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Automatic Detection of Negotiation in Collaborative Complex Problem Solving Interactions

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Abstract: When learners collaborate on complex problems and open-ended tasks, the mechanism of negotiation plays a crucial role in establishing a common understanding and achieving a shared goal among them. Research has shown that negotiation improves problem-solving processes, making it an essential skill to be developed among learners. In this study, we propose a method for automating the identification of negotiation in learners' discourse during collaboration. We leverage language models like BERT, RoBERTa, and GPT2 along with traditional machine learning models like logistic regression to detect utterances of negotiation in learners' discourse while they collaboratively solve engineering estimation problem in an Open-Ended Learning Environment (OELE) called Modeling Based Estimation Learning Environment (MEttLE). Our findings suggest that our approach can accurately identify negotiation utterances with a high accuracy of 0.924 and 0.781 kappa value with a relatively smaller training set. Our method is the first step in real-time detection of negotiation, thereby enabling educators to design scaffolds and environments to help learners engage in effective negotiations.

Keywords: negotiation, open-ended learning environments, collaboration, complex problem-solving.

1. Introduction

Collaborative problem-solving (CPS) is a vital skill involving multiple individuals working together to devise and sustain collective solutions to challenges (Fiore et al., 2017). CPS is crucial as the modern workforce increasingly demands seamless collaboration within diverse teams, efficient exchange of expertise, and effective communication across disciplinary boundaries (Pugh, Rao, Stewart, & D'Mello, 2022). To foster this skill, it is imperative to create opportunities for students to engage in productive CPS activities.

Despite the positive impact of CPS on both academic and social educational outcomes, significant challenges persist when implementing CPS effectively within everyday classroom settings (Johnson, Johnson, & Smith, 2007). Teachers encounter difficulties in structuring group interactions and monitoring fruitful collaboration (Van Leeuwen, Janssen, Erkens, & Brekelmans, 2013). Students also face hurdles in CPS, including uneven participation in group tasks (Freeman & Greenacre, 2010) and deficiencies in communication and collaborative skills (Li & Campbell, 2008; Pauli, Mohiyeddini, Bray, Michie, & Street, 2008).

To address these challenges, it is imperative to pinpoint and assess essential CPS processes exhibited by learners and offer diagnostic feedback (Fiore et al., 2017). This paper focuses on automating the identification of a critical CPS process—Negotiation—while students collaboratively tackle complex problem within an Online Environment for Learning and Education (OELE) called Modeling Based Estimation Learning Environment (MEttLE). This automated analysis will subsequently empower educators to provide valuable feedback to learners.

The mechanism of negotiation is vital for effective collaboration, particularly in complex problem-solving domains, enabling collaborators to employ diverse strategies and reach agreements through critical evaluation, justification, sensemaking, and co-construction of solutions (Hesse et al., 2015). Previous research has demonstrated the productive behaviours exhibited by learners when engaging in negotiation within OELEs during complex problem-solving tasks (Khwaja & Murthy, 2022). Therefore, fostering negotiation in such environments is crucial for supporting learners' problem-solving processes. However, identifying negotiation utterances in learners' discourse is challenging, particularly when the interactions are complex and multi-layered. Also, the manual identification of negotiation utterances is time-consuming and impractical for large-scale studies.

To address this gap, researchers have proposed a method for automating the identification of negotiation and other collaborative mechanisms in learners' discourse during the process of collaborative problem-solving (Flor et al., 2016; Pugh, Rao, Stewart, and D'Mello, 2022; Hao et al., 2017). We extend this work by leveraging state-of-the-art language models like BERT, RoBERTa, and GPT2 to automatically detect negotiation utterances in learners' discourse while they solve open-ended problems. Results show that GPT2 emerged as the best-performing model with an accuracy of 0.924 and a kappa value of 0.781. The novelty of our research lies in the fact that the models employed here demonstrate improved performance compared to existing approaches in automating the identification of negotiation utterances in learners' discourse during collaborative problem-solving. Additionally, the study presents a unique context by focusing on the engineering estimation problem, which is a frequent practice used by engineers and scientists when exact data and precise governing equations are unavailable (Mahajan, 2014).

