Chapter 7
Social Metacognition, Micro-Creativity, and Justifications: Statistical Discourse Analysis of a Mathematics Classroom Conversation

Ming Ming Chiu

In this chapter, I apply statistical discourse analysis (SDA, Chiu, 2008a) to Shirouzu's classroom data both to identify the locations and consequences of pivotal moments and to accompany other methodologies to yield multivocality insights. When asked to solve a novel problem, students try to create new ideas (*micro-creativity*) and assess their utility via explanations or justifications (Chiu, 2008a). [Micro-creativity occurs at specific moments, unlike the daily-life "small c" creativity of ordinary people and the "big C" creativity that affects societies (Sternberg & Lubart, 1999).] While micro-creativity provides grist for solving a problem, justifications support or refute an idea's usefulness by linking it to data, using a warrant, or supporting a warrant with backing (Toulmin, 2003). Hence, justifications are also a crucial component of the micro-creative process. A natural follow-up question is how classroom processes affect new ideas and justifications and whether their effects differ across time.

In this study, I address these issues by statistically modeling individual and conversation turn characteristics that affected micro-creativity or justifications as students solved a fraction problem in a Japanese classroom. This study contributes to the classroom process literature in four ways. First, I document when new ideas, correct ideas, and justifications occur, whether they occur uniformly during a lesson or more frequently in some time periods (*meso-time context*) than in others (Wise & Chiu, 2011). I statistically identify pivotal moments that divide the lesson into distinct time periods. Second, I test how the recent sequences of actions (*micro-time context*) affect the likelihoods of micro-creativity or justifications (Wise & Chiu, 2011). Third, I test whether the above effects differ across participants, classrooms, or time periods. Lastly, I discuss how other analysts' results and ideas have improved both SDA and its results. By understanding how the multivocality of several analyses informs one another, we can develop stronger methods and reap greater insights from a data set.

M.M. Chiu (✉)
University at Buffalo—State University of New York, Buffalo, NY, USA
e-mail: mingchiu@buffalo.edu

D.D. Suthers et al. (eds.), *Productive Multivocality in the Analysis of Group Interactions*, Computer-Supported Collaborative Learning Series 16,
DOI 10.1007/978-1-4614-8960-3_7,

Micro-creativity and Justification

Classroom participants' cognitive or social metacognitive processes might influence one another's thinking. This section focuses on how they might affect one another's micro-creativity and justifications.

Cognition

Classroom participants can build on one another's ideas to create new ideas through processes such as sparked ideas, error recognition, and jigsaw pieces (Paulus & Brown, 2003). Comments by one person (e.g., a key word) might spark another person to activate related concepts in his or her semantic network and propose a new idea (Nijstad, Diehl, & Stroebe, 2003). Specifically, a student might build on a correct idea to create another correct idea, or replace a flawed idea with a correct, new idea (Orlitzky & Hirokawa, 2001). Like fitting jigsaw pieces together, classroom participants can also put together different pieces to create a new idea (Milliken, Bartel, & Kurtzberg, 2003).

New ideas are often accompanied by justifications. Chiu and Khoo (2003) showed that classroom participants often supported their new ideas with justifications, especially before a disagreement. After a new idea, other classroom participants often evaluate its validity and give justifications to support their evaluation, especially if they disagree with a wrong idea (Orlitzky & Hirokawa, 2001).

Social Metacognition

Whereas individual metacognition is monitoring and controlling one's own knowledge, emotions, and actions, *social metacognition* is people's monitoring and control of one another's knowledge, emotions, and actions (Chiu & Kuo, 2009). Social metacognition can aid classroom problem solving through repetition, evaluation of one another's ideas, identification of problems (via disagreements or questions), or justification of different positions (Chiu & Kuo, 2009).

By repeating old information, students show shared understanding, common ground, and solidarity (Chiu, 2000a). Repetitions that organize and synthesize previous ideas can help classmates understand relationships among ideas, recognize gaps, and create a productive foundation for new ideas and correct ideas (Wise & Chiu, 2011). As repetitions review previously discussed ideas, they typically do not provoke new justifications.

Classroom participants often evaluate the previous speaker's action and problem-solving approach (Orlitzky & Hirokawa, 2001). For example, after one student says "three-sixths (3/6) is two," another student can respond by agreeing ("right"), using a neutral action ("what did you say?"), disagreeing ("no, that's wrong"), or changing the topic ("are you going to the party tonight?"). While agreements continue the current problem-solving path, disagreements and changes of topic (ignoring the previous action) try to change it (Chiu, 2001).

Evaluations can also be right or wrong in some contexts (such as simple mathematics problems). Correct evaluations support correct ideas ("three-sixths is one-half, uh-huh") or identify flawed ideas ("uh-uh, three-sixths is not two,"), thereby contributing to a foundation of partially shared understanding of correct ideas that group members can use to build new ideas, correct ideas, micro-creativity, or justifications. In contrast, incorrect evaluations reject correct ideas ("nope, three-sixths isn't a half,") or accept flawed ideas ("three-sixths is two, yeah"), embedding flaws in their partially shared understanding. Group members using this partially shared understanding can import these flaws into their new ideas, resulting in wrong ideas (Cobb, 1995).

Through their monitoring, classroom participants can recognize problems or difficulties (perturbations), express them through disagreements or questions, and address them with new ideas and justifications (Buchs, Butera, Mugny, & Darnon, 2004). Piaget (1985) defines two types of perturbations: (a) lacunae, gaps in understanding, often expressed through questions, and (b) obstacles, often expressed through negative feedback (disagreement).

