Learning Analytics for GenAI Augmented Collaborative and Dialogic Educational Approaches: A Generativity Theory Perspective*

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Abstract

Generative AI (GenAI) is increasingly used to support collaborative, discursive, and dialogic pedagogy. We explore ways to use learning analytics (LA) to make these hybrid human-GenAI practices visible and actionable. Borrowing from management and information systems research, we use a generativity theory perspective and treat GenAI-augmented classrooms as generative socio-technical systems. Using Thomas and Tee's seven components (architecture, community, governance, fit, combinatorial innovation, outcomes, feedback) to define categories of learning analytics, we demonstrate how generativity-informed LA can help distinguish generative from degenerative patterns of human-GenAI collaboration.

Keywords

Generative AI, learning analytics, generativity theory [1]

1. GenAI in Collaborative and Dialogic Pedagogy

Generative AI (GenAI) is increasingly applied to empower collaborative, discursive, and dialogic educational approaches. Wegerif and Casebourne [1] provide a dialogic theoretical foundation for integrating generative AI into pedagogical design, with a goal of promoting dialogic interactions that enhance learning experiences. This approach aligns with the broader trend of using AI as a collaborative partner in education, as discussed in various recent studies [2], [3], [4], [5]. These collaborative and dialogic educational approaches are especially useful for engaging learners as active participants who consume, as well as produce, knowledge. Although such approaches are not new – Socratic dialogues being a classic example – the conversational affordances of GenAI [6] make it an unusually good fit for them, enabling learners to co-construct knowledge with both human and non-human partners.

This trend raises a double challenge. Pedagogically, we need theories and designs that treat GenAI not only as a tool but as a partner in learning. Analytically, we need learning analytics (LA) that can make such hybrid human-GenAI educational activities analyzable. Given both the opportunities and risks of integrating GenAI deep in the educational process, we propose developing LA that help educators design and lead innovative human-GenAI learning environments. To achieve this goal, this extended abstract proposes a conceptual framework that connects dialogic GenAI pedagogy, generativity theory, and learning analytics to propose an approach for developing learning analytics that can support the design, monitoring and improvement of educational human-GenAI collaboration.

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2. Collaborative Learning with GenAI

As argued by Wegerif and Casebourne [1], the use of GenAI in education requires us to reconsider not only how we teach and learn, but what education is for. They propose a double dialogic pedagogy: education is both teaching thinking through dialogue, and inducting learners into the long-term, powerful dialogues of culture. GenAI, in this view, is not simply a source of answers but a new kind of participant in the educational process that can both expand or constrict the dialogic space in which thinking develops. This commonly accepted view that GenAI's integration into processes (educational, as well as other) can both promote better outcomes, as well as hinder the entire process is nicely illustrated by Wegerif and Casebourne proposal to treat GenAI as a *pharmakon*: a technology that can be both generative and degenerative. On the one hand, GenAI can widen access to voices, perspectives and ideas that would otherwise be unattainable, thereby contributing to collective intelligence. On the other hand, it can weaken the quality of the educational process by negatively impacting the cognitive and emotional processes that promote learning and creativity. Our task is thus to design learning environments that steer toward generativity and away from degenerativity.

From a learning analytics perspective, this challenge implies that we should care about how we configure the patterns of human-human and human-GenAI interactions in these learning environments in ways that support learners, and foster the kinds of high-quality dialogue and collaboration that increase the educational impact of these novel approaches. Yet, such educational settings, and substantially novel teaching and learning processes, might not be well served by commonly used LA that focus on describing and predicting individual learners' engagement, performance and pathways using traces such as clicks, submissions, forum posts and grades. It is necessary to examine the mechanics and goals of LA that can record and reflect the key inputs, processes and outcomes of learning environments that rely on human-GenAI collaboration, hybrid intelligence and new forms of participation. We seek a systematic conceptual tool for deciding which aspects of GenAI-enabled learning should be tracked and analyzed in order to evaluate, for example, whether the patterns we observe are generative or degenerative in terms of creativity, diversity of ideas and the distribution of agency across humans and AI. We propose that this conceptual tool can be Generativity Theory [7], [8].

