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Abstract: The quality of teacher interaction is essential for the effectiveness of professional learning communities (PLCs). The current study was based on dynamic systems theory to grasp the complexity of teacher interaction. We examined attractor states and attractor sequences in interaction in two teacher PLCs, using state space grids and orbital decomposition. Results reveal more high-quality attractors in PLC2 than in PLC1. The poster illustrates these analyses and discusses implications and directions for further research.

Introduction

Review studies have shown that peer teacher professional development (PTPD) is a successful means to improve teachers' knowledge and skills and student learning (Vescio et al., 2008). One example is a professional learning community (PLC), a group of teachers who share and examine their practice and collaborate on how to support student learning. Effective interactions within the PLC setting are key for teacher learning to occur, yet not all dialogues support teacher learning (see Little, 2003). To understand how teachers effectively exchange ideas and build knowledge during conversations, it is necessary to delve into these dialogues (Little, 2003). The current study aims to show that a nonlinear dynamic systems (NDS) approach to analyzing teacher interaction can provide insights into the quality of teacher interaction. According to NDS-theorists, development of any (social) system is nonlinear and should be studied as it evolves over time (Pincus, 2001). One of the core concepts of NDS is the notion of an attractor, referring to stable and recurrent behavior states or behavior sequences that a system (e.g., a group) prefers or tends to get stuck in (Hollenstein, 2013). Two analysis techniques that enable attractor identification are state space grids (SSG; Hollenstein, 2013), focusing on states that the system often returns to, and orbital decomposition (OD), in which sequences of interaction are analyzed (Guastello, 2000). In the current study, SSG and OD were applied to turn-taking and the content of teacher talk within PLCs.

The present study

The present exploratory study focused on attractor states and sequences in teacher interaction in PLCs. Our research questions concerned (1) the presence and nature of attractor states and attractor sequences in relation to teachers' turn-taking and content, and (2) the extent to which these attractors reflected high-quality teacher interaction, in reference to the PLCs' goals of interdependently designing differentiated instruction.

Method

Two PLCs participated in this study. PLC1 consisted of four teachers and met five times during one school year. PCL2 consisted of three teachers who met six times during one school year. Teachers were affiliated to two secondary vocational schools. The focus of both PLCs was to improve or implement differentiated instruction.

The authors coded transcripts of the teacher meetings for turn-taking and content. The content coding system was based on differentiated instruction: student characteristics that differentiated teaching is based on, and teaching aspects that are adapted to those student characteristics (Tomlinson et al., 2003). Inter-rater reliability was calculated for three transcripts; Cohen's κ was .70, .85, and .91. SSGs and OD were conducted using GridWare (Lamey, Granic, Lewis, & Hollenstein, 2004) and ORBDE (Peressini & Guastello, 2014). Attractor states and sequences were identified using the winnowing method that is described by Hollenstein (2013).

Results

State space grids

Figure 1 shows an example of an SSG, for a meeting of PLC1. The horizontal axis represents participating teachers, the vertical axis the categories of the content dimension. Categories located higher in the grids are higher order categories. Findings reveal that PLC2 more frequently visited higher order attractor categories than PLC1. Moreover, in PLC2 interaction revolved around only one teacher, whereas interaction was more scattered across teachers for PLC2, indicating larger interdependence in the latter group.

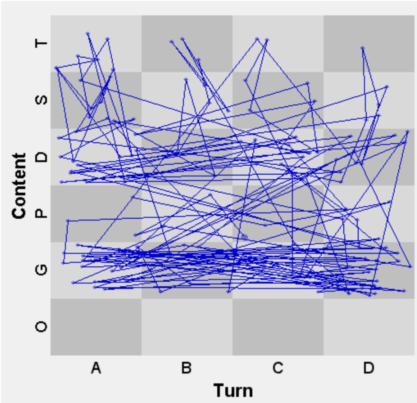

Figure 1. Example state space grid (SSG) from PLC1. A-D on the horizontal axis represent the participating teachers. O = Off-task, G = General teaching, P = Professional learning community, D = Differentiated instruction, S = Student characteristics, T = Teaching characteristics.

Orbital decomposition

Regarding the dynamics of turn-taking, we were looking for evidence of interdependence among teachers, as shown by their equal contributions on a micro-level. In other words, what we were looking for were patterns of interaction that comprised contributions from more than two, if not all, teachers. This was more the case for PLC2's attractor sequences than for PLC1's attractor sequences. For the content dimension, we were looking for evidence of connections between student and lesson characteristics, to show that teachers had in-depth conversations of how to combine those characteristics in strong instruction. Again, this was more present in the attractor sequences of PLC2 than those of PLC1, albeit only in the first, third, and sixth meeting of PLC2.

Conclusion and discussion

Our findings show higher-quality teacher interaction in PLC2 than in PLC1, both in terms of attractor states (deeper content categories) and attractor sequences (more interdependency; stronger connections between teaching and student characteristics). The current study inspires some next steps in this line of research. For instance, examining dialogue acts or conversational moves (e.g., who asks a question, who gives an opinion, who proposes an idea) would be interesting. Moreover, connecting outcomes of SSG or OD analyses to teacher learning outcomes would reveal the value of having high-quality attractors.

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