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Multimodal Behavior Analysis: Two Patterns of Collaborative Construction of Embodied Knowledge

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Authors
Sung, Hanall
Kim, Doy
Swart, Michael
et al.

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Multimodal Behavior Analysis: Two Patterns of Collaborative Construction of Embodied Knowledge

Hanall Sung (hanallsung@gmail.com)
Department of Educational Psychology, 1025 W. Johnson Street
Madison, WI 53706 USA

Doy Kim (doy.kim@wisc.edu)
Department of Educational Psychology, 1025 W. Johnson Street
Madison, WI 53706 USA

Michael I. Swart (mswart@wisc.edu)
Department of Educational Psychology, 1025 W. Johnson Street
Madison, WI 53706 USA

Mitchell J. Nathan (mnathan@wisc.edu)
Department of Educational Psychology, 1025 W. Johnson Street
Madison, WI 53706 USA

Abstract

This study investigates how individuals collaboratively constructed shared knowledge during a group activity. The dataset was collected from group activities for pre-service teachers in professional development. Participants designed body poses and action sequences that could help their students' mathematical conceptualization. Using k-means clustering and principal component analysis, patterns of individuals' contributions based on their verbal and gestural behavior identified two groups of individuals: (1) Those who contributed to the discussion by speaking and gesturing frequently (~ 25% of the participants), and (2) those who mostly listened and focused on design ideas presented by others. Furthermore, epistemic network analysis corroborated significant differences in discourse patterns between the clusters, the results of which has significant implications for collaborative embodied learning and application for teacher education and professional development.

Keywords: Embodied Cognition; Collaboration, Multimodal Analytics;

Introduction

How do humans collaborate? How do they collaboratively build knowledge? With an interest in the collaborative knowledge-building process, we investigated how teachers in professional development constructed knowledge about how to teach mathematics to their students.

In mathematics classrooms, students often communicate their thinking to teachers in the gestures they make when asking questions, explaining their thinking, and providing a rationale (Abrahamson et al., 2020). Despite the evidence that mathematical thinking has physically grounded origins (Lakoff & Núñez, 2000), many school-based mathematics curricula continue to emphasize abstract, a-modal-based approaches (i.e., symbolic, diagrammatic) that tend to neglect the embodied nature of mathematics, especially the role of gesture (Nathan, 2022). This creates practical issues in instruction and assessment where many math teachers are unaware of the valuable information contained in students' nonverbal behaviors that express what they know and how they know it. Students often convey non-redundant information in their gestures to their speech, and these instances can indicate when these students could benefit from additional scaffolding or instruction (e.g., Church & Goldin-Meadow, 1986, Goldin-Meadow et al., 1993).

Nathan (2022) argues that the grounded and embodied approach to student learning should be actively implemented in educational practices. The assertion posits that student learning should be more than just learning through listening to lectures and writing exams. Instead, it should involve a range of activities that include physical activities, role-playing, and simulations to enhance understanding and knowledge retention. In the author's explorations of how embodied learning can facilitate a new and more effective way of learning, Nathan emphasized the importance of applying tangible teaching pedagogy forms that engage students' to actively participate in their own learning process.

To investigate ways for supporting teachers, we developed a professional development (PD) workshop to raise teachers' awareness of students' embodied mathematical knowledge. Through an online research program, we enabled K-12 pre-service teachers to experience and reflect on their own embodied geometric reasoning. The PD was segmented into two parts: (1) an action-based video gameplay and (2) an embodied co-design activity based on their gameplay. For the gameplay activity, we used *The Hidden Village* (THV), a motion-capture video game in which players are guided to perform directed actions (i.e., upper-body movements) that are emblematic of geometric concepts and then evaluating the truth of geometric conjectures (e.g., "*The opposite angles of*

In M. Goldwater, F. K. Anggoro, B. K. Hayes, & D. C. Ong (Eds.), *Proceedings of the 45th Annual Conference of the Cognitive Science Society.*

two lines that cross are always the same”). After gameplay, teachers collaborated in a co-design activity in which they created their own directed actions for new conjectures using the content generating module of THV.