A person asking a question (elicitation) typically shows a gap in his or her understanding (except for artificial teacher questions, Tsui, 1992). For example, a student asks, "how did you get half?" This gap can motivate the need for a new idea and suggest a direction for creating one and its accompanying justifications. Thus, questions might aid creation of new ideas, correct ideas, or justifications.

Meanwhile, disagreements can aid micro-creativity and justifications both directly and indirectly. Disagreements can correctly identify obstacles to be overcome (e.g., "no, three-sixths can't be two because it has to be smaller than one.") and directly stimulate justifications that support creation of new ideas (Chiu, 2000b; Coleman, 1998). Furthermore, a disagreement (even if wrong) can stimulate the attention of classroom participants, helping them consider more aspects of the situation from other perspectives to create further justifications and possibly new ideas—especially from social loafers who might stop relying on others (Nemeth, Personnaz, Personnaz, & Goncalo, 2004).

Disagreements can also indirectly encourage reluctant classmates to express their ideas, especially after agreements and repetitions of an existing idea suggest a majority view (Nemeth et al., 2004). Thus, a disagreement by another member, regardless of its validity, legitimizes the existence of different opinions, freeing all classroom participants to express new ideas, including those unrelated to the specific disagreement (Nemeth et al., 2004). Hence, disagreements can aid new ideas, correct ideas, and justifications.

After perturbations provoke new ideas, justifications often follow. Chiu and Khoo (2003) showed that members of successful groups often anticipated criticisms and justified their new ideas. Likewise, after a person disagrees with a proposal, the original proposer might try to justify it by linking it to data, using a warrant, or

Table 7.1 Hypothesized model of the effects of classroom problem-solving process on the outcome variable correct contributions (symbols in parentheses indicate expected direction of relationship with the outcome variables: positive [+], negative [−], or unknown [?])

	→ Dependent variables		
Classroom processes	New idea	Correct idea	Justify
Cognition			
New idea	+	+	+
Correct idea	?	+	?
Social metacognition			
Repeat	+	+	−
Evaluate correctly	+	+	+
Question	+	+	+
Disagree	+	+	+
Justify	+	+	+

supporting a warrant with backing (Toulmin, 2003). In response, other members can present new ideas and justifications (Chiu, 2008b). Similarly, when a student shows a gap in understanding by asking a question, other members can respond with explanations and justifications (Lu, Chiu, & Law, 2011). As justifications support an idea's validity, justifications might help create *correct* new ideas rather than *wrong* new ideas (e.g., Chiu, 2001).

Present Study

In sum, this study statistically models how cognitive and social metacognitive processes influence the likelihoods of new ideas, correct ideas, and justifications (see Table 7.1). To reduce omitted variable bias, I control for time (Chiu, 2008a) and demographic variables (gender, teacher vs. student). Learning of other analysts' results inspired me to improve my analysis, and I have noted them as changes to the original analysis below.

Method

In this study, I examine a lesson in which a teacher helps students learn multiplication of fractions by folding paper (see Shirouzu chapter). Their classroom processes were videotaped and transcribed. My content analyses (Krippendorff, 2004) yielded multidimensional coding of each conversation turn. While the conversation turn is the unit of analysis, the unit of interaction is a sequence of one type of action following another. The interaction as a whole is characterized by the probabilities of these sequences, which is modeled with SDA (Chiu & Khoo, 2005). See Shirouzu chapter for participants, data, and procedure.

Table 7.2 Coding of an artificial classroom discourse segment along five dimensions

Person	Action	EPA	KC	Validity	Justify	IF
Bob	Do three-sixths	*	N	√	[]	!
Lyn	Three-sixths is, um, is–	+	R	√	[]	–
Don	Three sixths is two	+	N	X	[]	–
Bob	Wrong, three sixes is eighteen	–	N	X	[]	–
Lyn	What?	n	0	0	0	?
Jan	It's three sixths, not three sixes. Three is half of six, so three sixths is one-half	–	N	√	J	–

Variables

In addition to individual (gender, teacher vs. student) and time period variables (discussed below), each conversation turn was coded along five dimensions. The dimensions were *evaluation of the previous action* (EPA: agree [+], neutral [n], disagree [–], ignore/new topic[*]), *knowledge content* (KC: new idea [N], repetition [R], null content [0]), *validity* (right [√], wrong [X], null content [0]), *justify* ([J], no justification [], null content [0]), and *form of invitation to participate* (IF: command [!], question [?], statement [_.]). See Table 7.2.

Some variables are created from combinations of the above variables. For example, a correct evaluation is either agreeing with a correct, previous idea or disagreeing with an incorrect, previous idea.

Analysis

This section specifies the assumptions underlying the analysis, its purpose, units of interaction, representations of the data, and analytic manipulations.

Assumptions Underlying the Analysis

Theoretical assumptions. SDA (Chiu & Khoo, 2005) has several theoretical assumptions. First, as with any statistics (e.g., count, mean, standard deviation), SDA assumes that instances of a category (e.g., justification) with the same value (e.g., is vs. is not [coded as 1 vs. 0]) are sufficiently similar to be treated as equivalent for the purpose of this analysis. This specific study has three additional theoretical assumptions. Characteristics of recent conversation turns, participating individuals, and time constitute a micro-context in which future talk emerges. Third, characteristics of recent conversation turns, their authors, and the time period can influence characteristics of later conversation turns. Fourth, residuals reflect attributes related to the dependent variables that are not specified in the theoretical model and not correlated with the explanatory variables.

Methodological assumptions. Like traditional regressions, SDA assumes a linear combination of explanatory variables. (Nonlinear aspects can be modeled as nonlinear functions of variables [e.g., age squared] or interactions among variables [question x correct].) SDA also requires independent and identically distributed residuals and a modest, minimum sample size.

