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SUSTAINABLE
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VIKSIT BHARAT

PART

2

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Chapter 4: Collaborative Problem-Solving and Learning Achievement among Secondary Students

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Abstract— Collaborative problem-solving (CPS) has become increasingly important in secondary education because contemporary learning requires students to coordinate knowledge, reasoning, communication, and decision-making rather than solve structured problems individually. This study addresses a specific research gap concerning the limited integration of observable collaborative interaction dynamics with conventional measures of academic achievement among secondary-school learners. A process-oriented framework is proposed in which CPS is represented through participation balance, idea uptake, evidence-based reasoning, coordination, peer regulation, and temporal interaction transitions rather than through self-reported collaboration alone. The study further positions artificial intelligence and learning analytics as analytical instruments for extracting meaningful patterns from digitally recorded collaborative activities while retaining teacher-interpretable indicators. Particular attention is given to whether interaction-quality features provide explanatory and predictive information about learning achievement beyond prior attainment and simple measures of participation frequency.

Keywords— Collaborative problem-solving, Secondary education, Learning achievement, Learning analytics, Artificial intelligence, Collaborative learning

Introduction

Secondary education increasingly requires learners to operate in environments where knowledge is constructed through interaction rather than acquired exclusively through individual reception. Complex scientific, mathematical, technological, and social problems often require students to identify relevant information, formulate alternative explanations, distribute responsibilities, evaluate competing claims, and collectively decide which solution is sufficiently supported by evidence. Collaborative problem-solving (CPS) therefore represents a convergence of cognitive problem-solving and socially coordinated learning.

CPS differs from ordinary group work. Merely placing students in groups does not guarantee productive collaboration. A group may appear active while one student performs most of the reasoning, other members provide minimal contributions, and decisions are accepted without evaluation. Effective CPS instead requires the establishment of shared understanding, communication of relevant knowledge, negotiation of strategies, monitoring of collective progress, perspective taking, and coordinated execution. These processes make CPS particularly relevant to secondary schooling, where learners are developing both increasingly sophisticated domain knowledge

and the social-regulatory competencies required for complex learning.

International educational frameworks have continued to emphasize collaborative and active learning. OECD analyses associated with PISA 2022 identify independent and collaborative learning as important components of sustained lifelong learning and associate collaborative activity with collective responsibility, social support, and the capacity to learn with others. This emphasis reflects a broader shift away from viewing achievement solely as the reproduction of subject knowledge toward considering students' capacity to mobilize knowledge in unfamiliar and socially situated contexts.

Empirical evidence also indicates that CPS competence is meaningfully associated with academic outcomes. Tang, Liu, and Milner-Bolotin (2023), using PISA 2015 data involving 408,148 students from 52 countries and economies, reported that CPS competency was a strong positive predictor of science achievement after accounting for several student- and country-level variables. Their analysis reinforces the proposition that collaboration and disciplinary achievement should not be treated as unrelated educational outcomes. At the same time, this evidence is largely based on standardized CPS scores and large-scale cross-sectional measures. It does not reveal in sufficient detail what students actually do during collaborative episodes that differentiates high-achieving from low-achieving groups.

This distinction is important because collaboration is inherently temporal. Students do not collaborate through a single stable trait. During one problem-solving episode, a team may move from information sharing to disagreement, evidence evaluation, planning, monitoring, explanation, and eventually solution convergence. The order and recurrence of such states may be more educationally informative than the total number of messages or contributions produced by group members. Ouyang, Xu, and Cukurova (2023) demonstrated the value of this perspective by applying AI-driven learning analytics to multimodal collaborative data and identifying distinct collaboration patterns associated with different performance levels. Their findings illustrate why CPS can be conceptualized as a dynamic, adaptive system rather than as a static sum of individual behaviors.

