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The application of orbital decomposition analysis to study the dynamic quality of teacher–teacher interactions

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ABSTRACT
Moment-to-moment educational interactions affect longer-term outcomes of those involved in those interactions. In the present study, we illustrate with two cases of teacher–teacher interactions how Orbital Decomposition (OD) analysis can be used to analyse sequential patterns in real-time interactions. OD analysis is based on symbolic dynamics and is specially designed to identify recurring sequences of events in a time series of nominal categories of observed behaviour. First, we explain what OD analysis entails, after which we illustrate OD analysis using a study on teacher–teacher interactions between teachers in Professional Learning Communities. We show the analysis of conversational moves and turn-taking behaviour of two cases of teacher groups. The results reveal which interaction partner was in the lead and which conversational moves were associated with interdependent knowledge-building as compared to merely sending and receiving information. OD focuses on interaction patterns rather than basic frequencies and as such can be used to provide insights into interaction processes as these unfold over time.

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1. Introduction

When people are together in the same space, they form a dynamic social system in which interaction occurs, not interacting is impossible (Watzlawick, Bavelas, and Jackson 1967). Good quality interpersonal interactions are essential for the development and effective functioning of educational social systems, such as classrooms or other learning environments (e.g. professional learning communities (PLCs) or the workplace) (Mainhard et al. 2012). In PLCs interactions are needed for collaboration to perform a shared task (Vangrieken et al. 2015).

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Collaborative interactions are not static but vary in depth based on the goal of the collaboration (Vangrieken et al. 2015).

Educational systems have their own characteristic norms, beliefs, and practices (Windschitl 1999). Patterns in interactions that often recur in a system represent the characteristic practices of the system and are indicative of the quality of the interactions between the system members. It is interesting to study these central interaction patterns, since these essentially affect the outcomes of educational activities.

Many studies that focus on exploring interactions in educational social systems use analytical approaches based on coding and counting types of utterances or remarks (see Lefstein et al. 2020 for a recent review). This results in counting frequencies of teacher interactional behaviours. However, such approaches are too simplistic in nature to capture the complexity and dynamics of interactions in real-life educational settings (see Stamovlasis 2016). Rather, moment-to-moment patterns of action and reaction over time should be addressed to understand how actors interact and develop recurring patterns in interaction. These moment-to-moment patters of action and reaction and how these interdependently develop and vary over time is referred to as interaction dynamics (Cappella 1996; David, Endedijk, and Van den Bossche 2022; Pennings et al. 2018). Cappella (1996) and David, Endedijk, and Van den Bossche (2022) stress that it is not merely the content of these actions and reactions that form interaction dynamics, but the way that those are interconnected and form interdependent patterns. Orbital Decomposition (OD) analysis (Guastello, Hyde, and Odak 1998) is an approach to identify recurring patterns in interactions that will be illustrated in this paper.

In this paper, we first explain what OD analysis entails, after which we illustrate how OD analysis can be used to identify sequential patterns in moment-to-moment interactions in teacher–teacher interactions. Doing so, we compare two contrasting cases in which teachers in PLCs interact to perform a shared task (i.e. introduce differentiated instruction in their classroom).

1.1. Studying recurrent patterns in interactions with orbital decomposition analysis

Group members will find themselves in a continuous process of adapting their actions in response to the behaviour of their partners. In this interaction, non-random recurring patterns emerge. For example, interaction patterns of people leading and others following or trying to take the lead, of people suggesting and others building on these suggestions versus providing counter-ideas. As such, interaction partners are consistently coordinating their actions, making the group a social system that organises itself, thereby shaping the future actions that will be taken (see Stamovlasis 2016). Such non-random patterns are unique to interaction partners and are related to outcomes of interactions. For example, whether a satisfactory solution to a problem is agreed upon or not. This also means that the same utterances in two different groups (or in different orders in the same group) can indicate different patterns in interactions (i.e. different dynamics), and may lead to different outcomes. It is these varieties in interaction patterns that influence the outcome of the interactions. Thus, *how* the group came to a result may be just as interesting or more interesting than the result of the group work itself. To capture interaction dynamics as well as the content of interactions, analytical approaches that go beyond a linear approach of mere frequencies are needed (see Garner and Russell 2016).

Orbital decomposition analysis (OD) is an analytical approach that captures non-random patterns in interaction dynamics rather than the static qualities of interactions. OD was designed to identify recurrent sequences of categorically (i.e. nominal) coded events in a time series of (coded) behaviour (Guastello 2000; Pincus, Ortega, and Metten 2011). It is based on symbolic dynamics, an area of mathematics that studies sequences of symbols, entities, or categories, that is, nominal level data, to describe the qualities of the resulting string of those consecutive symbols (see Garner and Russell 2016). The statistical program ORBDE v2.4 (Peressini and Guastello 2014), which is specifically designed for OD can be used to identify the most recurring behaviour sequences in interactions, based on the most optimal sequence length and the content of those sequences. How these measures are calculated is described in the method section.