Purpose of Analysis

SDA (1) identifies pivotal moments along specific dimensions that divide the data into distinct time periods, (2) tests whether variables are linked to greater or reduced likelihoods of dependent variables of interest, and (3) tests whether these links differ across time periods.

Units of Interaction That Are Taken as Basic in the Analysis

While the unit of analysis is a conversation turn, the unit of interaction is a sequence of one type of action following another. The interaction as a whole is characterized by the probabilities of these sequences, which is modeled with SDA.

Representations of Data and Analytic Interpretations

I used the standard representations of a database table, a summary statistics table, a table of breakpoints, a time series graph, and a path diagram. I converted the initial data representation of a database table with one utterance per row to one conversation turn per row, keeping the given attributes such as time, actor, and content. Next, I added columns (variables) for coding the argumentative attributes of each conversation turn as occurring or not. Then, I performed statistical analyses to test relationships across this table of vectors, resulting in a summary statistics table, a table of breakpoints, and a table of results of regression models (via SDA). To aid reader comprehension, I capitalize on readers' understanding of spatial relationships to convert the tables into graphs and path diagrams.

Analytic Manipulations

Addressing the above hypotheses with this data set requires modeling (1) differences across time (time periods, serial correlation); (2) three binary, infrequent, dependent variables; and (3) sequences of conversation turns that can differ across people, show indirect mediation effects, or yield false positives. See Table 7.3.

To address these difficulties, a simplified version of SDA is used (Chiu, 2008b; Chiu & Khoo, 2005). First, a breakpoint analysis statistically identifies pivotal moments that separate distinct time periods. Differences due to time periods or

Table 7.3 Statistical discourse analysis strategies to address each analytic difficulty

Analytic difficulty	Statistical discourse analysis strategy
Differences across time	
Different time periods	Breakpoint analysis (Chiu and Khoo 2005)
Differences across time/serial correlation	I^2 index of Q-statistics (Huedo-Medina, Sanchez-Meca, Marin-Martinez, and Botella 2006)
Dependent variables	
Binary	Logit (Kennedy 2004)
Infrequent	Bias estimator (King and Zeng 2001)
Multiple	Multivariate outcome analyses (Goldstein 1995)
Explanatory variables	
Sequences of conversation turns	Vector auto-regression (VAR, Kennedy 2004)
Differences across people	Interaction terms (Kennedy 2004)
Indirect, mediation effects	Mediation tests (Sobel 1982)
False positives	Two-stage linear step-up procedure (Benjamini, Krieger, and Yekutieli 2006)

people are tested with interaction terms (Kennedy, 2004). If not modeled properly, resemblances among adjacent conversation turns can result in serial correlation of errors (Kennedy, 2004). An I^2 index of Q-statistics can test conversation turns in many time periods for serial correlation, which can be modeled if needed (Huedo-Medina et al., 2006).

Furthermore, the three dependent variables were binary and infrequent (new idea, correct idea, and justification). To model a binary-dependent variable, Logit or Probit is used. When dependent variables occur far less than 50 % of the time, standard regressions will yield biased results. To remove this bias, I used King and Zeng's (2001) bias estimator. Multiple outcomes can have correlated residuals that underestimate standard errors. To model several dependent variables properly, a multivariate outcome analysis is needed (Goldstein, 1995).

The explanatory variables can include sequences, differ across people, yield indirect effects, or show false positives. Sequences of explanatory variables are modeled with vector auto-regression (VAR, Kennedy, 2004). Different effects across people are tested with interaction terms (Kennedy, 2004). To test for indirect effects, Sobel's (1982) mediation test was used. Testing many hypotheses via explanatory variables raises the likelihood of a false positive (Type I error). To control for this false discovery rate (FDR), the two-stage linear step-up procedure was used, which outperformed 13 other methods in computer simulations (Benjamini et al., 2006).

Identify Pivotal Moments and Time Periods

Some actions (e.g., correct ideas) might occur more often at the end of a session (e.g., close to a solution) than at the beginning (e.g., discussion of a problem).

I operationalize *pivotal moment* as *a conversation turn that separates a portion of the conversation into two distinct time periods* (before and after) *with substantially different likelihoods of the focal variable* (e.g., correct ideas). The different likelihoods of the focal variable in the *before* and *after* time periods suggest that the interactions in the two time periods differ substantially.

SDA can statistically identify pivotal moments that divide a session into time periods with more vs. fewer correct ideas. These pivotal moments can then be used to test whether the relationships between explanatory variables and correct ideas differ across time periods (Chiu, 2008b). Initially, a univariate time-series model (auto-regressive order 1 model) has no pivotal moments. In (7.1), Correct_t indicates whether a correct idea occurs at conversation turn t. The regression coefficient β indicates whether Correct_t is related in some way to whether a correct idea occurred in the previous utterance, Correct_{t-1}, with constant C_0 and residual ε_t:

$$Correct_t = \beta Correct_{t-1} + C_0 + \varepsilon_t \tag{7.1}$$

Next, we added pivotal moments. The number of potential pivotal moments (i) can range from 1 to p, with corresponding pivotal moment location dummy variables ($Break_i$) and regression coefficients (C_i):

$$Correct_t = \beta Correct_{t-1} + C_0 + \varepsilon_t + C_1 Break_1 + C_2 Break_2 + \ldots + C_p Break_p \tag{7.2}$$

For each number of pivotal moments (first 1 break, then 2 breaks, … 6 breaks), all possible locations of pivotal moments were modeled. (Only six pivotal moments were tested because current microcomputers require over a year to test seven pivotal moments.) For each model, the Bayesian information criterion (BIC) was computed from the log-likelihood function L, n observations, and k estimated parameters: BIC $= [-2L + \ln(n)\,k]/n$. Information criteria indicate whether a model suitably balances parsimony and goodness of fit. Unlike other information criteria, the BIC yields a consistent estimator for the number of lagged variables in the true model (Kennedy, 2004). The best model has the lowest BIC.

