Curriculum and Teaching Methodology (2026)
Clausius Scientific Press, Canada

DOI: 10.23977/curtm.2026.090306
ISSN 2616-2261 Vol. 9 Num. 3

Instructional Design-Driven Generative Learning Analytics: A New Field under the "AI + Education" Initiative

Hongchang Li

The High School of Guiyang Affiliated to Beijing Normal University, Guiyang, Guizhou, China

Keywords: "AI + Education," generative learning analytics, instructional design-driven, human–AI collaborative assessment, data-driven instruction

Abstract: Generative learning analytics (GLA) is an emerging paradigm that embeds generative artificial intelligence into learning analytics, aiming to move from mere description toward actionable intervention. Instructional Design-Driven Generative Learning Analytics (IDD-GLA) refers to a systematic practice in which teachers, guided by instructional design, predefine the problem framework, data dimensions, and intervention strategies for learning analytics, and then rely on generative AI to interpret data, generate reports, and recommend pedagogical actions. This approach organically links analytics with instruction. IDD-GLA consists of five phases: diagnosing instructional problems, designing the analytical framework, AI-supported data interpretation, generating intervention strategies, and instructional reflection with iteration. The paper illustrates the value of this model through three typical application scenarios—personalized learning pathways, critical thinking cultivation, and data-informed teacher research—so as to offer a practical reference for researchers and practitioners.

1. Introduction

China's Ministry of Education, alongside eight other central departments, released *the Guiding Opinions on Accelerating AI-Empowered High-Quality Development of Education* in April 2025, calling for a deeper fusion of artificial intelligence with teaching, learning, management, evaluation, and research [1]. By December 2025, the Ministry had also launched the National Education Digitalization Strategy Initiative 2.0, with intelligence as a central pillar. These policy signals indicate that AI is no longer just a supplementary tool; it is becoming part of the basic infrastructure of schooling. At the same time, learning analytics—the systematic collection, measurement, and reporting of data about learners—has gained traction as a way to make instructional decisions more evidence-based. Yet traditional learning analytics remains largely descriptive and predictive. Dashboards and early-warning systems can flag at-risk students, but they rarely tell teachers what to do next [2]. The emergence of generative artificial intelligence (GenAI) offers a way out of this impasse. GenAI models can process unstructured learner artifacts, produce natural-language explanations, and generate context-sensitive suggestions for intervention [3]. Still, the use of GenAI-enhanced learning analytics in schools is scattered and experimental, partly because teachers lack a clear framework for connecting analytical outputs with their own instructional designs. This problem is becoming more urgent as AI enters more classrooms and as data-informed teaching becomes an expected professional competence. We therefore need a theoretically grounded, practically workable model that lets teachers, rather than algorithms, drive the analytics process. This paper proposes such a model—Instructional Design-Driven Generative Learning Analytics (IDD-GLA)—and illustrates its application through concrete teaching scenarios.

2. Literature Review

Learning analytics has grown into a recognizable field since the first International conference on Learning Analytics and Knowledge in 2011. Early work focused heavily on predictive models, dropout alerts, and dashboards that visualized online behavior [2]. Scholars stressed that analytics should not stop at displaying data but should feed directly into pedagogical decisions. However, the step from insight to action has always been difficult; teachers presented with a risk report often lack the contextual knowledge to turn it into a concrete teaching move [4]. In parallel, learning design was promoted as a necessary complement, with researchers arguing that analytics only become meaningful when the upfront instructional plan clarifies what is to be measured and why [5]. Integration of the two remained largely conceptual and technically demanding.

Generative AI changes this dynamic considerably. Large language models, unlike earlier machine learning tools, can work with natural language and can interpret essays, discussion transcripts, and reflective writing, producing coherent pedagogical recommendations in return [3]. The term “generative learning analytics” has recently appeared in the literature to describe this infusion of GenAI into analytics pipelines. A 2025 systematic review documents how applications expanded from simple content generation to more complex tasks—such as learner modeling, automated feedback, and adaptive intervention—between 2018 and 2024[6]. In teacher education, the well-known TPACK framework is being extended to an “AI-TPACK” version that captures the knowledge teachers need to integrate AI tools into specific subject areas [7]. Empirical work further shows that theory-driven learning analytics dashboards can strengthen human–AI collaboration in writing classes, enhancing self-regulated learning and performance [8]. Chinese scholars, for their part, have examined how generative AI can reshape evaluation, support personalized learning pathways, and build teachers’ data literacy [9]. Research on feedback has also demonstrated that AI-powered learning analytics can substantially improve students’ feedback literacy, helping them make sense of and act on AI-generated diagnostics [10]. Taken together, these studies confirm that combining GenAI with learning analytics is both feasible and valuable. Yet a coherent framework that positions the teacher, rather than the algorithm, at the center of the design process is still missing. That gap motivates the present study.