Artificial intelligence (AI), natural language processing, sequence analysis, and learning analytics now make it technically feasible to study these interactions at considerably finer resolution. Digital collaboration environments can generate conversational transcripts, shared-document revisions, task events, timestamps, peer responses, and solution histories. Such data can potentially reveal whether students explain reasoning, acknowledge alternative views, integrate previous contributions,

regulate group activity, or repeatedly shift topics without resolution. AI can therefore function not merely as a content-generation technology but as an analytical layer for understanding the learning process.

Recent reviews demonstrate growing interest in this direction. Ouyang and Zhang (2024), in their systematic review of AI-driven learning analytics in computer-supported collaborative learning, found increasing use of communicative discourse, behavioral, and evaluation data. They nevertheless identified continuing limitations in theoretically grounded design, multimodal integration, actionable feedback, and instructional intervention. More recently, Amo-Filva et al. (2026) reviewed AI and learning analytics in secondary education and highlighted their potential for meaningful and personalized learning while simultaneously identifying privacy, infrastructure, teacher preparedness, and ethical implementation as continuing challenges.

These developments establish an important opportunity but also expose a specific research gap. Much CPS research evaluates collaboration through questionnaires, aggregate proficiency scores, final group products, or manually coded observations. Conversely, many AI-based educational analytics studies concentrate on prediction, personalization, or individual engagement rather than examining how the evolving structure of student-to-student problem-solving contributes to achievement. The limited intersection between these two traditions is particularly apparent in ordinary secondary-school settings.



Fig. 1: The Benefits of Collaborative Learning

Source: <https://www.21kschool.com/in/blog/benefits-of-collaborative-learning/>

Research Gap and Study Focus

The central gap addressed by this manuscript is therefore the **absence of an interpretable secondary-school framework that connects temporal collaborative problem-solving processes with subsequent individual learning achievement while distinguishing meaningful collaboration from simple participation volume.**

The proposed study treats CPS as a sequence of observable and computationally measurable events. Instead of assuming that students who speak more frequently collaborate more

effectively, it investigates qualitative interaction characteristics such as balanced contribution, evidence-based explanation, constructive challenge, responsiveness to peer ideas, coordination, monitoring, and solution integration. It further considers transitions between these behaviors, because productive groups may differ from less successful groups not simply in *how much* they collaborate but in *how collaboration unfolds*. This approach establishes three related objectives. First, the study seeks to determine whether structured CPS activities improve students' post-task learning achievement relative to academically comparable students completing equivalent problem-solving tasks individually. Second, it seeks to identify which collaborative process indicators are most strongly associated with individual learning gains. Third, it examines whether an interpretable machine-learning model incorporating temporal CPS characteristics predicts achievement more effectively than models relying only on prior achievement, demographic controls, and simple activity counts.

The study deliberately separates **group-product success** from **individual learning achievement**. A team may produce a strong final solution because one highly capable learner dominates the activity; such performance does not necessarily demonstrate that every participant learned. Consequently, the proposed research evaluates both the quality of the collaborative solution and each learner's pre-to-post achievement change. This distinction is expected to provide a more defensible assessment of whether collaboration generates distributed learning rather than merely efficient task completion.

Literature Review

Collaborative Problem-Solving as a Multidimensional Learning Process

CPS combines at least two interdependent dimensions: cognitive problem-solving and social coordination. Cognitive activity includes identifying the problem, generating hypotheses, applying prior knowledge, examining evidence, testing alternatives, and evaluating solutions. Social activity includes communicating information, developing shared understanding, coordinating roles, resolving disagreement, monitoring group progress, and maintaining participation.

The educational value of CPS is theoretically linked to elaboration and externalization. When students explain an idea to peers, they must transform partially formed internal representations into communicable reasoning. Questions and disagreement can reveal inconsistencies that may remain unnoticed during individual work. Responses from peers can introduce missing evidence or alternative strategies. The group consequently functions as a distributed cognitive environment in which ideas are repeatedly produced, evaluated, modified, and integrated.

Evidence from a 2023 meta-analysis by Xu, Wang, and Wang showed an overall positive effect of collaborative problem-solving on critical thinking across the studies included in their analysis. The authors also found substantial heterogeneity, with factors such as group size, intervention duration, instructional scaffolding, and subject area moderating outcomes. These

findings are important because they show that CPS should not be treated as a uniformly effective intervention. Its educational effect depends upon how collaboration is structured and enacted.