Explanatory Model

Next, the explanatory model was estimated with multivariate logit (Goldstein, 1995):

$$\mathbf{Action}_{jy} = \beta_{0y} + \mathbf{e}_{jy} \tag{7.3}$$

$\mathbf{Action}_{jy}$ is a vector of y dependent variables (new idea, correct idea, and justification) for turn j. β_{0y} are its grand mean intercepts, and its residuals are $\mathbf{e}_{jy}$. First, the statistically identified time period dummy variables (**Time**) were entered into the regression model:

$$\begin{aligned}
&\mathbf{Action}_{jy} = \beta_{0y} + \mathbf{e}_{jy} + b_{ty}\mathbf{Time}_{jy} + \beta_{iy}\mathbf{Individual}_{jy} + \\
&\beta_{\mathbf{cy}}\mathbf{Current_Conversation_turn}_{jy} + \\
&\beta_{py}\mathbf{Previous_Conversation_turn}_{(j-1)y} + \\
&f_{py}\mathbf{Two_Conversation_turns_ago}_{(j-2)y} + \ldots + \\
&\beta_{xy}\mathbf{Interactions}_{jy}
\end{aligned} \tag{7.4}$$

Each set of predictors was tested for significance with a nested hypothesis test (χ^2 log likelihood, Kennedy, 2004), and nonsignificant variables were removed.

Then, individual characteristics were entered: teacher (vs. student) and girl (**Individual**). Next, characteristics of the current conversation turn were entered: repeat, correctly evaluate, agree, disagree, ignore, question, and command (**Current_Conversation_turn**). Then, characteristics of the previous turn were entered: justification (-1), correct (-1), new idea (-1), repeat (-1), correctly evaluate (-1), agree (-1), disagree (-1), ignore (-1), question (-1), and command (-1) (**Previous_Conversation_turn**). Next, the characteristics from two turns ago (**Two_Conversation_turns_ago**) were tested and so on until no variables were significant. To test for moderation, I added interactions of all significant variables (**Interactions**).

An alpha level of 0.05 was used. Testing many hypotheses raises the likelihood of a false positive (Type I error). To control for the FDR, the two-stage linear step-up procedure was used (Benjamini et al., 2006).

Path analysis estimated direct and indirect effects (Kennedy, 2004). As time constrains the direction of causality, the explanatory variables were ordered temporally in the path analysis. The odds ratio of each variable's total effect (E, direct plus indirect) was reported as the increase or the decrease (+E% or −E%) in the dependent variable (Kennedy, 2004).

This model was initially tested on the full data set. Upon learning that another analyst (Shirouzu) viewed the class discussion activity as the most important part of the lesson, I did a separate analysis on the class discussion activity subset of the data, delineated as occurring after the statistically identified primary pivotal moment (see details below). With 582 turns in the full data set, statistical power exceeded 0.99 for an effect size of 0.2 (Cohen, West, Aiken, & Cohen, 2003). With 134 turns in the subset, statistical power is 0.95 for an effect size of 0.3 (Cohen et al., 2003).

Sample Size

Green (1991) proposed the following heuristic sample size, N, for a multiple regression with M explanatory variables and an expected explained variance R^2 of the outcome variable:

$$N > \left(\left\{8 \times \left[\left(1 - R^2\right) / R^2\right]\right\} + M\right) \quad 1 \tag{7.5}$$

For a large model of 25 explanatory variables with a small expected R^2 of 0.10, the required sample size is 96 conversation turns: $= 8 \times (1 - 0.10)/0.10 + 25 - 1$. Less data are needed for a larger expected R^2 or for smaller models. In practice, two groups of students talking for half an hour will often yield more than 100 speaker turns, sufficient for SDA. In this data set, we converted the 582 utterances to 443 conversation turns, which exceeds the required sample size of 96. To aid comparisons across chapters, we use utterance identification numbers (rather than conversation turn identification numbers).

Results

Summary Statistics and Pivotal Moments

In the data subset in which the class compares student answers, the key variables occurred more often (especially new ideas, micro-creativity, correct evaluations, questions, and disagreements) than in the overall data set of the entire class (see Table 7.4). The percentages in the data subset are similar to those in other studies of face-to-face mathematics problem solving by groups of students (e.g., Chiu, 2008b).

SDA yielded five significant pivotal moments for micro-creativity and three pivotal moments for justifications (see Table 7.2 and Fig. 7.1). The micro-creativity pivotal moment at utterance 448 is strongly supported through its consistent identification in the optimal models of one, two, three, four, and five pivotal moments; hence, it is the *primary pivotal moment* (an idea raised through the three analysts' [Shirouzu, Trausan-Matu, and me] discussion of whether some pivotal moments are more important than others). Consider the pivotal moment at utterance 448, when several students recognize the equivalence of two different solutions. After students have solved the problem of finding 3/4 of 2/3 of a square sheet of paper, the teacher asks them to compare two students' solutions.

