Not a Team but Learning as One: The Impact of Consistent Attendance on Discourse Diversification in Math Group Modeling

Mark Abdelshiheed
mark.abdelshiheed@colorado.edu
Institute of Cognitive Science,
University of Colorado Boulder
Boulder, Colorado, USA

Jennifer K. Jacobs
jennifer.jacobs@colorado.edu
Institute of Cognitive Science,
University of Colorado Boulder
Boulder, Colorado, USA

Sidney K. D'Mello
sidney.dmello@colorado.edu
Institute of Cognitive Science,
University of Colorado Boulder
Boulder, Colorado, USA

ABSTRACT

This work investigates relationships between *consistent attendance* —attendance rates in a group that maintains the same tutor and students across the school year— and learning in small group tutoring sessions. We analyzed data from two large urban districts consisting of 206 9th-grade student groups (3 – 6 students per group) for a total of 803 students and 75 tutors. The students attended small group tutorials approximately every other day during the school year and completed a pre and post-assessment of math skills at the start and end of the year, respectively. ***First***, we found that the attendance rates of the group predicted individual assessment scores better than the individual attendance rates of students comprising that group. ***Second***, we found that groups with high consistent attendance had more frequent and diverse tutor and student talk centering around rich mathematical discussions. Whereas we emphasize that changing tutors or groups might be necessary, our findings suggest that consistently attending tutorial sessions as a group with the same tutor might lead the group to implicitly learn as a team despite not being one.

CCS CONCEPTS

• Applied computing → Collaborative learning; **• Social and professional topics → Student assessment**; **K-12 education**; **• General and reference → Empirical studies**; **• Mathematics of computing → Probability and statistics**.

KEYWORDS

Math Tutoring, Consistent Attendance, Talk Moves, Discourse Diversification, Implicit Teamness.

ACM Reference Format:
Mark Abdelshiheed, Jennifer K. Jacobs, and Sidney K. D'Mello. 2024. Not a Team but Learning as One: The Impact of Consistent Attendance on Discourse Diversification in Math Group Modeling. In *Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization (UMAP '24), July 01–04, 2024, Cagliari, Italy*. ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3627043.3659554

UMAP '24, July 01–04, 2024, Cagliari, Italy

ACM ISBN 979-8-4007-0433-8/24/07
https://doi.org/10.1145/3627043.3659554

1 INTRODUCTION

Learning in isolation could hinder the benefits of feedback and improvement, whereas working in collaboration bolsters productive thoughts and mutual gains. Substantial research has supported the benefits of collaborative learning by showing that students can achieve considerable learning gains by collaborating and working in teams [17, 57, 59]. These findings are significant when students collaborate with each other [63, 66, 70] or use intelligent team tutoring systems [13, 51]. Nevertheless, these investigations typically occur within learning environments that have been developed for collaboration or studies where students are explicitly assigned to a team with a shared interest in team (vs. individual) success. In this work, we focus on students attending small group tutoring sessions with a human tutor and investigate whether they implicitly learn as a team despite not being explicitly designated as one (i.e., having shared goals).

For traditional classrooms, decades of prior work have investigated attendance as one factor that distinguishes high-performing students and positively impacts their learning outcomes [8, 20, 22, 56, 65]. At the same time, considerable research has raised doubts about the significance of attendance and attendance policies by finding that they have null, minimal, or a ceiling effect on learning outcomes [27, 33, 40]. Regardless of the contradictory findings, attendance has been defined as showing up to class without taking into consideration external factors that contextualize whether attendance is meaningful or not.

In this work, we focus on students attending with a "consistent tutor" and a "consistent group," that is, attending tutorial sessions throughout the school year with the same tutor and students (i.e., without changing to another tutor or switching groups). Moreover, we compare group attendance rates —measuring the extent to which students in a group attend together— on predicting students' math assessment scores versus attendance rates of individuals (students) comprising that group.

We also examine the quality of student-tutor discourse during the tutorial sessions. Productive discussions and dialogues between teachers and students have been shown to facilitate collaborative learning compared to direct instruction methods [16, 53, 68]. The richness and quality of instructional discourse have been associated with the diversification of talk, whether between a teacher and students or students with each other [18, 46, 52]. However, as far as we know, no empirical studies have investigated the factors that might influence the diversity of discourse in tutorial sessions. We hypothesize that consistently attending as a group might be associated with more diverse discourse as it facilitates the creation and maintenance of common ground among participants [28].

1.1 Collaborative Learning & Teamness

Based on the improbability of continuous learning in isolation, it is widely acknowledged that humans learn from interacting with others [29, 39]. Collaborative (or Cooperative) learning is an instructional approach in which students complete a task where they can share ideas, think, or discuss with each other [15, 23, 38, 61]. Teamness is slightly different as it ***explicitly*** involves a unified outcome, shared interest in success, and the possibility of having a team leader [17, 36, 57]. Additionally, teamness extends the traditional notion of teams by focusing on ***how*** a team functions rather than the individuals comprising it [17].

Considerable research has shown the impact of collaborative learning on students' achievement and learning outcomes [63, 66, 70]. Terenzini et al. [66] conducted a widescale study on 480 undergraduates from six campuses to compare the performance of students who were taught 17 courses via active and collaborative instructional approaches relative to their peers who were taught six courses via conventional instructional methods of lectures and discussions. The results showed that the former students self-reported significantly higher gains in design, communication, and group skills, even after controlling for a variety of student pre-course characteristics. Yamarik [70] tackled students' learning outcomes more objectively by evaluating exam scores for 57 undergraduates who were taught via collaborative learning against their 59 control peers who were provided with the traditional lecture format. They found that students in the experimental group scored five to six points higher on midterm and final exams than those in the control group. More recently, Stump et al. [63] surveyed 150 engineering students to examine the relationship between self-reported informal collaboration and course grades. The findings revealed that students' reported use of collaborative strategies for learning course material was significantly predictive of course grades. In essence, a common feature in prior research studying effective collaborative learning is that the learning environments and collaboration activities have been designed for students to work together.

In a parallel vein, research in the field of team science has studied the notion of teamness and highlighted factors that yield better team outcomes [17, 43, 59]. Much of the work on teamness has emerged from non-educational contexts, including military, medical, and organizational teams [58]. Cooke et al. [17] articulated how a team differs from a group by having aligned goals and interests. Cooke et al. emphasized that *how* a team interacts and thinks —known as teamness— matters much more than the competence of individuals comprising the team. In other words, a team of experts is not an expert team. In the context of small group tutoring, Schmidt and Moust [59] posited that some factors that consolidate teamness include the 1) nature of problems posed to students, 2) cognitive processes elicited by group discussion that activate prior knowledge, 3) students' intrinsic motivation, and 4) tutor's expertise.

Prior research has yet to investigate whether students *implicitly* collaborate and act as teams during high-dosage, small group tutoring sessions. Additionally, if such implicit collaboration exists, a question arises about the factors influencing it. These are the questions we examined in the present research with a focus on students attending tutoring sessions as a group, though not necessarily a team.

1.2 Student Attendance and Academic Performance

Attendance and absenteeism are two of many factors that come to mind when identifying what distinguishes better-performing students from their less-well-performing peers. Indeed, decades of research have verified the influence of attendance on academic performance [9, 19, 22, 42, 48, 56, 65]. For example, Romer [56] showed that attendance in a macroeconomics course accounted for 31% of the variance of students' ($N = 116$) performance. Specifically, they found that there was a full letter grade difference between students who attended classes regularly and their peers with sporadic attendance. Romer [56] further revealed that the significant positive relationship between attendance and academic performance persisted after controlling for the prior grade point average and completion of instructional activities. Devadoss and Foltz [22] found similar results on the positive influence of attendance on students' grades by considering a larger sample of students ($N = 400$) and accounting for other factors such as motivation and aptitude. More recently, Teixeira [65] found similar results for 190 undergraduate students after controlling for motivation, aptitude, lecturer quality, and attendance policy. They found that absenteeism considerably lowered the students' final grade by about 10%. Furthermore, they argued that a mandatory yet flexible attendance policy would contribute to improving students' academic performance.

