# Temporal Patterns and Visualizations of Peer Talk: Toward Understanding the Process and Performance of Dialogic Collaborative Problem-Solving

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**Abstract:** Dialogic collaborative problem solving (CPS) describes how students collaboratively solve a problem mainly through talk. Existing studies intensively explored cumulative features of productive peer talk based on a coding-and-counting approach. Nevertheless, it has not been fully understood how utterances historically and dynamically unfold overtime and gradually shape the group solution quality. This dissertation aims to identify temporal patterns of peer talk that can distinguish high-performing groups from low-performing groups in the dialogic CPS and examine the degree to which these temporal patterns help better predict group solution quality.

## Introduction

Benefits of collaborative problem solving (CPS) have been intensively explored and well-established (e.g., Johnson & Johnson, 2016; Slavin, Lake, Hanley, & Thurston, 2014). CPS competence, as a relatively new construct, has been increasingly emphasized nowadays (e.g., Cukurova, Luckin, Millán, & Mavrikis, 2018; Griffin & Care, 2015; OECD, 2017).

Language is a powerful tool supporting human intra- and inter-thinking in CPS (Voygotsky, 1978). Discourse manifests cognition (Resnick et al., 1997, p.2). Certain forms of peer talk could induce higher-order thinking and larger amount of academic learning (Chi et al., 2018; Gillies, 2017; Sullivan & Barbosa, 2017).

Talk is historical and dynamic (Bakhtin, 1981; Mercer, 2008). Temporal analysis of interaction has been increasingly emphasized fairly recent in both Learning Analytics and Computer-supported Collaborative Learning communities (Chen, Wise, Knight, & Cheng, 2016; Chen, Resendes, Chai, & Hong, 2017; Csanadi, Eagan, Kollar, Shaffer, & Fischer, 2018; Knight, Wise, & Chen, 2017; Knight, Wise, Chen, & Cheng, 2015; Kapur, 2011; Mercer, 2008; Reimann, 2009; Swiecki, Ruis, Farrell, & Shaffer, 2019). Interaction patterns affect learning outcomes in collaborative learning (Cen, Ruta, Powell, Hirsch, & Ng, 2016). There are interdependencies of peer talk at multiple time scales (Wise & Chiu, 2011). It is necessary to know the temporal development of the dialogue in order to make educational sense of peer talk (Mercer, 2008) and further scaffold promotive interdependencies in collaboration.

The emerging temporal learning analytics face theoretical and technical challenges in analyzing time-series data and making educational sense of the results (Chen et al., 2016; Knight et al., 2017, 2015). Visual learning analytics as an emergent trend in making sense of learning data and supporting decision making of stakeholders has attracted lots of attention (Vieira, Parsons, & Byrd, 2018). It aims at leveraging computer and human power through integrating data mining as well as information visualization techniques. There are a lot of temporal visual learning analytic techniques that have been used to decompose the temporality of peer talk including the chronologically-oriented representation for discourse and tool-related activity (CORDTRA diagrams) (Hmelo-silver et al., 2009), Epistemic Network Analysis (ENA) (Gašević, Joksimović, Eagan, & Shaffer, 2018; Shaffer et al., 2009), Lag Sequential Analysis (LsA) (Chang et al., 2017; Chen et al., 2017; Kapur, 2011), Knowledge Building Discourse Explorer (KBDeX) (Oshima, Oshima & Matsuzawa, 2012; Oshima et al., 2019) and Markove Models (Reimann, 2009; Thompson et al., 2013).

## Goal of research

This dissertation aims at identifying core temporal patterns of peer talk in dialogic CPS in terms of turn-taking, joint knowledge construction and move-taking three aspects. These temporal patterns are expected to distinguish high-performing and low-performing groups and thus help better predict group performance.

## Methodology

This research will contain two phases. Phase 1 aims at identifying turn-taking, joint knowledge construction and move-taking patterns that can distinguish high-performing and low-performing groups. Quantitative and qualitative methods will be integrated to extract and interpret the patterns. Visualization techniques will be adopted not only to illustrate temporal patterns but also conduct exploratory data analysis to visually evaluate hypotheses and generate new assumptions.

It is hypothesized that there are more leadership rotations, progressive knowledge construction and co-constructive move-taking sequences in high-performing than the low-performing groups. To test these hypotheses, phase 1 will involve around 400 fourth-grade students from around 10 classes in mainland China. Each group will include 3 or 4 students and solve two process-open challenging mathematics problems. Before the test, students need to independently finish questionnaires on their demographic information, personality type, self-efficacy in CPS, and the degree to which they like to collaborate with their partners. After solving the two problems, students will be asked to evaluate their own performance, group performance, peer performance and the degree that they would like to collaborate with their partners again. Group discussion will be videotaped and transcribed. Their written discourse will be collected as well to facilitate the interpretation of peer talk. Leadership rotation in turn-taking will be analyzed by the change of betweenness centrality in social network through the KBDeX. Progressiveness of joint knowledge construction will be analyzed through lag sequential analysis and frequent sequence mining. Co-constructive move-taking sequence will be examined through the epistemic network analysis.

Phase 2 will use the same dataset with phase 1. Group performance will be represented by raw solution scores. Linear regression analysis will be adopted to model group collaboration and identify significant predictors of group performance. To automatically predict group performance in the early-stage, non-verbal features (e.g. individual prior knowledge, self-efficacy, personality, friendship etc.) and turn-taking features (e.g. number of turns/words and leadership rotation etc.) will be considered as potential predictors. To compare the impact of temporal features and cumulative features, all relevant cumulative verbal and non-verbal features and temporal patterns identified in phase 1 will be included as potential predictors.

## Expected contributions

This dissertation is expected to extend research on talk temporality and usage of visualizations in analyzing talk. It will extract temporal patterns of face-to-face peer talk and link it to group performance in the dialogic CPS context. It will help us better make sense of how peer talk shapes group performance from three aspects: turn-taking, joint knowledge construction and move-taking. Though it has been a core interest to predict group performance in the CSCL context, few efforts have been put to include temporal features of face-to-face peer talk. This dissertation will develop a regression model including core temporal features of peer talk to explain and predict group performance.

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