Table 7.4 Summary statistics of significant variables

	% in each data set	
Variable	Overall	Subset
Cognition		
Repeat	37	40
Correct idea	42	50
New idea	12	17
Micro-creativity	12	17
Social metacognition		
Evaluate correctly	24	43
Question	13	17
Disagree	1	3
Justify	7	9
Individual		
Teacher	27	31
Girl	28	21

Table 7.5 Micro-creativity and justification pivotal moments

# of pivotal moments	Micro-creativity BIC	At utterance # …					Justifications BIC	At utterance # …				
0	0.767						0.533					
1	0.766				**448**		0.464	**206**				
2	0.755			164	**448**		0.456	**206**			394	
3	0.750			164	**448**	476	0.433	**206**			394	537
4	0.750	20	39		**448**	476	0.445	**206**	310		394	537
5	0.747	20	39	164	**448**	476	0.447	**206**	310	359	394	537

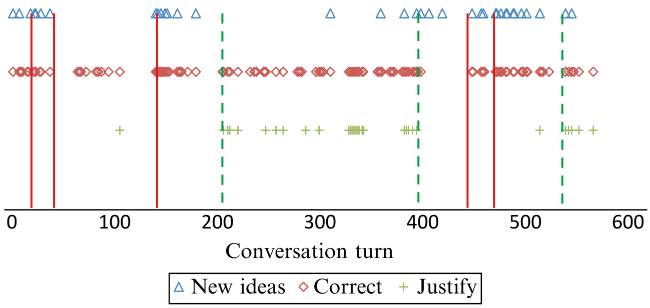

Fig. 7.1 Occurrences of three actions over time: new ideas, correct ideas, and justifications. *Red solid vertical lines* indicate pivotal moments for new ideas, and correct ideas. *Green dashed vertical lines* indicate pivotal moments for justifications

Utterance #	Person	Talk and actions
440–447	T:	Which should we begin with? N's and G's solutions [removes the solutions from the blackboard and puts them on the desk] are the ones completed first. This is a complete one. This is one example. This is another one [places another solution on the desk]. How do you compare?
448	**G, K, N:**	**The same**
449	T:	The same. Here, everyone agreed. This one and this one are the same. So, how do you compare these [N1 and G2]? This one and this one. Please

Students G, K, and N all say that the solutions are "the same," the first of many correct, new ideas (see Fig. 7.1). After listening to another analyst's (Trausan-Matu) discussion of collaborative utterances, I considered whether this pivotal moment consisted of more than this shared utterance and might include preceding or following utterances. As the teacher asked the question that elicited the student answers, the previous turn clearly contributes to this pivotal moment. Arguably, the teacher's confirmation of the students' shared answer in the following turn is also part of the pivotal moment. Hence, SDA only identifies the conversation turn at the heart of the pivotal moment, not its outer boundaries. Hence, the statistically identified conversation turn does not necessarily encapsulate all key aspects of the pivotal moment.

Qualitative methods are needed to examine both the boundaries of the pivotal moment and the mechanism by which it operates. For example, usage of a polyphonic framework (Trausan-Matu, Stahl, & Sarmiento, 2007) to identify the before and after threads of utterances separated by the pivotal moment can indicate where the conversation shifted from one thread to the next. Furthermore, ethnomethodologists (e.g., Sacks, 1995) might examine the detailed relationships among the words and actions near the pivotal moment to understand the mechanism(s) by which one thread becomes another.

The pivotal moments are not necessarily the same across variables. For example, SDA identifies three different pivotal moments for justifications (at utterances 206, 394, and 537). The *primary pivotal moment* at utterance 206 occurs in all the optimal models with one to five pivotal moments. Consider the pivotal moment at utterance 206. After several students have presented their initial solutions, the teacher demonstrates the common first step of several solutions.

Utterance #	Person	Talk and actions
205	Y:	[Standing in front of the blackboard.] First, let's fold the origami paper into three equal parts in this way. [Folds the origami paper into three equal portions.]
206	**T:**	**Yes. These are the same up to this point [while pointing out the first step of N's and G's first solutions].**
207–210	Y:	[Continues to fold after glancing at T's explanation.] Then, Yes. let's cut this 1/3 part like this. [Cuts it with scissors.] This paper is now divided into four portions, and this shape was obtained by cutting necessary ones from them.

The teacher folds the paper into three equal parts to justify his claim that the first step of the solutions of N and G are the same. This justification pivotal moment ignites a new time period with many justifications by students (see Fig. 7.1). As with the micro-creativity pivotal moment discussed above, the identified conversation turn does not encapsulate the entire pivotal moment, which is a continuation of an idea that started two turns earlier.

The analysts' discussion mentioned earlier also inspired a way to compare the relative importance of pivotal moments across dimensions; the reduction in BIC after adding a primary pivotal moment shows how much it alters the likelihood of its target phenomenon (e.g., justification) in the following time period. Comparing the primary pivotal moments of justifications and micro-creativity, the justification pivotal moment at utterance 206 has a larger impact on the likelihood of justifications in the subsequent time period compared to the impact of the pivotal moment at utterance 448 on subsequent micro-creativity (13 % > 0.1 %; 13 % = [0.533 − 0.464]/0.533; 0.1 % = [0.767 − 0.766]/0.767). In the next step of the analysis, all of these pivotal moments are entered into the explanatory model.

Explanatory Model

As shown in the explanatory models below, the significant relationships in the full data set and those of the subsample differed substantially. All reported results are from the final models with only significant variables.

Correct Idea, New Idea, and Justification in the Full Lesson

Time period, correct ideas, questions, correct evaluations, and agreement were linked to subsequent correct ideas (Fig. 7.2). A correct idea was 8 % more likely in the time period after the primary pivotal moment for micro-creativity. After a correct idea in the previous turn, a correct idea in the current turn was 6 % more likely. If a correct idea and question both occurred in the previous turn, a correct idea was 9 % less likely to follow. Examination of the classroom videotape showed that correct ideas accompanied by questions were often followed by acknowledgements.