3. A New Field under the “AI + Education” Initiative: Generative Learning Analytics

Generative learning analytics is already reshaping education in at least four respects.

First, teachers’ instructional decision-making is shifting. Instead of relying solely on intuition and experience, teachers can now use AI-driven analysis of process data to build a sharper picture of students’ cognitive states, knowledge gaps, and preferred learning strategies. Zhejiang Province’s 2025 *Framework for AI Literacy of Primary and Secondary School Teachers (Trial)* formally recognizes data-driven decision-making as a component of teachers’ professional competence.

Second, the nature of student feedback is changing. Rather than receiving only a score or a grade, learners can obtain AI-generated diagnostic reports that include personalized suggestions. Studies suggest that GenAI’s interpretative capabilities and dashboard visualizations strengthen students’ feedback literacy, enabling them to understand evaluations more deeply and act on them [10].

Third, the evaluation paradigm is moving from outcome-focused assessment toward process-oriented insight. AI can track students' cognitive trajectories, collaborative patterns, and strategic choices during complex tasks, making previously invisible learning processes visible.

Fourth, classroom relationships are being restructured. Human–AI collaborative evaluation positions the teacher as a designer of learning and an interpreter of higher-order thinking, while the AI functions as an assessment agent that handles routine analysis and initial feedback. The central challenge here is to create a shared "ruler"—a structured, computable rubric that embodies expert judgment in a form that both humans and machines can use [3].

4. From Generative Learning Analytics to Instructional Design-Driven Generative Learning Analytics

Despite its promise, GLA does not always work well in practice. Teachers frequently report that AI-generated reports, while rich in data and visually polished, feel detached from the current teaching rhythm or fail to address the questions that matter most. The core difficulty is that standard analytics tools follow a "data-first" logic—collect large volumes of data, mine patterns, and present findings—whereas teachers operate with a "problem-first" logic: they start with a specific instructional question and then determine what data, analyses, and interventions are needed.

Instructional Design-Driven Generative Learning Analytics (IDD-GLA) is proposed as a way to bridge this gap. It is an approach in which teachers, guided by a systematic instructional design, pre-plan the problem framework, data dimensions, and intervention strategies, and then leverage GenAI for data interpretation, report generation, and instructional recommendations. Three principles underpin this model.

(1) The instructional design architecture comes first. The teacher's overall plan—diagnosis of problems, learning objectives, assessment criteria, and intervention logic—must be in place before any data are collected or analyzed. This ensures that analytics serve a clear purpose rather than becoming an end in themselves. Such a view aligns with the long-standing position that instructional design is the blueprint for teaching, translating learning theories into concrete objectives, methods, and evaluation plans.

(2) Human–AI collaboration is complementary. IDD-GLA adopts a "human-in-the-loop" arrangement: the teacher acts as instructional designer and decision-maker; the AI serves as data interpreter and report generator. The teacher's role during the design phase is to diagnose problems, structure the analytical framework, and pre-plan interventions, while the AI, during execution, aggregates data, recognizes patterns, and produces natural-language reports. This division makes optimal use of human judgment and machine computation.

(3) Analysis directly feeds action. The ultimate aim of IDD-GLA is to shorten the distance between analytical results and teaching decisions. GenAI turns data into instructional suggestions, personalized plans, or immediate feedback, creating a tight feedback loop between evaluation and strategy adjustment.

IDD-GLA is operationalized through five phases—Diagnosing Instructional Problems (Seek), Designing the Analytical Framework (Design), Collecting Data and Facilitating AI-Powered Interpretation (Analyze), Generating Intervention Strategies (Generate), and Engaging in Instructional Reflection and Iteration (Iterate)—abbreviated as the S-DAGI model (see Figure 1).

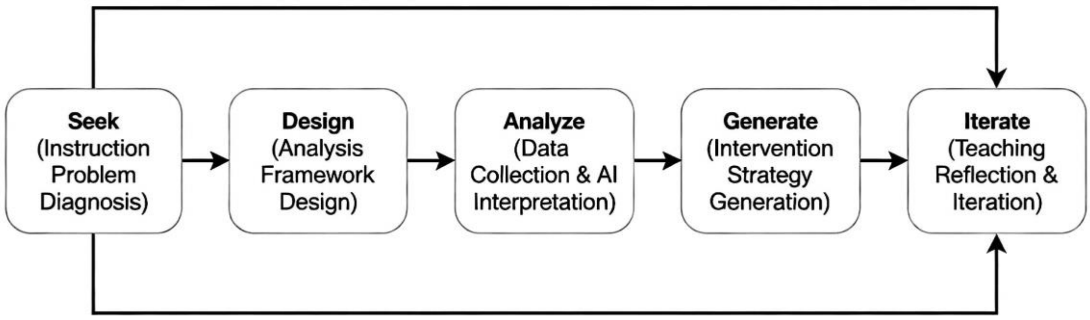

Figure 1 The S-DAGI Model of Instructional Design-Driven Generative Learning Analytics

Phase 1: Diagnosing instructional problems. The process begins with a pedagogical question, not a technology. The teacher analyzes the learning situation, identifies the main difficulties of the unit, and pinpoints the typical obstacles students face. For instance, a high school Chinese language teacher might notice that many students produce "broken chains of reasoning" in argumentative essays, but the break occurs at different points for different students—some in evidence selection, others in logical inference, still others in drawing conclusions.

