<u>Analytic Tool Presenter: Putting Temporal Analytics into Practice workshop</u>

How are variables at different levels related? Sequences of individual/group processes and their outcomes

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Educators are often interested in whether variables at different levels are related to one another (message-level, individual-level, group-level, etc.). For example, during group problem solving, do more sequences of *correct evaluation* → correct, new idea (*micro-creativity*) raise groups' final solution scores? A correct evaluation is (a) agreeing with a correct idea or (b) disagreeing with a flawed idea. I showcase two statistical methods to test these relations, using higher-level vs. lower-level dependent variables. To exemplify these two methods, I apply them to one data set of 3,234 turns of talk by 80 students in 20 groups of 4 solving an algebra problem.

A **higher-level outcome regression** is limited to large data sets: *ordinary least squares* (OLS) for continuous variables (e.g., test scores of 0-100), *Logit/Probit* for dichotomous variables (right vs. wrong) or *ordered Logit/Probit* for ordered variables (wrong, partially correct, or correct). In our above example, the group outcome is solution score: (a) correct (3), (b) wrong answer but correct solution procedure (2), (c) wrong solution procedure but correct understanding of problem (1), or (d) wrong understanding of problem (0). For each group, we compute the *ratio* of total instances of the *correctly evaluate→micro-creativity* sequence over total sequences of 2 turns. Next, we run an ordered Logit regression for the outcome *solution score* the above ratio as an explanatory variable. A significant, positive regression coefficient indicates that groups with proportionately more *correctly evaluate→micro-creativity* sequences tend to have higher solution scores. We can also include other control variables (e.g., mean mathematics grade of each group). We also apply ordered Probit to test whether the results depend on the distribution assumptions of ordered Logit.

However, this approach requires substantial data. For example, detecting a medium effect of 0.3 requires 84 groups for an 80% likelihood of success (112 groups for a 90% likelihood).

A **lower-level outcome regression** requires fewer data and tests subtler hypotheses. These analyses vary from simple regressions to *statistical discourse analysis*. The simplest version is a regression (OLS, Logit/Probit or ordered Logit/Probit as discussed above) with explanatory variables indicating actions in preceding messages/turns of talk (e.g., correctly evaluate [-1], also known as *lagged variables*). To model *correctly evaluate→micro-creativity*, we run a *Logit* regression with *micro-creativity* as the dependent variable and *correctly evaluate [-1]* as an explanatory variable. To test whether groups that solve the problem correctly are more likely to use this sequence, we add two independent variables, (a) *solution_score* and (b) the interaction *solution_score* * *correctly evaluate [-1]*. If *solution_score* has a significant, positive, regression coefficient, then groups with higher solution scores are more likely to show *micro-creativity*. If *solution_score* * *correctly evaluate [-1]* has a significant, positive, regression coefficient, then groups with higher solution scores are more likely to have *correctly evaluate→micro-creativity* sequences.

To model control variables for the higher-level outcome *solution_score*, we run two regressions. To remove the effects of the control variables on *solution_score*, we run a regression on the outcome *solution score* with all control variables (e.g., mean mathematics grade of each group) to obtain the unexplained part of solution score (namely its residual, *solution_score_residual*). Then, we run the same lower-level outcome regression above except that we replace all instances of *solution_score* with *solution_score_residual*. (Note that 2-stage regressions like this one can introduce errors at each stage, in this case when computing residuals.)

Lower-level outcome regressions can test more hypotheses with fewer data. For example, detecting a medium effect of 0.3 requires 84 turns for an 80% likelihood of success. (Two pairs of students chatting for 30 minutes will often produce over 100 turns.)

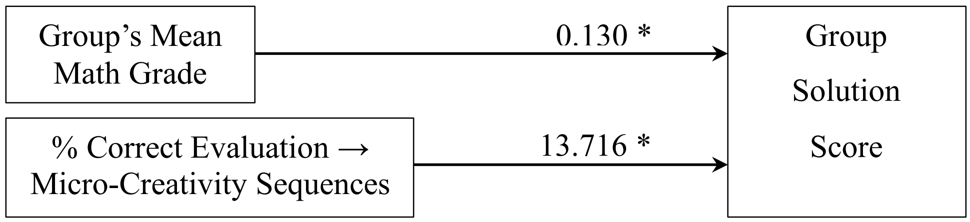

Figure 1. Higher-level dependent variable regression (ordered logit) modeling *group solution score* with *group's mean mathematics grade* and percentage of sequences that are *correct evaluation → micro-creativity*.