Teachers’ gameplay and co-design activities provided opportunities to understand how performing mathematically related movements that engage body-based actions can support geometric thinking. For teachers, we hypothesized that these embodied learning activities would not only improve teachers’ awareness of students’ gestures during mathematical thinking and communication, but it would also improve teachers’ abilities to accurately assess students’ geometric reasoning by interpreting their gestures. For the current study, we processed multimodal data from the recordings of the teachers’ collaborative discussions (i.e., transcripts, discourse, directed action designs, and gestures) and conducted a multi-tiered algorithmic-based approach to explore patterns in their collaborative constructions of embodied knowledge and discourse.

Theoretical Framework

Studies have shown that mathematics can be learned through action-based interventions (Abrahamson & Sánchez-García, 2016; Smith et al., 2014). Drawing from the theory of *Gesture as Simulated Action* (GSA; Hostetter & Alibali, 2019), gestures activate perceptual-motor processes in the brain by simulating action, often co-articulated with speech or thought. Underlying these processes, Nathan's (2017) *Action-Cognition Transduction* (ACT) posits that these sensorimotor experiences induce cognitive states through a reciprocation of feedforward (predictive) and feedback (reactive).

By creating an intervention that uses directed actions, we provide a body-based way for learners to (predictively) conceptualize the spatial dimensions, relationships, and transformations of geometric objects relevant for promoting mathematical reasoning. Thus, ACT-based interventions (see Nathan & Walkington, 2017) (Figure 1) can be tools that teachers can use to help transform symbolic formalisms of typical instruction into action-based interventions that ground abstract concepts (Alibali & Nathan, 2007; Roth, 2001).

In this study, we explore how teachers produce verbal and gestural contributions to co-construction of new embodied math knowledge during the action-based intervention that we provided as a teacher professional development. Specifically, we have processed the data from teachers’ collaborations in designing *directed actions* for geometric conjectures.

Figure 1: Action facilitates concepts (Nathan & Walkington, 2017).

Pedagogical Content Knowledge

Pedagogical Content Knowledge (PCK) is a term that refers to the ability of a teacher to understand how specific facts and ideas can be presented in a way that makes them most effectively learned by the students in their classroom (Shulman, 1986). It is a combination of the knowledge of the particular content area with the knowledge of how to teach it, and it involves an understanding of the different ways in which students learn, the various teaching styles that can be used, and the best strategies for helping students meet their goals.

Figure 2: Pre-service teachers collaborative gestures (Schenck et al., 2022).

Collaborative Gestures & PCK

Schenck, Walkington, and Nathan (2022) (Figure 2) highlighted that, when working collaboratively on a mathematical problem, pre-service teachers use gestures to collectively construct their understanding and problem-solve.

Research Questions Are there distinct patterns in pre-service teachers’ collaborative verbal and gestural construction of pedagogical content knowledge? If so, what are they?

Methods

Participants

We recruited thirty-three mathematics pre-service teachers (i.e., college students who intend to become teachers and are in an appropriate training program) from universities in the United States. During an online teacher professional development intervention, they were initially divided into groups of four to groups, but final group size ranged from two to five members due to scheduling challenges. Consequently, we had total of 9 groups: one with two members, two with three members, five group with four members, and one with five members. Participants received either a monetary reward ($100 e-gift card) or extra course credit. Participation took place entirely online using Zoom. Each participant’s individual and collaborative audio and video were recorded.

Materials

The Hidden Village (THV) and Conjecture Editor (THV-CE)

During the action-based gameplay, teachers experienced mathematically relevant body-based actions by mimicking the in-game avatar's movements, along the storyline of the game. After the gameplay, users author geometry conjectures and design their own sets of movement-based directed actions during the following co-design activity. Teachers in PD collaboratively co-designed mathematically relevant directed actions (i.e., generated 3 poses of the avatar for players to mimic movements; see Figure 3). Once designed, users could preview their sequence of directed actions as a fluid animation. As a remote co-design activity (conducted virtually during the Covid-19 pandemic), a researcher operated the editing tool under participants' directions.