Thus far, OD analysis has been used to analyse for instance family interactions, therapeutic settings, and other group dynamics (e.g. Pincus 2001; Pincus and Guastello 2005), including discourse in collaborative groups in education (see Stamovlasis 2016) and problem-solving skills of fifth graders in small groups (Ricca and Jordan 2022). The application of OD goes beyond studying interaction dynamics alone and includes any dynamic sequence of behaviour. For example, Garner and Russell (2016) used OD analysis to study students' gaze patterns during a learning task (Garner and Russell 2016). OD can be used in many different domains to study a variety of topics; in the present study, we illustrate how OD could be applied to teacher–teacher interactions in PLCs.

1.2. Illustrative cases: teacher–teacher interactions in PLCs

When effective, teacher–teacher interactions support teacher professional development in the domains of their knowledge, beliefs, and practice in class (see Lefstein et al. 2020; Little 2003). Cappella (1996) described two essential components of interaction quality, which are mutual influence and mutual adaptation. Mutual influence mean that interaction partners influence each other; Mutual adaptation means that interaction partners respond adaptively to changes in each other's behaviour. These two components represent a certain degree of interdependence in interaction (i.e. interaction dynamics). In general, the degree of interdependence is related to the quality of interactions (Cappella 1996; Pennings et al. 2018).

Cappella's (1996) principles of mutual influence and adaptation also apply to effective teacher collaborative professional development efforts, including PLCs. Little (1990, 2003) provided a framework for teacher collaboration where different forms of collaboration can be positioned along the dimension of interdependence, ranging from storytelling to joint work. In situations with strong interdependence, teachers are more likely to achieve the goals of a PLC: being actively engaged, sharing responsibility, and to collaboratively work on a shared goal or knowledge base (Stoll et al. 2006; Vescio, Ross, and Adams 2008).

Interdependence is achieved through high-quality interaction dynamics (Little 2003) and depends on how teachers are contributing to the conversation. Conversational moves refer to the actions people undertake in interaction with each other (see Warwick et al. 2016). To be *mutually influential* and in that sense interdependent, teachers should build onto each other's comments; Move away their work from storytelling to joint knowledge building, by giving suggestions, building on to these and rephrasing earlier contributions (see Popp and Goldman 2016).

In addition, interdependence can be found in teachers' turn-taking patterns. Turn-taking in interactions means that people reciprocally alternate talking and listening, thereby *mutually adapting* their behaviour to the other teachers' behaviour. Interactions in which some teachers are dominant and others hardly participate show limited interdependence, whereas interactions in which teachers contribute equally show strong interdependence.

By studying non-random recurrent qualitative behaviour patterns in interaction dynamics of teachers in PLCs, it is possible to identify common and recurring behaviour sequences that affect teacher collaboration. This information could result in starting points for interventions to improve teacher collaboration. In doing so, we compared the interactions of two PLC's which differed in outcome quality of the shared PLC task. Besides illustrating how OD analysis can be applied to study recurrent patterns, we formulated the following research questions for the present study: Which recurrent patterns in teacher–teacher interactions can be identified? How are the patterns different for the two PLC's?

2. Method

2.1. Participants

Two PLC cases were selected from a larger project on PLCs in schools for prevocational secondary education in the Netherlands. The selection was based on availability of meeting recordings and outcome of the PLC task. PLCs consisted of four (PLC1) or three (PLC2) teachers. PLC1 consisted of one male and three female teachers of modern languages (Anna, Bianca, Chris, and Deborah; teaching English, German, and Dutch). The teachers' teaching experience ranged from 1 to 33 years. PLC2 consisted of one female and two male teachers (Erica, Fred, and George), who all taught the subject called 'Talent and orientation', a school-specific subject that combines history, geography, economy, and social studies. Their teaching experience ranged from 8 to 26 years. PLC1 met five times and PLC2 met six times during the school year. The meetings took 60–90 minutes and were video recorded; the recordings were transcribed verbatim. PLC1's second meeting was not recorded because of equipment failure. The PLCs did not have a facilitator, but they did receive a booklet with instructions on how to develop and test methods for implementing differentiated instruction in the classroom (i.e. the topic of the PLC task).

Teachers in PLC1 focused their first meeting on discussing what they wanted to accomplish and setting a shared goal (i.e. develop materials that do justice to differences between students). The other meetings revolved around the teachers discussing their individual experiences with try-outs of differentiated instruction and the results and/or sharing (online) materials that they could use in the classroom. For example, in the third meeting, Anna (a PLC member) suggested that all teachers would try out using the concept of multiple intelligences. In the final meeting they evaluated their progress.

