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Cooperative Learning Strategies and Communication Skills among School Students

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Abstract— Cooperative learning is increasingly viewed as a structured pedagogical approach for developing both academic competence and interpersonal communication among school students. This study proposes a multimodal framework for examining how structured cooperative-learning strategies influence oral expression, active listening, turn-taking, responsiveness, argument construction, and equitable participation in classroom interaction. A central research gap is that much existing work evaluates communication through post-intervention questionnaires or aggregate performance scores, while comparatively less attention is given to the interaction processes through which communication develops during cooperative tasks. The proposed study therefore conceptualizes communication as an observable and temporally evolving classroom behavior rather than exclusively as a self-reported educational outcome. It further introduces an artificial-intelligence-assisted analytical layer in which anonymized interaction transcripts and participation sequences can be examined for communication patterns while teacher-rated rubrics remain the primary criterion measure.

Keywords— Cooperative Learning, Communication Skills, School Students, Collaborative Interaction, Learning Analytics, 3

Introduction

Communication competence has become an increasingly important educational outcome as contemporary schooling moves beyond the transmission of subject knowledge toward the development of competencies required for collaborative problem solving, digital participation, and lifelong learning. Students are expected not merely to recall information but to explain ideas, listen to alternative viewpoints, ask relevant questions, negotiate meaning, justify decisions, and construct knowledge with peers. These capabilities are especially important in classrooms where learning increasingly involves projects, discussions, digital resources, and collaborative problem-solving activities.

Despite this emphasis, conventional classroom organization can provide unequal opportunities for communication. Teacher-led instruction frequently concentrates speaking opportunities in a relatively small number of confident students, while quieter learners may participate primarily as listeners. Even ordinary group work does not automatically resolve this problem. A group may appear collaborative while one or two members dominate its discussion, another student records the final answer, and less confident members contribute minimally. The educational issue is therefore not simply whether students are placed into groups, but whether the structure of group interaction creates meaningful and relatively equitable opportunities to communicate.

Cooperative learning addresses this problem by organizing students around shared tasks while incorporating mechanisms such as positive interdependence, individual accountability, peer interaction, assigned responsibilities, and group reflection. In contrast with loosely organized group work, structured cooperative learning attempts to make the contribution of individual learners relevant to collective task completion. Students may consequently need to explain their reasoning, listen to peers, request clarification, challenge interpretations constructively, summarize a discussion, and reach a negotiated conclusion.

Recent evidence supports the educational relevance of these interaction processes. A 2023 systematic review of learning-community research identified communication alongside learning outcomes, motivation, and anxiety as an important

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dimension of collaborative educational environments. Research has also shown that students' roles during collaborative activity can shape group interaction and collaborative problem-solving processes, suggesting that the organization of participation is consequential rather than incidental.

The communication benefits of cooperative instruction have also received empirical attention. Munawaroh and colleagues examined cooperative learning and communication skills among seventh-grade students using an experimental framework. Studies employing particular cooperative structures have similarly investigated Think–Pair–Share in relation to mathematical communication and Talking Chips in relation to elementary students' communication performance. More recent secondary-school research has moved beyond generic collaboration by explicitly training transactive communication—the ability to refer to, build upon, and transform a partner's ideas. Such findings reinforce the argument that the *quality and structure* of peer discourse deserve direct investigation.

Research Gap

A significant limitation in the existing literature is that cooperative learning and communication are often connected through a relatively simple intervention-outcome model: one instructional technique is implemented, communication is measured before and after the intervention, and the difference between experimental and comparison groups is estimated. This approach can establish whether an intervention is associated with improvement, but it provides less information about *how communication develops inside cooperative interaction*.

Three related gaps are particularly important.

First, many studies concentrate on a single cooperative-learning technique. This makes it difficult to determine whether communication improvement arises from cooperative learning generally or from specific structural properties such as individual preparation, mandatory turn-taking, role rotation, peer teaching, or reciprocal explanation.

Second, communication is frequently represented by a total test, questionnaire, or rubric score. Such measures are useful but can conceal differences among communication dimensions. A student might become more willing to speak without becoming a better listener; another might produce clearer explanations while continuing to dominate discussion. Communication competence should therefore be examined multidimensionally.

