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Idea Tracing Analysis (ITA): A Temporal-Structural Methodology for Modeling Collaborative Discourse and Contextualizing Multimodal Interactions

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Abstract: Understanding learners 'behaviors in collaborative problem solving (CPS) is critical yet challenging due to its dynamic, multimodal nature. We introduce Idea Tracing Analysis (ITA), a method that models collaborative discourse as the evolution of interconnected ideas. ITA represents interactions as temporally aligned idea networks, capturing how ideas emerge, transform, and connect across participants. This approach provides a temporal and structural lens on collaboration, enabling analysis of group-level knowledge-building trajectories and the contextualization of multimodal interactions.

Introduction

One of the central goals in collaborative problem-solving (CPS) research is to understand how students act and interact—how they construct joint problem spaces or establish common ground through both verbal and nonverbal behaviors (Graesser et al., 2018; Stahl & Hakkarainen, 2021; Suthers et al., 2010; Wise et al., 2021). A deeper understanding of these interactional processes enables the design of more effective CPS activities and actionable supports (Jung et al., 2025). However, CPS processes are inherently *nested* and *situated* (Borge & Mercier, 2019). *Nested* refers to the interdependence between actions occurring at multiple levels, such as individual and group cognition (Barron, 2003; Stahl, 2005). *Situated* highlights that collaboration unfolds dynamically through moment-to-moment interactions in which common ground is continuously negotiated and updated (Cornelius & Herrenkohl, 2004; Graesser et al., 2018). At the same time, face-to-face collaboration is multimodal, involving speech, gesture, gaze, and interactions with artifacts. Multimodal learning analytics (MmLA) has enabled researchers to capture these channels and infer key collaboration constructs (Cukurova et al., 2018; Ochoa, 2022). However, interpreting multimodal behaviors without grounding them in an interactional context remains challenging.

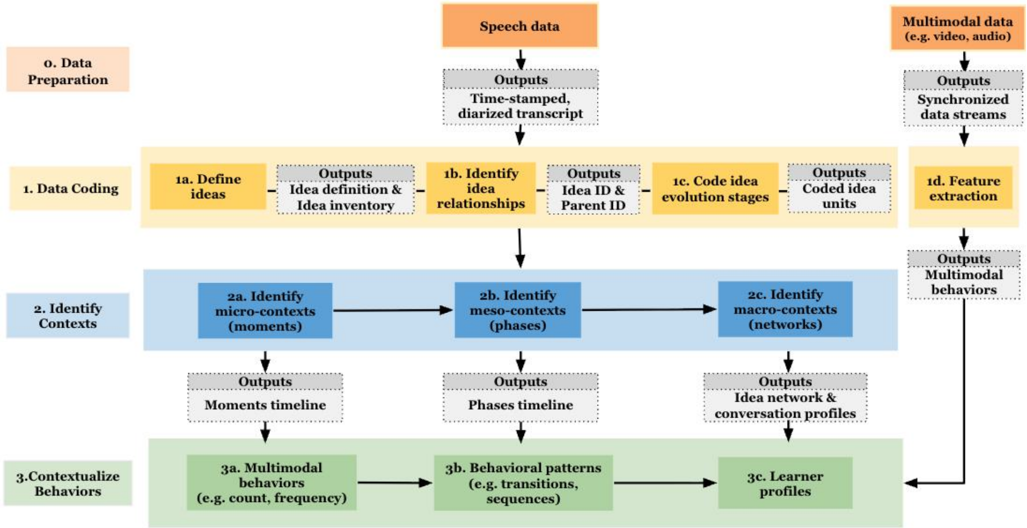
To address this gap, we propose Idea Tracing Analysis (ITA), a methodology that models collaborative discourse through the temporal and structural evolution of ideas. This is built on CSCL perspectives that emphasize idea improvement as central to collaboration (Scardamalia & Bereiter, 2005). Prior work has examined ideas as units of analysis through uptake (Suthers et al., 2010) and idea-based metrics such as distribution and similarity (Chen et al., 2015; Zhu & Chen, 2023). ITA extends this work by tracing how ideas are introduced, elaborated, connected, and transformed over time, capturing their evolving relationships. By representing discourse as dynamic idea structures, ITA identifies collaboration contexts across multiple timescales and informs the interpretation of multimodal behaviors. In this way, ITA positions ideas as a bridge between interactional contexts and individual behaviors, providing a quantitative yet contextualized means of linking multimodal indicators with constructs, a connection often missing in current multimodal collaboration analytics (Huang & Ochoa, 2025).

