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Assessing verbal interaction of adult learners in computer-supported collaborative problem solving

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Abstract

The objective of this study is to explore new ways of assessing collaborative problem solving (CPS) processes based on different modalities of audio data and their combination. The data collection took place in an educational lab setting during an experiment with adult teams from professional contexts who collaboratively solved multiple problems as part of a CPS training. From audio data, both verbal (ie, speech) and non-verbal (ie, pitch) aspects were extracted. Four analysis methods were used, including (a) content analysis; (b) linguistic inquiry and word count; (c) verbal entrainment analysis; and (d) acoustic–prosodic entrainment based on pitch data. Insights are given into the CPS processes of the participating groups using these measures and relevant relationships between some of these measures are further investigated. Based on content analysis, it was found that most of the interactions during the CPS process are task oriented, whereas team-oriented interactions are less present. Second, three measures of proportion of contribution in CPS were investigated and clear differences in participation patterns between and within teams were found. We suggest that a combination of utterance count and words per sentence could provide valuable insights for quantity and equality of participation. Third, the study explored pronoun use and found that the most frequently used personal pronouns were first-person singular. Next, the results indicated a relationship between pronoun use and the relative frequency of interactions. Fourth, a rather weak relationship between lexical entrainment measures and the acoustic–prosodic measures were found, suggesting that these measures are indicative of separate communicative aspects in CPS. This study contributes to a better understanding of which type of audio-based data is most informative to teachers and students as a feedback or assessment tool. This study complements previous research as it focuses on spoken human-to-human communication collected in an authentic context.

KEYWORDS

audio data, collaborative problem solving, content analysis, linguistic inquiry, linguistic style matching

Practitioner notes

What is already known about this topic

- Support and guidance systems for learning coaches, teachers and learners are needed to foster the educational quality of collaborative problem solving (CPS) activities.
- CPS is a complex process and measuring the quality of CPS processes remains challenging.
- Multimodal learning analytics, focusing on verbal and non-verbal data sources and using content analysis, linguistic inquiry and word count and verbal and acoustic entrainment measures could be valuable to measure the quality of CPS.

What this paper adds

- The majority of interactions during CPS processes are task oriented or cognitive of nature, whereas team-oriented interactions are less present.
- Utterance count and words per sentence should be used in combination, as they are indicative of different aspects.
- Pronoun use in learners' discourse is related to the types of CPS interactions.
- Lexical entrainment measures and acoustic–prosodic are indicative of distinctive communicative aspects in CPS.

Implications for practice and/or policy

- Quality indicators of CPS processes should include both verbal and non-verbal measures of students' interactions.
- Educational researchers and the (Edtech) industry should further leverage their forces to foster the development of (semi-)automated systems for measuring the quality of CPS processes.
- It should be further investigated how quality indicators of CPS processes can be most meaningful to trainers, teachers and learners, for example, through the use of dashboards.

INTRODUCTION

The increasing complexity of problems in contemporary society often necessitates collaboration among stakeholders with diverse expertise, making it evident that these challenges cannot be effectively addressed by individuals alone (Graesser et al., 2022; Neubert et al., 2015). As a response, collaborative problem solving (CPS) is of increasing importance in today's society (Kyllonen, 2018). Competencies related to CPS (eg, critical thinking, problem-solving and collaboration) are recognized by many stakeholders in education (eg, OECD, 2017) and in the labour market (eg, World Economic Forum, 2020). CPS, as a method, is recognized to foster foundational competencies. It is described by OECD (2017) as a process in which multiple agents try to solve a problem “by sharing the understanding and effort required to come to a solution and pooling their knowledge, skills and efforts to reach that solution” (p. 47). As described by Dillenbourg (1999), it is a collaborative process that distinguishes itself from cooperative processes through its emphasis on symmetry, shared goals and division of labour. CPS stands out from other collaborative approaches due to four key characteristics: (a) a collective focus on achieving a common goal in addressing a unique problem; (b) the ability of students to assess the quality of their solutions throughout the problem-solving process; (c) the distribution of roles and tasks among team members; and (d) the diverse perspectives and resources each team member brings to facilitate the identification of solutions (Graesser et al., 2018). To measure CPS, multiple frameworks have been designed (eg, Griffin et al., 2012; OECD, 2017). Building on previous research, a competency framework for CPS has been proposed by Sun et al. (2020, 2022). They distinguish three main facets of CPS. The first facet, “constructing shared knowledge”, consists mainly of cognitive aspects. The second facet, “negotiating/coordination”, mainly covers task-related aspects. The third facet, “maintaining team function”, is mainly related to team-oriented aspects.