Third, contemporary learning analytics provide opportunities to investigate classroom interaction at a finer level of resolution, yet such approaches remain underused in school-based cooperative-learning research. AI-assisted analysis of anonymized transcripts can potentially identify participation distribution, questioning, response patterns, explanatory turns, and semantic responsiveness. These computational indicators should not be treated as substitutes for teacher judgment; instead, they can provide an additional analytical layer for explaining why particular cooperative structures work.

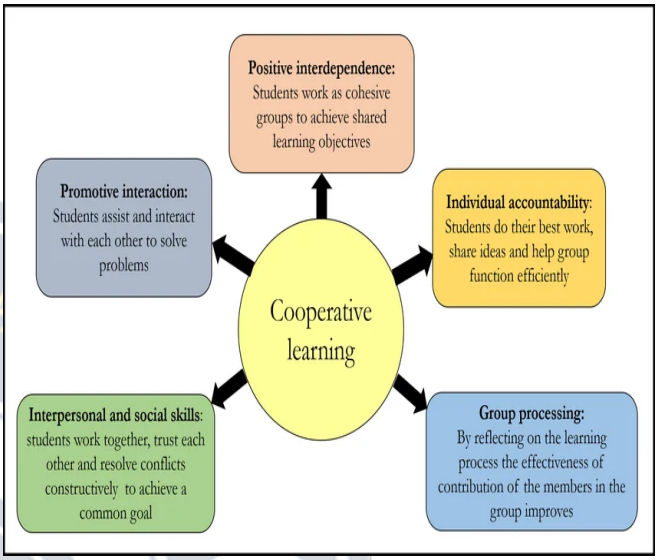


Fig. 1: Five basic steps in cooperative learning

Source: *https://www.researchgate.net/figure/Five-basic-steps-in-cooperative-learning_fig1_317280500*

The present manuscript is built around this gap. It proposes an **interaction-sensitive cooperative communication framework** that compares multiple cooperative-learning structures while combining teacher observation, performance assessment, peer-interaction indicators, and explainable computational analysis. The central premise is that improvement in communication is mediated not simply by being a member of a group but by the distribution and quality of communicative opportunities generated within that group.

Accordingly, the study is designed around three objectives: to compare the effects of differently structured cooperative-learning strategies on multidimensional communication competence; to identify interaction characteristics associated with communication gains; and to evaluate whether interpretable machine-learning models can identify patterns associated with strong communication development from classroom interaction data.

This orientation also creates an appropriate connection between educational research and contemporary AI/ML methodology. Rather than positioning artificial intelligence as an instructional replacement, the proposed framework uses AI as an analytical instrument. Such an approach is particularly relevant to responsible educational technology

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because the primary pedagogical intervention remains human-centered cooperative learning, whereas computational techniques are used to understand classroom processes that are difficult to capture through aggregate scores alone.

Literature Review

Cooperative Learning as Structured Social Learning

Cooperative learning is grounded in the premise that carefully organized peer interaction can support cognitive as well as social development. Its effectiveness depends on more than physical proximity between learners. Productive cooperation requires a task architecture in which learners perceive a shared goal but retain individual responsibility for contributing to that goal.

Positive interdependence is particularly important because it changes the function of classroom communication. When successful completion requires information, reasoning, or contributions distributed among group members, communication becomes necessary to task performance. Students cannot simply divide a worksheet and independently complete unrelated sections. They need to exchange information and integrate individual contributions.

Individual accountability provides a complementary mechanism. Without accountability, cooperative activity may permit social loafing or dominance by academically stronger students. Structured strategies attempt to ensure that each learner must explain, answer, teach, summarize, or otherwise contribute. Consequently, communication practice becomes distributed more widely across the group.

The role of interaction structure is supported by contemporary research on collaborative problem solving. A systematic review published in *Thinking Skills and Creativity* concluded that students' roles influence behavior and group interaction and that productive roles can change during collaborative activity depending on learner characteristics, context, and teacher support. This suggests that assigning and rotating communicative functions may be more educationally productive than leaving participation entirely spontaneous.

Cooperative Learning and Communication Development

Communication competence is multidimensional. For school students, it includes intelligible oral expression, active listening, responsiveness, appropriate questioning, explanation of reasoning, respectful disagreement, non-verbal attentiveness, and adaptation of a message in response to feedback. These dimensions are closely aligned with the interaction demands of cooperative learning.

