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## Dialogism: A Framework for CSCL and a Signature of Collaboration

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**Abstract:** As Computer Supported Collaborative Learning (CSCL) gains a broader usage in multiple educational scenarios facilitated by the use of technology, the need for automated tools capable of detecting and stimulating collaboration increases. We propose a computational model using *ReaderBench* that assesses collaboration from a dialogical perspective. Accordingly, collaboration emerges from the inter-twining of different points of view or, more specifically, from the inter-animation of voices pertaining to different speakers. Collaboration is determined from the intertwining or overlap of voices emitted by different participants throughout the ongoing conversation. This study presents a validation of this model consisting of a comparison between the output of our system and human evaluations of 10 chat conversations, selected from a corpus of more than 100 chats, in which Computer Science students debated on the advantages and disadvantages of CSCL technologies (e.g., chat, blog, wiki, forum, or Google Wave). The human evaluations of the degree of collaboration between the participants and the automated scores showed good overlap as measured by precision, recall, and *F1* scores. Our overarching conclusion is that dialogism derived from the overlapping of voices can be perceived as a signature for collaboration.

**Keywords:** CSCL, dialogism, collaboration assessment, cohesion, voice inter-animation

### Introduction

Computer Supported Collaborative Learning (CSCL) technologies, with emphasis on chats and forums, have gained a broader usage as a viable alternative to classic educational scenarios. Such technologies facilitate the development of learning environments in which knowledge is collaboratively built and shared (Stahl, 2006), based on the inter-twining of collective and individual learning processes (Cress, 2013).

Dialogism was introduced by Bakhtin (1981) as having multivocality and polyphony as key features. Koschmann (1999) later proposed dialogism as a paradigm for CSCL. Accordingly, multivocality is centered on the multitude of meanings and the dialogue between multiple voices, whereas polyphony encapsulates multiple points of view and voices while focusing on their inter-animation, as well as the inter-relationships captured in their co-occurrences and overlap. Wegerif (2006) also considered dialogism as a theoretical starting point that can be used for developing tools to teach thinking skills. As Bakhtin (1981) proposed, voices contained within utterances influence each other, interact one with another and can be reflected one within the other. This process of voice inter-animation occurs progressively from simple repetitions to complex referential relationships between utterances. In addition, the inter-animation of voices or of personal points of view is a key component for ensuring the success of a collaborative learning activity (Wegerif, 2006). However, only a few elaborations of CSCL models based on dialogism have been proposed, and even fewer approaches provide automatic analytic tools – e.g., Dong’s design of team communication (Dong, 2005), *Polyphony* (Trausan-Matu, Rebedea, Dragan, & Alexandru, 2007), or the *Knowledge Space Visualizer* (Teplovs, 2008).

Following from our development of several systems inspired from the dialogical approach (i.e., *PolyCAFe* (Trausan-Matu & Rebedea, 2010; Dascalu, Rebedea, Trausan-Matu, & Armit, 2011; Trausan-Matu, Dascalu, & Rebedea, 2014) and *ReaderBench* (Dascalu, Trausan-Matu, & Dessus, 2013a), we propose a computational model to assess collaboration based on the inter-twining or overlap of voices pertaining to different speakers, therefore enabling a transversal analysis of subsequent discussion slices. We present a large-scale validation consisting of a comparison between the output of our system and human evaluations. In addition, we describe the results of a study with multi-participant chat conversations in which members were asked to debate on given topics and were assessed in terms of the collaboration among themselves. Our overarching conclusion is that dialogism derived from the overlapping of voices can be perceived as a signature for collaboration.

## Philosophical implications of dialogism and the polyphonic model

Dialogism was introduced by Bakhtin (1981, 1984) and is centered on dialogue reflected in “any kind of human sense-making, semiotic practice, action, interaction, thinking or communication” (Linell, 2009, pp. 5-6). This definition of dialogism is naturally focused on the dialogue between two or more individuals exchanging utterances, but may well be present in any text as “life by its very nature is dialogic ... when dialogue ends, everything ends” (Bakhtin, 1984, p. 294). In addition, dialogue can be also perceived from a more abstract perspective as having multiple valences: ‘internal dialogue within the self’ or ‘internal dialogue’ (Linell, 2009, ch. 6), ‘dialogical exploration of the environment’ (Linell, 2009, ch. 7), ‘dialogue with artifacts’ (Linell, 2009, ch. 16), ‘dialogue between ideas’ (Marková, Linell, Grossen, & Salazar Orvig, 2007, ch. 6) or ‘paradigms’ (Linell, 2005, ch. 6). Nevertheless, in each context, discourse is modeled from a dialogical perspective as interaction with others, essentially towards building meaning and understanding.