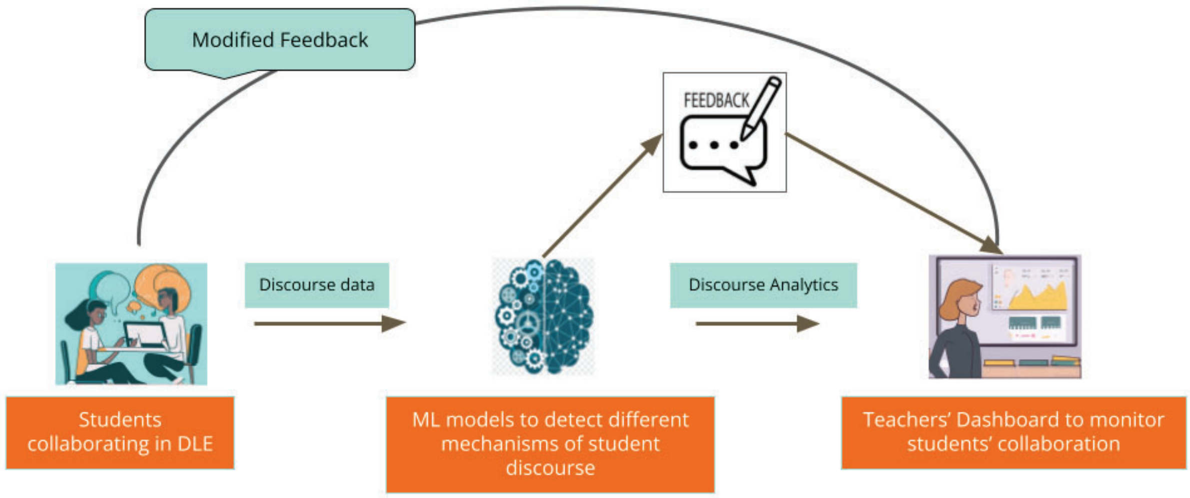

Figure 1. The figure shows a collaboration between two students, and the discourse data is captured and converted to transcripts. This transcript is then analysed by the ML models for generating discourse analytics for teachers and personalised feedback for students, which is first delivered to the teacher, who has the agency to modify it before delivering it to students.

The study constitutes a part of a larger research that aims to enhance productive behaviours in collaborations by providing students with personalised feedback (Fig. 1). Here, the teacher will have access to the discourse analytics affording them the agency to modify the feedback provided by the models. The overarching goal is to attain insightful perspectives on the evolution of different and essential collaborative learning mechanisms during collaboration. This can help educators design scaffolds to enable learners to engage in productive behaviours.

The paper is structured as follows: Section 2 presents the background and literature synthesis, followed by the OELE description in Section 3. We then delineate the research goal and procedure in Section 4. Subsequently, we present the results in Section 5, leading to the discussion and conclusion in Section 6.

2. Background and Related Work

In this section, we first highlight the significance of negotiations in the process of collaborative problem-solving. The second sub-section discusses the theoretical CPS framework that we have employed for the manual coding of the data. Then, we discuss the state-of-the-art text classification algorithms. Finally, we discuss different studies that aim to detect negotiation in discourse data.

2.1 Negotiation and Problem-solving

Effective collaboration in Computer Supported Collaborative Learning (CSCL) research necessitates negotiation when dealing with divergent opinions and ideas from peers. Negotiation plays a crucial role in complex problems and open domains that require critical examination, the convergence of ideas, and contributions from all collaborators to arrive at a suitable solution (Carell & Herrmann, 2009). In this context, it can be defined in various ways, including resolving conflicts, attempting to agree on goals, and critically examining different perspectives (Baker, 1994; Fleck et al., 2009). Learners engaged in a negotiation must present their ideas, defend their positions, and use various strategies to reach an agreement. This process must ultimately result in a shared understanding of the problem to ensure that all collaborators have reasoned and agreed upon a common ground in problem-solving (Beers, 2006). Through negotiation, learners can engage in meaningful discussions and sensemaking, exchange ideas, learn from their peers, and contribute to productive outcomes. It is particularly vital in OELEs, where learners need to explore new ideas, tools and critically examine complex problems. Therefore, it is essential to identify and understand negotiation utterances and design scaffolds to foster it among learners to support their problem-solving abilities.