In the context of tutorials, substantial work has further verified the role of attendance in student learning [8, 20, 30]. Alexander and Hicks [8] investigated associations between tutorial attendance in introductory psychology courses on the grades of assignments and lab reports. The study occurred over four academic years with a total of 14 classes and 383 students. Results revealed a positive correlation between attendance and grades in all classes, with a significant correlation achieved in 13 out of 14 classes. Deane and Murphy [20] found that attendance of tutorial-based activities for medical students was positively and significantly correlated with their exam scores. The results persisted after controlling for several confounding factors, including gender, age, and country of origin.

Interestingly, several studies have suggested that absenteeism may be caused by class environments rather than students' aptitude [21, 49, 50] and suggested that some students can succeed despite absenteeism [42]. Moos and Moos [50] found that high absenteeism rates were correlated with highly competitive environments, excessive teacher control, and inadequate teacher support. Demir and Karabeyoglu [21] revealed that students' self-reported assessment of the school environment explained 83% of the variance of their commitment level to the school. They found that combining the students' commitment with parental control explained 22% of the variance in absenteeism. Lukkarinen et al. [42] found a significant positive relationship between class attendance and performance on exams. However, they also identified a distinct group of students who studied independently, skipped classes, and performed well on exams. They elaborated that these students had compelling reasons for absenteeism as well as an ability to learn independently.

There is also considerable work doubting the significance of attendance and attendance policies on learning outcomes [11, 27, 33, 40, 62]. Hyde and Flournoy [33] and Gendron and Pieper [27] found no correlation between students' attendance and grades. Credé et al.

[19] recreated the original data from Hyde and Flournoy [33] and Gendron and Pieper [27] and found a significant curvilinear relationship between attendance and grade outcomes in both cases. Specifically, the data from Hyde and Flournoy [33] showed that the best-performing students had either very high or very low attendance rates, whereas struggling students were most likely to have average rather than poor attendance. On the other hand, the data from Gendron and Pieper [27] revealed a ceiling effect of attendance on grade outcomes in that the benefits of attendance on grades appear to diminish once an average level of attendance has been reached. Berenson et al. [11] found that an enforced attendance policy was not a significant predictor of academic achievement. Levine [40] compared the influence of three attendance policies on academic achievement: one with *enforced* attendance, another *implicitly* not requiring attendance, and a third *explicitly* not requiring attendance. The results showed that the type of attendance policy had no significant effect on achievement.

In short, there is no consensus on whether attendance is a reliable predictor of academic achievement in traditional classrooms regardless of the students' age group (undergraduates or K-12). With respect to the present focus on small group tutoring sessions, the classic view of attendance —which isolates the student from their human tutor and group companions— hinders the ability to contextualize whether attendance is a meaningful construct or not. In this work, we attempt to address this issue in *high-dosage, small group tutoring sessions* by focusing on students with "***consistent***" attendance, who stay with their assigned tutor (not changing the tutor) and maintain their group membership. Additionally, we consider the average attendance rate of the group and compare it to the attendance rates of individuals comprising the group to investigate which would better predict student achievement. We also examine variability in tutorial discourse as one factor that might be associated with consistent attendance in small group tutoring sessions, as discussed next.

1.3 Instructional Discourse & Discourse Diversity

Discussions between students and teachers have long been the object of intensive study in educational research. Numerous theories purport that students learn primarily through collaborative interactions and dialogue, particularly in instructional settings [7, 45, 67]. There is a growing body of empirical evidence to support these theories, leading to the conclusion that students learn more from dialogic instruction as compared to direct instruction [4, 16, 53, 68]. For example, Abdelshiheed et al. [4] found that the human tutors' talk moves that encouraged mathematical *reasoning* were significantly predictive of assessment scores of higher-achieving students, whereas the tutors' talk moves that *revoiced* students' mathematical contributions and ideas were a significant predictor for lower-achieving students.

Three popular perspectives to understand productive teacher-student discourse are exploratory [10, 44], transactive [12, 37], and accountable [47, 54, 55] talk. Exploratory talk involves students sharing relevant knowledge and information as the dialogue proceeds critically and constructively while respecting others' ideas. Periodically, members try to reach agreement about major ideas after all ideas are treated as worthy of attention and consideration. Transactive talk involves students transforming arguments and building on each other's reasoning and contributions. This process involves refuting arguments till the group discussion reaches a final, convincing argument.

Accountable talk theory defines a set of explicit discursive techniques that can promote rich, knowledge-building classroom discussions [47, 54, 55]. The motive behind accountable talk is that everyone should be held accountable for what they say to identify the type of talk that is most consequential and moves learning forward. At the heart of accountable talk is the notion that teachers should organize discussions promoting equitable participation in a rigorous learning environment where students' thinking is publicly and explicitly available to everyone in the classroom. Accountable talk outlines **three** general requirements of classroom discussions: they should be accountable to the learning community, to content knowledge, and to rigorous thinking [52, 69]. In this work, we focus on ***talk moves***, which is an application of accountable talk.

Talk moves represent the micro-level details of discourse within each accountability category, helping to ensure that instructional conversations will be productive in nature [4, 35, 52, 64]. Their use indicates that teachers are actively working to ensure the classroom culture encourages equitable participation, forefronts student contributions, and values student reasoning. Teachers skillful in facilitating rigorous, student-led discussions employ a variety of talk moves as tools to support participation, engagement, and learning [46, 52]. Researchers have argued that attending to talk move patterns and diversity is particularly instructive when evaluating the quality of instructional discourse [4, 18].

In essence, improving the *quality* of instructional discourse has been established as a promising approach to enhance students' *learning outcomes*. One way of enriching instructional discourse quality is through richness and diversity of learning discourse [46, 52]. In addition, attendance has been shown sometimes to positively impact learning outcomes [8, 20, 30]. However, prior work has yet to connect attendance with discourse (i.e., talk moves) diversification. This work investigates whether attendance in tutoring sessions as a group is associated with diversification of talk moves (i.e., using a variety of talk moves categories).

1.4 Present Study

We analyzed attendance and discourse in the context of small group tutorial sessions. We examined whether group-level attendance rates better predicted individual student achievement than individual-level attendance rates and how group attendance was a predictor of the diversity of tutorial discourse. We drill into the notion of attendance as follows:

- Staying with the originally assigned tutor, referred to as "***consistent tutor***."
- Maintaining group membership by not switching groups, referred to as "***consistent group***."
- Focusing on groups that include at least *two* students satisfying the previous two criteria on *every* tutorial session in the year, referred to as "***consistent attendance***."
- Considering the attendance rate of the *group* and comparing it to that of the *individuals* comprising the group.

Note that we are ***not*** claiming that changing tutors or switching groups is by itself problematic. Rather, if staying with the same tutor and maintaining consistent group membership were found to have positive outcomes on learning, then more attention and future research should be directed towards the assignment and allocation of groups and tutors. Hence, students who attended with more than one tutor or group are ***not*** included in our analyses, enabling us to disregard irregularities in attendance patterns that may hinder the generalizability of our analyses and results. This work addresses two Research Questions (RQs):

- **(RQ1): Relationship between attendance rates (individual vs. group) and learning outcomes**. How do *individual* attendance rates of students versus that of their *group* predict individual learning outcomes?
- **(RQ2): Relationship between group attendance and talk moves diversification**. Based on RQ1 findings, do the groups' attendance rates predict the diversification of tutor and student talk moves?

Table 1: Distribution of Students' Tutorial Attendance Rates: Overall (Regardless of Tutor and Group) and Consistent Attendance (Including Students Only Attending with Original Tutor and Group)

Attendance %	Overall Attendance		**Consistent** Attendance	
	# Students	# Cumulative	# Students	# Cumulative
[0, 10]	23	23	8	8
[10, 20]	61	84	23	31
[20, 30]	124	208	43	74
[30, 40]	145	353	81	155
[40, 50]	181	534	128	283
[50, 60]	225	759	159	442
[60, 70]	233	992	161	603
[70, 80]	178	1170	94	697
[80, 90]	131	1301	64	761
[90, 100]	85	1386	42	803

2 PARTICIPANTS AND PROCEDURE

The participants in this study were 9th-grade students from two large urban (a Northeastern and a Midwestern) public school districts. Students received high-dosage tutoring approximately every other day as part of their regular school day (i.e., a second math period). They worked in a small group setting with a human tutor, where each group consisted of at most six students.