Idea Tracing Analysis (ITA): An illustrated description

We introduce Idea Tracing Analysis (ITA) through an illustrative walkthrough. Figure 1 provides an overview of the process, which unfolds across four stages. We begin with *Stage 0*: Data Preparation, where speech is transcribed and multiple streams of multimodal data are synchronized into a unified dataset. In *Stage 1*, ideas are coded for their relationships and evolution stages, while multimodal behavioral features are extracted. *Stage 2* identifies collaboration contexts at the micro-, meso-, and macro-levels through idea metrics. Finally, *Stage 3* situates multimodal behaviors within these contexts to uncover behavioral patterns and construct learner profiles that reflect the nested and dynamic nature of collaboration.

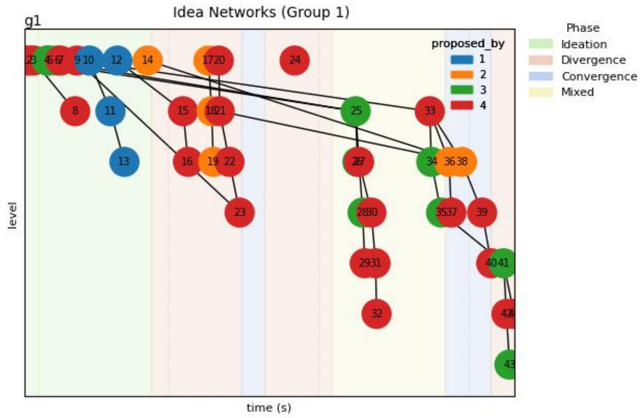
To illustrate ITA, we draw on data from a study of active listening in CPS, where 30 university students collaborated in groups of three to four on a 20–30 minute design challenge. Their interactions were captured through audio, video, and smart pen data. Figure 2 presents a macro-level example of idea evolution as a proposer–idea network, where nodes represent ideas and directed links capture how ideas build on one another. Each idea is linked to its proposer, enabling analysis of both idea development and the distribution of contributions across group members. Shaded regions indicate meso-level collaboration phases, allowing examination of how ideas evolve across temporal and structural dimensions.

Figure 1
High-level Overview of Idea Tracing Analysis (ITA) Methodology



This analysis shows how collaboration unfolds over time by tracing how ideas are proposed, elaborated, connected, and taken up across participants. It reveals overall patterns of collaboration, such as how balanced, cohesive, or fragmented group interactions are. These identified contexts further support the interpretation of multimodal behaviors—for example, when a participant builds on others 'ideas, how this verbal action reshapes idea structures, and how such processes unfold over time.

Figure 2
The Temporal and Structural Evolution of Ideas (Example)



Conclusion

This paper introduces Idea Tracing Analysis (ITA), a methodology that traces idea evolution to identify collaboration contexts and situate multimodal behaviors within them. Building on prior work in collaborative discourse analysis and MmLA, ITA moves beyond frequency- and sequence-based approaches to reveal when and where behaviors such as gaze, gesture, and verbal actions become meaningful. ITA contributes to collaborative discourse analysis by treating ideas not only as indicators of collaborative processes but also as an analytic lens for identifying interactional contexts and interpreting multimodal behaviors beyond verbal discourse. It advances MmLA by situating behaviors within multi-level contexts and offering a systematic pipeline—from data preparation to context identification and behavior interpretation.

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