2.2 Collaboration Learning Mechanisms Framework to identify negotiation

To identify and comprehensively understand instances of negotiation among learners within MEttLE (Kothiyal & Murthy, 2018), we employed the Collaboration Learning Mechanisms (CLM) framework developed by Fleck et al. (2009). This framework centres on two pivotal mechanisms for collaborative learning within open problem contexts: coordination and discussion. Within these mechanisms, the CLM framework emphasises how specific actions and verbal interactions represent different aspects of collaboration and how they collectively contribute to productive outcomes in collaborative problem-solving activities. The collaborative discussion mechanism entails the exchange of information, ideas, and negotiation of meaning, while the coordination mechanism underscores joint attention, awareness, and narration. This framework helped us identify and understand the mechanism of negotiation that involved verbal discourse of disagreeing, conflicting, proposing alternatives, criticising, explaining, and justifying one's idea, and actions such as undoing, deleting, nodding head to depict disagreement, etc. CLM defines negotiation as a conversation that involves all parties being critically and constructively engaged with each other's proposals for joint consideration. We then further added 9 more mechanisms of collaboration based on our data. To ensure the reliability and validity of our approach, two researchers independently calculated the inter-rater reliability for 10% of the dataset, resulting in a robust kappa score of 0.7, indicative of strong agreement between the researchers. Among the various collaborative mechanisms, we observed that learners were engaged in negotiation approximately 31.5% of the time during their problem-solving activities.

Table 1. *The table presents the episode of Negotiation from Group 2, where both the learners S3 and S4 read the problem statement and immediately get into a discussion on how to solve it. S3 is seen to propose a solution method that S4 does not easily accept.*

Student	Utterences	Time	Codes

S3	lets just skip the part like there will be some delays ..assume that the entire time we have the same velocity like it was 0, then it reaches to its maximum ...	0:24:18	Negotiation
S4	(shakes head in disagreement and then rereads Problem statement and says) So the entire track is 50 meters. So you have to consider that it will start from a stop position initially	0:24:32	Negotiation
S3	Yes, it will start from stop position but .what I am saying is it will not gradually increase from the stop position . For this problem, let us just assume that it will directly reach the end point ..	0:24:50	Negotiation
S4	Yes but (interrupts S3) But there needs to be some assumption behind this right? What are you basing your assumption on?	0:25:06	Negotiation
S3	I am just reducing all the functions like..whatever the 3rd parameters	0:25:11	Negotiation

2.3 Text Classification

Text classification, a machine-learning technique used to categorise open-ended text into predetermined categories, has gained significant attention in research. Its application to coding discourse data addresses the time and labour-intensive nature of manual coding processes. While manual coding can consume days of effort, machine learning models can accomplish the same task within a few minutes, thereby substantially reducing the required time and resources.

Recent advancements in large language models have presented opportunities to enhance classification accuracy further. Among these models, Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018) have emerged as a notable text representation model specifically designed for natural language processing. BERT distinguishes itself from previous models by generating dynamic and contextualised word representations through unique training tasks, such as masked-language modelling and next-sentence prediction. Leveraging the mechanism of transfer learning, BERT can be readily adapted to downstream tasks with relative ease.

In addition to BERT, another influential language model is RoBERTa (Liu et al., 2019). RoBERTa, based on transformer architecture, has garnered attention for its remarkable language generation capabilities. Pretrained on a massive corpus of text data, RoBERTa exhibits exceptional performance across various natural language processing tasks, including text classification. By capturing contextual dependencies and semantic relationships between words and phrases, RoBERTa effectively comprehends and generates coherent text.

Another prominent language model worth mentioning is GPT2 (Generative Pretrained Transformer 2). GPT2 is a transformer-based model known for its impressive language generation capabilities. It is trained on a massive corpus of text data and has demonstrated exceptional performance in a wide range of natural language processing tasks, including text classification. GPT2 captures the contextual dependencies and semantic relationships between words and phrases, enabling it to understand and generate coherent text.

To summarise, the availability of powerful language models such as BERT, GPT2, and RoBERTa offers researchers the opportunity to enhance the accuracy of text classification. Their proficiency in capturing contextual information, coupled with their transfer learning capabilities and demonstrated success across various natural language processing tasks, positions them as promising options for automating the categorisation of discourse data.

2.4 Collaboration Analytics

Collaboration Analytics pertains to the methodologies and strategies employed in the automated or semi-automated capture, analysis, mining, and extraction of data concerning interactions among collaborators (Schneider et al., 2021). We ground our work in the existing domain of linguistic modelling of collaborative problem-solving. In this sub-section, we shall discuss the existing research that makes use of advanced NLP methods to analyse discourse data in CPS. This discourse data emerge either from the text chats or is transcribed from the speech) and is used to model various skills during CPS, including negotiation, regulation, argumentation etc.