Empirical research provides evidence for this connection. Munawaroh et al. investigated communication development through cooperative learning in social-studies instruction using a randomized pretest-posttest control-group approach with seventh-grade students. In another context, research on Grade 9 students used cooperative techniques to develop English speaking performance assessed through dimensions including grammar, pronunciation, vocabulary, interaction, and fluency. These studies demonstrate that cooperative structures can be adapted to both subject-based communication and language-oriented performance.

However, communication outcomes are likely to depend on how cooperation is operationalized. Think–Pair–Share, for example, creates an individual thinking period followed by paired verbalization before whole-group participation. Research with eighth-grade students has examined this approach specifically in relation to mathematical communication. The structure may particularly benefit students who require preparation time before public participation because it lowers the immediate communicative demand associated with whole-class responses.

Talking Chips follows a different logic. Participation tokens or equivalent turn-regulation mechanisms restrict repeated contributions from dominant speakers until other members have participated. A study involving fourth-grade students reported higher post-test communication scores for students exposed to a Talking Chips cooperative model than for the comparison group. Although context-specific findings should not automatically be generalized, the underlying mechanism is relevant: communication development may depend partly on whether an instructional design distributes opportunities to speak.

Jigsaw learning generates another communication mechanism. Students acquire responsibility for a component of the learning material and subsequently communicate that knowledge to peers. This creates information interdependence because group understanding depends on peer explanation. A 2024 systematic literature review specifically examined the Jigsaw model in relation to elementary students' communication skills and reported generally favorable findings across the studies it reviewed.

These approaches illustrate why treating "cooperative learning" as a single homogeneous intervention can be theoretically restrictive. Think–Pair–Share regulates preparation and progressive disclosure; Talking Chips regulates participation; Jigsaw creates information dependence and peer teaching; rotating-role tasks distribute communicative responsibilities. Each may therefore influence different components of communication competence.

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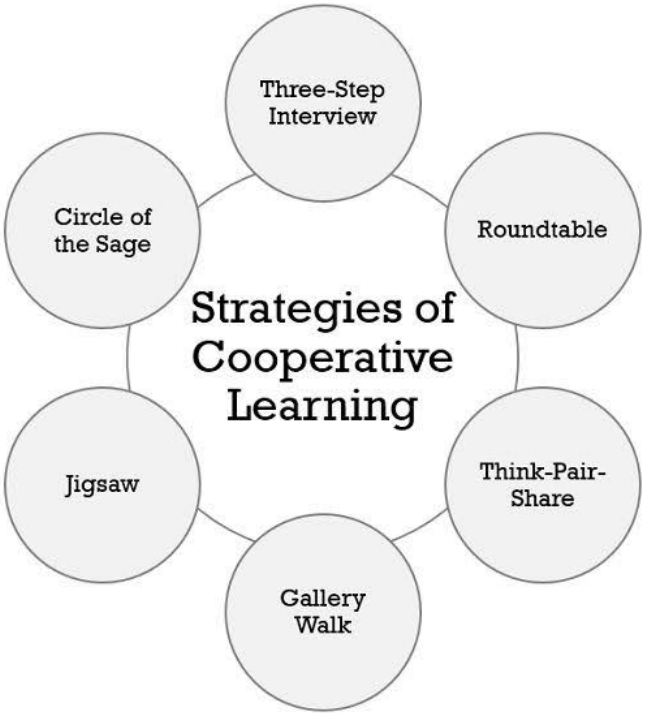


Fig. 2: Strategies of Cooperative Learning

Source: *https://keydifferences.com/difference-between-collaborative-learning-and-cooperative-learning.html*

From Speaking Frequency to Interaction Quality

One of the most important developments in recent collaborative-learning research is the distinction between the quantity and quality of classroom talk. A student who speaks frequently is not necessarily communicating effectively. Repetition, interruption, unrelated comments, and unilateral explanation can increase talk time without improving collaborative knowledge construction.

High-quality interaction is more reciprocal. Learners respond to previous contributions, request clarification, elaborate peers' ideas, justify agreement or disagreement, and connect multiple viewpoints. This concept is closely related to transactive communication.

A 2024 study in *Learning and Instruction* developed and evaluated lesson-integrated training designed to strengthen transactive communication among secondary-school students. The intervention targeted students' capacity to refer to a learning partner's ideas and transform those contributions into more elaborated ideas. This research is particularly relevant because it indicates that productive collaborative discourse can be explicitly scaffolded rather than assumed to emerge naturally from group placement.