In order to properly introduce the polyphonic model presented in detail later on within this section, we must first present the three core and inter-dependent concepts of discourse analysis: *utterances* briefly defined as units of analysis, *voices* as distinctive points of view emerging from the ongoing discussion, and *echoes* as the replication of a certain voice, the overtones and repetitions of the specific point of view that occur later on, with further implications in the discourse. Although the complexity of an utterance may vary greatly from a simple word or exchange to a set of inter-twined utterances or even to an entire novel (Bakhtin, 1986), our analysis adheres to Dong’s perspective of separating utterances based on turn-taking events between speakers (Dong, 2009). Therefore, introducing a new point of view or contribution from a different participant divides the discourse by potentially modifying the inner, ongoing perspective of the current speaker. At a more fine-grained level, words, seen as the constituents of utterances, provide the liaisons between utterances and deepen the perspective of others’ contributions into one’s discourse. Obviously, utterances may contain more than a single voice, as well as alien voices to which the current voice refers (Trausan-Matu & Stahl, 2007). An *alien* voice is part of a turn uttered by a given participant that is later replicated in another one, marking therefore the transfer among different participants and their corresponding points of view with regards to the voice’s central word.

Therefore, the main goal of a discussion can be described in terms of voice inter-animation and achieving true *polyphony* (Bakhtin, 1984) in which conflicting views, various angles, and multiple perspectives concur; all the previous aspects should also be covered in a truly collaborative conversation. However, as voices express ideas and opinions, polyphony can be used to perform a deep dialogical discourse analysis by summing up multiple voices co-occurring within the same discussion thread.

Nevertheless, we must also emphasize an intrinsic problem that “it is indeed impossible to be ‘completely dialogical’, if one wants to be systematic and contribute to a cumulative scientific endeavor” (Linell, 2009, p. 383). The later point of view also augments the duality between individual involvement and actual collaboration throughout a given CSCL conversation, as it is impossible to focus on both the animation with other participants’ utterances and sustainably provide meaningful contributions. In the end, a balance needs to be achieved between individuals, without facing discourse domination in terms of participation.

The *polyphonic model* (Trausan-Matu, Stahl, & Zemel, 2005; Trausan-Matu & Stahl, 2007; Trausan-Matu et al., 2014) follows the ideas of Koschmann (1999) and Wegerif (2005) and investigates how Bakhtin’s theory of polyphony and inter-animation (Bakhtin, 1981, 1984) can be used for analyzing the discourse in chat conversations with multiple participants for which classic approaches are not appropriate. Therefore, the polyphonic model focuses on the idea of identifying voices in the analysis of discourse and building an internal graph-based representation, whether relying on the utterance graph (Trausan-Matu et al., 2007) or the cohesion graph (Dascalu et al., 2013a). To this end, links between utterances are analyzed using repetitions, lexical and semantic chains, as well as cohesive links, and a graph is built in order to highlight discussion threads. Nevertheless, in both internal representations, lexical or semantic cohesion between any two utterances can be considered the central liaison between the analysis elements within the graph.

Moreover, of particular interest is the multi-dimensionality of the polyphonic model (Trausan-Matu, 2013). First, the *longitudinal* dimension is reflected in the explicit or implicit references between utterances, following the conversation timeline. This grants an overall image of the degree of inter-animation of voices spanning the discourse. This polyphony can now be used as a signature for collaboration, as the interactions between multiple participants of the conversation are reflected in their voices. Second, *threading* highlights voices evolution in terms of the interaction with other discussion threads. Third, the *transversal* dimension is useful for observing a differential positioning of participants, when a shift of their point of interest occurs towards discussing other topics.