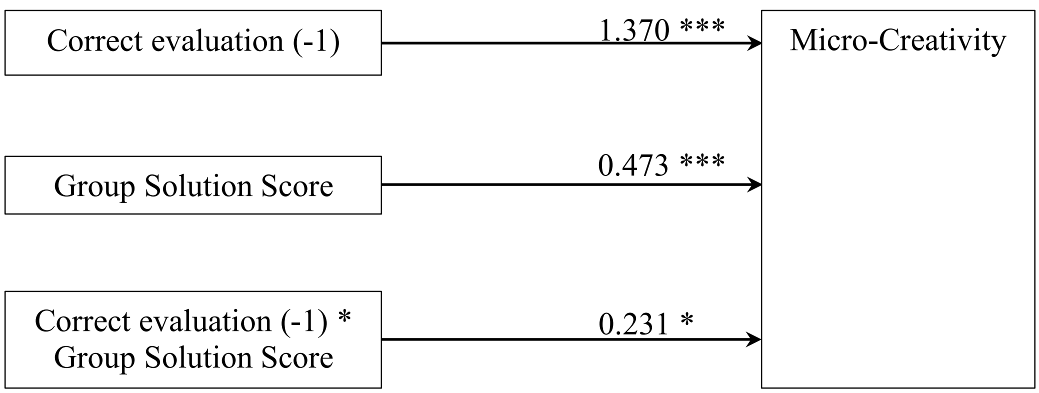

Figure 2. Lower-level dependent variable regression modeling *micro-creativity* with *correct evaluation in the previous turn (-1), group's solution score* and their interaction.

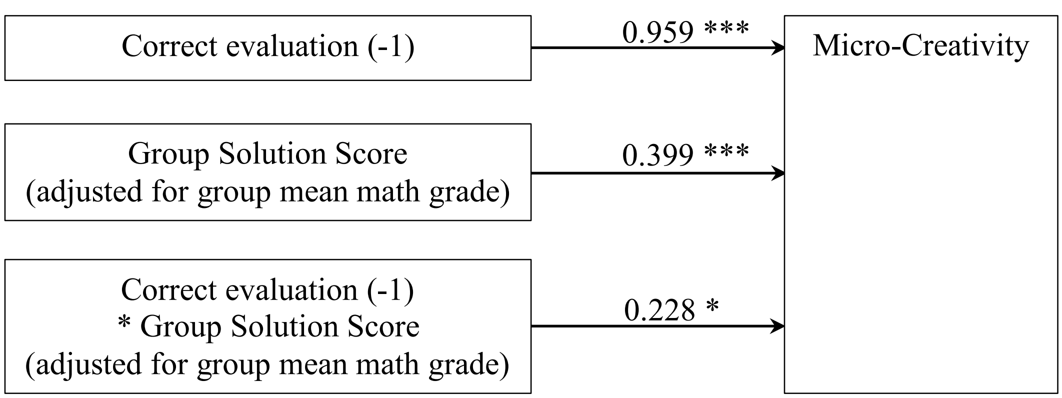

Figure 3. Lower-level dependent variable regression modeling *micro-creativity* with *correct evaluation in the previous turn (-1), group's solution score adjusted for mean mathematics grade* and their interaction.

Table 1.

Summary of 3 ordered logit regression models of group solution score (N =20 groups)

	Group Solution Score		
Explanatory variable	Model 1	Model 2	Model 3
Math grade	0.152**		0.130*
	(0.050)		(0.058)
% Correct evaluation (-1)		12.802*	13.716*
→ Micro-creativity		(5.415)	(6.764)
Explained variance	0.217	0.213	0.339

Table 2.

Summary of 3 statistical discourse analysis models of micro-creativity (N = 3,234 turns of talk)

	Micro-creativity					
Explanatory variable	Model 1		Model 2		Model 3	
Correct evaluation (-1)	0.976	***	1.370	***	0.959	***
	(0.093)		(0.248)		(0.095)	
Solution			0.473	***		
			(0.063)			
Correct evaluation (-1) * Solution			0.231	*		
			(0.101)			
Solution (adjusted for Math grade)					0.399	***
					(0.081)	
Correct evaluation (-1)					0.228	*
* Solution (adjusted for Math grade)					(0.113)	
Variance at each level	Explained variance					
Group (0.1%)	0.000		0.531		0.591	
Time period (58.7%)	0.040		0.071		0.053	
Turn of talk (41.2%)	0.028		0.039		0.031	
Total explained variance	0.035		0.058		0.044	