Tutors were assigned a coach who provided supervision and helped to ensure alignment between the tutoring materials and the students' classroom learning. We note that there was **no overlap** in the group-tutor-coach assignment. In other words, each group of students was assigned to a single tutor, and each tutor was assigned to a single coach. Tutors and coaches were provided as part of a partnership between the participating school districts and ***Saga Education***, a non-profit tutoring service provider.

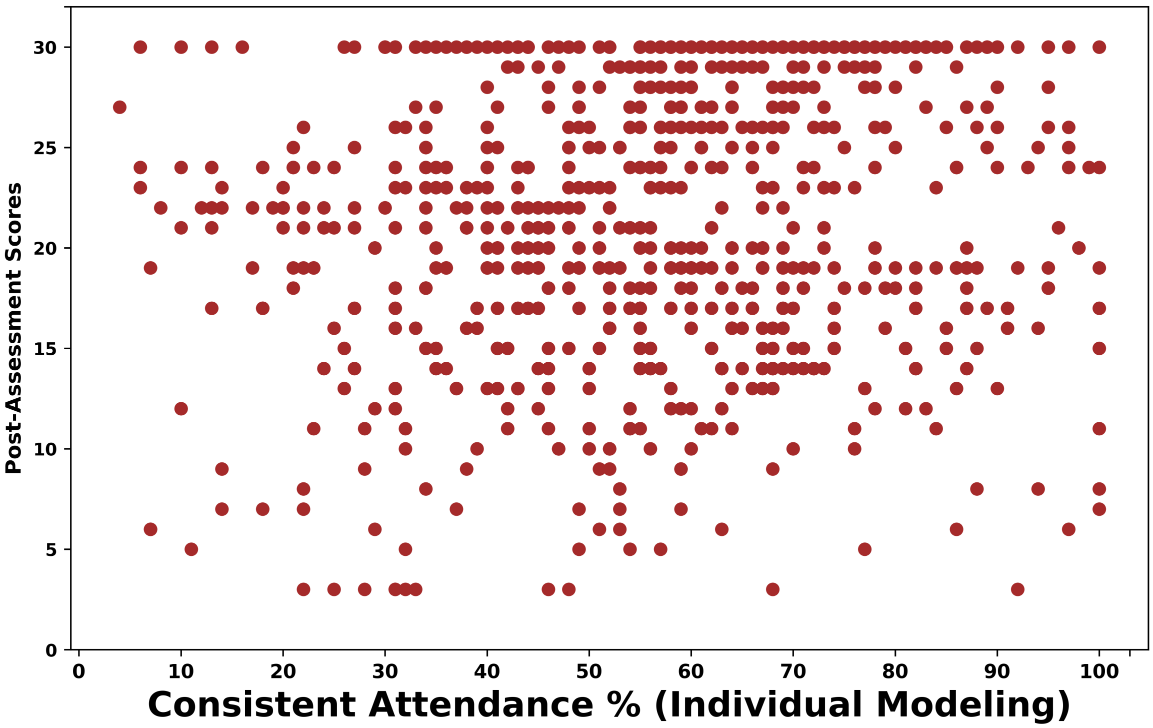
The frequency and duration of tutorials depended on many factors, such as the school schedule, the teacher's pace, the tutor's pace, and the group's pace. Typically, the tutorial lasted for 30 to 60 minutes, and students received 2 – 3 tutorials a week, yielding roughly 70 – 85 tutorials in the school year. Tutorials were audio and video recorded as part of the standard protocol used by *Saga Education*.

At the start of the school year, the learning coordinators at *Saga Education* considered the students' schedules, classroom math teacher, and student group preferences when assigning students to tutorial groups. Students might change tutors or groups for several reasons. Additionally, groups might be assigned new tutors in case of tutor absences or attrition. During the school year, students completed five rounds of a math skills assessment. In this work, we focus on the *first* and *last* assessment rounds as they occur at the start and end of the year, respectively. This allows us to maximize the number of tutoring sessions between assessment periods, yielding the largest possible sample size of tutorials per group. Specifically, the first assessment round is treated as the *pre-assessment*, the sessions are regarded as the tutoring intervention, and the last assessment round is treated as the *post-assessment*. The pre- and post-assessment each consists of 30 questions that are graded in a binary manner, resulting in integer scores within the [0, 30] range.

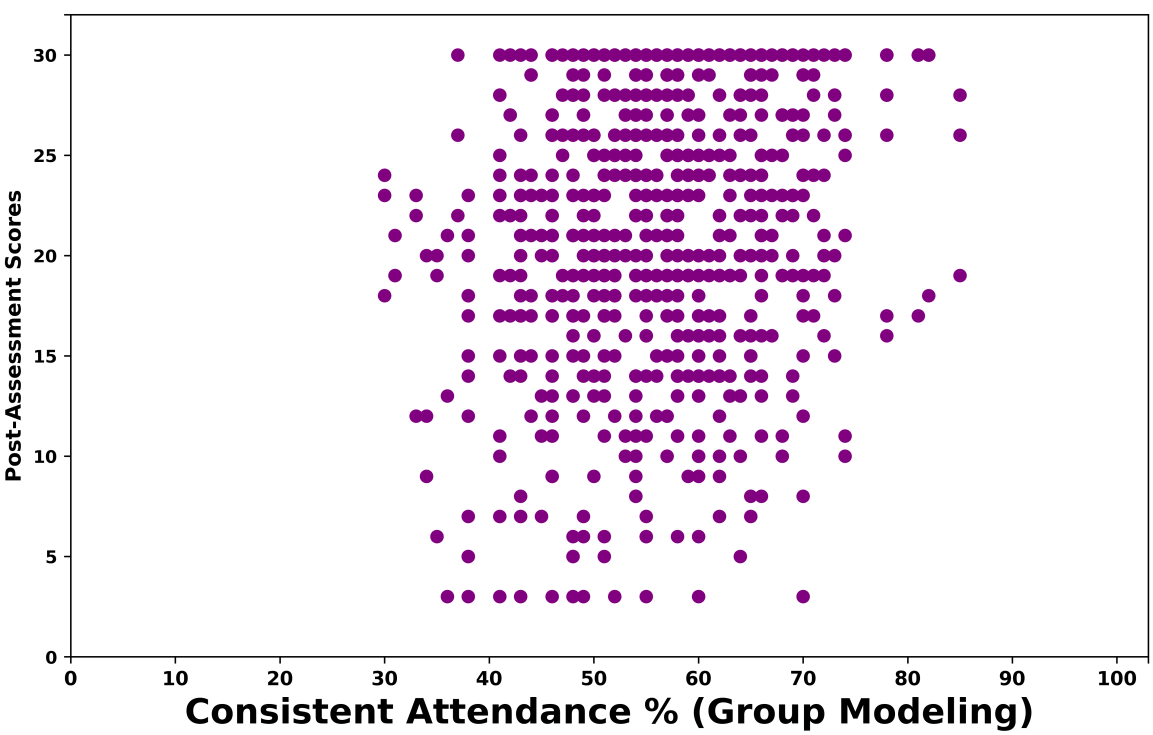
We combined students from the two districts to maximize the sample size. Initially, we analyzed data from 1386 students across the two school districts. While we had no access to their school attendance rates, we accessed and analyzed their tutorial attendance rates, as shown in the first three columns of Table 1. We found that many students changed tutors, which would hinder our goal of assessing group behavior of students attending with a fixed tutor. Hence, students were included in our analyses **only** if they met ***all*** these conditions:

(1) ***Assessment Scores Availability***: must have pre-assessment and post-assessment scores (no missing data).
(2) ***Consistent Tutor and Group***: must attend with the same tutor and maintain group membership during the entire school year. Therefore, we excluded students who changed tutors or groups and excluded any group of students whose tutor changed regardless of the reason (e.g., schedule change, illness, attrition).
(3) ***Consistent Group Attendance***: must be a part of a group where, in every tutorial, there are at least ***two*** attending students who satisfy the previous two conditions. This condition guarantees that we analyze students who were always part of a group during the year. In other words, this condition ensures that an included student will always have at least one more student with consistent attendance in any given tutorial. Based on this criterion, the only way to include a group that has a maximum of 2 students is for those two students to attend all tutorials during the year, which never happened in our data. Therefore, as shown in the first column of Table 2, the minimum number of students in a group was three, as we analyzed only groups where each tutorial had at least two attending students with consistent attendance and available assessment scores.