## Dialogical Voice Inter-Animation Model

From a computational perspective, until recently, the goals of discourse analysis in existing approaches oriented towards conversations analysis were to detect topics and links (Adams & Martell, 2008), dialog acts (Kontostathis et al., 2009), lexical chains (Dong, 2006), or other complex relations (Rosé et al., 2008). The polyphonic model emphasizes the Natural Language Processing dimension of the analysis by taking full advantage of Latent Semantic Analysis (Landauer & Dumais, 1997), Latent Dirichlet Allocation (Blei, Ng, & Jordan, 2003), semantic distances from the lexicalized ontology *WordNet* (Budanitsky & Hirst, 2006), and Social Network Analysis (Wasserman & Faust, 1994).

The voice identification process resides in building lexical chains and merging them into semantic chains through cohesion (Dascalu, Trausan-Matu, & Dessus, 2013b). Due to the limitation of discovering lexical chains (Galley & McKeown, 2003) through semantic distances in ontologies (Budanitsky & Hirst, 2006) that only consider words having the same part-of-speech, the *merge* step is essential as it enables consideration of different parts-of-speech and unites groups of concepts based on identical lemmas or high cohesion values. Therefore, an iterative algorithm similar to an agglomerative hierarchical clustering algorithm (Hastie, Tibshirani, & Friedman, 2009) is used. In order to merge clusters, the algorithm starts from the identified lexical chains seen as groups of already clustered words and uses the cohesion between the corresponding groups of words as the distance function if this value is greater than an imposed threshold.

As semantic chains span across the discourse, the context generated by the co-occurrence or repetitions of tightly cohesive concepts is similar to the longitudinal dimension of voices. Echoes can be highlighted through cohesion based on semantic similarity, while the attenuation effect is reflected in the considered distance between analysis elements. Moreover, by inter-twining different semantic chains within the same utterance, we are able to better grasp the transversal dimension of voice inter-animation. Therefore, after manually selecting the voices of interest, the user can visualize the conversation as an overlap of co-occurring semantic chains that induce polyphony (see Figure 1). The chart follows the conversation timeline expressed in utterance identifiers and a voice is displayed within the interface as the three most dominant concepts (word lemmas). Different speakers that uttered a particular voice are demarcated with randomly assigned colors, consistent throughout a conversation for each participant.

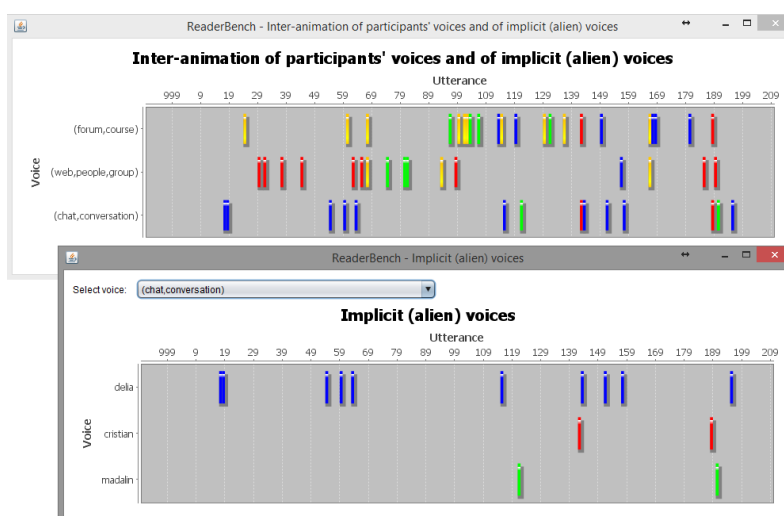


Figure 1. Voices (e.g., chat - conversation) split per participant and their corresponding distributions throughout the conversation.

In order to achieve genuine collaboration, the conversation must contain threads of utterances integrating key concepts or 'voices', that inter-animate in a similar way to counterpoints in polyphonic musical fugues (Trausan-Matu et al., 2005; Trausan-Matu & Stahl, 2007). As collaboration is centered on multiple participants, a split of each voice into multiple viewpoints pertaining to different participants is required. A *viewpoint* consists of a link between the concepts pertaining to a voice and a participant, through their explicit use within one's contributions in the ongoing conversation. We opted to present this split in terms of implicit (alien) voices (Trausan-Matu & Stahl, 2007) (see Figure 1), as the accumulation of voices through transitivity in inter-linked cohesive utterances clearly highlights the presence of alien voices. In addition, this split presentation of semantic chains per participant is useful for observing each speaker's coverage and distribution of dominant concepts throughout the conversation.