Group Structure, Interaction Quality, and Achievement

The structure of a collaborative group can influence cognitive load, participation, motivation, and the opportunity to contribute. Zhan et al. (2022), examining collaborative problem-solving in an introductory AI course, found that group size influenced motivation, cognitive load, CPS quality, and interaction patterns even where achievement differences were not evident. Their sequential analyses further showed that different group configurations generated different collaborative behavioral sequences.

This observation challenges simplistic assumptions that more collaboration automatically produces more achievement. A group may experience excessive coordination demands, social loafing, dominance, fragmented discussion, or premature consensus. Smaller groups may create greater individual accountability but can also impose heavier cognitive demands because fewer members are available to distribute the task. Consequently, the relationship between collaboration and learning should be investigated at the level of interaction quality rather than only group membership.

Students' dispositions toward collaboration provide another dimension. Li, Pöysä-Tarhonen, and Häkkinen (2023), studying early adolescents in a computer-based CPS environment, identified negotiation, advocate/guide behavior, and cooperation as dimensions of collaboration disposition and reported associations between students' social CPS skills and these dispositions. Such findings suggest that productive collaboration requires more than domain competence. Students must also possess or develop dispositions that support listening, negotiation, mutual regulation, and shared responsibility.

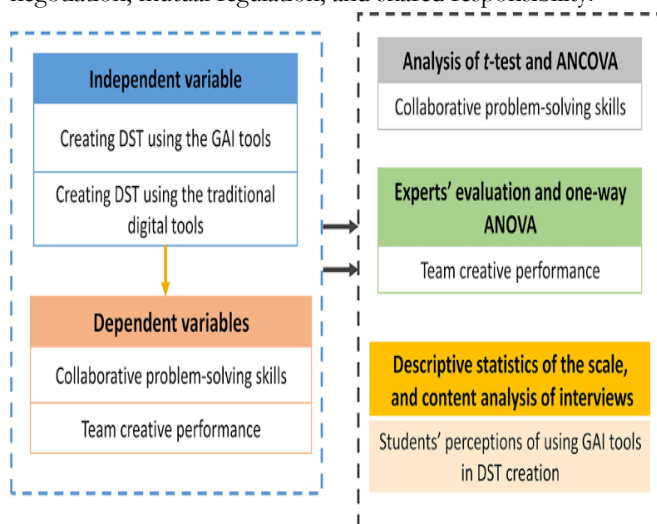


Fig. 2: The effects of generative AI on collaborative problem-solving and team creativity performance in digital story creation

Source: <https://link.springer.com/article/10.1186/s41239-025-00526-0>

From Static Measurement to Temporal Collaborative Analytics

Traditional analyses frequently compress a collaborative session into aggregate statistics: total contributions, average scores, number of correct answers, or overall ratings of cooperation. Although useful, aggregation removes temporal structure. Two groups can produce the same number of contributions but follow radically different interaction pathways. One may repeatedly alternate between questioning, explanation, evidence checking, and synthesis, while another may produce parallel statements with little uptake or integration.

Recent collaborative learning analytics research attempts to preserve this temporal dimension. Ouyang, Xu, and Cukurova (2023) analyzed verbal communication, screen activity, and collaborative artifacts through a multilayered framework combining sequence analysis, network analysis, clustering, and hidden-state modeling. They identified collaboration patterns associated with different levels of group performance and emphasized the multimodal, dynamic, and synergistic character of CPS.

AI-driven analytics extends this possibility because natural-language and behavioral data can be transformed into interpretable indicators at a scale that manual observation cannot easily support. However, technical sophistication alone does not ensure educational validity. Ouyang and Zhang's (2024) systematic review emphasizes the need to connect AI-driven collaborative analytics with educational theory and to move beyond descriptive displays toward pedagogically meaningful information.