Utterance #	Person	Talk and actions
547	Y:	I thought all (answers) are 1/2 of the whole. What do you all think?
548	N, F, K, O:	Ok.

After Y presents a correct idea (1/2) and asks for other's opinions ("What do you all think?"), four students (N, F, K, and O) simply agree ("Ok").

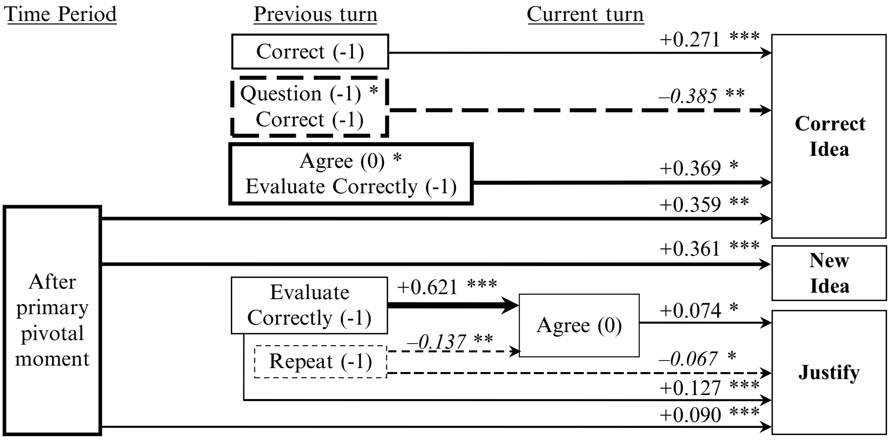

Fig. 7.2 Path diagram modeling correct idea, new idea, and justification in the full data set. *Solid lines* indicate positive links. *Dashed lines* indicate negative links. *Thicker lines* indicate stronger links. *$p<0.05$, **$p<0.01$, ***$p<0.001$

In contrast, a correct idea was 10 % more likely after a correct evaluation in the previous turn and an agreement in the current turn. These variables accounted for 20 % of the variance of correct ideas.

New ideas were 9 % more likely after the primary pivotal moment for micro-creativity. No other variables were linked to new ideas for this data set. This time period variable accounted for 7 % of the variance of new ideas.

Time period, correct evaluations, repetitions, and agreements were linked to justifications. A justification was 2 % more likely in the time period after the primary pivotal moment for micro-creativity. After a correct evaluation, a justification was 5 % more likely. After a repetition however, a justification was 2 % less likely. Meanwhile, justifications were 7 % more likely to occur with an agreement in the same turn. While correct evaluations yielded 16 % more agreements in the next turn, repetitions yielded 3 % fewer agreements in the next turn. These variables accounted for 15 % of the variance of justifications.

Correct Idea, New Idea, and Justification in the Subsample

Time period and correct evaluations were linked to correct ideas. A correct idea was 7 % more likely after the secondary pivotal moment of micro-creativity in utterance 467. Moreover, a correct evaluation in the previous turn or the current turn raised the likelihood of a correct idea by 12 or 11 %, respectively (see Fig. 7.3). These variables accounted for 42 % of the variance of correct ideas in this data subset.

Time period, correct evaluations, repetitions, and justifications were linked to new ideas. A new idea was 9 % more likely after the secondary pivotal moment. After a correct evaluation three turns ago, a new idea was 9 % more likely. After a

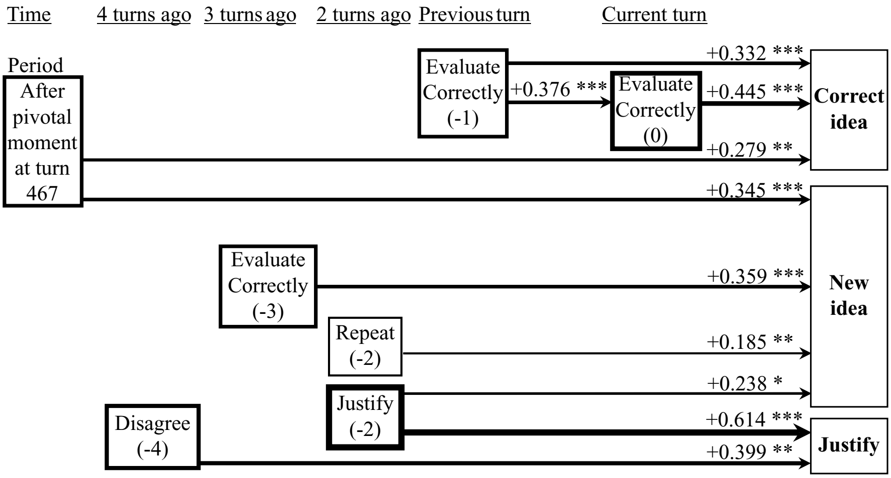

Fig. 7.3 Path diagram of correct idea, new idea, and justification in the data subset after the primary pivotal moment for micro-creativity. *Solid lines* indicate positive links. *Dashed lines* indicate negative links. *Thicker lines* indicate stronger links. *$p<0.05$, **$p<0.01$, ***$p<0.001$

repetition or a justification two turns ago, a new idea was 5 or 6 % more likely, respectively. These variables accounted for 38 % of the variance of new ideas in this data subset.

Justification was 10 or 15 % more likely after a disagreement four turns ago or a justification two turns ago. These variables accounted for 54 % of the variance of justifications.