After applying the previous inclusion criteria, the last two columns of Table 1 show the *final set of* ***included*** 803 *students*. Table 1 shows



(a) Individual (Student) Attendance Rate ($r = .16, p < .0001$)



(b) Group Attendance Rate ($r = .22, p < .0001$)

Figure 1: Relationship between Attendance Rates (Individual vs. Group) on Individual Post-Assessment Scores

Table 2: Comparing Consistent Attendance (%) and Pre- and Post-Assessment Scores (Out of 30) Across Different Groups

Students per Group	# Groups	# Students	Attendance Rate of Students (%) Mean (SD)	**Pre**-Assess. of Students Mean (SD)	**Post**-Assess. of Students Mean (SD)
3	96	288	55.3 (20)	15.8 (5.3)	21.7 (6.8)
4	56	224	57.1 (21)	15.3 (5.8)	21.6 (7.0)
5	33	165	58.3 (20)	15.9 (6.1)	22.2 (7.1)
6	21	126	56.3 (20)	15.5 (5.8)	21.6 (7.3)
	Total = 206	Total = 803			

that most students had 40 − 80% of "**consistent**" attendance. Altogether, these students had 75 tutors who, in turn, had 20 coaches. Therefore, we investigate our two research questions (RQ1 in Section 3 and RQ2 in Section 4) on this set of 206 groups with 803 students, 75 tutors, and 20 coaches.

3 RELATIONSHIP BETWEEN ATTENDANCE RATE (INDIVIDUAL VS. GROUP) & LEARNING OUTCOMES

3.1 Methods (RQ1: Individual vs. Group Modeling of Attendance Rate)

Our goal was to investigate the association of two methods of modeling consistent attendance with students' math post-assessment scores. First, we investigated the traditional ***individual*** modeling, where the attendance rate of students is considered individually, disregarding the group they belong to. Second, we investigated the ***group*** attendance rate, where each student in a group gets assigned the *same, averaged* attendance rate of individuals (students) who are members of that group. A high group attendance rate reflects that students in a given group are *attending* ***together*** *more often*. The choice of *averaging* for the group modeling of attendance rates was motivated by aiming to investigate whether the group modeling method is appropriate **rather** than identifying *which* group modeling method is better.

Before comparing the two methods for modeling attendance rates, we investigated whether the number of students in a group impacted students' individual attendance rates (referred to as *AR*) or their pre- and post-assessment scores (referred to as *Pre* and *Post*, respectively). A Shapiro-Wilk test suggested non-normality on *AR* ($W = 0.993, p = .001$), *Pre* ($W = 0.994, p = .005$), and *Post* ($W = 0.926, p < .0001$). Therefore, we compared the four rows of Table 2 using a Kruskal-Wallis test on each of the three metrics —*AR*, *Pre*, and *Post*. We found no significant effect of group size on *AR* ($H(3) = 4.04, p = .26$), *Pre* ($H(3) = 0.91, p = .83$), and *Post* ($H(3) = 0.92, p = .82$).

3.2 Results (RQ1: Individual vs. Group Modeling of Attendance Rate)

Figure 1 shows students' post-assessment scores against the attendance rates of individual students (Fig. 1a) and that of groups they belong to (Fig. 1b) as a preliminary evaluation of each modeling method. We found that both significantly correlated with post-assessment scores, but the group attendance rates had a higher correlation ($r = .22, p < .0001$) than their individual counterparts ($r = .16, p < .0001$).

To investigate whether the results of group attendance (Fig. 1b) were observed by chance, we randomly generated 10,000 pseudo groupings, each following the same group size distribution in Table 2. In other words, we recreated the same distribution of group sizes and student counts of Table 2 while shuffling students to form groups that never existed. We computed the correlation between group attendance and post-assessment scores for each pseudo grouping, and the highest observed correlation was $r = .02$. This suggests that the correlation in Figure 1b is not randomly observed.

Hence, we proceeded to analyze the two modeling methods (individual vs. group) by fitting a Bayessian, Poisson Generalized Linear Mixed-effects Model (GLMM) with a log link function with this specification:

$$Post \sim Pre + Individual\_Attendance + Group\_Attendance$$
$$+(1|Coach/Tutor)$$

where *Post* is the dependent variable; *Pre*, *Individual_Attendance*, and *Group_Attendance* are the fixed effects that were centralized to decorrelate the predictors; and the random intercept of *Tutor* nested within *Coach*. We found a minimal correlation ($r = -.005$) between the two types of attendance and between *Pre* and *Group_Attendance* ($r = -.03$). Meanwhile, a higher correlation was found between *Pre* and *Individual_Attendance* ($r = .09$).

Table 3 summarizes the main outputs of our model. *Pre* scores were not a significant predictor of post-assessment scores: $z = -1.13$, $p = .26$. While both individual and group attendance rates significantly predicted post-assessment scores, the *group* attendance rate ($z = 9.39$, $p < .0001$) was a stronger predictor than the individual attendance rate ($z = 2.51$, $p = .01$), as confirmed with a general linear hypothesis test (GLHT) comparing the two estimates: $z = 7.3$, $p < .0001$.

Regarding random effects, the model had a small residual variance ($\sigma^2 = .04$), a small, within-coach, between-tutor variance ($\tau_{tutor:coach} = .01$), a minimal between-coach variance ($\tau_{coach} = 0$), and an Intraclass Correlation coefficient (ICC) of 0.13 . This suggests little variability in post-assessment scores was found at the tutor and coach levels.

To sum up, both individual and group attendance rates significantly predicted the post-assessment scores even after controlling for pre-assessment scores and the effects of tutors and coaches. However, the group modeling was a better fit for the data than

Table 3: Bayesian, Poisson GLMM Regression Table of Individual and Group Attendance Rates on Post-Assessment Scores

Term	Estimate	Std. Error	z-value	$\Pr(>\lvert z\rvert)$
Intercept (Post-Assessment)	3.08	0.013	229.8	$< .0001^{****}$
Pre-Assessment [fixed effect]	-0.001	0.001	-1.13	.26
Individual Attendance Rate [fixed effect]	0.001	0.0004	2.51	$.01^{*}$
Group Attendance Rate [fixed effect]	0.008	0.0008	9.39	$< .0001^{****}$

the individual modeling of attendance rates, suggesting that group attendance is a more promising modeling approach to predicting students' learning outcomes.

4 RELATIONSHIP BETWEEN GROUP ATTENDANCE RATE & TALK MOVES DIVERSIFICATION

The significant relationship between the group attendance rate and the students' post-assessment scores inspired us to investigate factors that may be contributing to such an association. Next, we investigated whether the group modeling of attendance rate predicted the quality and richness of discourse during tutorials.

4.1 Methods (RQ2: Group Attendance & Discourse Richness and Diversification)

The framework of talk moves [35, 52, 64] categorizes an utterance made by a tutor or student into one of many labels —as shown in Table 4— capturing different dimensions of communication and learning. For the purposes of our analyses, utterances that did not fall into any of these categories were excluded. Table 4 provides descriptions of the six tutor and four student talk moves included in this study. Both tutor and student talk moves have three broad categories: learning community, content knowledge, and rigorous thinking. The learning community talk moves are mostly non-content-related icebreakers, the content knowledge talk moves mainly test knowledge of factual mathematical statements without involving thinking, and the rigorous thinking talk moves involve mathematical thinking.

To automatically capture and measure talk moves, we trained a Robustly Optimized Bidirectional Encoder Representations from Transformers Pretraining Approach (RoBERTa)[41] model that was fine-tuned on large data sets of talk in classrooms and a small number of Saga tutoring sessions. Details on model training and validation are discussed in Booth et al. [14]. The model was moderately accurate with a macro F1 of 0.77 for tutors and 0.68 for students.