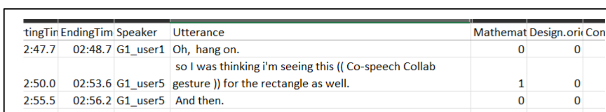
Figure 3: Pre-service teachers collaboratively discussing to create new directed actions for given conjectures during the co-design activity (Sung et al., 2021).

Procedures

On the day of the intervention, participants took part in a 3.5 hour-long online session that contains a series of activities, including: each teacher took part in (1) pre-intervention surveys and semi-structured interviews, (2) online gameplay of THV with another teacher in pairs, and (3) co-design activity through a whole-group discussion in a group of teachers (range from two to five), and (4) post-intervention surveys and semi-structured interviews.

Data Sources, Coding & Analyses

Figure 4 provides a sample of a transcription of speech and coding of gestures that was used to investigate how the embodied interventions impacted teachers' awareness and abilities to interpret students' gestures. Each utterance was coded with respect to the seven verbal and gestural codes.



tingTin	EndingTim	Speaker	Utterance	Mathemat	Design.orie	Con
2:47.7	02:48.7	G1_user1	Oh, hang on.	0	0	
2:50.0	02:53.6	G1_user5	so I was thinking i'm seeing this ((Co-speech Collab gesture)) for the rectangle as well.	1	0	
2:55.5	02:56.2	G1_user5	And then.	0	0	
2:56.3	02:58.6	G1_user1	Oh, I see I see sorry I misread that	0	0	

Figure 4: Segmented transcription data for ENA.

Coding Scheme This study identified the seven verbal and gestural ways pre-service teachers contributed to the discourse about pedagogical content knowledge while engaging in a group activity. Seven binary codes on verbal and gestural behavior were used to evaluate each utterance as to what type of contribution was made (Table 1).

Table 1: Coding scheme.

Code Type	Name	Description
Verbal	Mathematical Thinking (V_MT)	Discussing mathematical concepts such as angles, lines, and conjectures
Verbal	Design Oriented (V_DO)	Talking about how to design directed actions to help students' understanding and visualization of given geometric conjectures, with the concentration of design aspects.
Verbal	Consensus Building (V_CB)	Building consensus while collaboratively designing directed actions for given conjectures
Gestural	Co-Speech Initiative (G_CI)	Producing a gesture accompanying speech, which was original and had no connection with the previously shown gesture by others
Gestural	Co-Speech Collaborative (G_CC)	Producing a gesture accompanying speech, following up with the previously shown gesture by others. Must be evidence that the person doing the echoing, mirroring, or alternating was looking at the original gesturer
Gestural	Non-speech initiative (G_NI)	Producing a gesture without any speech, which was original and had no connection with the previously shown gesture by others
Gestural	Non-Speech Collaborative (G_NC)	Producing a gesture without any speech, following up with the previously shown gesture by others. Must be evidence that the person doing the echoing, mirroring, or alternating was looking at the original gesturer

Contribution Scores From the coded transcript data, we calculated individual participants' *contribution scores*. A contribution score of an individual represents the ratio of an individual's contribution to the total contribution made by the group with respect to one of the seven verbal and nonverbal manners of contribution. Mathematically speaking, a contribution score is a function of one of the seven behavioral code and an individual that is defined as the proportion of code occurrences made by the individual against the total occurrences made by all members of the group, weighted by the utterance span. For example, Individual *i*'s contribution score for Mathematical thinking was calculated as below. Assume that Individual *i* was in a group, where there were four people.