After identifying the semantic chains that become voices and, in accordance to Miller's law (1956), a simple moving average (Upton & Cook, 2008) was applied on the voice distribution for five datum points representing consecutive utterances, with a split horizon of one minute between adjacent contributions. In other words, we weighted the importance of each concept occurrence over five adjacent utterances if there were no breaks in the discourse larger than an imposed, experimentally determined, threshold of one minute. Exceeding this value would clearly mark a stopping point in the overall chat conversation, making the expansion of the singular occurrence of the voice over this break unnecessary. This step of smoothing the initial discrete voice distribution plays a central role in subsequent processing as the expanded context of a voice's occurrence is much more significant than the sole consideration of the concept uttered by a participant in a given contribution.

Moreover, by applying *pointwise mutual information* (PMI) (Fano, 1961) between the moving averages of all pairs of voice distributions that appear in a given context of five analysis elements, we obtained a local degree of voice inter-weaving or synergy (Dascalu et al., 2013b). Therefore, collaboration is assessed as the cumulated PMI value obtained from all possible pairs of voices pertaining to different participants (different viewpoints) within subsequent contexts of the analysis. From an individual point of view, each participant's overall collaboration is computed as the cumulated mutual information between an individual's personal viewpoints and all other participant viewpoints. In other words, by comparing individual voice distributions that span throughout the conversation, collaboration emerges from the overlap of voices pertaining to different participants.

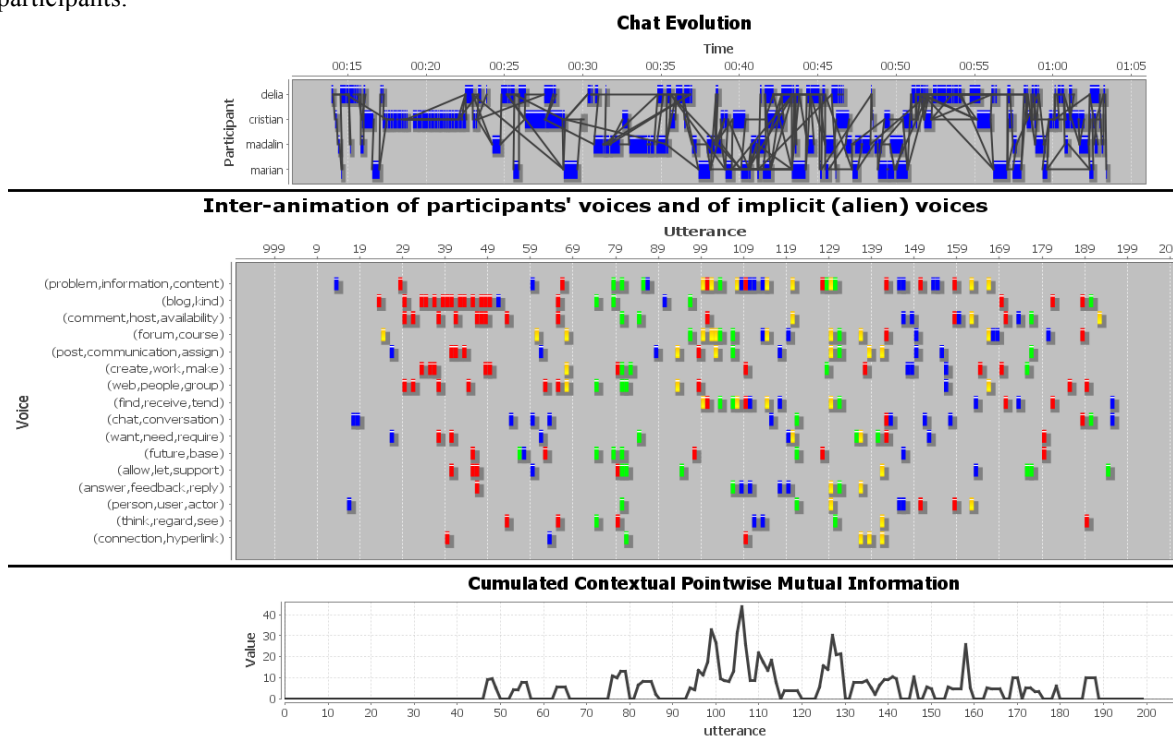


Figure 2. Collaboration evolution viewed as voice overlap between different participants (intertwining of different viewpoints), including the automatic identification of intense collaboration zones in contrast to the conversation timeline and utterance distribution.