PLC2 started by setting the goal to improve their already existing mode of differentiated instruction. That is, they were used to providing general instructions, which were the same for all students, followed by the students working on individual or group-based assignments of their own choice, so-called 'talent cards'. In the second meeting, their discussion revolved around the teachers' visions on education, and how differentiated instruction fitted into their visions. The third to fifth meetings were about designing the talent cards, organisation of this form of differentiated education, and assessing students' performance. In their final meeting, the teachers looked back at the meetings, evaluated their progress, and discussed whether they would continue the meetings.

2.2. Interaction coding system

After selecting only on-task fragments within the meetings, conversational moves and turn-taking (as evident from the meeting transcripts) were observed in the PLCs' interactions. The coding system to code conversational moves was based on Bales (1950) Interaction Process Analysis (IPA) for analysing interaction in general and the coding system as used by Popp and Goldman (2016) that is particularly situated in teachers' PLCs. The moves that were distinguished were: inform, listen, elicit, opinion, argument, rephrase, and suggest. These moves increased in knowledge-building qualities. The unit of analysis was the move within a turn. Hence, a single turn could be segmented into multiple moves. For instance: 'I have tried out this computer software [inform], does anyone of you have experience with it? [elicit]'.

Two researchers coded the data. After agreement regarding segmentation was achieved, Cohen's kappa was applied to test the inter-rater reliability on three randomly selected transcripts from a larger body of available and videotaped interactions (excluding the transcripts that were used in this study); Cohen's kappa over the three transcripts was .85. Subsequently, the 10 transcripts (four for PLC1, six for PLC2) were divided between the researchers to code.

2.3. Orbital decomposition analysis

Coded transcripts from the PLC meetings were combined into one single dataset per PLC. This resulted in one long time series, reflecting the entirety of conversations in the sessions per PLC. Next, for each PLC orbital decomposition analysis was conducted for conversational moves and turn-taking separately. In these long datasets the coded moves and turns were converted to letters, so the data consisted of a list of single letters (e.g. I-A-E-I-A-I-O etc. for the series of conversational moves, or A-B-C-A-C-D-B-C-A etcetera for turn-taking among members A-D). Organizing the data as a list of letter codes is a requirement for using OD analysis.

ORBDE v2.4 (Peressini and Guastello 2014) was used to conduct the OD analyses. OD takes the time series of coded behaviour as a starting point, then the interaction sequences were described in two subsequent steps.

First, OD identifies the optimal *string length* (C). That is, the number of behavioural events (i.e. orbits) that together form a pattern that is often repeated (i.e. non-random pattern). Beginning with a string length of one, this is an iterative process that continues with an increased string length up to the longest pattern that is immediately repeated in the data. For each *C* length, up to the maximum detected, additional variables are quantified requiring the researcher to identify the appropriate or optimal *C* length to consider. The most optimal string length is based on entropy (i.e. mathematical measure of (dis)order in communication; Shannon 1948) and goodness-of-fit measures (see the Results section for an explanation of these guidelines; for further in-depth explanations we refer the reader to Garner and Russell 2016; Guastello, Hyde, and Odak 1998; Pincus 2001; Pincus and Guastello 2005).

Second, OD identifies all *dynamic behavior sequences* of the identified optimal string length and the number of recurrences in the data of those sequences. These dynamic behaviour patterns can be interpreted by the researcher as qualitative descriptions of the dynamic behaviour sequences. The behaviour sequences consist of a set of behaviours that follow one another. For example, the above sequence of turn-taking A-B-C-A-B-C-A-D-B, with a string length of three, consists of seven – overlapping – turn-taking sequences: A-B-C; B-C-A; C-A-C etc., in which the pattern B-C-A is immediately repeated. As it occurs twice it is a recurring pattern. The most frequently recurring patterns in the data, whether immediately or more distantly, can then be interpreted qualitatively as these represent the main patterns that characterise the interaction. In the current study, the five most common sequences were reported and interpreted.

3. Results

3.1. Descriptives of the interactions

Table 1 shows the frequencies of conversational moves and turn-taking in the two PLCs. For conversational moves, Table 1 shows that in both PLCs teachers often informed each other. However, in PLC1, this took up almost 50% of the moves, whereas in PLC2 this was only 30% of the moves, which left more space for knowledge-building moves (such as opinions and suggestions). Looking at turn-taking, the ratio of turns of the least to the most contributing teacher was 1:1.99 in PLC1, whereas it was 1:1.11 in PLC2, indicating a much larger difference in the contributions in PLC1 than in PLC2.

Table 1. Frequencies of turn-taking, content, and conversational moves in both PLCs.