- $I \in 1,2,3,4$: index for individuals
- U_t: number of total utterances made by the group
    - U_i: the number of total utterance made by Individual *i*
    - Therefore, $U_t = U_1 + U_2 + U_3 + U_4$
- t_{ki}: Utterance span. StartingTime - EndingTime of the k^{th} utterance made by Individual *i* ($k \in 1,2,...,U_i$)
- $V.MT_{ki}$: *V_MT* value of k^{th} utterance of Individual *i* ($k \in 1,2,...,U_{ik} \in 1,2,...,U_i$) (i.e. 0 or 1)
- $C(V.MT,i)$: Individual *i*'s contribution value (`V_MT`)

$$C(V.MT, i) = \frac{\sum_{k=1}^{U_i} (t_{ki} \times V.MT_{ki})}{\sum_{j=1}^{4} \sum_{k=1}^{U_i} (t_{kj} \times V.MT_{kj})}$$

K-Means Clustering Analysis K-Means clustering is an unsupervised machine-learning algorithm that splits a data set into a set of *k* clusters, such that objects within the same cluster are highly similar. Each cluster has a centroid which corresponds to the mean of points assigned to the cluster. The algorithm minimizes within-cluster variances using the sum of squared Euclidean distances

$$W(C_k) = \sum (x_i - \mu_k)^2$$

where x_i is a data point belonging to the cluster C_k; μ_k is the mean value of the points assigned to the cluster C_k. Therefore, the cost function is

$$\sum^{k}{}_{k}=1 \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

(original from Hartigan-Wong algorithm (1979)). We used `factoextra` package of Kassambara and Mundt (2020) to render the cluster analysis in R.

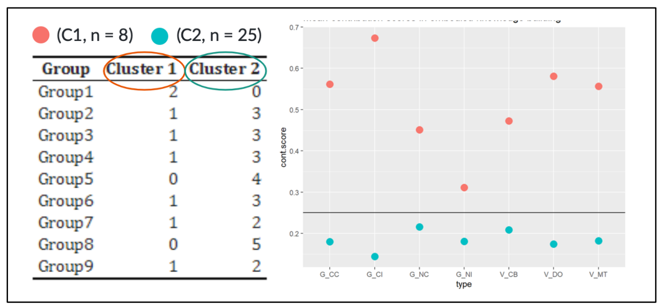
Principal Component Analysis (PCA). Principal component analysis (PCA) was used for dimensionality reduction. We sought to maximize the amount of variance explained by a given set of variables by transforming the data into a set of uncorrelated variables, also known as principal components. We used `psych` package of Revelle (2022). To examine whether there were distinct patterns, the individuals were classified for the seven verbal and nonverbal contribution scores.

Epistemic Network Analysis (ENA). The transcripts were also analyzed using *epistemic network analysis* (ENA; Shaffer et al., 2016), a discourse analysis technique for identifying and quantifying the connections among cognitive elements in a discussion. The data was segmented by a turn of talk and coded using an automated coding process (nCoder; Marquart et al., 2018) based on regular expression matching techniques. All six emergent codes were validated using comparisons between a human rater and nCoder and pairwise Cohen's kappa scores ranged between $0.90 \leq \kappa \leq 0.98$ and Shaffer's rho values $\rho < 0.05$ (Shaffer, 2017).

ENA builds dynamic models of discourse as a nodal network and then calculates a mean centroid around which the discussion centers, weighting the connections between codes (Shaffer, 2017). ENA codes correspond to the epistemic elements that characterize a discourse. The edges reflect the relative frequency of co-occurrence between two codes. To test for differences between the networks of pre- and post-interview, we applied a two-tailed paired-sample t-test, assuming unequal variance to the location of points in the projected ENA space, then used the corresponding network graphs to interpret any statistically significant differences.

Results

The clustering algorithm recommended two clusters, and, as a result, k-means clustering with k=2 was carried out.



Group	Cluster 1	Cluster 2
Group1	2	0
Group2	1	3
Group3	1	3
Group4	1	3
Group5	0	4
Group6	1	3
Group7	1	2
Group8	0	5
Group9	1	2

Figure 5: Proportional distribution between C1 and C2

Figure 5 highlights some noteworthy differences between the clusters. The adjusted test of independence shows that individuals were fairly evenly represented across groups, with a ratio of 1:3, respectively ($\chi^2_{df=8} = 6.60$, $p = .58$). Figure 5 also shows that C1 individuals' contribution scores were higher across all seven measures compared to C2 individuals.