The present study consequently distinguishes **participation volume** from **interaction quality**. The distinction has methodological consequences. Measuring only how many times students speak may reward verbal dominance. A stronger evaluation should consider whether participation is distributed across members and whether contributions demonstrate listening, responsiveness, elaboration, and constructive negotiation.

Communication Equity and Student Participation

Communication development is also an equity issue. Classroom interaction can reproduce differences associated with confidence, prior achievement, language proficiency, friendship networks, or perceived social status. Students who already communicate confidently may gain the greatest benefit from unstructured discussion because they obtain more opportunities to speak and receive more peer feedback.

Cooperative structures may reduce this imbalance when they incorporate individual accountability and controlled participation. Nevertheless, assigning students to groups does not guarantee equality. Dominance can persist unless task rules deliberately distribute communicative responsibility.

This concern motivates the proposed study's use of a **participation-balance indicator**. Instead of evaluating only total group interaction, the analysis will examine how evenly communicative turns are distributed. A group in which four students contribute approximately proportionately represents a different interaction environment from one in which a single student produces most substantive statements.

Communication equity also supports the use of rotating roles. Roles such as facilitator, evidence checker, questioner, summarizer, and reporter require students to perform different discourse functions across learning sessions. Rotation is important because permanent role assignment could unintentionally reinforce existing patterns—for example, repeatedly making the most confident student the presenter.

Cooperative Learning in Digitally Mediated Education

The period following 2021 has further expanded the meaning of cooperative learning because peer interaction increasingly occurs across physical, blended, and digitally supported learning environments. Research on online cooperative learning has examined communication and teamwork development in technology-mediated contexts, demonstrating that cooperative principles can extend beyond conventional face-to-face classroom arrangements.

Digital environments simultaneously create analytical opportunities. Written discussion boards, collaborative documents, classroom transcripts, and appropriately consented audio-derived transcripts can produce interaction records that are more detailed than conventional observation notes. These data can be used to study the sequence and distribution of communication.

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Nevertheless, computational analysis requires methodological restraint. A model cannot reliably infer complete interpersonal competence from word counts or isolated linguistic features. Cultural communication styles, second-language proficiency, classroom norms, and task difficulty may all affect observable patterns. AI-generated indicators should therefore complement rather than replace human assessment.

Artificial Intelligence and Explainable Communication Analytics

The proposed research extends cooperative-learning analysis through interpretable machine learning. After anonymization and appropriate ethical safeguards, classroom transcripts can be transformed into interaction features such as number of substantive turns, question frequency, response latency where technically reliable, explanatory elaboration, acknowledgment of peer contributions, lexical diversity, participation distribution, and topic-relevant semantic continuity.

Machine-learning models can then test whether these interaction indicators predict improvement in independently rated communication performance. Because the educational objective is explanation rather than automated student ranking, interpretable models are preferable to unnecessarily opaque architectures. Regularized regression and tree-based ensemble methods, for example, can be compared to determine whether nonlinear combinations of participation and discourse characteristics improve predictive performance.

The analytical objective is not to claim that an algorithm can determine whether a child is a "good communicator." Rather, the model asks a narrower question: **which observable characteristics of structured cooperative interaction are associated with independently assessed communication improvement?**

This distinction is important for responsible educational AI. Teacher-rated performance, student tasks, and observational evidence remain the principal educational measures. Computational indicators provide secondary evidence concerning mechanisms of change.

Proposed Methodology

The proposed study adopts a **quasi-experimental, multimodal learning-analytics design** to investigate whether structured cooperative-learning strategies improve communication skills among school students and to identify the interaction mechanisms associated with such improvement. Unlike conventional studies that treat cooperative learning as a single intervention, the design differentiates among cooperative structures according to the type of communication they require.

The proposed sample consists of **240 students from Grades 7–9**, drawn from multiple school classrooms. Students are organized into four instructional conditions of approximately 60 learners each: Jigsaw cooperative learning, Think–Pair–Share (TPS), Rotating-Role Collaborative Problem Solving (RRCPS), and a comparison condition based predominantly on conventional teacher-directed instruction supplemented by ordinary group exercises.

The intervention is planned for eight instructional weeks. The same broad curriculum-linked communication objectives are maintained across experimental conditions to reduce content-related confounding. Teachers receive structured lesson protocols specifying task duration, grouping arrangements, expected student responsibilities, and assessment procedures.