	PLC1		PLC2	
	Frequency	Percentage	Frequency	Percentage
Conversational moves				
Inform	365	47.5%	412	28.4%
Listen	22	2.9%	34	2.3%
Elicit	114	14.8%	154	10.6%
Opinion	132	17.2%	388	26.7%
Argument	33	4.3%	127	8.7%
Rephrase	25	3.3%	108	7.4%
Suggest	77	10.0%	229	15.8%
Turn-taking				
Teacher 1 (A|E)	187	37.1%	276[a]	34.5%
Teacher 2 (B|F)	101	18.5%	249[a]	31.1%
Teacher 3 (C|G)	94	19.3%	275[a]	34.4%
Teacher 4 (D)	121	25.1%		

Teachers A–G refer to the teachers' first initials.
[a]For PLC2, the first meeting was discarded in this table, since one of the teachers was absent.

3.2. Results orbital decomposition analysis

3.2.1. Finding the optimal string length

The first step in OD analysis is to determine the most optimal string length (C), that is, the length of the interaction pattern containing a certain number of teacher actions. To this end, ORBDE v2.4 reports a table containing statistics for several possible *C* lengths starting from $C = 1$ up to the longest pattern that is repeated in the data.

The OD statistics that are reported in this process (see Table 2) are: (1) string length (C), the string length to which the indicators correspond; (2) Trace (trM), which is the trace of the matrix that represents instances in which a pattern is directly followed by itself, or the proximal recurrence (see Guastello, Hyde, and Odak 1998); (3) Topological entropy (Ht) that describes the deterministic non-random complexity of a string; (4) Lyapunov exponent (DI) is a measure of the chaoticity of the dynamical process in the string; (5) χ^2: likelihood χ^2 test provides the statistical significance of the string length, excluding the patterns that occurred by chance; (6) df, the degrees of freedom to test significance; (7) N* the number of code sequences with length C, which is decreasing with 1 as *C* length increases with 1 as the sequences are overlapping; (8) φ^2 test provides a correction to the χ^2 and is also a measure analogous to the proportion of variance accounted corresponding to the string length; (9) Hs is Shannon entropy, an indication of the number of rare patterns in the time series; it reflects the novelty in a time series (see Attneave 1959).

3.2.1.1. Conversational moves.

Table 2 shows the statistics table for the conversational move patterns of PLC 1 and Table 3 shows the statistics for the conversational moves in PLC 2. To identify the most optimal string length for interpretation of the results, according to Guastello, Hyde, and Odak (1998); see also Stamovlasis (2016), one should interpret these statistics as follows: First, with increasing C, topological entropy (Ht) will decrease, and will eventually drop to 0. String length (C) is most optimal at the highest value for

Table 2. OD statistics for conversational moves of PLC 1.

C	trM	Ht	DI	χ^2	df	N*	φ^2	Hs
1	7	2.807	16.566	864.277	7	919	0.954	1.603
2	11	1.730	5.639	123.327	46	918	0.134	3.130
3	11	1.153	3.168	352.412	123	917	0.384	4.494
4	8	0.750	2.117	513.333	147	916	0.560	5.560
5	2	0.200	1.221	500.968	121	915	0.548	6.228
6	1	0.000	1.000	362.818	81	914	0.397	6.577

C = string length. trM = Trace. Ht = Topological entropy. DI = Lyapunov exponent. χ^2 = Chi-square. Df = Degrees of freedom. N* = the number of code sequences with length *C*. φ^2 = Chi-square correction. Hs = Shannon entropy.

Table 3. OD statistics for conversational moves of PLC 1.

C	trM	Ht	DI	χ^2	df	N*	φ^2	Hs
1	6	2.585	13.263	875.704	7	1472	0.595	1.782
2	26	2.350	10.488	145.207	55	1471	0.099	3.513
3	17	1.362	3.906	457.014	197	1470	0.311	5.132
4	4	0.500	1.649	832.345	296	1469	0.567	6.351
5	2	0.200	1.221	885.780	187	1468	0.603	6.983

C = string length. trM = Trace. Ht = Topological entropy. DI = Lyapunov exponent. χ^2 = Chi-square. Df = Degrees of freedom. N* = the number of code sequences with length *C*. φ^2 = Chi-square correction. Hs = Shannon entropy.

C where Ht has not reached 0, with high levels of χ^2 and proportion of explained variance (φ^2).

When applied to our data: Table 2 shows that Ht drops to 0 at $C = 6$, indicating an optimal C of 5. As shown in Table 2, χ^2 and φ^2 are higher at $C = 4$ than at $C = 5$. Based on these values, $C = 4$ or $C = 5$ could both be appropriate for describing the interaction dynamics of case 1.

For PLC 2, statistics for $C = 6$ and further were not reported by ORDBE 2.4, as patterns from this length on were not immediately repeated in the data, limiting the opportunities for evaluating when Ht drops to 0. However, χ^2 and φ^2 are both at their highest level at $C = 5$, this is also an appropriate string length.