The paper by Flor et al. (2016) presents a study that investigates the use of automated techniques for accurately categorising interactions in collaborative problem-solving within simulated science tasks. It applies natural language processing (NLP) methods to analyse and classify these interactions using Naïve Bayes (NB) and Hidden Markov Models (HMM). The results reveal the effectiveness of the automated classification models in accurately identifying and categorising various types of interactions, achieving an average accuracy of 59.2%.

Pugh, Rao, Stewart, and D'Mello (2022) investigated the feasibility of detecting seven cognitive and social CPS skills (including sharing information, negotiation, etc.) in classroom and lab settings. The participants were middle school kids who collaboratively solved math and physics problems. They achieved an AUROC value of 0.78 in the classroom setting and 0.83 in the lab setting using BERT.

The work by Hao et al. (2017) focuses on developing an automated annotation system called CPS-rater. This tool annotates the discourse into various CPS skills like negotiation, regulation etc. They have used different models, including Random Forest (RF) and NB. Linear chain conditional random field emerged as the best model, achieving an accuracy of 0.732 and a kappa value of 0.636.

To summarise, several studies have contributed to the field of automated analysis and classification of interactions in collaborative problem-solving (CPS) activities. Building upon these previous works, our study aims to extend the existing research by introducing novel contributions. Firstly, we focus on the specific context of the engineering estimation problem within collaborative problem-solving. This contextual specificity provides unique insights and findings applicable to the domain of engineering problem-solving. Secondly, our work employs advanced machine learning models that have demonstrated improved performance compared to existing approaches. By utilising these models, we aim to enhance the accuracy and efficiency of automated identification and categorisation of negotiation utterances in learners' discourse during collaborative problem-solving. These advancements contribute to the broader understanding and advancement of automated analysis techniques in the domain of CPS, addressing the need for more precise and effective analysis of collaborative interactions.

3. Learning Environment

The Modelling-Based Estimation Learning Environment (MEttLE), as shown in Figure 2, is an open-ended learning environment designed to scaffold novice learners in their estimation problem-solving. The tool's five sub-goals trigger a model-based estimation process that is essential for solving the estimation problem (Figure 2a). The three-phased model-building sub-goals, which include functional, qualitative, and quantitative aspects, help learners create, contextualise, and evaluate models of complex problems, one calculation, and one evaluation. MEttLE also includes metacognitive prompts (Figure 2b) that encourage learners to reflect on their models and problem-solving processes, as well as simulators (Figure 2c), hints, an info centre, guide me, question prompts, and a problem map to facilitate the modelling process. Novice learners have the flexibility to choose any path and revisit any sub-goals at any time in MEttLE.

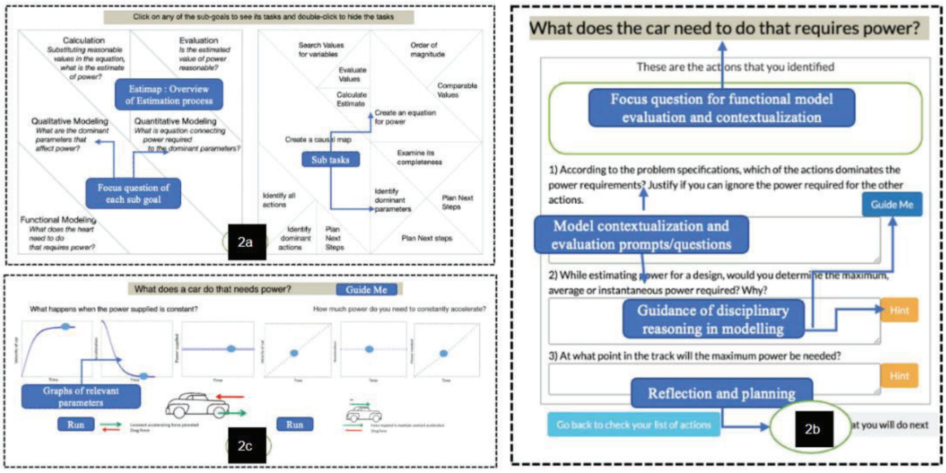

Figure 2. Overview of MEttLE Interface with sub-goals (2a), Detailed sub-goal with Metacognitive Prompts and other scaffolds (2b) and Simulator-4(2c).