3. A Brief Introduction to Generativity Theory

In management and information systems research, generativity theory has been developed to explain why some digital platforms and infrastructures support ongoing, unprompted innovation and value creation by participants. The collaborative and dialogic educational environments described above [1], [2], [3], [4], [5] are highly analogous to the environments which Generativity Theory is used to analyze: socio-technical systems that enable unexpected innovation and change, driven by its users, rather than only by the system's designers. Where traditional views of learning often emphasize what flows into learners as input, a generativity perspective foregrounds what flows out of learners as creative, dialogic output. In such collaborative and dialogic environments, participants learn by simultaneously receiving information and generating new understandings. This learning by creating rather than merely absorbing is the kind of process Generativity Theory is designed to capture and explain.

In brief, Thomas and Tee's [8] generativity framework uses seven interrelated components that jointly shape this generative capacity: *generative community, generative architecture, generative governance, generative fit, combinatorial innovation, generative outcomes and generative feedback*. Together, these components enable analyzing the interplay between affordances, structures, incentives and patterns of use in these environments. If we apply this framework to Wegerif and Casebourne's double dialogic pedagogy, the *generative community* describes the human (e.g. teachers, learners) and non-human (GenAI) participants who are active in the environment and co-produce meaning; the *generative architecture* describes how the components that comprise this environment (e.g. participants, technologies, information sources, classrooms) are configured and connected; *generative governance* comprises rules and norms that determine how the participants interact with the environment; *generative fit* concerns the alignment between the community and the architecture; *combinatorial innovation* occurs when participants combine, process and remix each other's ideas and, when relevant, artefacts, as they learn and collaborate; the *generative outcomes* include the learning that takes place, creative products, evolving viewpoints and other learning outcomes; and *generative feedback* is the input that feeds the three inputs: generative community, architecture and governance with the goal of improving the generative outcomes. In the case of learning environments, LA are an important component of the generative feedback.

4. Examples of Generativity-informed Learning Analytics

The *generative community* component concerns which human and non-human actors contribute to meaning-making and learning, and with what roles and degrees of agency. Liu et al. [9] use learning analytics to open the "black box" of student collaboration with generative AI in an instructional design course: drawing on log traces, they apply lag sequential analysis and epistemic network analysis to compare high- and low-performing groups, revealing characteristic patterns in more successful collaborations. Generativity theory proposes to extend this approach by developing LA that treat GenAI as integral members of the learning community by broadening participation metrics so that AI turns are included in reply graphs and epistemic networks. In addition, new LA could estimate the relative share of human-authored, AI-authored, and human-edited AI text across a collaborative task. These indicators can then be used to examine whether roles are distributed in ways that support learners' agency and dialogic engagement, or whether AI contributions crowd out human voices.

From a *generative architecture* perspective, GenAI-augmented learning environments can be understood as socio-technical configurations of platforms, tools, and tasks that enable or constrain particular patterns of human-GenAI interaction. Misiejuk et al.'s [10] systematic review of empirical studies maps where GenAI currently enters the LA pipeline, showing that most work still uses GenAI to automate discrete subtasks such as discourse coding, scoring, or text classification, while only a few studies integrate GenAI more deeply into dashboards or classroom tools to support human-GenAI collaboration. Yan et al. [11] situate GenAI's roles within Clow's LA cycle, arguing that GenAI can analyze unstructured data, generate synthetic learner data, enrich multimodal interactions, and support interactive and explanatory analytics across the full pipeline. Viewed through generativity theory, these contributions suggest learning analytics that monitor "architecture in use": for example, analytics that trace which GenAI tools and prompt types are invoked at which stages of a dialogic task, or that visualize typical human-human-AI interaction flows across the LA cycle. Such analytics can help designers see how the actual architecture of practice supports or hinders collaboration and dialog.

5. Conclusion

Within the constraints of an extended abstract, our contribution is necessarily schematic. Borrowing a model from management and information systems research, we outlined, rather than fully elaborated, a generativity-based framework for learning analytics in GenAI-augmented collaborative and dialogic settings. We offered the seven generativity components as a structured lens for deciding what to analyze in hybrid human-GenAI collaborative educational settings and sketched examples of learning analytics that analyze generative community and architecture.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT and Claude for drafting and paraphrasing, as well as for brainstorming and content enhancement. During and after using these

AI tools, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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