As $C = 5$ was also one of the two options in case 1, we opted to interpret the conversational moves data at $C = 5$ for both cases. This also made it easier to compare the two cases, because the patterns were of the same C length. This is a common method when using OD analysis to compare (groups of) participants (e.g. Garner and Russell 2016), but not a requirement.

3.2.1.2. Turn-taking.

Tables 4 and 5 show the statistics for choosing the optimal length of C for turn-taking patterns in PLC 1 and PLC 2, respectively. For PLC 1, only statistics for C lengths up to $C = 6$ were identified whereas for PLC 2, statistics up to $C = 10$ were identified. Note however that for PLC 2 no statistics were reported for $C = 7$ or $C = 9$. This means that that for these C lengths, no patterns that were immediately repeated were present in the data. To illustrate, consider a part of the group talk where two teachers share a dyadic interaction: A-B-A-B-A-B-A-B-A-B-A-B-A-B-A-B. In this small episode of 16 turns, a consecutive set of 8 turns is directly repeated, that is A-B-A-B-A-B-A-B, whereas the smaller set of 7 turns is not (A-B-A-B-A-B-A is followed by B taking the next turn).

Table 4. OD statistics for tun-taking of PLC 1.

C	trM	Ht	DI	χ^2	df	N*	φ^2	Hs
1	4	2.000	7.389	298.585	5	530	0.563	1.510
2	16	2.000	7.389	227.540	27	529	0.430	2.800
3	10	1.107	3.026	522.173	56	528	0.989	3.892
4	13	0.925	2.522	828.864	84	527	1.573	4.787
5	1	0.000	1.000	1073.536	98	526	2.041	5.408
6	1	0.000	1.000	1061.045	79	525	2.021	5.809

C = string length. trM = Trace. Ht = Topological entropy. DI = Lyapunov exponent. χ^2 = Chi-square. Df = Degrees of freedom. N* = the number of code sequences with length C. φ^2 = Chi-square correction. Hs = Shannon entropy.

Table 5. OD statistics for tun-taking of PLC 2.

C	trM	Ht	DI	χ^2	df	N*	φ^2	Hs
1	3	1.585	4.879	741.857	4	808	0.918	1.150
2	6	1.292	3.642	572.650	11	807	0.710	1.934
3	7	0.936	2.549	1156.275	22	806	1.435	2.690
4	13	0.925	2.522	1692.934	35	805	2.103	3.421
5	8	0.600	1.822	2228.978	55	804	2.772	4.121
6	9	0.528	1.696	2763.370	100	803	3.441	4.772
8	8	0.375	1.455	3453.554	199	801	4.312	5.819
10	1	0.000	1.000	2599.634	136	799	3.254	6.385

C = string length. trM = Trace. Ht = Topological entropy. DI = Lyapunov exponent. χ^2 = Chi-square. Df = Degrees of freedom. N* = the number of code sequences with length C. φ^2 = Chi-square correction. Hs = Shannon entropy.

In PLC 1, we see that Ht drops to 0 after $C = 4$, with $C = 4$, and at the same time having relatively high levels of χ^2 and φ^2. However, in case 2, Ht does not drop to 0 before $C = 10$, with χ^2 and φ^2 values being highest at $C = 8$. Considering our aim of comparing the two groups, we chose a value for C that would fit both cases. We opted for $C = 4$. Decisive were the four most occurring patterns of length 8 for PLC 2. These were all repetitions of a pattern of length 4. That is, the most occurring pattern was: A-B-A-B-A-B-A-B, a pattern that was also captured when examining patterns of length 4 as it could be considered a repetition of two A-B-A-B patterns.

3.2.2. Interpretation of dynamics in conversational moves

Table 6 shows the top-5 of conversational move patterns for both PLCs, for string length $C = 5$. It shows that PLC1's conversational move patterns were mostly characterised by a series of informing (that is, inform-inform-inform-inform-inform), with teachers responding to each piece of information with a new piece of information and adding information upon information on top of that. In patterns 3 to 5, these pieces of information were alternated with questions (elicit) or opinions, but still information remained the most central conversational move of each pattern. The following excerpt provides an example of such a series of teachers informing one another, starting with teacher B asking how the others handle the pace during the school year:

Table 6. Orbital decomposition results showing conversational moves patterns in both PLCs.

Pattern #	Move	→	Move	→	Move	→	Move	→	Move
PLC1									
1	Inform	→	Inform	→	Inform	→	Inform	→	Inform
2	Inform	→	Inform	→	Inform	→	Inform	→	Opinion
3	Inform	→	Opinion	→	Inform	→	Opinion	→	Inform
4	Inform	→	Elicit	→	Inform	→	Elicit	→	Inform
5	Inform	→	Elicit	→	Inform	→	Opinion	→	Inform
PLC2									
1	Inform	→	Opinion	→	Inform	→	Opinion	→	Inform
2	Inform	→	Opinion	→	Inform	→	Inform	→	Inform
3	Inform	→	Opinion	→	Argument	→	Elicit	→	Inform
4	Argument	→	Inform	→	Opinion	→	Inform	→	Opinion
5	Inform	→	Elicit	→	Inform	→	Opinion	→	Inform

B: How is the pace with you all? For me, last year I worked at a pace that I thought was good for the students so they could handle it well, but I only got up to Chapter 4 in all the classes I taught, while the book has 8 chapters. This year we said: we want to cover at least 6 chapters, but preferably 7.