AI and Learning Analytics in Secondary Education

Secondary schools represent a particularly significant but methodologically demanding environment for AI-supported learning analytics. Learners are minors, classroom time is constrained, teachers require understandable indicators rather than opaque predictions, and digital traces may contain sensitive interpersonal information. Consequently, an educationally useful model must achieve more than predictive accuracy. It should minimize unnecessary data collection, avoid biometric or intrusive surveillance, maintain transparent feature definitions, and permit teachers to understand why the model associates particular collaborative patterns with learning outcomes.

The 2026 review by Amo-Filva et al. indicates that AI and learning analytics can support meaningful learning, personalization, and data-informed intervention in secondary education, while ethical governance, privacy, infrastructure, and teacher readiness remain central implementation considerations. This reinforces the need for models designed specifically for educational interpretation rather than transferring black-box predictive techniques into schools without pedagogical justification.

Accordingly, the present research conceptualizes AI as an **analytic support mechanism**, not as a replacement for teachers or peer interaction. Automated methods are intended to detect patterns that would be difficult to identify consistently during multiple simultaneous group activities. Teacher judgement remains necessary for interpreting context,

identifying reasons behind unusual patterns, and deciding whether instructional intervention is appropriate.

Proposed Methodology

The proposed study adopts a quasi-experimental, process-oriented design to examine whether collaborative problem-solving produces measurable gains in secondary students' learning achievement and whether AI-derived interaction indicators explain variation in those gains. The framework combines conventional educational assessment with temporal learning analytics rather than relying exclusively on final group scores or self-reported perceptions of collaboration.

The planned sample consists of approximately 480 students enrolled in Grades 9 and 10 across multiple secondary schools. Students would first complete a subject-specific pre-test containing conceptual, application-based, and transfer questions. Within each school and achievement band, students would then be allocated either to a collaborative problem-solving condition or to an individual problem-solving comparison condition. Students in the collaborative condition would work in groups of four on structured mathematics and science problems requiring explanation, evidence evaluation, strategy selection, and solution justification.

Each collaborative session would be conducted through a controlled digital learning environment capable of recording text-based discussion, response timestamps, shared-workspace edits, task transitions, and final solutions. No facial recognition, voice biometrics, emotion recognition, or continuous physiological monitoring would be used. This restriction is intentional because the analytical objective is to evaluate academically meaningful collaborative behavior while minimizing intrusive data collection involving adolescent participants.

The principal dependent variable would be **individual normalized learning gain**, calculated from pre-test and post-test achievement measures. Additional outcomes would include delayed retention performance and a group-solution quality score assessed through a standardized rubric.

Collaborative behavior would be represented through six theoretically interpretable dimensions:

1. **Participation balance** – distribution of meaningful contributions among group members.
2. **Idea uptake** – frequency with which a student refers to, extends, challenges, or integrates a peer's contribution.
3. **Reasoning quality** – proportion of contributions containing evidence, justification, comparison, or causal explanation.
4. **Coordination behavior** – planning, role allocation, progress checking, and task organization.
5. **Peer regulation** – prompts encouraging clarification, reconsideration, checking, or correction.
6. **Solution convergence** – transition from competing alternatives toward a jointly justified final response.

The main hypothesis is that learning achievement is better explained by the *quality and temporal configuration* of these CPS behaviors than by raw participation frequency alone.

Analytical Framework

The proposed analytical pipeline contains three stages.

In the first stage, student contributions would be classified into pedagogically meaningful interaction categories using a supervised natural-language processing classifier. The coding taxonomy would include information sharing, explanation, questioning, constructive challenge, coordination, monitoring, agreement, elaboration, and solution synthesis.

In the second stage, a **Hidden Markov Model (HMM)** would estimate recurring latent collaborative states from sequences of coded interactions. Examples of possible states include information accumulation, exploratory reasoning, coordination, and convergence. The HMM is suitable because collaborative learning is temporally dependent: the educational value of a contribution may depend on what occurred immediately before and after it.