Figure 2 presents the voices with the longest semantic chain span throughout the conversation and displays the tight correlation between the conversation's time evolution depicting the links from the cohesion graph (Dascalu et al., 2013a) among participants' utterances ordered chronologically and the results from our collaboration assessment model. A high density of links between participants determines collaboration, whereas timeframes with monologues from a single participant (e.g., utterances with IDs ranging from 27 to 50) have limited or no collaboration. Afterwards, collaboration increases as multiple participants become involved in the ongoing discussion. In addition, within the cumulated contextual PMI view, all of the voices from the conversation are considered (even those that have as low as 3 constituent words); this explains the greater cumulative values encountered in the graph. Each peak of collaboration obtained through PMI corresponds to a

zone with a high transversal density of voices emitted by different speakers (e.g., utterances with IDs ranging from 95 to 105 from the following excerpt that involves all participants involved in the conversation):

- Cristian: one thing about wiki. it is easy for many people to post on them  
 Marian: you can also find good information on forums  
 Cristian: but if no one is keeping tab on the content it can get pretty confusing  
 Marian: and you can also search for information on forums  
 Marian: and anyone can post on forums  
 Madalin: in forums knowledge tends to be dispersed and somewhat lower in density  
 Marian: I agree  
 Delia: me too

## Validations of Collaboration and the Identification of Collaboration Zones

The validation experiment focuses on the assessment of 10 chat conversations, selected from a corpus of more than 100 chats, that took place in an academic environment in which Computer Science students from the 4<sup>th</sup> year undergoing the Human-Computer Interaction course at our university debated on the advantages and disadvantages of CSCL technologies (e.g., chat, blog, wiki, forum, or Google Wave). Each conversation involved 4 or 5 participants who each first debated on the benefits and disadvantages of a given technology, and then later proposing an integrated alternative that encompassed the previously presented advantages. Afterwards, 110 4<sup>th</sup> year undergraduate and master students were asked to manually annotate 3 chat conversations, grading each participant on a 1-10 scale in terms of collaboration (inter-change of ideas with other participants) and identifying intense collaboration zones as segments of the conversations with a high degree of collaboration among the participants.

We opted to distribute the evaluation of each conversation due to the high amount of time it takes to manually assess a single discussion (on average, users reported 1.5 to 4 hours for a deep understanding) (Trausan-Matu, 2010). In the end, we had on average 33 annotations per conversation and the overall results presented in Table 1 indicate a reliable automatic evaluation of collaboration. The high values of intra-class correlations (ICC) and Cronbach's alpha (see Table 1) between the evaluators of each chat indicate few disagreements between raters. Pearson correlations and non-parametric correlations (Spearman's Rho) were determined between automatic and human mean ratings for each conversation. The preliminary results of the experiments presented in detail in this paper were included in Dascalu, Trausan-Matu, and Dessus (2014).

Table 1. Collaboration assessment (\*p < .05).

Conversation	Average ICC among raters	Cronbach's alpha among raters	Pearson correlation	Agreement (Spearman's Rho)
Chat 1	.944	.969	.846	.900*
Chat 2	.769	.821	.157	.100
Chat 3	.641	.727	.759	.300
Chat 4	.871	.907	.932	.900*
Chat 5	.936	.960	.892	.700
Chat 6	.949	.958	.897	.462
Chat 7	.853	.907	.537	.600
Chat 8	.890	.923	.326	.400
Chat 9	.886	.969	.540	.400
Chat 10	.703	.862	.636	.600
<b>Average</b>	<b>.844</b>	<b>.900</b>	<b>.652</b>	<b>.536</b>

As an interpretation of the results presented in Table 1, we can observe that predictions are accurate except for two conversations in which we could identify atypical behaviors: specifically for chat 8 – dominance of the conversation by certain participants at given moments – and specifically for chat 2 – similar involvement of multiple participants made the differentiation among them more difficult and more prone to error. Nevertheless, the overall evaluations are partially biased as some raters took into consideration quantitative factors to estimate collaboration (i.e., the number of contributions) instead of focusing on the quality of the dialogue and on the way utterances, pertaining to different participants, inter-animating.

Table 2. Identified intense collaboration zones.