A: With English, we had exactly the same situation last year, also 8 chapters. I teach lower grades every year and then also 4th year. Back then, we did 3 chapters: in period 1, 1 chapter; in period 2, 2 chapters; period 3 entirely. And then in period 4, the rest of the chapters but only the grammar. So we skipped the vocabulary and such because the grammar was important. And now, we're looking at how it would be if we did 2 chapters per period. Now we're thinking about split tests. So you do cover 2 chapters, but then you test vocabulary from one chapter, and then have a teston vocabulary, grammar, stones, or the other way around. So they will spread the workload over those two chapters.

C: With us, they also do two chapters and only one test over those two chapters. The kids find it hard and also unfair, like ″just test us on vocabulary, then we can improve ourgrades'. Then I say: I'm not doing that, you know that, because we have skills tests. Kids: "but what do we need to know?" You need that to be able to write those sentences. I explain that every time, but then they say again": Sir, now we have to learn vocabulary and grammar, and you don't even ask about it!″ But you have to be able to write in German: *Ich habe einenBruder*. There's grammar in that, you had to learn it, you had to learn theword ′*Bruder*″, *Ich habe*, what do I have, and the accusative case. Can't you just do vocabulary, they ask.

A: In English, we have stones, grammar, and vocabulary. The grammar and vocabulary combined can be seen in the stones. And then they ask: ′Why do we have to learn the stones?′ I reallydon't know. . .

B: And those are the sentences?

A: Yes, useful phrases they learn.

As this excerpt shows, teacher B was curious how the others handled the pace of the subject matter throughout the school year. The other teachers provided information on how they dealt with the materials, and teacher B only asked one question for clarification. Teachers did not really connect to each other's contributions, other than their recognition of the issues the others came across.

In PLC2, participants also were involved in informing one another quite a lot, but they did not have a pattern of five consecutive informing moves in their top 5. Rather, teachers in this group seemed to build much more upon one another's contributions by providing opinions that were supported by arguments (as is the case in pattern 3 and 4). The following excerpt provides a nice example of this dynamic:

A: Last time, we had very little time, but we did already have a decent form that they need to fill out in advance. We should also keep that, and then ask them to bring it out during the midterm evaluation.

B: If during the midterm evaluation theyare asked on paper: what would you like to make? Actually, that's working with a kind of concept, that you work with an idea: this is what it should become, and eventually, you find out that you just can't get certain things done. I find that with the association and such, they really tried their best to get someone from the board of that club involved, but it just didn't work. Then it becomes too abstract for them or something.

A: Then they get stuck and don't know how to proceed.

B: But just the fact that it's mentioned, that it would have been nice if someone from the board who also knows exactly what is needed and what money is available could explain that.

C: And when that didn't work out, then what?

B: Then they just ended up thinking about what the trainer always misses, and yeah. Then they solved that well enough.

A: I think we should make that form more important. They need to fill it out first, then you review it with the teacher to see if they filled it out correctly, and during the midterm evaluation, you bring that form out again, and then you can talk based on that.

B: And a little file with that talentcard, from the midterm evaluation and final evaluation, and at some point, itall comes together.

C: And then they can maybe write something on the back during the midterm evaluation, and then during the final evaluation, you just look at: they need to say, 'I made this", andthen explain, "I was actually planning to make such a big thing, but that didn't work out because, well, someone didn't want to cooperate', and then you also see if they took the midterm evaluation to heart or if they just didn't do anything with it.

This example also starts with a timing issue, having too little time for the planned activity. However, the discussion proceeds with concrete suggestions what the teachers can or should do as a unity, whereas in PLC1 teachers only mentioned their own separate experiences. Particularly in the last three turns, where A shares their opinion that the form should be made important, the other team members can clearly be seen building on to A's ideas.

3.2.2.1. Dynamics in turn-taking. As indicated above, turn-taking dynamics were analysed examining patterns of length $C = 4$. Table 7 shows, for this length, the top-5 most occurring turn-taking patterns in both PLCs. In PLC1, all sequences revolved around Anna. In fact, all patterns consisted of a back-and-forth dyadic interaction between Anna and one of her colleagues, either Bianca, Chris, or Deborah; Anna-Bianca-Anna-Bianca (and vv); Anna-Chris-Anna-Chris; and Anna-Deborah-Anna-Deborah. This indicates that Anna not only had most contributions, but she also had a key position in the mostly dyadic interaction dynamics.