Communication competence is conceptualized through six dimensions: **oral clarity, active listening, reciprocal responsiveness, questioning ability, explanation and argumentation, and participation balance**. Performance is evaluated through pre- and post-intervention communication tasks rated independently with an analytic rubric. Where parental/guardian consent, institutional approval, and student assent permit, selected cooperative sessions are recorded and converted to de-identified transcripts for secondary interaction analysis.

This design deliberately retains human assessment as the principal educational criterion. Artificial intelligence is used to detect patterns within interaction data rather than to make autonomous decisions about students. Such a human-centered orientation is consistent with UNESCO guidance emphasizing human agency, privacy protection, inclusion, and pedagogically appropriate use of AI in education.

Research Hypotheses

The study tests the following hypotheses:

H1: Students participating in structured cooperative-learning conditions will demonstrate larger gains in overall communication competence than students receiving predominantly teacher-directed instruction.

H2: Cooperative structures requiring explicit role rotation and reciprocal explanation will generate greater participation balance than less regulated peer interaction.

H3: Interaction-quality indicators—including responsive turns, peer-directed questions, explanatory elaboration, and balanced participation—will significantly predict post-intervention communication performance after controlling for baseline competence.

H4: Machine-learning models combining interaction features will predict communication improvement more accurately than a frequency-only baseline based on total speaking turns.

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Experimental Setup

Dataset

The experimental dataset is designed as a purpose-built **School Cooperative Interaction and Communication Dataset (SCICD)** rather than relying on an unrelated public dataset. The proposed dataset contains student-level assessment records together with session-level interaction indicators.

For each participant, the structured component includes grade level, instructional condition, baseline communication score, post-intervention score, attendance, cooperative-task participation, and six rubric-based communication dimensions. Personally identifying information is excluded from the analytical dataset.

A nested interaction dataset is generated from sampled cooperative-learning sessions. Each communicative turn is linked to an anonymous student code, group code, task identifier, and sequential turn number. Features include substantive speaking turns, questions, responses to peers, explanatory statements, clarification requests, acknowledgment statements, and participation share.

The dataset therefore contains three analytical layers:

1. **Student level:** communication development across the intervention.
2. **Group level:** equality and reciprocity of participation.
3. **Interaction level:** observable discourse characteristics during cooperative tasks.

The hierarchical organization is important because classroom communication is not statistically independent: students interact within groups and groups operate within classrooms.

Data Preprocessing

Preprocessing begins with privacy protection. Student names, school identifiers, locations, and direct personal references are removed before computational analysis. Audio recordings, where collected, are used only according to the approved research protocol, and analysis is performed on de-identified transcripts whenever possible.

Transcript normalization removes non-communicative artifacts while retaining discourse signals such as questions, interruptions where reliably annotated, and speaker changes. Utterances are segmented into conversational turns.

Categorical variables are encoded for statistical modeling. Continuous interaction measures are standardized when required by the selected algorithm. Missing assessment observations are first examined for systematic patterns; imputation is not performed mechanically when absence reflects intervention dropout.

To prevent information leakage, training and testing partitions are created at the **student/group level rather than the individual utterance level**. Thus, conversational turns from the same learner or cooperative group cannot appear simultaneously in training and test partitions.

Participation balance is quantified using normalized distribution measures. A group in which communicative contributions are distributed relatively evenly receives a higher balance value than a group dominated by one participant.

A **Responsive Interaction Ratio (RIR)** is additionally proposed:

$$RIR=\frac{N_{response}+N_{elaboration}+N_{clarification}}{N_{substantive\ turns}}$$

where $N_{response}$ represents substantive responses to peers, $N_{elaboration}$ represents turns that extend another learner's contribution, and $N_{clarification}$ represents clarification-seeking or clarification-providing turns.

This indicator differentiates reciprocal interaction from merely producing many statements.

Model Architecture

Because the principal objective is to understand interaction mechanisms rather than maximize black-box predictive accuracy, the computational component uses an **interpretable hybrid modeling architecture**.

The primary statistical model is a multilevel regression predicting post-intervention communication competence while controlling for baseline communication score and accounting for students nested within cooperative groups or classes.