Phase 2: Designing the analytical framework. Drawing on the diagnosis, the teacher constructs a systematic framework. This includes selecting data types, designing rubrics, and setting the dimensions that the AI will later use for interpretation. For the argumentative writing example, the teacher could build on Toulmin's model of argument, examining six elements—claim, grounds, warrant, backing, qualifier, and rebuttal—and turn them into a structured analytical roadmap for the AI.

Phase 3: Collecting data and AI-powered interpretation. As students work, the system gathers logs, texts, and peer review records. Guided by the pre-designed framework, the AI not only produces descriptive statistics but also generates qualitative reports with pedagogical explanations and action suggestions [6].

Phase 4: Generating intervention strategies. On the basis of the pre-planned intervention logic, the AI automatically produces differentiated suggestions—whole-class teaching adjustments, tiered small-group tasks, or individualized learning pathways. Empirical work confirms that theory-driven dashboards can enhance human–AI collaboration and improve self-regulated learning and performance [8].

Phase 5: Instructional reflection and iteration. The teacher implements the AI-generated suggestions, observes student responses, collects new data, evaluates the effect, and launches another improvement cycle. IDD-GLA is thus a continuous process, not a one-off technical operation.

5. Application Scenarios of Generative Learning Analytics in Teaching

IDD-GLA can be applied in a variety of teaching situations. Three illustrative scenarios are outlined below.

Scenario 1: Personalized learning pathway planning. In a secondary school mathematics unit on functions and derivatives, a teaching research group could use IDD-GLA to diagnose students' conceptual states. Through pre-tests and classroom observation, teachers identify three broad profiles: those who can recite definitions but struggle with application, those who can solve problems mechanically yet lack deep understanding, and those who can flexibly combine multiple methods. They then design an analytical framework with three dimensions—knowledge mastery, strategy preference, and error patterns. Students work on an intelligent platform that captures response data and problem-solving steps. GenAI generates a learning portrait for each student and recommends a subsequent pathway.

Scenario 2: Cultivating critical thinking. Critical thinking is inherently difficult to assess because it is implicit, multidimensional, and context-bound. A teaching team in an ideological and political education course could apply IDD-GLA to build a critical-thinking training and analysis system. At the design stage, they develop structured rubrics and indicators for each of the six dimensions identified in the Delphi Report—interpretation, analysis, evaluation, inference, explanation, and self-regulation. The system then collects students' writing on current affairs and transcripts of classroom debates. AI analyzes the depth, breadth, and logical coherence of the arguments, produces visual thinking maps, and suggests targeted exercises. In this way, teachers gain a systematic overview of the class's critical thinking development and students become aware of their own weak spots.

Scenario 3: Data-informed teacher research and decision-making. GLA also supports teachers' professional growth. In collective lesson planning, teacher teams can use IDD-GLA to move beyond vague discussions of "what students don't understand" and focus instead on specific types of cognitive difficulty, typical error patterns, and their pedagogical causes. For example, a primary mathematics group could compare "fraction operations" data across six classes, discover that different classes struggle with different aspects of the same topic, and then design differentiated remediation plans. This shifts collective lesson planning from experience exchange to evidence-based decision-making [11].

6. Enhancing Teachers' Capacity for IDD-GLA

Teachers are at the heart of educational change, and IDD-GLA places new demands on their professional competence. As the TPACK framework evolves toward an AI-TPACK paradigm, teachers must learn to weave AI tools into subject-specific pedagogy [7]. Three areas of capacity-building deserve attention.

First, building analytical thinking and reducing data anxiety. Some teachers assume that learning analytics requires a background in data science, but IDD-GLA is not about turning teachers into data analysts; it is about using instructional design to steer data analysis. Hands-on workshops that take teachers from "I have a pedagogical problem" to "I have a usable analytical report" can build both confidence and methodological awareness.

Second, progressing gradually through the S-DAGI phases. Teachers need to move gradually from diagnosing problems to designing frameworks, guiding data interpretation, crafting interventions, and reflecting on outcomes. One can think of three levels: at the introductory level, teachers use AI to interpret existing data and generate reports; at the proficient level, they run the full cycle from diagnosis to intervention; at the expert level, they adjust strategies flexibly across different contexts and compare data across classes and grades.