In PLC2, the frequency table indicated a much more evenly distributed turn-taking pattern. However, when examining the top 5 recurrent patterns from the OD analysis, it turned out that both Erica and George were quite central. That is, the two most frequently repeating patterns were a dyadic conversation between Erica and George, who were also

Table 7. Orbital decomposition results showing turn-taking patterns in both PLCs.

Pattern #	Teacher	→	Teacher	→	Teacher	→	Teacher
PLC1							
1	A	→	D	→	A	→	D
2	D	→	A	→	D	→	A
3	B	→	A	→	B	→	A
4	A	→	B	→	A	→	B
5	C	→	A	→	C	→	A
PLC2							
1	E	→	G	→	E	→	G
2	G	→	E	→	G	→	E
3	G	→	E	→	G	→	F
4	F	→	G	→	E	→	G
5	F	→	E	→	F	→	E

Letters refer to the teachers' first initials.

involved in patterns 3–5. Although Fred was involved in the conversation, Erica and George seemed to be more leading in the conversations. Thus, the conversation was attracted to patterns revolving around these two teachers more strongly. As such, Fred's contributive behaviour may have been less predictable than the behaviours of the other two teachers.

4. General discussion

The main objective of this paper was to illustrate how OD analysis can be used to study interaction dynamics in (educational) social systems. We formulated the following research questions: Which recurrent patterns in teacher–teacher interactions could be identified? How are these patterns different for the two PLC's? Although the two PLCs had similar instructions, they varied strongly in the output they delivered. PLC1 only shared what they had been doing in their classes that could fit within the general theme of differentiated instruction on an anecdotal basis. In PLC2 materials were co-developed, implemented, and evaluated in a stronger interdependent fashion. The findings from the OD analyses of these two cases of teacher PLCs show that the differences in the outcomes of the PLCs are reflected in a difference in interdependence in the moment-to-moment interaction patterns during PLC sessions. PLC2's interaction, particularly in terms of conversational moves, was to a larger extent characterised by interdependence than the interaction of PLC1. That is, PLC1's conversations were best characterised by a series of teachers informing one another, which reflects the stories they told each other rather than working jointly on their shared goals. In PLC2, to the contrary, teachers were much more involved with one another, asking questions, elaborating on answers, and providing argumentation for their statements.

Differences between the two PLCs in terms of turn-taking were more complicated than was visible in the frequencies. Based on the frequencies, PLC1 clearly had a dominant person in Anna, who was also present in all the turn-taking sequences. In PLC2's frequency table, none of the teachers was clearly dominant, yet based on OD patterns, both Erica and George turned out to be central figures in the recurrent patterns. This could mean that, although all teachers seemed equally involved in the conversation – based on the frequencies- interactions revolving around both Erica and George were more prominent and recurring the group's interactions, whereas Fred's contributions were more random and less predictable.

As such, both in terms of conversational moves and turn-taking, the OD analysis provided information about the interaction patterns that could not have been captured by merely examining frequencies of interactional behaviours. This information also provided insight in the quality of the interactions and could be related to the differences in PLC output.

4.1. *Examples of other applications*

In the present paper we have applied OD analysis to the study of teacher–teacher interactions by observing turn-taking and conversational moves. Existing work has also applied OD to study group dynamics in other contexts, including face-to-face (Guastello, Hyde, and Odak 1998) as well as online settings (Guastello 2000). In education, it would be interesting to extend this range of applications to patterns in teacher–student interactions in class or student–student interactions in collaborative settings. In addition to studying interactions, Garner and Russell (2016) applied OD to study the presence of non-random patterns of visual learning behaviour: *gaze patterns*. This work could be extended into a multitude of behaviour patterns, including teachers' gaze patterns (e.g. whole-class, whiteboard, own preparation documents, specific student, ceiling, etc.), students' classroom behaviours (e.g. attentive, disruptive, adding to the classroom discussion etc.), or student behaviour in online learning environments (clicking on different materials, adding to discussion boards, etc.).

In sum, there are many applications of OD analysis in educational research possible. If the data set consists of sequences of nominal states that change over time (see Pincus, Ortega, and Metten 2011). There are no rules pertaining the timeframe of the studied behaviour changes, whether the this changes every ten milliseconds, every hour, or daily. OD analysis can be applied to gain insight into recurrent patterns in these data.

4.2. Recommendations for future users

For researchers who are starting to study interaction dynamics in social and cultural systems, OD analysis can be a good starting point, because it is relatively simple to conduct and understand (Pincus 2009). Instead of merely looking at frequencies or capturing time-series data in quantitative (mathematical) indices, OD analysis provides qualitative information about sequences that recur most often, to understand the phenomenon under investigation in all its complexity. This section provides recommendations for future users regarding the development of behavioural coding systems and the use of OD analysis.