We used Shannon's ***entropy*** [60] to measure discourse diversification, quantified here as uncertainty (i.e., inverse of predictability) in talk move use. Hence, a higher entropy means a more even distribution of talk moves (i.e., less predictable), while a lower entropy suggests focusing on specific talk moves (i.e., more predictable). The entropy was calculated for Tutor Talk Moves (TTMs) and Student Talk Moves (STMs) as follows:

$$TTMs\_Entropy = -\sum_{TTM \in TTMs} p(TTM)\ \ln(p(TTM)) \qquad (1)$$

$$STMs\_Entropy = -\sum_{STM \in STMs} p(STM)\ \ln(p(STM)) \qquad (2)$$

4.2 Results (RQ2: Group Attendance & Discourse Richness and Diversification)

We fit two Bayessian, Gaussian GLMMs (one for TTMs and one for STMs) with log links with these specifications:

$$TTMs\_Entropy \sim Avg\_Pre + Group\_Attendance + (1|Coach/Tutor)$$

$$STMs\_Entropy \sim Avg\_Pre + Group\_Attendance + (1|Coach/Tutor)$$

where *TTMs_Entropy* and *STMs_Entropy* are the tutor and students talk move entropies computed via Equation 1 and 2, respectively; *Avg_Pre*, and *Group_Attendance* are the fixed effects that were centralized to decorrelate the predictors; and the random intercept of *Tutor* nested within *Coach*. Specifically, for each model, we had a total of 206 records, one record per group. Hence, we computed the average pre-assessment score of a given group to be a fixed effect in the model. For the tutor talk moves, we computed the percentage of each move by dividing the count of each move over the sum of all moves after aggregating across all tutoring sessions. We did the same procedure for students' talk moves while also aggregating the talk moves of all students in a given group. We found a small correlation between the *Avg_Pre* and *Group_Attendance*: $r = -.034$ and $r = -.035$ for the two respective models.

Table 5 summarizes the main outputs of both models. The group's *Avg_Pre* was not a significant predictor of entropies of tutor ($t = 0.08$, $p = .93$) and student ($t = 1.21$, $p = .23$) talk. However, the group attendance rate significantly predicted the entropies of the tutor ($t = 56.5$, $p < .0001$) and student ($t = 30.7$, $p < .0001$) talk moves. Very little (close to zero) variance was explained by the random effects. The ICCs of the two models were 0.12 and 0.14, respectively. These findings suggest little variability in discourse diversification (entropy) at the tutor and coach levels.

We additionally investigated whether group attendance predicted the percentage of each talk move (tutor or student). Therefore, we fit a series of Bayessian, Gaussian GLMMs (one per talk move) with log links using these model specifications:

$$TalkMove\_Percentage \sim Avg\_Pre + Group\_Attendance + (1|Coach/Tutor)$$

where *TalkMove_Percentage* is one of the ten talk moves of Table 4; *Avg_Pre*, and *Group_Attendance* are the fixed effects that were centralized to decorrelate the predictors; and the random intercept of *Tutor* nested within *Coach*. Tables 6 and 7 summarize our findings

Table 4: Description of Tutor and Student Talk Moves

Category	Talk Move	Description
Tutor Talk Moves		
Learning Community	Keeping Everyone Together	Orienting students to each other and to be active listeners
	Get Students to Relate to Others' Ideas	Prompting students to react to what another student said
	Restating	Verbatim repetition of all or part of what a student said
Content Knowledge	Pressing for Accuracy	Eliciting mathematical contributions and vocabulary
Rigorous Thinking	Pressing for Reasoning	Eliciting explanations, evidence, thinking aloud, and ideas' connection
	Revoicing	Repeating what a student said while adding on or changing the wording
Student Talk Moves		
Learning Community	Relating to Another's Idea	Using, commenting on, or asking questions about other students' ideas
	Asking for More Info	Asking tutor for help or more information
Content Knowledge	Making a Claim	Making a mathematical claim or factual statement
Rigorous Thinking	Providing Evidence	Explaining or stating own thinking, or providing evidence

Table 5: Bayesian GLMM Regression Table of Group Attendance Rate on Talk Moves Diversification (i.e., Entropy)

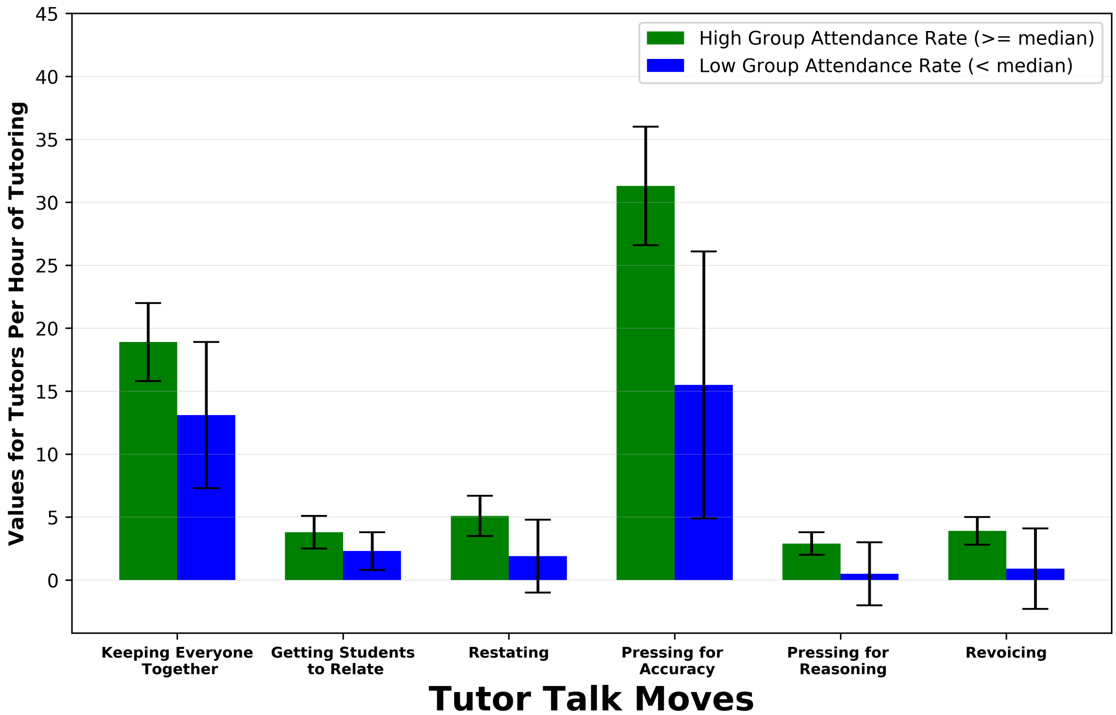
Term	Estimate	Std. Error	t-value	$Pr(>\|z\|)$
Tutor Talk Moves (TTMs)				
Intercept (Entropy)	0.17	.0043	39.7	$< .0001^{****}$
Avg. Pre-Assessment [fixed effect]	8e-5	.0009	0.08	.93
Group Attendance Rate [fixed effect]	.015	.0002	56.5	$< .0001^{****}$
Student Talk Moves (STMs)				
Intercept (Entropy)	0.11	0.0073	15	$< .0001^{****}$
Avg. Pre-Assessment [fixed effect]	0.002	0.0015	1.21	.23
Group Attendance Rate [fixed effect]	0.013	0.0004	30.7	$< .0001^{****}$

for the tutor's and students' talk moves, respectively. The group attendance rate significantly predicted the percentage of all talk moves except for tutors' Keep Everyone Together (KET) and the students' Providing Evidence (PE).