Third, deepening integrated literacy. Effective IDD-GLA demands the simultaneous application of content knowledge, pedagogical knowledge, and technological knowledge. Teachers' subject-matter expertise determines their ability to pinpoint problems and design appropriate analytical dimensions; their grasp of instructional design shapes the quality of frameworks and interventions; and their understanding of GenAI tools affects the technical quality of implementation. The core of developing teachers' learning analytics competence is therefore not technical skill alone, but the flexible integration of AI literacy with subject and pedagogical knowledge in real classroom settings [12].

7. Conclusion

This study set out to address the persistent gap between data-driven insight and instructional action in learning analytics. Using theoretical analysis and scenario illustration, it proposes the IDD-GLA model and its S-DAGI operational framework, which structures the analytics process into five linked phases. The three application scenarios—personalized pathways, critical thinking, and data-informed teacher research—show that IDD-GLA enables teachers to act as instructional architects who steer generative AI toward pedagogically meaningful outputs. Three directions for capacity building were also identified: fostering analytical thinking, following a phased progression, and blending content, pedagogical, and technological knowledge.

The findings suggest that IDD-GLA can serve as a practical bridge between the affordances of GenAI and the realities of classroom work, nudging the "AI + Education" agenda from a technology-driven to a pedagogy-centered orientation. As GLA becomes more common, an important question remains: when AI can automatically handle data analysis and report generation, do teachers still need a solid grounding in data literacy? We argue that the answer lies not in the ability to compute but in the capacity to ask the right questions and to judge the educational significance of the answers. Teachers need to grasp basic principles—how data are collected, what analytic logics are at play, what biases may arise—so that they can communicate effectively with intelligent systems and exercise sound professional judgment.

Looking back, Thorndike once made invisible learning outcomes visible through psychometric measurement. Today, IDD-GLA makes visible the previously hidden logic of teachers' instructional decision-making. Future research should test the S-DAGI model empirically in varied subject areas and grade levels, and track its long-term impact on both teacher development and student learning.

Acknowledgements

The author is grateful to the anonymous reviewers and the editorial board for their careful reading and constructive suggestions, which have notably strengthened the manuscript.

References

[1] Yang, X.M., Zeng, J.Y., & Li, X. (2025). Refined scenarios and practical paths for the deep integration of artificial intelligence and education: An exploratory multi-case analysis. Open Education Research, 31(1), 82-92.

[2] Gu, X.Q., Liu, Y., & Hu, Y.L. (2017). The application of learning analytics technology: Seeking data-supported solutions for learning improvement. Open Education Research, 23(2), 104-112.

[3] Zhu, Z.T., & Hu, J. (2024). Internal logic and practical paths of generative artificial intelligence empowering evidence-based teaching. e-Education Research, 45(5), 32-39.

[4] Lockyer, L., Heathcote, E., and Dawson, S. (2013) Informing Pedagogical Action: Aligning Learning Analytics with Learning Design. American Behavioral Scientist, 57(10), 1439-1459.

[5] Gu, X.Q., Du, H., Peng, H.C., & Zhu, Z.T. (2021). Theoretical framework, practical paths, development context and future prospect of smart education. Journal of East China Normal University (Educational Sciences), 39(8), 1-18.

[6] Bozkurt, A., Xiao, J., Lambert, S., et al. (2025) Machine Learning and Generative AI in Learning Analytics for Higher Education: A Systematic Review of Models, Trends, and Challenges. Applied Sciences, 15(15), 8679.

[7] Scherer, R., Siddiq, F., & Tondeur, J. (2023). Preparing teachers for artificial intelligence: Validating an AI-TPACK scale for preservice educators. Teaching and Teacher Education, 144, 104368.

[8] Lim, L., & Gasevic, D. (2020). Learning analytics dashboards for writing: How visualisation supports students' self-regulated academic writing. The Internet and Higher Education, 56, 100761.

[9] Zhang, Y., Yang, Z.H., & Qin, F. (2025). Risk research, attribution analysis and ecological governance of artificial intelligence empowering educational transformation. e-Education Research, 46(7), 22-29.

[10] Ng, S., & Carless, D. (2024). Student engagement with AI-generated analytic feedback: A feedback literacy lens on generative learning analytics. Assessment & Evaluation in Higher Education, 49(8), 1124-1140.

[11] Mandinach, E.B., and Gummer, E.S. (2016) What Does It Mean for Teachers to Be Data Literate: Laying Out the Skills, Knowledge, and Dispositions. Teaching and Teacher Education, 60, 366-376.

[12] Celik, I. (2023) Towards Intelligent-TPACK: An Empirical Study on Teachers' Professional Knowledge to Ethically Integrate Artificial Intelligence (AI)-Based Tools into Education. Computers in Human Behavior, 138, 107468.