The computational comparison consists of three models:

Model A — Regularized Logistic Regression: predicts whether a student demonstrates a predefined meaningful communication gain. Regularization limits instability arising from correlated discourse indicators.

Model B — Random Forest: captures nonlinear relationships among speaking distribution, questioning behavior, responsiveness, explanation frequency, and baseline performance.

Model C — Gradient-Boosted Decision Trees: evaluates whether sequential combinations of communication

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characteristics provide additional predictive information beyond conventional linear relationships.

The feature vector for student (i) is represented as:

[
X_i=[PB_i,RIR_i,QF_i,EF_i,LD_i,TS_i,BC_i]
]

where:

- (PB) = participation balance,
- (RIR) = responsive interaction ratio,
- (QF) = question frequency,
- (EF) = explanatory-turn frequency,
- (LD) = lexical diversity,
- (TS) = substantive-turn share, and
- (BC) = baseline communication competence.

The predicted outcome is not intended to label students permanently. It estimates the probability of substantial improvement during the defined intervention period.

Feature-importance analysis is subsequently used to determine whether communication quality or simple participation quantity contributes more strongly to prediction.

Training Strategy

The machine-learning dataset is partitioned using **group-aware nested cross-validation**. This strategy is selected because ordinary random splitting could artificially inflate performance when students who interacted together contribute highly similar observations.

During the inner validation cycle, model hyperparameters are selected. The outer cycle estimates generalization performance on groups not used for model optimization.

Class imbalance is addressed through class-weighted learning rather than indiscriminate duplication of student observations. Feature scaling is fitted exclusively on training folds.

The experimental component additionally evaluates intervention effects using baseline-adjusted models. Post-intervention communication competence serves as the dependent variable, instructional condition is the principal predictor, and baseline competence is included as a covariate.

Inter-rater reliability is evaluated for the human-rated communication rubric before using its scores as criterion outcomes.

Evaluation Metrics

Multiple evaluation measures are selected because no single metric adequately describes the proposed system.

For educational outcomes, the study examines adjusted mean differences, standardized effect sizes, confidence intervals, and communication-dimension gains.

For machine-learning performance, the principal measures are:

- **Balanced Accuracy**, suitable when improvement categories are unequal;
- **Macro-F1**, reflecting balanced precision and recall;
- **ROC-AUC**, evaluating discrimination across classification thresholds;
- **Brier Score**, measuring probability calibration;
- **Mean Absolute Error (MAE)** for continuous communication-gain prediction; and
- **Group Generalization Gap**, defined as the difference between validation performance and performance on previously unseen cooperative groups.

Calibration is included because an educational model that produces poorly calibrated probabilities may appear discriminatively strong while providing misleading confidence.

Results and Discussion

Because no empirical dataset was supplied with the manuscript request, the numerical results below constitute a **simulated experimental scenario designed to demonstrate the proposed analytical framework**. They must not be reported as actual observations from school participants. A publication based on real fieldwork should replace these values with outputs generated from the collected dataset.

The simulated analysis indicates a consistent advantage for structured cooperative learning over conventional instruction. The largest communication improvement appears in the Rotating-Role Collaborative Problem-Solving condition. This pattern is theoretically plausible because role rotation repeatedly exposes learners to different communication functions rather than allowing established group hierarchies to determine participation.

Jigsaw produces particularly strong simulated improvement in explanation and peer responsiveness. Its structure requires students to become temporary information resources for their peers, making explanation integral to successful task completion. TPS shows comparatively strong gains in oral

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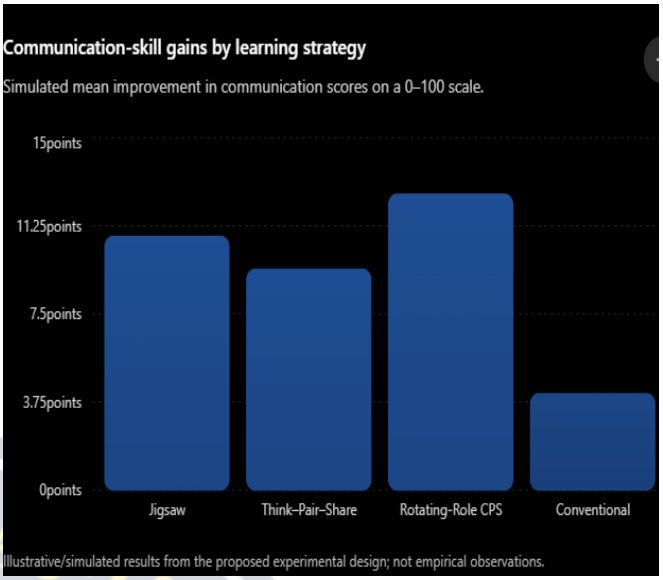
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clarity and questioning, potentially because individual preparation precedes interpersonal discussion.