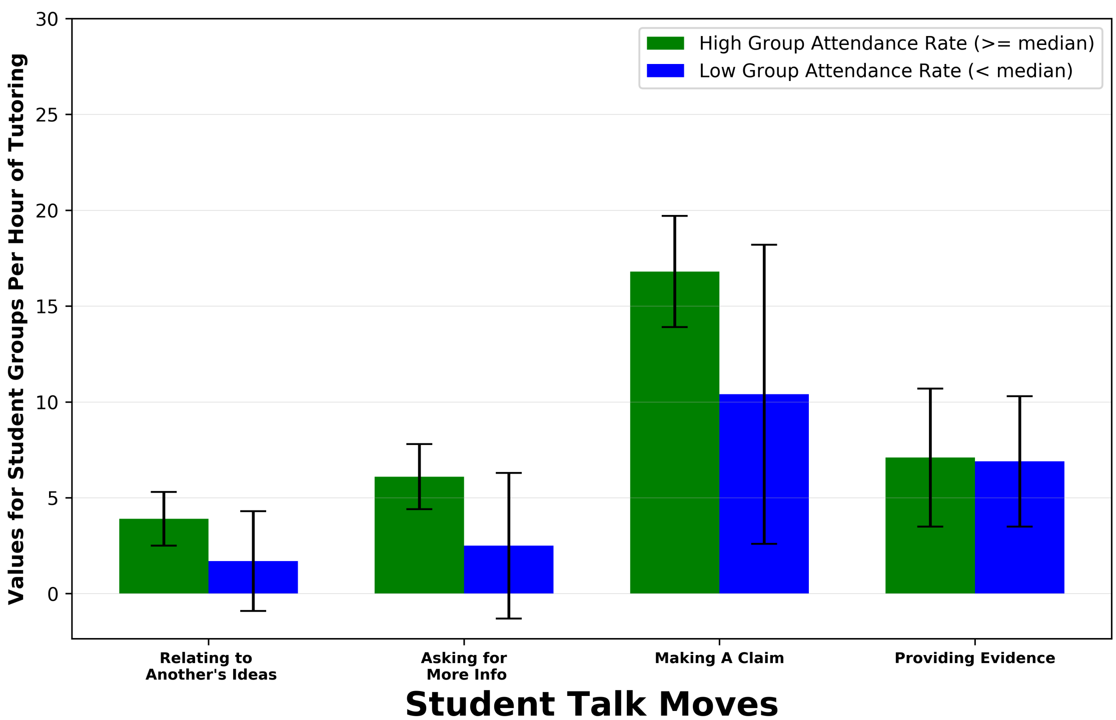
Figure 2 illustrates the relationship between high and low group attendance rates (using a median split) on the tutor and student talk moves per hour. Figures 2a and 2b show that having a higher group attendance generally resulted in more talk moves except for the Providing Evidence category. Even though the graph shows differences for the Keeping Everyone Together talks move, this difference was not statistically significant, as noted above. In brief, our results indicated that student groups who had a high rate of consistently attending together had patterns of student and tutor talk that were more diverse and also quantitatively higher in terms of most talk moves.

5 DISCUSSIONS & CONCLUSIONS

Our results showed that rates of group attendance in high-dosage tutoring sessions predict students' math assessment scores significantly better than individual attendance rates. This finding suggests that consistent group attendance is an important construct to consider when analyzing collaborative learning. We also found that the more a group of students *attended tutorials together and with the same tutor*, the more they engaged in discourse associated with accountable talk and the more they had diverse tutor and student



(a) Tutor Talk Moves



(b) Student Talk Moves

Figure 2: Comparing Hourly Talk Moves Mean(SD) across Groups of High and Low Attendance Rates

Table 6: Bayesian GLMM Regression Table of Group Attendance Rate on *Tutor* Talk Moves' Percentage

	Keep Together		Get Students to Relate		Restating		Press for Accuracy		Press for Reasoning		Revoicing	
Term	Est.	p	Est.	p	Est.	p	Est.	p	Est.	p	Est.	p
(Intercept)	-1.13	< **.001**	-3.51	< **.001**	-2.57	< **.001**	-0.91	< **.001**	-3.35	< **.001**	-3.02	< **.001**
Avg. Pre	0.01	.55	0.03	.08	0.01	.5	-0.01	.33	0.01	.66	-0.02	.12
Group Attnd.	0	.99	0.04	< **.001**	0.04	< **.001**	-0.02	< **.001**	0.04	< **.001**	0.04	< **.001**

Table 7: Bayesian GLMM Regression Table of Group Attendance Rate on *Students* Talk Moves' Percentage

	Relating to Another's Ideas		Asking for More Info		Making Claim		Providing Evidence	
Term	Estimate	p	Estimate	p	Estimate	p	Estimate	p
(Intercept)	-2.17	< **.001**	-1.74	< **.001**	-0.83	< **.001**	-1.56	< **.001**
Avg. Pre	0.01	.39	-0.02	.15	-0.01	.25	0.01	.33
Group Attnd.	0.02	< **.001**	0.02	< **.001**	-0.02	< **.001**	0.01	.2

talk moves, suggesting that the discussions were likely to be more collaborative and of higher instructional quality.

Taken together, our results suggest that the students with higher group attendance were learning as a **team** *despite not being one*. That is, the students in these groups had no unified goal or shared interest in each other's success. In other words, our findings suggest that students implicitly collaborated and learned as a team as they worked together over the course of a school year, although they were never explicitly mandated to collaborate or had a shared goal.

Our work contributes to the literature by showing that implicit teamness and collaboration exist, as attendance could sometimes predict learning outcomes compared to the substantial work that considers students' learning in intelligent team tutoring systems [13, 51] or e-learning environments [1–6, 24–26, 31, 32, 34]. Finally, we note that the group modeling of attendance and the exclusion of students who changed tutors or groups from our analyses do ***not*** imply that students should necessarily stay with the same group and tutor. Attention, care, and policies are needed to assign students to the appropriate groups and tutors and make changes when appropriate.

6 LIMITATIONS & FUTURE WORK

We acknowledge that our work had at least five limitations and areas for improvement:

(1) The lack of access to school attendance information hindered comparisons against tutorial attendance. A more rigorous approach to investigate RQ1 would be adding the modeling of school attendance and its impact on predicting post-assessment scores.
(2) The lack of access to students' demographics such as gender, race, and ethnic groups. Future work should investigate whether demographics influence attendance rates and the means of mitigating such influence if it exists.
(3) The choice of averaging the individual attendance rates of students within a group to obtain the group attendance rate has its own limitation by oversimplifying the modeling approach. In the context of this work, we aimed to test whether the group modeling works rather than which group modeling method is better. Nevertheless, this work is a step toward future comparisons of many group modeling approaches.
(4) Due to many students missing assessments in the middle of the school year, we measured attendance *only* between the first and last assessment rounds. Future work can investigate the significance of attendance once considered in shorter durations between consecutive assessment rounds.
(5) This work would have significantly benefited from the presence of qualitative analysis, such as surveys or interviews, that investigates whether students who consistently attended with the same group and tutor felt implicit teamness or a formation of community and bond.

ACKNOWLEDGMENTS

The authors would like to thank Robert (Bobby) Moulder from the University of Colorado Boulder for his effort in making this work possible. This research was supported by the Learning Engineering Virtual Institute (LEVI) program and the National Science Foundation (grants #2222647 and #1920510). All opinions are those of the authors and do not reflect those of the funding agencies.

REFERENCES

[1] Mark Abdelshiheed, Tiffany Barnes, and Min Chi. 2023. How and When: The Impact of Metacognitive Knowledge Instruction and Motivation on Transfer across Intelligent Tutoring Systems. *International Journal of Artificial Intelligence in Education* (2023), 1–34. https://doi.org/10.1007/s40593-023-00371-0
[2] Mark Abdelshiheed, John W. Hostetter, Tiffany Barnes, and Min Chi. 2023. Bridging Declarative, Procedural, and Conditional Metacognitive Knowledge Gap Using Deep Reinforcement Learning. In *Proceedings of the 45th annual conference of the cognitive science society*. 333–340.
[3] Mark Abdelshiheed, John W. Hostetter, Tiffany Barnes, and Min Chi. 2023. Leveraging deep reinforcement learning for metacognitive interventions across intelligent tutoring systems. In *International Conference on Artificial Intelligence in Education*. Springer, Cham, Switzerland, 291–303. https://doi.org/10.1007/978-3-031-36272-9_24

[4] Mark Abdelshiheed, Jennifer K. Jacobs, and Sidney K. D'Mello. 2024. Aligning Tutor Discourse Supporting Rigorous Thinking with Tutee Content Mastery for Predicting Math Achievement. In *International Conference on Artificial Intelligence in Education*. Springer, Cham, Switzerland.