To solve the estimation problem in this study, the solver is tasked with estimating the power of a car while comprehending the underlying problem system. To achieve this, they must analyse how the car behaves under the given operating conditions, determine the dominant parameters for these conditions, and create an equation involving the dominant parameters. Additionally, they must make assumptions and approximations to create and determine a simplified model of the problem context and its corresponding mathematical equation. One noteworthy aspect of MEttLE is its open design, which provides immense opportunities for collaborative learning wherein learners undertake meaningful discussions and negotiations to solve this problem.

4. Methods

4.1 Participants

The participants in this study were three dyads comprising two female and four male students (age range of 18-21 years) from 3rd or 4th-year undergraduate engineering colleges in Mumbai. Students from mechanical or electronics engineering were chosen as participants, as the problem in MEttLE required knowledge specific to these disciplines. The students were paired randomly based on their availability based on a pre-study Google form that collected their demographic details. IRB approval from our institution was sought.

4.2 Procedure and Data Collection and Data Analysis

The study was conducted in a research lab setting where the three engineering undergraduate dyads participated on different days. The researcher explained the study goal, the procedure, and the data that would be collected, after which the participants signed the consent form. The lab setup involved a single computer with MEttLE for both participants, who had to solve the estimation problem in it collaboratively. They were asked to articulate their views explicitly during the collaboration. On average, the time taken by pairs to interact with MEttLE was 90 minutes. Data was collected from multiple sources, like screen recording using OBS Studio (OBS, 2021), which ran on a laptop containing MEttLE as well as audio and video data; however, for this study, we only used the transcription of their audio data. Learners' discourse data was then passed to an AI tool called Otter.ai for speech-to-text transcription. Further, researchers coded the data using the CLM framework to identify learners' negotiation instances.

4.3 Feature extraction, model training, and evaluation

In this study, we employed three traditional machine learning classifiers, namely Logistic Regression (LR), NB, and RF. We used the features obtained via TF-IDF (Spärck Jones, 1972) and the Word2Vec (Mikolov et al., 2013) approach. The intention of using these classifiers was that they are employed in most of the research in the domain of learning analytics. Additionally, we used three state-of-the-art pre-trained neural networks for natural language processing that include BERT, RoBERTa, and GPT2. These models were trained for binary classification problem, i.e. to classify discourse data into two categories: the presence of negotiation (labelled as 1) and the absence of negotiation (labelled as 0) We shall first discuss the feature extraction, model training of traditional machine learning models before delving into large language models. TF-IDF Feature Extraction:

We employed the TfidfVectorizer from the sklearn.feature_extraction.text module to convert the text data into numerical features. The vectoriser was configured with parameters such as a minimum document frequency of 5 and a maximum of 10,000 features. This ensured that only frequently occurring words were considered, and the feature dimensionality was controlled.

In addition to TF-IDF, we trained a Word2Vec model using the gensim library. The Word2Vec model learned word embeddings from the training sentences with specific hyperparameters, such as size = 100, window = 5, min_count = 1, and workers = 4. These parameters were selected based on prior experimentation and domain knowledge.

The training data was preprocessed and divided into two sets: one for the TF-IDF-based approach and the other for the Word2Vec-based approach. For TF-IDF, the training data was transformed into TF-IDF features using the fitted vectoriser. For Word2Vec, the training data sentences were tokenised and converted into word embeddings using the trained Word2Vec model. The target variable was created by encoding the labels as integers.

We trained three classifiers, LR, RF, and NB, on the training data. We evaluated the performance of the classifiers on the test data using various metrics like classification accuracy, F1-score, and kappa value (explained at the end of this section).

For BERT, we tokenised the texts using the Hugging Face Transformers library's tokeniser function and converted them to input features with padding and truncation. We split the data into a training set and a validation set and labelled each instance of discourse as either negotiation or non-negotiation. We then created training and validation datasets as PyTorch TensorDatasets, using the input features and labels. We fine-tuned the pre-trained BERT model for our specific task of classifying negotiation and non-negotiation discourse data. We defined the training parameters, such as batch size, number of epochs, and learning rate, and used the AdamW optimiser and the Cross-Entropy Loss function. In our case, we considered a batch size of 16, and the number of epochs was taken to be four. The learning rate was set as 2*(10)-5.

We then created data loaders for the training and validation datasets and trained the model on the training set for a fixed number of epochs using mini-batches. During each epoch, we optimised the model's weights using backpropagation and stochastic gradient descent.

