So What? Unpacking the Complexities in Collaborative Problem Solving with AI-Augmented Sense-Making

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Abstract. Visual representations of data in dashboards have the potential to translate learning process data into actionable insights for educational stakeholders. This is particularly useful for teachers when their capacity to monitor students is further strained in orchestrating complex activities, such as paired collaborative problem-solving. Despite great interest in dashboards over the past decade, their effectiveness has been under scrutiny with concerns about the cognitive overload for users with limited data literacy, thus questioning their practical utility in supporting decision-making and reflective practices. In this paper, we present a functional prototype for K-12 teachers and demonstrate the use of generative AI to unpack rich details of collaborative problem-solving processes in mathematics. Through a case study, we share our human-centered approach to design, ensuring that AI-augmented insights are not only interpretable and actionable, but centered around authentic needs. Based on the insights and experiences in the co-design session, our tool includes features, such as a contextualized description of students' breakthrough and struggle moments. This work contributes to ongoing efforts to support users' sense-making process of data visualizations in dashboards by leveraging generative AI.

Keywords: Learning Analytics · Dashboard · CSCL · Co-design · Human-in-the-loop · Generative Artificial Intelligence · Large Language Models

1 Introduction

Over the past decade, dashboards have become an instrumental part of educational technology, helping translate learning process data into actionable insights for educators, learners, and other stakeholders [7,15,17,18]. A key element of dashboard design is visual representations of data in a way that highlights meaningful patterns across students' learning processes [16]. Dashboards and data visualization thereof are particularly useful for teachers in facilitating and orchestrating complex activities and the use of digital tools, where it is often difficult to monitor classrooms that are likely working on different parts at any given time

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[6,17]. Dashboards can not only be used in-class for greater awareness and in situ decision-making, but they can also capture and document fine-grained traces of student progress [9,12].

Despite the potential, the effectiveness of dashboards remains questionable [7]. One of the known limitations is the cognitive load on teachers' ability to understand visually encoded information about students' learning processes to be able to use dashboards to effectively orchestrate a classroom [13]. To better support teacher's real-time sense-making, recent work has started to explore AI in dashboard designs [5,20]. One of the recent examples included integrating AI chatbots into dashboards, allowing users to ask for contextualized explanations of data visualization [20]. However, few studies have considered a human-centered approach for AI-augmented dashboards, raising greater concerns for K–12 education contexts where there is greater need for support in orchestrating computer-supported collaborative leaning activities.

In this paper, we present a functional prototype, specifically for K-12 teachers, and demonstrate the use of generative AI to unpack rich details of collaborative problem-solving processes in mathematics. Through a case study, we share our human-centered approach to design and development to ensure that AI-augmented insights are not only interpretable and actionable but centered around authentic needs. Specifically, we report on how we extracted key insights by grounding ourselves in the teacher's perspectives directly and indirectly in Sect. 1. Then, we discuss how generative AI was leveraged to provide detailed accounts of paired collaborative learning processes in math Sect. 3. In the last part Sect. 4, we illustrate the key features of our tool.

2 Grounding in the Teacher Perspective

In dashboard design, taking a human-centered design approach has been promising to distill the most relevant information from big process data [1,2,12]. In our study, teacher input guided our early stages of the design, revealing insights for greater support in data sense-making than we previously imagined. Specifically, we worked with a math teacher at a research development school in the southeastern U.S. who volunteered out of genuine interest in providing new learning opportunities for her students[1]. Her willingness to integrate it into her classroom distinguishes our work from studies that prioritize technological proficiency [14].

Two researchers visited the school for a week to design and lead onboarding sessions for GraspableMath (GM), a math notation tool and classroom-based platform where mathematical objects are reified as physical objects that students can manipulate and transform on screen. GM was chosen because its developers had recently released a collaborative whiteboard prototype that allows students to interact with the same math content simultaneously like Google Docs (see [19] for details). Each researcher then led a collaborative problem-solving activity using GM in the classroom for Grade 6 ($n = 43$), who had consented to

[1] This study was conducted under IRB-approved protocol #IRB202301185 at the University of Florida.

the study. The teacher was present in both settings. This structure allowed the teacher to focus on different aspects of collaborative problem-solving in the classroom while the researchers facilitated the activities.

After a week of collaborative activity, two researchers and the teacher engaged in an open reflection on collaborative activities as facilitators and observers, we asked: "*What are some superpowers that you would find useful specifically during a collaborative math activity in which students are interacting with GM?*" While this question may be effective in eliciting needs from participants [6], in our case, the question was less effective because teachers generally reported positive observations from the collaborative activity, with greater focus on the novelty of collaborative activities in math classrooms, as most platforms have students working in isolation (e.g., MathSpace, FluidityMath, MathDragon, DudaMath). To further guide the discussion, we asked: *"Which aspects of collaboration do you find empowering for you or engaging for your students? How would you rank them in order of importance, and why?"* This question revealed interesting insights about teacher's priorities in collaborative activities, which focused on (1) combined work from both partners, followed by (2) higher-level thinking, (3) engagement, and (4) feedback.