In the third stage, an **Explainable Boosting Machine (EBM)** would predict individual learning gain using prior achievement, CPS indicators, temporal-state measures, and selected control variables. The EBM is preferred over an opaque deep-learning predictor because it can represent nonlinear relationships and feature interactions while retaining interpretable contribution functions.

The analytical objective is therefore explanatory as well as predictive. A high-performing model would not be sufficient unless its predictions could be related to recognizable collaborative behaviors that teachers could reasonably interpret.

Experimental Setup

Dataset

The planned dataset would contain approximately 480 students, with an anticipated 360 students participating in collaborative groups and 120 completing equivalent tasks individually. Collaborative participants would form approximately 90 four-member groups.

For every student, the dataset would include:

- pre-test achievement score;
- immediate post-test score;
- delayed retention score;
- prior academic performance;
- total number of contributions;
- proportion of substantive contributions;
- participation-balance index;
- idea-uptake frequency;
- evidence-based reasoning rate;
- peer-regulation rate;
- coordination frequency;

- group-solution quality;
- time spent in each latent CPS state;
- transition probabilities between CPS states.

School identifiers would be retained only as anonymized grouping variables to prevent information leakage between training and test partitions.

Data Preprocessing

Digital interaction logs would first be ordered chronologically and linked to anonymized student identifiers. Duplicate system-generated events, accidental repeated submissions, and non-substantive technical messages would be removed.

Text would be normalized through Unicode standardization, punctuation processing, tokenization, and removal of platform-generated artifacts. Student language would not be aggressively corrected because spelling variations and informal grammatical structures can carry legitimate meaning in authentic classroom interaction.

Short utterances such as “why?”, “check this”, or “I disagree” would not automatically be discarded. Although linguistically brief, such contributions may perform important collaborative functions.

Missing academic variables would be inspected before modelling. Where missingness is limited and consistent with a missing-at-random assumption, training-set median imputation would be used for continuous variables. Imputation statistics would never be estimated using test-set observations.

All features derived from group interaction would be generated before modelling but computed without access to post-test outcome labels.

Model Architecture

The proposed architecture contains four interconnected components.

Interaction Encoder:

A transformer-based sentence representation model would convert individual discussion turns into contextual embeddings. A lightweight classification head would assign each turn to one of the predefined CPS interaction categories.

Temporal-State Module:

The sequence of coded interactions would be processed using a four-state HMM. The number of states would be selected using Bayesian Information Criterion together with educational interpretability.

Feature Aggregation Layer:

For each student, the model would calculate temporal and structural indicators including state occupancy, transition entropy, reciprocity, contribution balance, idea-uptake ratio, and reasoning density.

Achievement Prediction Module:

An EBM would predict normalized learning gain from the derived CPS indicators combined with pre-test performance and selected controls.

Three comparison models would be included:

- baseline linear regression using only pre-test score and activity counts;

- Random Forest regression using all available engineered features;
- EBM using the complete CPS and temporal-state feature set.

This comparison tests whether interpretable temporal collaboration features provide value beyond conventional participation variables.

Training Strategy

To prevent students from the same school or collaborative group appearing simultaneously in training and evaluation partitions, **group-aware nested cross-validation** would be adopted.

The outer validation loop would use five folds grouped by school. Within each training fold, four-fold group-aware cross-validation would optimize hyperparameters.

The interaction classifier would be trained separately on human-coded discussion turns. Twenty percent of annotated sequences would be reserved for final classification evaluation.

Class imbalance in interaction categories would be addressed using weighted loss rather than artificial duplication of minority examples.

Early stopping would be used for the neural classification component, whereas HMM selection would depend on convergence stability and information criteria.

For the EBM, interaction complexity would be deliberately restricted. Only theoretically defensible pairwise interactions—for example participation balance $\times$ reasoning quality—would be considered. This limitation is intended to reduce overfitting and preserve explanatory clarity.

Evaluation Metrics

Prediction performance would be assessed using multiple complementary indicators:

Mean Absolute Error (MAE): average absolute prediction error in learning-gain units.