All other variables were not significant. Notably, gender, teacher (vs. student), and their interactions were not significant, showing that these variables and their relationship did not differ significantly with respect to gender or position in this data set.

Discussion

This study examines antecedents of students' micro-creativity, new ideas, correct ideas, and justifications as they solve a fraction problem under the guidance of their teacher. SDA statistically identified five pivotal moments and six distinct time periods of high vs. low micro-creativity but a different set of three pivotal moments and four time periods of frequent vs. infrequent justifications. The explanatory models provide support for some of the hypotheses but differ substantially across time, as shown in the different results of the full data set vs. its subset. Furthermore, other analysts' methods and results provided multivocality grist for further insights and methodological developments.

Pivotal Moments and Time Periods

The statistically identified pivotal moments showed distinct time periods and different degrees of importance. New ideas, correct ideas, and justifications occurred more frequently in some time periods than in others. Inspired by Trausan-Matu's discussion of collaborative utterances, I found that a pivotal moment can have boundaries beyond a single turn, incorporating aspects of both earlier and later turns. Also, the pivotal moments and time periods identified for micro-creativity and justifications differed, showing that a pivotal moment along one dimension is not necessarily a pivotal moment along another dimension.

Statistical identification of a pivotal moment is also an invitation to understand its mechanism(s) through a multivocality cycle of further qualitative and statistical analyses. A detailed, qualitative analysis of the actions, changes, and their relationships around the pivotal moment (e.g., via ethnomethodology, Sacks, 1995) can suggest a mechanism(s) that alters the interaction. Such examinations of multiple pivotal moments can provide comparative case studies to test whether these hypothesized mechanisms are idiosyncratic or not. After specifying these mechanisms through operationalized variables, SDA can test these mechanism hypotheses across the entire data set (e.g., Wise & Chiu, 2011).

A comparison of our three analysts' (Shirouzu, Trausan-Matu, and me) pivotal moment results also inspired a method to assess their relative importance. All three analysts identified one common pivotal moment, which suggested that it was more important than the others. Returning to my analyses, I saw that the pivotal moment with the largest corresponding reduction in the BIC would indicate the greatest impact on the target phenomena (e.g., justifications). Furthermore, this reduction in BIC measure applies across different target phenomena, so it serves as a general method for comparing the relative impact of different breakpoints.

Explanatory Models

The results of the explanatory models showed some support for many cognition hypotheses (correct ideas) and social metacognition hypotheses (repetitions, correct evaluations, disagreements, and justifications), but they differed across time periods. The results partially supported the correct idea hypotheses but did not support the new ideas or micro-creativity hypotheses, in part due to reflective practices. Only a correct idea unaccompanied by a question was often followed by another correct idea; a correct idea in the form of a question was often followed by a simple agreement rather than a correct idea. The significant interaction between correct idea and question also highlights the importance of the immediate temporal context in moderating the effect of a specific action. As shown above, students often reflected on ideas, especially new ones, which hindered chains of new ideas or micro-creativity. Whether these reflections follow ideas regularly in Japanese classrooms or other classrooms remain open questions.

The analyses of the full data set and the data subset show another benefit of multivocality. After Shirouzu indicated that the data subset (class discussion) was the most substantive part of the lesson, SDA was applied to only the data subset to test if the relationships among independent and dependent variables differed in both the data subset and in the full data set. The results showed that the explanatory model for the entire data set differed from that of the data subset for *all* significant explanatory variables, showing that the relationships among variables differed entirely across time periods. These different explanatory models across time periods highlight the time-dependent nature of the statistical relationships and suggest that statistical models without proper modeling of time periods can be incomplete. Statistical methods such as SDA are needed to test whether relationships among variables and their accompanying hypotheses are supported, rejected, or not significant in both the entire data set and in each time period.

Identification of these differences in relationships among variables across time periods raises the question of why these differences occur. The above multivocality cycle of qualitative and statistical analyses of pivotal moment mechanisms might help account for these differences. If the pivotal moment mechanisms do not account for them, then the SDA results suggest where to look; researchers can conduct qualitative analyses (e.g., ethnomethodology, Sacks, 1995) of instances in which an independent variable-dependent variable relationship occurs in one time period and instances in which it does not occur in another time period. Comparative case studies can then yield hypotheses regarding moderation variables, which in turn can be tested by SDA.

Conclusion

This analysis shows how SDA can both identify the locations and consequences of pivotal moments and accompany other methodologies to yield multivocality insights. SDA of a classroom lesson showed the impacts of the meso-time context of time periods within a lesson and the micro-time context of recent conversation turns. The statistically identified pivotal moments distinguished time periods for each dependent variable and yielded different relationships among variables across time periods. While the statistical analysis identified a conversation turn at the heart of each pivotal moment, detailed discourse analysis showed that the boundary of the pivotal moment often extended to earlier and later turns. The statistical analysis identified a set of pivotal moments and its time periods of higher vs. lower micro-creativity but a different set of pivotal moments and time periods for more vs. fewer justifications. Lastly, the explanatory models differed across time periods, highlighting the importance of the meso-time context.

Methodologically, this analysis shows how multivocality can suggest cycles of analyses and help develop further statistical methods. SDA identified pivotal moments, time periods, and differences in relationships across time periods that can ignite cycles of further qualitative and statistical analyses. Detailed qualitative analysis (e.g., ethnomethodology) of pivotal moments and contrast cases of relationships between variables (that occur in one time period but not in another) can specify candidate mechanism hypotheses that can be operationalized and tested with SDA. Furthermore, the three analysts' identification of one common pivotal moment inspired a statistical method (change in BIC) to test the relative importance of different pivotal moments. In short, this study showed not only how SDA can be applied but also how its use with other methods yields further benefits.