[5] Mark Abdelshiheed, Robert Moulder, John W. Hostetter, Tiffany Barnes, and Min Chi. 2024. Example, Nudge, or Practice? Assessing Metacognitive Knowledge Transfer of Factual and Procedural Learners. *User Modeling and User-Adapted Interaction* (2024).

[6] Mark Abdelshiheed, Guojing Zhou, Mehak Maniktala, Tiffany Barnes, and Min Chi. 2020. Metacognition and Motivation: The Role of Time-Awareness in Preparation for Future Learning. In *Proceedings of the 42nd annual conference of the cognitive science society*. 945–951.

[7] Robin Alexander. 2020. *A dialogic teaching companion*. Routledge, Philadelphia, PA, US.

[8] Vic Alexander and Richard E Hicks. 2016. Does class attendance predict academic performance in first year psychology tutorials? *International Journal of Psychological Studies* 8, 1 (2016), 28–32. https://doi.org/10.5539/ijps.v8n1p28

[9] Ruel F Ancheta1i, Deny Daniel, and Reshma Ahmad. 2021. Effect of Class Attendance on Academic Performance. *European Journal of Education Studies* 8, 9 (2021), 116. https://doi.org/10.46827/ejes.v8i9.3887

[10] Douglas Barnes. 2008. Exploratory talk for learning. *Exploring talk in school* 1 (2008), 1–15.

[11] Sarah B Berenson, Glenda Carter, and Karen S Norwood. 1992. The at-risk student in college developmental algebra. *School Science and Mathematics* 92, 2 (1992), 55–58. https://doi.org/10.1111/j.1949-8594.1992.tb12141.x

[12] Marvin W Berkowitz and John C Gibbs. 1985. The process of moral conflict resolution and moral development. *New Directions for Child and Adolescent Development* 1985, 29 (1985), 71–84.

[13] Desmond Bonner, Stephen Gilbert, Michael C Dorneich, Eliot Winer, Anne M Sinatra, Anna Slavina, Anastacia MacAllister, and Joseph Holub. 2016. The challenges of building intelligent tutoring systems for teams. In *Proceedings of the human factors and ergonomics society annual meeting*, Vol. 60. SAGE Publications, Los Angeles, CA, 1981–1985.

[14] Brandon M Booth, Jennifer Jacobs, Jeffrey B Bush, Brent Milne, Tom Fischaber, and Sidney K DMello. 2024. Human-tutor Coaching Technology (HTCT): Automated Discourse Analytics in a Coached Tutoring Model. In *Proceedings of the 14th Learning Analytics and Knowledge Conference*. ACM, New York, NY, USA, 725–735. https://doi.org/10.1145/3636555.3636937

[15] Kenneth A Bruffee. 1993. *Collaborative learning: higher education, interdependence, and the authority of knowledge*. John Hopkins University Press, Baltimore, MD, US.

[16] Gaowei Chen, Carol KK Chan, Kennedy KH Chan, Sherice N Clarke, and Lauren B Resnick. 2020. Efficacy of video-based teacher professional development for increasing classroom discourse and student learning. *Journal of the Learning Sciences* 29, 4-5 (2020), 642–680. https://doi.org/10.1080/10508406.2020.1783269

[17] Nancy J Cooke, Myke C Cohen, Walter C Fazio, Laura H Inderberg, Craig J Johnson, Glenn J Lematta, Matthew Peel, and Aaron Teo. 2023. From Teams to Teamness: Future Directions in the Science of Team Cognition. *Human Factors* (2023), 00187208231162449. https://doi.org/10.1177/0018720823116244

[18] Richard Correnti, Mary Kay Stein, Margaret S Smith, James Scherrer, Margaret McKeown, James Greeno, and Kevin Ashley. 2015. Improving teaching at scale: Design for the scientific measurement and learning of discourse practice. *Socializing intelligence through academic talk and dialogue* (2015), 303–320.

[19] Marcus Credé, Sylvia G Roch, and Urszula M Kieszczynka. 2010. Class attendance in college: A meta-analytic review of the relationship of class attendance with grades and student characteristics. *Review of Educational Research* 80, 2 (2010), 272–295. https://doi.org/10.3102/0034654310362998

[20] Richard P Deane and Deirdre J Murphy. 2013. Student attendance and academic performance in undergraduate obstetrics/gynecology clinical rotations. *Jama* 310, 21 (2013), 2282–2288. https://doi.org/10.1001/jama.2013.282228

[21] Kamile Demir and Yasemin Akman Karabeyoglu. 2015. Factors associated with absenteeism in high schools. *Eurasian Journal of Educational Research* 16, 62 (2015), 37–56.

[22] Stephen Devadoss and John Foltz. 1996. Evaluation of factors influencing student class attendance and performance. *American Journal of Agricultural Economics* 78, 3 (1996), 499–507. https://doi.org/10.2307/1243268

[23] Pierre Dillenbourg. 1999. What do you mean by collaborative learning?

[24] Sidney K D'Mello and Art Graesser. 2023. Intelligent tutoring systems: How computers achieve learning gains that rival human tutors. In *Handbook of educational psychology*. Routledge, UK, 603–629.

[25] Ge Gao, Song Ju, Markel Sanz Ausin, and Min Chi. 2023. HOPE: Human-Centric Off-Policy Evaluation for E-Learning and Healthcare. In *Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems*. ACM, New York, NY, USA, 1504–1513.

[26] Ge Gao, Xi Yang, and Min Chi. 2024. Get a Head Start: On-Demand Pedagogical Policy Selection in Intelligent Tutoring. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 38. AAAI, Washington, DC, USA, 12136–12144.

[27] P Gendron and Paul Pieper. 2005. Does attendance matter? Evidence from an Ontario ITAL.

[28] Arthur C Graesser, Sidney D'Mello, and Whitney Cade. 2011. Instruction based on tutoring. *Handbook of research on learning and instruction* 1 (2011), 422–440.

[29] James G Greeno, Allan M Collins, Lauren B Resnick, et al. 1996. Cognition and learning. *Handbook of educational psychology* 77 (1996), 15–46.

[30] PM Horn and AI Jansen. 2009. An investigation into the impact of tutorials on the performance of economics students. *South African Journal of Economics* 77, 1 (2009), 179–189. https://doi.org/10.1111/j.1813-6982.2009.01194.x

[31] John W. Hostetter, Mark Abdelshiheed, Tiffany Barnes, and Min Chi. 2023. A self-organizing neuro-fuzzy q-network: Systematic design with offline hybrid learning. In *Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems*. ACM, New York, NY, USA, 1248–1257.

[32] John W. Hostetter, Cristina Conati, Xi Yang, Mark Abdelshiheed, Tiffany Barnes, and Min Chi. 2023. XAI to increase the effectiveness of an Intelligent Pedagogical Agent. In *Proceedings of the 23rd ACM International Conference on Intelligent Virtual Agents*. ACM, New York, NY, USA, 1–9. https://doi.org/10.1145/3570945.3607301

[33] Richard M Hyde and DJ Flournoy. 1986. A case against mandatory lecture attendance. *Academic Medicine* 61, 3 (1986), 175–6.

[34] Md Mirajul Islam, Xi Yang, John W. Hostetter, Adittya S. Saha, and Min Chi. 2024. A Generalized Apprenticeship Learning Framework for Modeling Heterogeneous Student Pedagogical Strategies. In *Educational Data Mining*.