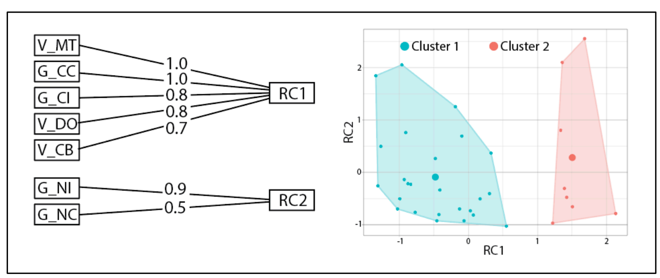


Figure 6: PCA showing cluster characteristics.

Figure 6 depicts the results of the Principal component analysis (PCA). The model on the left shows the patterns of the teachers' contributions can be categorized twofold: (1) *co-speech* occurrences (RC1) and (2) *non-speech* (RC2). The visualization on the right illustrates that C1 scored higher in co-speech contribution compared to C2, while there were no differences between the two clusters in non-speech contribution.

Epistemic Network Analysis (ENA, Figure 7) corroborated the PCA findings, with reliability, further clarifying a significant difference in discourse patterns between C1 and C2 ($\bar{x}_{C1} = -0.95$, $\bar{x}_{C2} = 0.30$, $t_{(29.04)} = 4.25$, $p < 0.01$, $d = 1.16$). From this large effect size, interpretation of the ENA plots show C1 demonstrating more incidences

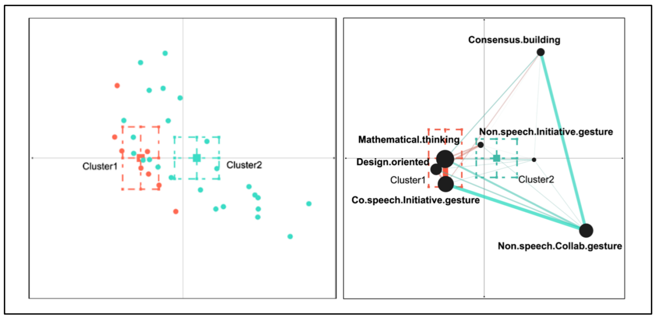


Figure 7: ENA plots of differences in discourse between Clusters 1 & 2.

of verbal mathematical thinking (V_MT), co-speech collaborative gestures (G_CC), and verbal design oriented (V_DO) utterances; C2 showed stronger connections between non-speech collaborative gestures (G_NC), co-speech collaborative gestures (G_CC), and verbal consensus building (V_CB).

Discussion

The results illustrate two groups of individuals that show distinct patterns in collaboratively constructing mathematical knowledge. Cluster 1 represents individuals who consist one-fourth of the group in a group activity setting. Making more contributions than any other group members, Cluster 1 individuals' roles could be considered as leaders since they make most of the group's contributions themselves. Specifically, their contributions to the discourse are mostly through speech-related processes and are distinguished by their verbal articulation of how the designed actions relate to mathematical concepts and how these actions could help students' understanding, a finding corroborated by ENA.

Cluster 2 represented approximately three-fourths of the group in the activity setting. In general, these are the teachers whose contributions focused on listening rather than speaking. They made less contributions than Cluster 1 individuals across all verbal and nonverbal measures, and this difference was more pronounced for speech-related processes. Moreover, Cluster 2 focused on comprehending the embodied design ideas presented by others to reach to the consensus.

Recent research by Walkington et al. (2022) demonstrated not only that relevant actions (informed by gestures) are crucial to conceptualization, but also that learners whose explanations included gestures that *replayed* those actions led to superior performances in proof production for geometry.

This study can help educational practitioners, teacher educators and policy-makers make curricular decisions. It informs them on the patterns of discourse and knowledge-building and helps quantify and qualify how collaborative discourse can contribute to teacher training.

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