References

Benjamini, Y., Krieger, A. M., & Yekutieli, D. (2006). Adaptive linear step-up procedures that control the false discovery rate. *Biometrika, 93*, 491–507.

Buchs, C., Butera, F., Mugny, G., & Darnon, C. (2004). Conflict elaboration and cognitive outcomes. *Theory into Practice, 43*, 23–30.

Chiu, M. M. (2000a). Group problem solving processes: Social interactions and individual actions. *Journal for the Theory of Social Behavior, 30*(1), 27–50.

Chiu, M. M. (2000b). Status effects on solutions, leadership, and evaluations during group problem solving. *Sociology of Education, 73*(3), 175–195.

Chiu, M. M. (2001). Analyzing group work processes. In F. Columbus (Ed.), *Advances in psychology research* (Vol. 4, pp. 193–222). Huntington, NY: Nova Science.

Chiu, M. M. (2008a). Effects of argumentation on group micro-creativity. *Contemporary Educational Psychology, 33*, 382–402.

Chiu, M. M. (2008b). Flowing toward correct contributions during group problem solving: A statistical discourse analysis. *Journal of the Learning Sciences, 17*(3), 415–463.

Chiu, M. M., & Khoo, L. (2003). Rudeness and status effects during group problem solving. *Journal of Educational Psychology, 95*, 506–523.

Chiu, M. M., & Khoo, L. (2005). A new method for analyzing sequential processes: Dynamic multi-level analysis. *Small Group Research, 36*, 600–631.

Chiu, M. M., & Kuo, S. W. (2009). From metacognition to social metacognition: Similarities, differences, and learning. *Journal of Education Research, 3*(4), 1–19.

Cobb, P. (1995). Mathematical learning and small-group interaction: Four case studies. In P. Cobb & H. Bauersfeld (Eds.), *The emergence of mathematical meaning: Interaction in classroom cultures* (pp. 25–130). Hillsdale, NJ: Lawrence Erlbaum Assoc.

Cohen, J., West, S. G., Aiken, L., & Cohen, P. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences*. Mahwah, NJ: Lawrence Erlbaum.

Coleman, E. (1998). Using explanatory knowledge during collaborative problem solving in science. *The Journal of Learning Sciences, 7*, 387–427.

Goldstein, H. (1995). *Multilevel statistical models*. Sydney: Edward Arnold.

Green, S. B. (1991). How many subjects does it take to do a regression analysis? *Multivariate Behavioral Research, 26*, 499–510.

Huedo-Medina, T. B., Sanchez-Meca, J., Marin-Martinez, F., & Botella, J. (2006). Assessing heterogeneity in meta-analysis. *Psychological Methods, 11*, 193–206.

Kennedy, P. (2004). *A guide to econometrics*. Cambridge: Blackwell.

King, G., & Zeng, L. (2001). Logistic regression in rare events data. *Political Analysis, 9*, 137–163.

Krippendorff, K. (2004). *Content analysis*. Thousand Oaks, CA: Sage.

Lu, J., Chiu, M. M., & Law, N. (2011). Collaborative argumentation and justifications. *Computers in Human Behavior, 27*, 946–955.

Milliken, F. J., Bartel, C. A., & Kurtzberg, T. R. (2003). Diversity and creativity in work groups. In P. B. Paulus & B. A. Nijstad's (Eds.), *Group creativity* (pp. 32–62). New York, NY: Oxford University Press.

Nemeth, C. J., Personnaz, B., Personnaz, M., & Goncalo, J. A. (2004). The liberating role of conflict in group creativity. *European Journal of Social Psychology, 34*, 365–374.

Nijstad, B. A., Diehl, M., & Stroebe, W. (2003). Cognitive stimulation and interference in idea generating groups. In P. B. Paulus & B. A. Nijstad (Eds.), *Group creativity: Innovation through collaboration* (pp. 137–159). New York, NY: Oxford University Press.

Orlitzky, M., & Hirokawa, R. Y. (2001). To err is human, to correct for it divine. *Small Group Research, 32*, 313–341.

Paulus, P. B., & Brown, V. (2003). Ideational creativity in groups. In P. B. Paulus & B. A. Nijstad (Eds.), *Group creativity* (pp. 110–136). New York, NY: Oxford University Press.

Piaget, J. (1985). *The equilibrium of cognitive structures*. Chicago: University of Chicago Press.

Sacks, H. (1995). *Lectures on conversation*. Oxford: Blackwell.

Sobel, M. E. (1982). Asymptotic intervals for indirect effects in structural equations models. In S. Leinhart (Ed.), *Sociological methodology* (pp. 290–312). San Francisco, CA: Jossey-Bass.

Sternberg, R. J., & Lubart, T. I. (1999). The concept of creativity. In R. J. Sternberg (Ed.), *Handbook of creativity* (pp. 3–15). New York, NY: Cambridge University Press.

Toulmin, S. E. (2003). *The uses of argument*. Cambridge: Cambridge University Press.

Trausan-Matu, S., Stahl, G., & Sarmiento, J. (2007). Supporting polyphonic collaborative learning. *E-service Journal, 6*(1), 58–74.

Tsui, A. (1992). A functional description of questions. In M. Coulthard (Ed.), *Advances in spoken discourse analysis* (pp. 89–110). London: Routledge.

Wise, A., & Chiu, M. M. (2011). Analyzing temporal patterns of knowledge construction in a role-based online discussion. *International Journal of Computer-Supported Collaborative Learning, 6*, 445–470.