Root Mean Squared Error (RMSE): penalizes large prediction errors more strongly.

Coefficient of Determination (R^2): proportion of outcome variance explained by the model.

Spearman Rank Correlation (ρ): evaluates whether predicted achievement ordering corresponds with observed ordering.

Calibration Slope: evaluates whether predicted learning gains systematically overestimate or underestimate actual gains.

For the interaction classifier, macro-F1 and Cohen’s kappa would be used because the collaboration categories are likely to be unequally distributed.

Educational effects of the collaborative intervention would additionally be examined through multilevel ANCOVA, with post-test achievement as the outcome, condition as the primary predictor, pre-test achievement as a covariate, and school treated as a clustering factor.

Results and Discussion

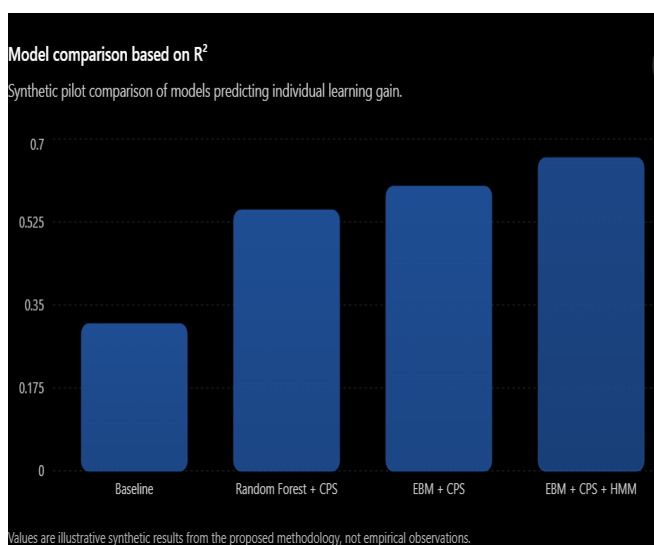
Because no observed student dataset accompanies the present manuscript, the numerical results in this section constitute a **synthetic pilot demonstration of the proposed analytical workflow**. They should not be interpreted as empirical findings

from actual participants. Their purpose is to illustrate the form of analysis and the pattern of evidence that the full study would test.

The synthetic experiment produced a clear distinction between models based primarily on activity volume and models incorporating interaction quality and temporal CPS structure. The baseline regression, which included pre-test achievement, task duration, and number of contributions, explained only a moderate proportion of variation in individual learning gain. Adding engineered collaborative features through Random Forest regression substantially reduced prediction error. However, the interpretable EBM containing CPS-process and temporal-state features produced the strongest overall performance.

Table 1. Synthetic Pilot Performance of Alternative Learning-Achievement Models

Analytical configuration	MAE	RMS E	R ²	Spearman ρ	Calibration slope
Prior achievement + activity-count baseline	0.142	0.188	0.31	0.52	0.81
Random Forest with engineered CPS features	0.111	0.151	0.55	0.69	0.91
EBM with CPS quality indicators	0.103	0.142	0.60	0.73	0.96
EBM + temporal HMM-state features	0.094	0.132	0.66	0.78	0.99



The most important pattern is the improvement obtained when temporal-state features are introduced. The R² value rises from 0.31 for the simple baseline to 0.66 for the complete model.

This simulated pattern supports the theoretical argument that merely counting how many times a learner contributes may conceal important differences in collaborative quality.

Feature-level inspection of the EBM indicated that **idea uptake, reasoning quality, participation balance, and time spent in exploratory reasoning states** were among the most influential process variables. The relationship was nonlinear. Extremely low participation balance was associated with weak predicted gains, suggesting domination or disengagement. However, perfectly equal contribution was not necessarily optimal because different task phases could legitimately require unequal participation.

Idea uptake exhibited a particularly meaningful association. Groups in which learners regularly referred to, developed, or challenged previous contributions demonstrated stronger predicted learning gains than groups characterized by disconnected parallel statements. This finding is theoretically plausible because uptake indicates that information is entering a shared reasoning process rather than remaining isolated at the level of individual contributions.