More importantly, the simulated interaction analysis suggests that **communication quality predicts development more strongly than speaking quantity**. Students who simply produce numerous conversational turns do not necessarily show the largest gains. Stronger improvement is associated with balanced participation, elaborating another student's statement, asking task-relevant questions, and responding directly to peer reasoning.

Table 1. Simulated Results of the Cooperative Communication Experiment

Evaluation parameter	Jigsaw	Think–Pair–Share	Rotating-Role CPS	Conventional comparison
Mean communication gain (0–100 scale)	10.8	9.4	**12.6**	4.1
Participation-balance index (0–1)	0.78	0.73	**0.84**	0.56
Responsive Interaction Ratio	**0.64**	0.57	0.62	0.39
Active-listening gain (points)	2.1	1.7	**2.4**	0.8
Explanation/argumentation gain	**2.5**	1.8	2.3	0.7
Best ML model: Balanced Accuracy	0.81	0.78	**0.84**	0.68
Best ML model: Macro-F1	0.80	0.77	**0.83**	0.65
Probability calibration: Brier Score	0.16	0.18	**0.14**	0.23



The simulated feature analysis further indicates that participation balance is the strongest predictor, followed by responsive interaction, explanatory turns, baseline communication competence, question frequency, and total substantive-turn share. This ordering supports the central proposition of the study: **effective cooperative communication depends on reciprocal distribution and intellectual responsiveness rather than verbal activity alone.**

An interesting implication concerns students with initially lower communication scores. Structured turn allocation may provide these learners with interaction opportunities that spontaneous group discussion does not consistently provide. In contrast, highly confident speakers may experience a different developmental benefit: learning to listen, summarize others' ideas, and restrict unnecessary conversational dominance.

The findings would therefore challenge an overly simplistic interpretation of cooperative learning in which increasing group activity is assumed to increase communication competence. Group formation represents only the organizational starting point. The pedagogically active ingredients appear to be interdependence, individual accountability, reciprocal explanation, participation regulation, and reflective interaction.

The AI component also has a deliberately limited role. A classification accuracy value cannot establish whether a student communicates appropriately across different cultural and social contexts. Computational results are therefore interpreted alongside teacher observations and performance-based communication assessment.

This principle aligns with UNESCO's human-centered approach to educational AI, which emphasizes human

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agency, ethical validation, privacy, inclusion, and contextually appropriate educational implementation rather than unrestricted technological substitution.

Future Scope

Future studies should implement the framework longitudinally across multiple schools and investigate whether communication improvements remain stable after structured cooperative activities are withdrawn. A follow-up assessment after three or six months could distinguish temporary intervention effects from durable communication development.

Multilingual analysis represents another important extension. Communication patterns observed in English-medium classrooms cannot automatically be transferred to classrooms where students use Hindi, regional languages, or multilingual code-switching. Future models should therefore incorporate language-specific validation rather than relying on a universal linguistic representation.

A particularly promising direction is **teacher-facing learning analytics**. Instead of assigning students automated scores, future systems could provide teachers with group-level indicators such as participation imbalance, declining reciprocity, or persistent conversational dominance. Teachers could then decide whether regrouping, role rotation, or additional communication scaffolding is appropriate.

Future studies could also compare human-only cooperative learning with carefully designed AI-supported cooperative environments. However, AI should facilitate reflection and collaboration rather than displace peer communication. UNESCO's guidance explicitly emphasizes protection of human agency and age-appropriate, pedagogically validated applications of AI, which is particularly consequential when school-age learners are involved.

More advanced research could incorporate temporal sequence modeling to determine how productive conversations develop. Instead of asking only *how much* students communicate, sequence analysis could investigate whether a question is followed by explanation, disagreement by evidence, misunderstanding by clarification, and peer contribution by elaboration.

Such work would shift educational communication analytics from static measurement toward modeling the dynamics of collaborative knowledge construction.