In line with these characteristics, different aspects are of importance for the quality of interactions in CPS (eg, Baltzersen, 2022), one of which is positive interdependence among team members (Cukurova, Luckin, & Baines, 2018). This interdependence occurs when team members' outcomes are dependent on other team members' actions (Johnson & Johnson, 2009). Other aspects include (cognitive) diversity (Frigotto & Rossi, 2012; Kavadias & Sommer, 2009; Phillips, 2018), joint coordination (Amon et al., 2019; Barron, 2000), and equal participation among team members (Baltzersen, 2022; Hu & Chen, 2022; Shah & Lewis, 2019).

Since CPS is a complex process and construct (Cukurova, Luckin, & Baines, 2018; Graesser et al., 2018), support and guidance systems for learning coaches, teachers and learners are needed to foster the educational quality of CPS activities. An important aspect in doing so is the measurement of team dynamics and processes in CPS to inform these stakeholders. To this extent, learning analytics focusing on different data sources can be used. One of the major data sources for learning analytics in collaborative learning is audio data. In recent years, new technologies and techniques, integrating artificial intelligence, have emerged, which allow users to get better insights in these types of data (Tan et al., 2022). More specifically, automatic speech recognition, which falls under the field of natural language processing (NLP), a research field concerned with the computer-based processing of natural language text or speech (Geman & Johnson, 2001), allows users to get real-time transcriptions for multiple languages (Yu & Deng, 2015). Additional NLP techniques can be used to automatically assess these interactions (Boyd & Schwartz, 2021; Dowell & Kovanović, 2022). Whereas Coh-Metrix, TAALES, TAACO and Readerbench focus on text cohesion and complexity and give insight into how groups perform in terms of the content of learning, techniques such as LIWC look at the psycholinguistic usage of language and give insights into how individuals are engaged in the collaborative tasks, as well as how groups work together on a social and interpersonal level. A recent example showcasing how NLP techniques can be applied to provide feedback to learners in the context of CPS has been described by Stewart et al. (2023). However, research on how the quality of CPS can be most effectively measured is limited (Graesser et al., 2020). This research aims to fill this gap by investigating how learning analytics can be more easily used to support teachers (or coaches) and learners.

LEARNING ANALYTICS FOR CPS

Several definitions and conceptualizations exist to describe the concept of learning analytics. One of the widely adopted definitions was defined in function of the first International Conference on Learning Analytics and Knowledge, stating that learning analytics refers to measuring, collecting, analysing and reporting of data concerning learning contexts and learners, to better understand and optimize learning and learning environments (Siemens, 2013; Winne, 2017). Currently, the range of learning analytics and application domains is already very broad (Cukurova et al., 2020). For example, in their taxonomy, Di Mitri et al. (2018) give an overview of contextual and behavioural (ie, non-verbal and verbal) data sources, which are further categorized per body part (eg, mouth, eyes and heart) and signal channel (eg, tone, galvanic skin response and temperature).

Learning analytics can focus on multiple aspects of CPS. In line with the computer-supported collaborative learning (CSCL) process model designed by Kreijns et al. (2002; see also Kreijns & Kirschner, 2018), three components can be distinguished, including (a) social interaction; (b) meta-cognitive and socio-cognitive processes; and (c) social and socio-emotional processes. These aspects can be generalized to CPS contexts, for which multiple social and cognitive competencies are required (OECD, 2017). To capture this broad range of CPS group processes, there is a need to combine several data channels and methodologies, which is captured in the literature on multimodal learning analytics (MMLA).

MMLA for CPS

MMLA is defined by Giannakos et al. (2022) as “the collection and analysis of rich data leveraging multiple data channels” (p. 4). Cukurova and colleagues (2020) refer to the advantages of MMLA in two ways. First, research has indicated the added value of MMLA instead of unimodal data to predict learning outcomes (Emerson et al., 2020; Olsen et al., 2020). Second, MMLA enables monitoring of important factors influencing learning (eg, engagement), which are often difficult to capture or analyse (Cukurova et al., 2020). This is in line with one of the twelve commitments to ground and grow MMLA, as formulated by Worsley et al. (2021), suggesting that MMLA assists in making the invisible visible.