Conversation	No. of utterances	Manually annotated collaboration zones	Automatically identified intense collaboration zones	P	R	F1	<i>r</i>
Chat 1	339	[37; 128], [167; 298]	[27; 38], [47; 66], [81; 128], [172; 238], [250; 279], [305; 321], [339; 343]	.84	.75	.79	.32
Chat 2	283	[13; 49], [68; 131], [144; 169], [193; 207], [229; 236], [245; 266]	[9; 46], [55; 75], [85; 113], [134; 149], [167; 184], [196; 203], [217; 233], [261; 271]	.63	.58	.60	.35
Chat 3	405	[36; 315]	[16; 20], [32; 136], [148; 189], [203; 226], [239; 255], [270; 301], [333; 377]	.80	.77	.79	.46
Chat 4	251	[19; 148], [184; 194], [203; 212]	[26; 60], [68; 125], [135; 139], [178; 244]	.72	.79	.75	.43
Chat 5	416	[28; 98], [120; 265], [280; 287], [346; 362]	[19; 228], [243; 280], [303; 314], [329; 361], [395; 403]	.73	.91	.81	.30
Chat 6	378	[64; 227], [248; 308], [321; 359]	[16; 27], [48; 90], [100; 229], [241; 370]	.81	.97	.88	.36
Chat 7	270	[40; 97], [108; 128], [145; 220], [232; 257]	[27; 39], [47; 93], [104; 110], [119; 135], [143; 170], [198; 202], [210; 221], [253; 261]	.78	.59	.67	.37
Chat 8	389	[30; 127], [140; 154], [189; 208], [235; 285], [299; 356]	[17; 39], [71; 161], [256; 283], [311; 382]	.73	.64	.68	.20
Chat 9	190	[51; 65], [80; 190]	[76; 85], [94; 114], [124; 173]	.95	.61	.74	.48
Chat 10	297	[27; 75], [89; 104], [139; 287]	[18; 57], [65; 124], [138; 150], [168; 179], [188; 196], [205; 209], [249; 258], [266; 287]	.75	.59	.66	.21
<b>Average</b>				<b>.77</b>	<b>.72</b>	<b>.74</b>	<b>.35</b>

With regards to the identification of intense collaboration zones, each evaluator provided individual scores for collaboration and identified areas of collaboration in the conversation as intervals of type  $[x; y]$ , where  $x$  and  $y$  are utterance IDs. All manual annotations were afterwards cumulated in a histogram that presented, for each utterance, the number of raters who considered it to be part of an intense collaboration zone. In the end, a greedy algorithm (Dascalu et al., 2013a) was applied on this histogram in order to obtain an aggregated version that reflected the intense collaboration zones emerging as an overlap of all annotations (see third column of Table 2). Based on the highlighted intense collaboration zones from Table 2, there is a good overlap reflected in the number of utterances marked as pertaining to a collaboration zone in both manual and automatic processes, as well as in terms of accuracy measured as precision, recall, and *F1* score between the annotated collaboration zones and our dialogical model. This indicates that our polyphonic-dialogic model is a good estimator of the annotated zones, therefore demonstrating the feasibility of our approach.

## Conclusions and Future Research Directions

Based on dialogism and on the polyphonic model, we have devised an automatic method capable of identifying collaboration based on the inter-animation of voices. As the validations demonstrated the accuracy of the models built on dialogism, we can state that the proposed methods emphasize the dialogical perspective of collaboration in CSCL environments. We opted to present the evolution of voice synergy through PMI instead of polyphony because our computational model uses co-occurrences and the overlap of voices within a given context. In order to emphasize the effect of inter-animation that would induce true polyphony, we envisage the use of argumentation acts and patterns (Stent & Allen, 2000) for highlighting the interdependencies between voices and how a particular voice can shed light on another.

This approach opens up the exploration of multiple research questions. For example, one line of our research will further examine the relations between student collaboration in chat forums and performance in on-line courses. We also envision the use of this approach to assess narrative features of novels, highlighting different points of view from different characters. Still further, another set of experiments might focus on the assessment of students' self-explanations that can be perceived as a 'dialogue' between the author's text and students' thoughts viewed as echoes of the voices from the initial text, highlighting in the end relevant reading strategies employed by the learner (e.g., paraphrases, bridging, or knowledge inference). In sum, our approach opens up a host of opportunities to further explore collaboration from a dialogical perspective across a wide range of contexts.

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