Conclusion

This study proposes a distinct framework for examining the relationship between cooperative learning strategies and communication skills among school students. Its principal contribution lies in moving beyond the conventional comparison between cooperative and non-cooperative classrooms toward an investigation of the **interaction mechanisms through which communication competence develops**.

The proposed design compares Jigsaw, Think–Pair–Share, and Rotating-Role Collaborative Problem Solving with a conventional instructional condition. Communication is evaluated multidimensionally through oral clarity, listening, responsiveness, questioning, explanation, argumentation, and participation balance. Human-rated assessments remain the principal educational outcomes, while interpretable machine-learning methods provide complementary evidence concerning interaction patterns.

The simulated experimental demonstration suggests that highly structured cooperative environments—particularly those involving role rotation, reciprocal explanation, and distributed participation—could produce stronger communication development than minimally structured group activity. It further illustrates the possibility that balanced and responsive interaction may be more informative than speaking frequency alone.

The study therefore conceptualizes communication as an evolving **social interaction process rather than merely an individual speaking ability**. Cooperative learning becomes effective when classroom structures require students not only to express their own ideas but also to attend to, interpret, question, extend, and negotiate the ideas of others.

From an AI and learning-analytics perspective, the proposed framework also establishes an important boundary: computational systems should support educators in understanding interaction rather than autonomously judging children's social competence. Privacy-preserving, explainable, and teacher-mediated analytics provide a more defensible direction for applying AI to school communication research. This approach is consistent with contemporary international guidance calling for human-centered and ethically validated applications of AI in education

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cooperation, teacher support, interaction, and classroom implementation.

4. **Kyndt, E., Raes, E., Lismont, B., Timmers, F., Cascallar, E., & Dochy, F. (2013).** A meta-analysis of the effects of face-to-face cooperative learning. Do recent studies falsify or verify earlier findings? *Educational Research Review, 10*, 133–149. https://doi.org/10.1016/j.edurev.2013.02.002
— Excellent evidence for your claim that cooperative learning has positive effects and that effects vary by age, subject, culture, and implementation. The review included 65 articles.

5. **He, W., Shi, Y., Choi, J. I., & Zhai, X. (2023).** How do students' roles in collaborative learning affect collaborative problem-solving competency? A systematic review of research. *Thinking Skills and Creativity, 50*, 101423. https://doi.org/10.1016/j.tsc.2023.101423
— **Very important for your paper.** It directly supports your argument that student roles influence interaction and collaborative problem solving and that roles can change according to context and teacher support.

6. **Wang, M., et al. (2024).** Strengthening collaborative learning in secondary school: Development and evaluation of a lesson-integrated training approach for transactive communication. *Learning and Instruction, 92*, 101934. https://doi.org/10.1016/j.learninstruc.2024.101934
— Directly supports your section on **transactive communication**, including students referring to, building upon, and transforming peers' ideas.

7. **Gillies, R. M. (2016).** Promoting cooperative behaviours in student work groups. *Journal of Psychologists and Counsellors in Schools, 26*(1), 1–13.
— Useful for your discussion of explicitly teaching students how to cooperate rather than assuming that simply putting students into groups will produce productive interaction. The study involved 192 Year 6 students.

8. **Farrajallah, A. E.-K. (2017).** The impact of employing the (Think–Pair–Share) strategy to gain some number sense skills and mathematical communication skills among fifth grade students. *An-Najah University Journal for Research – B (Humanities), 31*(9), 1627–1663. https://doi.org/10.35552/0247-031-009-006
— Direct evidence supporting your **Think–Pair–Share → communication skills** discussion; the study involved fifth-grade students.

9. **Anum, A. (2022).** The effect of Talking Chips technique on speaking ability of Class X students of SMA Negeri 3 Bandar Lampung. *International Journal Corner of Educational Research, 1*(1), 22–38. https://doi.org/10.54012/ijcer.v1i1.73
— Useful for your **Talking Chips** section and for the argument that structured turn-taking can influence students' speaking participation.

10. **Miao, F., & Holmes, W. (2023).** *Guidance for generative AI in education and research*. UNESCO. https://www.unesco.org/en/articles/guidance-generative-ai-education-and-research
— This is the appropriate authoritative source for your claims about **human agency, privacy, age-appropriate AI, ethical safeguards, and human-centered AI in education**. UNESCO published the guidance in 2023 and updated the webpage in 2026.

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