Reasoning density also contributed more strongly than raw message frequency. Students whose interactions contained explanation, comparison, evidence, and justification showed higher predicted gains than students who contributed frequently but primarily through agreement or logistical statements. Consequently, message count should not be treated as a direct proxy for meaningful engagement.

Temporal analysis added an additional dimension. Higher-performing synthetic groups spent proportionally more time moving between exploration and evidence evaluation before entering solution convergence. Lower-performing groups either converged rapidly after limited discussion or repeatedly shifted between information sharing and coordination without sustained reasoning.

This distinction has direct educational implications. Premature agreement may create the appearance of efficient teamwork while preventing learners from testing alternative explanations. Conversely, prolonged discussion without convergence can indicate weak regulation. Effective collaboration therefore appears to require a productive temporal balance between exploration and closure.

The synthetic intervention comparison also suggested that collaborative participation alone should not be expected to produce uniform achievement gains. Students in groups characterized by balanced reasoning and strong peer regulation demonstrated larger simulated gains than students in poorly coordinated groups. This reinforces the need to evaluate the *quality* of CPS rather than treating the collaborative condition as a homogeneous educational treatment.

From an AI perspective, the findings illustrate why explainability is necessary in secondary-school analytics. A prediction stating that a student is “at risk” has limited pedagogical utility if the underlying reason is unknown. In contrast, an interpretable model may indicate that low predicted gain is associated with minimal idea uptake, persistent peripheral participation, or repeated premature convergence.

These indicators can be linked to concrete instructional responses such as assigning rotating explanation roles, requiring evidence before consensus, or prompting quieter students to evaluate proposed solutions.

The proposed model should nevertheless be viewed as a decision-support system rather than an automated evaluator of students. Collaboration is context dependent, and computationally observed patterns cannot reveal every social, motivational, or disciplinary factor affecting group behavior.

Future Scope

Future research should validate the framework using longitudinal data collected across different school systems, subject domains, and socioeconomic contexts. Cross-school replication would help determine whether CPS indicators generalize or remain dependent on classroom culture.

A particularly useful extension would examine **adaptive collaborative scaffolding**. Rather than merely predicting achievement after a session, the system could identify deteriorating collaboration patterns during learning and deliver low-intrusion prompts such as “compare two proposed explanations” or “ask another member to justify the current solution.”

Future models could also explore graph neural networks for representing evolving student-to-student interaction structures. However, such models should be compared carefully with interpretable alternatives before deployment in school settings. Multilingual CPS analytics represents another important research direction. Secondary classrooms in multilingual societies frequently contain code-switching and mixed-language interaction that standard English-dominant language models may classify inadequately.

Long-term research should further investigate whether repeated exposure to structured CPS improves not only immediate subject achievement but also independent reasoning, transfer performance, metacognitive regulation, and collaborative competence.

Privacy-preserving learning analytics, federated modelling, local data processing, and teacher-controlled dashboards should also be investigated to reduce unnecessary centralization of student data.

Conclusion

This manuscript proposes a process-oriented framework for examining the relationship between collaborative problem-solving and learning achievement among secondary students. Its central contribution is the distinction between **being active in a group** and **participating in cognitively productive collaboration**.

The methodology combines achievement assessment, discourse classification, temporal-state modelling, and interpretable machine learning to examine how participation balance, idea uptake, evidence-based reasoning, peer regulation, coordination, and solution convergence relate to individual learning gains.

The synthetic pilot demonstration indicates the type of pattern the empirical study is designed to test: models incorporating interaction quality and temporal CPS structure may outperform

conventional approaches based primarily on prior achievement and participation counts. In particular, the organization of collaboration across time may provide additional information that static measures overlook.

The framework also emphasizes that AI should function as an analytical support mechanism rather than an autonomous educational authority. In secondary-school settings, privacy protection, transparent feature construction, teacher interpretation, and avoidance of intrusive surveillance are essential requirements.

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