To evaluate the performance of the model, we used the validation set, which the model had not seen during training. The same procedure was applied for RoBERTa and GPT2 as well, and the hyperparameters were also chosen to be the same. For performance evaluation, we chose the following four metrics:

1. Classification accuracy (CA): the ratio of the number of correct classifications to the total number of classifications.
2. F score (F1): is the harmonic mean of recall and precision.
3. Kappa (κ): measures agreement between the actual and the predicted labels by considering the by-chance prediction. κ is calculated using Eq. (1), where P0 is the overall accuracy of the model and Pe is the measure of the agreement between the model predictions and the actual class values as if happening by chance.

$$\frac{P_0-P_e}{1-P_0} \quad \ldots\ldots\ldots (1)$$

5. Result

This section describes the results of the prediction models developed for classification.

Table 2. *The evaluation metric of performance of ML models on “negotiation” classification.*

Text Features	Classifier	CA	F1	Kappa
TF-IDF	LR	0.818	0.777	0.283
	NB	0.794	0.712	0.070
	RF	0.903	0.893	0.664
Word2Vec	LR	0.784	0.6890	0
	NB	0.369	0.355	0.076
	RF	0.873	0.853	0.530
	BERT	0.907	0.906	0.722
	RoBERTa	0.889	0.889	0.675
	GPT2	0.924	0.924	0.781

The performance of various machine learning and deep learning models was evaluated on the task of classifying discourse data into negotiation and non-negotiation. The models were trained on a dataset with 1989 instances and tested on a dataset with 686 instances, and this data split was done on a group level, i.e., data from two groups was used for training, and it was tested on the discourse of the remaining group. The dataset was preprocessed using standard NLP techniques like tokenisation, stop-word removal, and stemming. Two types of features were used for training the traditional machine learning models: TF-IDF and Word2Vec.

The machine learning models used in this study were LR, NB, and RF. The deep learning models used were BERT, RoBERTa, and GPT2.

The results of the experiment are summarised in Table 2. The performance of the models was evaluated using classification accuracy, the F1-score, and the kappa metric (explained in the previous section). The results show that deep learning models outperformed traditional machine learning models in terms of F1-score and kappa value. GPT2 achieved the best F1-score and kappa values of 0.924 and 0.781, respectively.

The NB model exhibited the lowest performance, achieving an F1-score of 0.355 when utilising Word2Vec features. Similarly, LR demonstrated the least favourable kappa score of 0 when employing the Word2Vec features, suggesting that its classification results were not significantly different from those that could be attributed to random chance alone. In addition, the results indicate that the choice of feature representation also plays a crucial role in the performance of the models. The results demonstrate that the traditional machine learning models showed better performance with TF-IDF features.

Overall, the results of this study suggest that deep learning models like BERT, RoBERTa, and GPT2 are more effective than traditional machine learning models for the task of classifying discourse data into negotiation and non-negotiation. The choice of feature representation also plays a significant role in the performance of the models

6. Discussion and Conclusion

In conclusion, this study proposes an approach for automating the identification of negotiation in learners' discourse during collaboration. By leveraging language models like BERT, RoBERTa, and GPT, we accurately identified negotiation utterances in learners' discourse while they solved complex engineering estimation problems in an OELE called MEttLE with high precision and recall.

The practical applications of our research have the potential to impact educational settings greatly. We envision the utilisation of language-based collaboration analytics (CA) models in authentic educational environments for targeted interventions to enhance CPS skills. One key application involves the deployment of automated reports to teachers who oversee multiple groups of students engaged in CPS activities. These reports, accessible through a teacher dashboard, could provide insights into each group's engagement with various aspects of CPS, such as constructing shared knowledge. This functionality empowers teachers to identify groups requiring additional support and allocate their resources effectively. Moreover, teachers can pinpoint individual students' strengths and weaknesses, facilitating the establishment of personalized improvement goals.

Furthermore, the proposed approach isn't limited to teacher-facing analytics; it can also provide learner-facing feedback to foster CPS skill development. CA models could offer individual team members insights into their contributions and demonstration of different CPS skills. This personalized feedback enhances self-awareness, self-reflection, and the evaluation of strengths and weaknesses among learners. Such feedback facilitates tracking skill improvement across multiple collaborative engagements.

Nonetheless, our study is not without limitations. Our results suggest that our approach can accurately identify negotiation utterances in this specific context, but the generalizability of our method to other learning environments and contexts needs to be further investigated. Additionally, the study relied on language models to identify negotiation, which may not capture nonverbal cues and context-specific language use. Future research could explore the use of multimodal methods to identify negotiation in discourse.

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