In a recent systematic review, Sharma and Giannakos (2020) identified the main areas of implementation and technologies and methodologies used in research on MMLA. Of the 42 selected studies, 17 studies were found to focus on data of learning teams (ie, collaborative settings) instead of data of individuals. Within these selected studies, the focus was to a large extent on university students. No studies were found focusing on teams taking part in adult education. Regarding the data modalities used, studies mostly included log, video, gesture and audio data.

Interactional data in CPS

Conversational data is an important source for measuring the quality of collaboration in CPS (OECD, 2017), which can be studied in a multimodal way. It is a combination of both verbal (ie, speech) and non-verbal (ie, tone, pitch, volume and speed) data modalities. Recent literature on MMLA for CPS focusing (partially) on audio sources include the work of Nasir et al. (2021), Stewart et al. (2021), Sullivan and Keith (2019) and Vrzakova et al. (2020). In some of these studies, the focus is on the verbal aspect of the audio data. For example, Sullivan and Keith (2019) used qualitative content analysis in combination with NLP techniques to identify students' problem-solving processes in a computational environment.

Non-verbal sources were considered by Nasir et al. (2021) and Vrzakova et al. (2020). Nasir et al. (2021) explored how collaborative learning behavioural profiles can be identified in a problem-based activity using audio data, log data and video data. For the auditive aspect of the data analysis, voice activity detection was used to identify markers such as speech activity, silence and pauses. Vrzakova et al. (2020) related speech rate (words per second), interaction and face and upper body movements to teams' subjective and objective performance outcomes. Stewart et al. (2021) used both acoustic prosodic features and speech data to automatically model three key CPS facets derived from the framework of Sun et al. (2020) in an online CPS environment involving triads. Additionally, in their research, Cukurova, Luckin, Millán, et al. (2018) show how to measure CPS quality based on students' hand positions and head directions, which are also indicative of non-verbal aspects of learners' interaction.

In general, social interactions in CPS have been mostly analysed based on learners' verbal input in digital learning environments (Cukurova, Luckin, Millán, et al., 2018) using content analysis. A coding scheme for this kind of analysis was designed by Sun et al. (2020). Further research by Sun et al. (2022) using this coding scheme indicated categories that are predictive of CPS performance. Researchers, including Hao et al. (2017), have also focused on the automatization process of annotating conversational CPS data through the design of a CPS coding system. Additional methods have been used for classifying utterances in CPS conversations and CSCL conversations (Rosé et al., 2008). Current research (eg, Stewart et al., 2019) often analyses the word use in CPS activities using linguistic inquiry and word count (LIWC). LIWC is a text analysis methodology that counts the number of words per predefined category (Tausczik & Pennebaker, 2010). These include functional and grammatical categories, as well as psycholinguistically relevant categories. Stewart et al. (2019), for example, used LIWC in combination with content analysis to automatically model CPS processes, which are based on predefined facets of CPS defined by Sun et al. (2020).

According to Tausczik and Pennebaker (2010), the LIWC output can be used as indicator of social coordination and group processes. Previous research in several research fields (eg, Atabek & Yildiz, 2010; Yazdi-Amirkhiz et al., 2014) has focused on the use of personal pronouns, one of the most commonly used function words, in conversations. Pronoun metrics can, for example, be a way to assess progress in online collaborative work (Demmans Epp et al., 2017). More specifically, Thompson et al. (2013) propose that changes in the frequency of the first-person plural pronoun indicate changes in focus from individual to group concerns. Differences in patterns of pronoun use may also suggest differences in collaboration quality (Demmans Epp et al., 2017). Inclusive personal pronouns (ie, “we”) can reduce social and psychological distance between participants, contributing to a sense of group membership and cohesion. Additionally, personal pronoun use has been found to be related to whether a person is self-oriented or collectively oriented and to the status of a person within the group (eg, Boyd & Schwartz, 2021). More specifically, the study of Kacewicz et al. (2014) points out that more other focus is an indicator of higher rank in a group.

Another output of LIWC is word count, which can, according to Tausczik and Pennebaker (2010), reveal whether a person is engaged in a conversation or task focused, and who is dominating a conversation, which may in turn also indicate status among group members. Earlier research has shown that a high heterogeneity in terms of participation is an indicator of processes of social loafing or free riding (see Weinberger & Fischer, 2006). The length of a learners' contribution can, on the other hand, be indicative of ones' level of depth or detail in a CSCL conversation (Rosé et al., 2008). Using LIWC, this could be observed through the measure of words per sentence.

