served and underserved learners (Craig et al., 2013), but also were less used in the Global South than in wealthier contexts, despite some successful projects explicitly serving underserved and Global South learners at scale (cf. Rajendran & Muralidharan, 2013; Levonian & Henkel, 2024; Sun et al., 2024).

Unlike this previous generation of educational technology—more tightly designed and verified by humans—much of the use of generative AI in education today is being implemented directly by teachers or even by students themselves. Therefore, another question is whether the rapid move to incorporate generative AI may actually produce negative consequences for students. Not all generative AI-based systems will be designed thoughtfully and with pedagogical concerns in mind (and general-purpose chatbots certainly aren't designed with this in mind). The use of less well-designed systems, that may give students the answer at inappropriate times or support them too much, creates the risk of students becoming overly reliant on GenAI, which may inhibit the development of deep understanding or independent problem-solving. Heavily scaffolded short-level performance may in some cases come at the cost of fundamental understanding that supports future learning and successful work. There are thus many pedagogical concerns and challenges as generative AI becomes an increasingly prominent part of education.

Conclusion: The Potential of GenAI in Educational Contexts

The integration of generative AI into educational contexts represents a significant evolution in the landscape of education, an advance on the previous generation of artificial intelligence in education. Earlier applications of learning analytics and educational data mining focused on modeling student knowledge, behavior, and engagement from interaction data, and using this to improve the quality of learning support. Generative AI brings this forward in many ways—improving the quality of detection, broadening the scope of what can be detected, and creating new and richer contexts for assessment and learning. Generative AI is expanding both the types of data available and the methods through which educational inference and support can occur. The advent of new learning tools not only enables (or at least facilitates) novel forms of detection, such as analyzing open-ended student discourse or behavior in less structured environments, but also reshapes the very nature of student data by altering how learners approach tasks and creating new forms of human-AI communication that may differ from previous interactions (both human-human and human-computer). This dual role—as both analytical tool and active participant—complicates traditional approaches to interpreting learning, raising new questions about model validity and the attribution of observed performance.

At the same time, the widespread availability and flexible utility of generative AI introduce both opportunities and concerns in terms of educational equity and pedagogy. While GenAI may increase access to high-quality educational tools globally, it also risks deepening divides where resources for design, integration, and infrastructure are limited. Furthermore, as the use of generative AI in classrooms grows—sometimes led by students and teachers independently of formal curriculum design—it becomes essential to consider its implications for learner autonomy, over-reliance, and the development of enduring understanding. As generative AI continues to influence both the data collected and the environments in which students learn, the fields of learning analytics and educational technology must adapt their methods, frameworks, and assumptions to remain effective and relevant. At the same time, the opportunities to benefit students and teachers are impressive. Generative AI is on track to become an important part of education, and the time is now to figure out how to best integrate it with what has been learned in learning analytics and educational data mining over the last 15-20 years. By doing so, we increase the chance that it can fully achieve its potential as a technology to transform education in positive ways.

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