We then shared a data visualization created from demo data. To gauge the interpretability and actionability of visualization, we asked "*What did you learn from this visualization, and what would you do?*" Although the visualization provided a general summary of collaborative processes (see [10] for more details), it offered only limited insight into understanding problem-solving processes. For example, the teacher noticed that one student made more contributions on the whiteboard than the other, but it was not clear how individual actions were relevant, whether students were building on each other's work or working independently. While there are examples of on-demand AI interpretation using chatbot interfaces (e.g., VizChat [20]), our interaction with the teacher, as well as our experiences in facilitating collaborative activities, revealed that it may be often unrealistic and resource-intensive to come up with questions to ask. With concrete insights on what teachers need and would likely benefit from, we developed an AI-augmented dashboard that not only visualizes the complex collaborative math problem-solving process but also provides detailed summaries of collaborative learning, including mathematical concepts that students engaged with or struggled with.

3 Building AI-Augmented Sense-Making Tool

Our AI-augmented analytics pipeline is focused on translating collaborative problem-solving log data into meaningful information that supports teachers in better understanding student learning and decision-making. Moreover, language models suffer from contextual windows while handling large-scale interaction logs, which can influence their capacity to analyze complete session data. As illustrated in Fig. reffig:system-architecture, our system solves these issues by

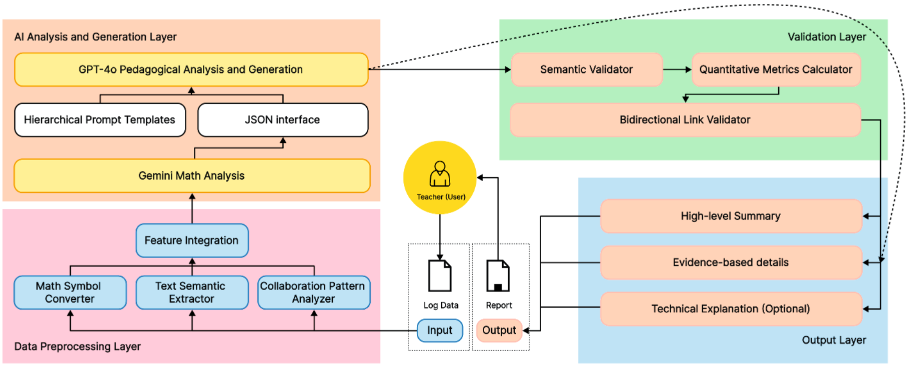


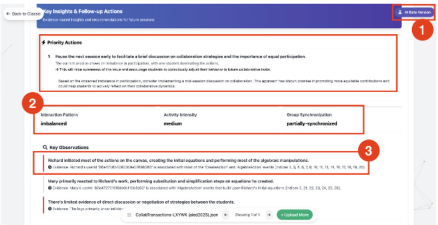
Fig. 1. A system architecture of our AI-augmented analysis, involving three key layers: (1) Data Preprocessing for feature extraction and integration, (2) AI Analysis and Generation with dual-provider architecture, and (3) Validation and Output for ensuring quality and generating multi-level explanations.

means of a well-designed three-phase architecture combining targeted data preprocessing, context-aware artificial intelligence analyses, and pedagogically based insights generating (Fig. 1).

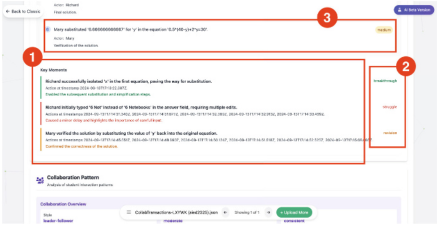
Knowledge Pre-processing and Feature Extraction. The pre-processing stage involved a novel feature extraction approach, which is well-suited for collaborative learning in math. Using a domain-specific transformation pipeline, the approach can greatly reduce data complexity while maintaining pedagogically meaningful patterns. For instance, both the symbolic process and the underlying reasoning processes are preserved when handling the mathematical solution sequence "$2x + 3 = 7 \rightarrow 2x = 4 \rightarrow x = 2$." Usually reducing the data by 70–80%, this selective retention method helps retain important information, such as mathematical reasoning strategies.