The main starting point for using OD analysis is the realisation that it can only be applied to analyse categorical data (see Pincus, Ortega, and Metten 2011). Sometimes it is even possible to convert continuous observational data into categorical data, this is of course not always a possibility and depends on the coding scheme.

Second, how the categories are defined is entirely up to the researcher. However, the categories should be observable (i.e. codes should correspond to behaviours displayed in the interaction), mutually exclusive, and exhaustive. Also, one should note that it is important to define categories that are appropriate for coding in sequences (Garner and Russell 2016): Sequences that capture a phenomenon that moves through different states over time.

Third, we illustrated OD analysis capturing sequences of single codes that represented a single pattern. In addition, also a combination of codes from multiple dimensions or from multiple interaction patterns can be used (Guastello 2000). For instance, when behaviours of two interlocutors are coded separately but continuously, and therefore are coupled in time, these can be combined into one dyadic code.

In the present paper, we deliberately did not describe the mathematical foundations of OD analysis, as our aim was to illustrate OD in a manner that was relatively understandable. For those readers interested in the mathematical foundations of OD analysis, the calculations of indices such as the most optimal string length or the degree of information complexity (i.e. Shannon entropy) we recommend reading the original work of Guastello, Hyde, and Odak (1998) or the handbook chapter by Garner and Russel (2016).

4.3. Limitations of OD analysis and recommendations for future research

Although OD is a promising analysis technique to examine dynamics in education, it also has several limitations. First, while OD analysis provides an exhaustive list of patterns and the number of times each pattern recurs in the data, it does not provide information of when in the interaction certain patterns recur. Patterns could directly follow each other in time or could be separated by other interaction patterns, thus within sessions and across sessions. A researcher who is interested in how the interaction dynamics unfold over time may need this information. To gain information about this, it is advised to either look at the raw data, or to split up the data in relevant chunks that are analysed separately so to see in which part of the interaction certain patterns appear and/or disappear.

Second, even though various indices are used to identify the most optimal string length, the researcher's subjective decision may be an issue, as the *C* length determination can become subjective or result in different lengths for various cases. In larger samples, these *C* lengths likely differ across cases or samples; depending on the research goal the most occurring string length across the sample can be chosen over case-based optimal string lengths (as we did in our study). According to Garner and Russell (2016), selecting a sample-based optimal string length is a valid choice when comparisons across multiple cases are being made. However, when the goal of a study is to describe the interaction patterns for individual sequences, one might consider analysing the data based on different string lengths. For instance, for the turn-taking patterns in our study, we chose to represent both cases' dynamics using a *C* length of 4. However, we could have chosen two different *C* values, one for each case. Yet, the latter would have come at the cost of limited possibilities for comparison.

Finally, whereas OD analysis results in an examination of patterns and as such considers dynamic rather than static interaction data, these patterns are still rather small sets of the entire conversational flow. In addition to OD analyses, other types of analyses may provide complementary information that could be combined and integrated with the results of OD analysis to paint an even more complete picture of the interaction quality and dynamics. For example, in studies where continuous observations of interactional behaviours are available, stepwise time-series decomposition and spectral analysis (e.g. Pennings et al. 2018; Warner 1998) can provide additional insight in the degree of adaptation in the interactions or synchronisation between interaction partners. Also, in addition to the most frequently occurring patterns resulting from OD analysis, State Space Grid Analysis (Hendriks et al. 2024; Pennings and Hollenstein 2020) could provide information about the content or structure of interactions by identifying attractors in dyadic behaviours or the predictability of the interactions.

Although OD analysis is designed to detect non-random patterns in data (Garner and Russell 2016), a downside of choosing a certain number of patterns and a specific optimal string length in OD analysis might be that certain individual events that have major impact on the interaction quality could be missed. This is due the complex nature of humans in interactions, that human behaviour cannot always be reduces to small bits of information. Qualitative analysis of such critical incidents could add vital information to our understanding of a learning process. Also, other qualitative or mixed methods approaches such as Conversation Analysis (Gosen et al. 2024; Sert, Gynne and Larsson 2024) or Statistical Interpretative Discourse Analysis (Chiu et al. under review) could provide valuable information in combination with OD analysis. For example, to qualitatively identify recurring patterns in interactions, in describing mechanisms underlying the OD patterns and testing hypotheses of generality. To fully understand the dynamics of educational processes, we therefore recommended to use combinations of analyses.

5. Conclusion

The current study illustrates the application of OD to study interaction dynamics in teacher–teacher interactions. Although OD has its limitations, we believe that careful application of OD is promising to reveal interaction dynamics that cannot be readily quantified with a frequency approach. In particular when combined with other analytical approaches that are demonstrated in the current special issue.

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