LIWC has also been used to identify lexical entrainment in dyads and teams. This is the alignment in linguistic representations employed by individuals (Pickering & Garrod, 2004). A measure for lexical entrainment is language style matching (LSM). LSM represents the amount of similarity in the functional linguistic style or the psychological similarity among multiple persons (Heuer et al., 2020; Ireland & Pennebaker, 2010). Whereas originally, LSM was mainly calculated among dyads (Ireland & Pennebaker, 2010), recent research (Heuer et al., 2020) indicates that it is also possible to measure this in larger teams, which brings opportunities for its use in research on collaborative learning and CPS processes in triads and even larger teams.

Next to lexical entrainment, advancements in research have also been made regarding acoustic–prosodic entrainment. This is the process in which dialogue partners converge in terms of speech rate, loudness and pitch (Lubold & Pon-Barry, 2014; Weise & Levitan, 2018). Research by Weise and Levitan (2018) indicates that the different entrainment measures are indicative of different independent behaviours. The use of these parameters to gather insights on the quality of CPS processes is still under-investigated and needs further attention.

Research gaps

Studying (social) interactions in CSCL and CPS is a complex task (Kreijns et al., 2003). To do so effectively, MMLA are needed (Worsley & Blikstein, 2018). Although more research is carried out on the opportunities offered by these MMLA, Di Mitri et al. (2018) indicate that there is still a shortage of research focusing on timely interventions and feedback (eg, via dashboards) for learners. Additionally, only a limited number of studies focus on interactional data of teams in CSCL learning tasks and CPS tasks (eg, Cukurova, Luckin, Millán, et al., 2018; Giannakos et al., 2022).

Next, several researchers indicate that the research focus should go beyond monitoring low-level behaviours and focus on higher-level constructs to monitor quality of collaboration (Stewart et al., 2019). One avenue for doing so is the use of verbal and non-verbal data to investigate natural language communication (eg, Lin et al., 2021; Praharaj et al., 2022). However, examples of studies taking into account verbal and non-verbal data are limited (eg, Stewart et al., 2021), and so is the research on the use of LIWC. This suggests that there is a gap in the literature when it comes to leveraging MMLA, including verbal and non-verbal data analysis, for examining social interactions in computer-supported CPS.

PURPOSE AND RESEARCH QUESTIONS OF THE PRESENT STUDY

We intend to contribute to the existing research by examining how we can make statements about team dynamics and processes in CPS based on verbal and non-verbal data modalities, exploring several methodologies. In the current study, we more specifically focus on

(a) content analysis, (b) semi-automatic analysis based on LIWC, (c) LSM and (d) acoustic data analysis.

Building on previous research (Staarman et al., 2005; Sun et al., 2020) that has highlighted the relatively low presence of team functioning aspects, compared to cognitive aspects, in team members' discourse within CPS, the first aim of this study is to explore the relative share of different aspects of team communication during group performances. To this extent, the first research question is as follows: *(1) What is the share of cognitive aspects, task-oriented aspects and team functioning aspects during CPS?* Based on previous literature, including Staarman et al. (2005) and Sun et al. (2020), it is hypothesized that there will be less utterances related to team functioning aspects compared to cognitive and task-oriented aspects.

Equality of participation is an important factor for the quality of CPS group behaviour (Baltzersen, 2022). One way to measure this aspect is by looking at the number of utterances per participant. However, other possibilities exist. LIWC, for example, includes parameters such as word count and words per sentence. Yet, insights are lacking on how these measures relate to each other. Therefore, the second aim is to investigate the relationship among different indicators of proportion of contribution. Two research questions are formulated: *(2a) To what extent does the proportion of contribution differ between participants in the participating teams in terms of (a) word count, (b) words per sentence and (c) number of utterances? (2b) How do these three indicators of proportion of contribution relate to each other?*

Furthermore, research has shown multiple theories on personal pronoun use for team conversations. There is still a lack of research on personal pronoun use in learners' discourse. Therefore, the following research questions are formulated: *(3a) To what extent do individuals in a group position themselves towards other individuals and the group as a whole as defined in pronoun use? (3b) How does the pronoun use of a person relate to the relative frequency of the types of interactions?* Based on Atabek and Yildiz (2010), we hypothesize that the singular and plural first-person pronouns will be used most frequently, followed by the second-person pronouns and the third-person pronouns.