Dual-Provider AI Analysis Pipeline. The dual-provider design focuses on the complementary strengths of multiple AI models through a sequential-parallel processing pipeline [3]. Gemini-2.0-flash-exp first analyzes mathematical content to identify key patterns, such as inference processes, misconceptions, and strategies. Along with contextual metadata, this is passed to GPT-4o, which is optimized for generating pedagogically relevant narratives, or detailed explanations. Examples include how a student interacted with other students for collaborative problem-solving, and how students used a specific strategy (e.g. distributive property), indicating a breakthrough moment.

We also have **Multi-stage Validation and Output Generation**, a pipeline designed to acknowledge ambiguity and present multiple interpretations rather than making definitive claims when encountering edge cases, making it transparent for the users to consider uncertainties in AI-augmented analysis for certain unique cases.



(a) AI-Generated Teaching Recommendations: Insights into student collaboration patterns. The numbered highlights indicate key observations.



(b) Problem-Solving Analysis: Breakdown of key problem-solving moments. Red boxes highlight critical points for teacher intervention.

Fig. 2. AI-augmented Dashboard Insights: Visualizing student collaboration and problem-solving dynamics.

4 Case Study of Functional Prototype

We present a case study based on real-world collaborative problem-solving data from college students, demonstrating how our AI-augmented feature on the current collaborative learning dashboard[2] helps teachers make sense of student data in a meaningful way, such as group dynamics, and key problem-solving strategies. Although the reports are created for each group, we examine two groups of students who engaged in the same activity, and compare similarities and differences in their collaboration. All names displayed in images and discussions are pseudonyms, and the data have been anonymized to protect student privacy.

AI-Augmented Summary of Collaboration. Two groups of students were tasked with solving a system of linear equations in a collaborative whiteboard. In one group, the AI identified an imbalanced interaction pattern where *Richard initiated most of the actions on the canvas, creating the initial equations and performing most of the algebraic manipulations,"* while his partner *primarily reacted to Richard's work, performing substitution and simplification steps on equations he created."* This pattern resulted in limited reciprocal discussion, with the AI detecting *"no explicit communication events recorded."*

The second group exhibited a more distributed workload, though with occasional shifts in participation dominance. The AI noted that *"initial equation setup was more evenly divided, with both students contributing independently before engaging in substitution and simplification collaboratively."* However, the report also indicated that *"one student took a leading role in verification steps, while the other followed rather than questioning or contributing alternative approaches."*

Highlights in Collaborative Problem-Solving. The AI system flagged key problem-solving moments where teacher intervention could be beneficial. As seen

[2] The dashboard is now publicly available at https://gmdashboard.viablelab.org/ai/, featuring demo with anonymized student data.

in Fig. 2b, the system identified crucial points such as a **breakthrough** when *"Richard successfully isolated 'x' in the first equation, paving the way for substitution."* Additionally, areas of **struggle** were highlighted, including multiple failed text edits when Richard initially mistyped a variable name, causing minor delays. Finally, the AI flagged **revision** steps where Mary validated Richard's solution by substituting values back into the original equation, confirming the correctness. The highlights in Fig. 2a indicate quick summaries of group synchronization, activity intensity, and key observations to help teachers quickly assess collaboration quality.

5 Discussion and Conclusion

In this paper, we present an AI-augmented dashboard prototype that is inspired by a need for better support for the sense-making of students' collaborative problem-solving processes beyond data visualization. Our case study showed the potential of leveraging AI-augmented explanatory summaries from log data, which enabled the exploration of the fine-grained, action level log data without video or audio data.

In the design of AI-powered tools, human-in-the-loop is not only useful for validation and improving accuracy but also to spark significant conversations about trust and transparency. For example, existing research-practice partnerships, such as our own context, allow us to discuss with teachers fundamental details, such as how student performance should be measured and represented in the visual displays. This can help demystify a black-box nature of the complex algorithms that hide how summaries or analyses are undertaken. Establishing a shared understanding that data is less neutral, objective measurement of learning but one of many representations [8] of what teachers might already know from their experience would help teachers to consider AI components in dashboards as possible supporting evidence to drive their decisions when monitoring complex tasks such as orchestration of collaborative activities.

This work has several limitations that future work should address to further validate and enhance the practical utility of the tool. First, our work is limited to exploring relatively only a portion of the entire collaborative problem-solving process or key takeaways from data. Future work can explore more narrative, story-telling approaches to data communication [4,11] to account for users' varying goals and needs. Also, any efforts to integrate generative AI for analysis raise questions of accuracy and require external validation, which can introduce similarly resource-intensive processes in the design. Future research needs to assess the accuracy, reliability, and informativeness through practical use cases based on research-practice partnerships. Addressing these areas is important to fulfill the untapped potential of dashboards to go beyond instrument, or by-product but rather a bridge iterating between research and practice.

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