[35] Jennifer Jacobs, Karla Scornavacco, Charis Harty, Abhijit Suresh, Vivian Lai, and Tamara Sumner. 2022. Promoting rich discussions in mathematics classrooms: Using personalized, automated feedback to support reflection and instructional change. *Teaching and Teacher Education* 112 (2022), 103631. https://doi.org/10.1016/j.tate.2022.103631

[36] Steve WJ Kozlowski and Georgia T Chao. 2012. The dynamics of emergence: Cognition and cohesion in work teams. *Managerial and Decision Economics* 33, 5-6 (2012), 335–354. https://doi.org/10.1002/mde.2552

[37] Ann Cale Kruger. 1993. Peer collaboration: Conflict, cooperation, or both? *Social Development* 2, 3 (1993), 165–182. https://doi.org/10.1111/j.1467-9507.1993.tb00012.x

[38] Marjan Laal and Seyed Mohammad Ghodsi. 2012. Benefits of collaborative learning. *Procedia-social and behavioral sciences* 31 (2012), 486–490. https://doi.org/10.1016/j.sbspro.2011.12.091

[39] Jean Lave and Etienne Wenger. 1991. *Situated learning: Legitimate peripheral participation*. Cambridge university press, Cambridge, England.

[40] Judith R Levine. 1992. The Effect of Different Attendance Policies on Student Attendance and Achievement. In *Meeting of the American Psychological Association*. ERIC, Boston, MA, US.

[41] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692* (2019).

[42] Anna Lukkarinen, Paula Koivukangas, and Tomi Seppälä. 2016. Relationship between class attendance and student performance. *Procedia-Social and Behavioral Sciences* 228 (2016), 341–347. https://doi.org/10.1016/j.sbspro.2016.07.051

[43] General Stanley McChrystal, Tantum Collins, David Silverman, and Chris Fussell. 2015. *Team of teams: New rules of engagement for a complex world*. Penguin, Broadway, NY, US.

[44] Neil Mercer, Sara Hennessy, and Paul Warwick. 2019. Dialogue, thinking together and digital technology in the classroom: Some educational implications of a continuing line of inquiry. *International Journal of Educational Research* 97 (2019), 187–199. https://doi.org/10.1016/j.ijer.2017.08.007

[45] Neil Mercer and Karen Littleton. 2007. *Dialogue and the development of children's thinking: A sociocultural approach*. Routledge, Philadelphia, PA, US.

[46] Sarah Michaels and Catherine O'Connor. 2015. Conceptualizing talk moves as tools: Professional development approaches for academically productive discussion. *Socializing intelligence through talk and dialogue* (2015), 347–362.

[47] Sarah Michaels, Catherine O'Connor, and Lauren B Resnick. 2008. Deliberative discourse idealized and realized: Accountable talk in the classroom and in civic life. *Studies in philosophy and education* 27 (2008), 283–297. https://doi.org/10.1007/s11217-007-9071-1

[48] Randy Moore. 2003. Attendance and performance. *Journal of College Science Teaching* 32, 6 (2003), 367.

[49] Sarah Moore, Claire Armstrong, and Jill Pearson. 2008. Lecture absenteeism among students in higher education: A valuable route to understanding student motivation. *Journal of Higher Education Policy and Management* 30, 1 (2008), 15–24. https://doi.org/10.1080/13600800701457848

[50] Rudolf H Moos and Bernice S Moos. 1978. Classroom social climate and student absences and grades. *Journal of educational psychology* 70, 2 (1978), 263. https://doi.org/10.1037/0022-0663.70.2.263

[51] Alec Ostrander, Desmond Bonner, Jamiahus Walton, Anna Slavina, Kaitlyn Ouverson, Adam Kohl, Stephen Gilbert, Michael Dorneich, Anne Sinatra, and Eliot Winer. 2020. Evaluation of an intelligent team tutoring system for a collaborative two-person problem: Surveillance. *Computers in human behavior* 104 (2020),

105873.
[52] Catherine O'Connor and Sarah Michaels. 2019. Supporting teachers in taking up productive talk moves: The long road to professional learning at scale. *International Journal of Educational Research* 97 (2019), 166–175. https://doi.org/10.1016/j.ijer.2017.11.003
[53] Catherine O'Connor, Sarah Michaels, and Suzanne Chapin. 2015. "Scaling down" to explore the role of talk in learning: From district intervention to controlled classroom study. *Socializing intelligence through academic talk and dialogue* (2015), 111–126.
[54] Lauren B Resnick, Christa SC Asterhan, and Sherice N Clarke. 2018. Accountable Talk: Instructional Dialogue That Builds the Mind.
[55] Lauren B Resnick, Sarah Michaels, and Catherine O'Connor. 2010. How (well structured) talk builds the mind. *Innovations in educational psychology: Perspectives on learning, teaching and human development* 163 (2010), 194.
[56] David Romer. 1993. Do students go to class? Should they? *Journal of economic perspectives* 7, 3 (1993), 167–174. https://doi.org/10.1257/jep.7.3.167
[57] Eduardo Salas, Terry L. Dickinson, Sharolyn A. Converse, and Scott I. Tannenbaum. 1992. Toward an understanding of team performance and training. In *Teams: Their training and performance*. Ablex Publishing, Westport, CT, US, 3–29.
[58] Eduardo Salas and Stephen M Fiore. 2004. Why team cognition? An overview. In *Team cognition: Understanding the factors that drive process and performance*, Eduardo Salas and Stephen M Fiore (Eds.). American Psychological Association, Washington, DC, 3–8. https://doi.org/10.1037/10690-001
[59] Henk G. Schmidt and Jos H. C. Moust. 2000. Factors affecting small-group tutorial learning: A review of research. In *Problem-based learning: A research perspective on learning interactions*. Lawrence Erlbaum Associates Publishers, Mahwah, NJ, US, 19–51.
[60] Claude Elwood Shannon. 1948. A mathematical theory of communication. *The Bell system technical journal* 27, 3 (1948), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x
[61] Barbara Leigh Smith and Jean T MacGregor. 1992. What is collaborative learning.
[62] Karen L St. Clair. 1999. A case against compulsory class attendance policies in higher education. *Innovative Higher Education* 23 (1999), 171–180. https://doi.org/10.1023/A:1022942400812
[63] Glenda S Stump, Jonathan C Hilpert, Jenefer Husman, Wen-ting Chung, and Wonsik Kim. 2011. Collaborative learning in engineering students: Gender and achievement. *Journal of engineering education* 100, 3 (2011), 475–497. https://doi.org/10.1002/j.2168-9830.2011.tb00023.x
[64] Abhijit Suresh, Jennifer Jacobs, Charis Harty, Margaret Perkoff, James H Martin, and Tamara Sumner. 2022. The TalkMoves dataset: K-12 mathematics lesson transcripts annotated for teacher and student discursive moves. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*. European Language Resources Association, Marseille, France.
[65] Aurora AC Teixeira. 2016. The impact of class absenteeism on undergraduates' academic performance: evidence from an elite Economics school in Portugal. *Innovations in Education and Teaching International* 53, 2 (2016), 230–242. https://doi.org/10.1080/14703297.2014.937730
[66] Patrick T Terenzini, Alberto F Cabrera, Carol L Colbeck, John M Parente, and Stefani A Bjorklund. 2001. Collaborative learning vs. lecture/discussion: Students' reported learning gains. *Journal of Engineering Education* 90, 1 (2001), 123–130. https://doi.org/10.1002/j.2168-9830.2001.tb00579.x
[67] Lev Vygotsky et al. 1978. *Mind in society: The development of higher psychological processes*. Harvard University Press, Cambridge, MA.
[68] Noreen M Webb, Megan L Franke, Marsha Ing, Jacqueline Wong, Cecilia H Fernandez, Nami Shin, and Angela C Turrou. 2014. Engaging with others' mathematical ideas: Interrelationships among student participation, teachers' instructional practices, and learning. *International Journal of Educational Research* 63 (2014), 79–93. https://doi.org/10.1016/j.ijer.2013.02.001
[69] Mikyung Kim Wolf, Amy C Crosson, and Lauren B Resnick. 2006. Accountable Talk in Reading Comprehension Instruction. CSE Technical Report 670. *National Center for Research on Evaluation, Standards, and Student Testing (CRESST)* (2006).
[70] Steven Yamarik. 2007. Does cooperative learning improve student learning outcomes? *The journal of economic education* 38, 3 (2007), 259–277. https://doi.org/10.3200/JECE.38.3.259-277