Last, recent research on communication in collaborative processes focuses on verbal entrainment and acoustic–prosodic entrainment measures. It is unclear how these concepts evolve during CPS activities and how both measures relate to each other. Therefore, two research questions are formulated: *(4a) How do lexical–and acoustic–prosodic entrainment evolve during the CPS exercise? (4b) How does lexical entrainment relate to acoustic–prosodic entrainment in a CPS task?* Based on Weise and Levitan (2018), it is hypothesized that the relationship between both variables will be rather weak.

METHOD

Study context

The focus of this study is on spoken human-to-human communication among four team members during a CPS task. This complements research focusing on communication through written text, such as text chats (Hao et al., 2017; Isari et al., 2016) or via chat agents (Rosen, 2014), which is sometimes seen as a limited medium for CPS interactions (Graesser et al., 2018; Herborn et al., 2020; Nouri et al., 2017).

The data collection for this study took place during the summer of 2022 in an educational lab at KU Leuven campus Kortrijk, in which classroom analytics can be collected (see Raes et al., 2022). The study is situated within the project Supporting Teamwork in Ambient Learning Spaces. In light of this project, a 4-hour training on CPS was designed for professionals (see Buseyne et al., 2023).

Sample

The participants in this study ($n=32$) were eight mixed-gender teams from Flemish companies active in several domains, recruited through one of the projects' partners. Availability sampling was thus used. Each team consisted of four members within the same job domain (eg, directors, recruiters, functional analysts and software developers) but taking up different roles within the team. They had been working with each other for several months to several years before voluntarily participating in the study.

Data collection

This paper focuses on data collected during one CPS activity in the training, which is framed as a selection test activity (see Buseyne et al., 2023). In this task, participating groups ($n=8$) had to solve as many problems as possible in 30 minutes. These problems addressed a wide range of abilities (eg, verbal, numerical and logical reasoning; spatial insight; detail orientation; memory). Groups were free to choose whether they wanted to allocate certain roles to the individual members during the task. During the CPS task, participants' conversations were recorded on team level using overhead microphones and computer microphones and individually per participant using headsets. In addition, video recordings were made for each of the groups using dome cameras.

Data processing methods

In contrast to earlier research (eg, Vrzakova et al., 2020), it was chosen not to use automatic speech recognition for the transcription of our verbal conversations because no available software provided good performance. This constatation is in line with research of Feng et al. (2021), pointing towards a lower automatic speech recognition performance for Flemish Dutch. In what follows, the four audio analysis methods are introduced.

Content analysis

For the first research question, content analysis was used. Participants' utterances were annotated using a computer-supported CPS coding scheme (see Annex A), which is based on Meier et al. (2007) and Sun et al. (2020). The coding scheme includes three levels: the category-level, the sub-category-level and the item-level. In line with the competency model of Sun et al. (2020), the coding scheme consists of three categories. The first category consists mainly of cognitive aspects and is defined as "establishing, constructing and maintaining shared knowledge and understanding". The second category, "negotiating and coordinating for task completion and problem solving", mainly covers task-related aspects. The third category is mainly related to team-oriented aspects and is called "maintaining team function and organization".

As part of the content analysis process, an independent data coder was trained to use the coding scheme for all data. Simultaneously, both the appointed data coder and the first author, coded one of the eight groups' transcribed data. Inter-rater reliability testing was done, to assure the reliability of the coding process. Based on Cohen's kappa (Cohen, 1960), substantial agreement was reached both for the overall item level ($\kappa=0.75$), the sub-category level ($\kappa=0.79$) and the category level ($\kappa=0.89$). In case of any doubts during the further coding process, individual cases were discussed. Next, the absolute and relative frequency of each of the categories was calculated per group and per task within the CPS activity.

Relative frequencies (on the individual level or team level) were calculated based on the total number of utterances (per individual or team). Therefore, the sum of the relative frequencies of the categories is not always equal to 100%.

Linguistic inquiry and word count

For the second and third research question, LIWC software (Pennebaker, Booth, et al., 2015; Pennebaker, Boyd, et al., 2015; van Wissen & Boot, 2017) was used to assess participants' discourse on the individual and group level, overall and per phase of the CPS task. LIWC measures taken into account in this study include word count, words per sentence and use of pronouns.

Language style matching

For the fourth research question, LSM was calculated, based on the formula as defined by Heuer et al. (2020). In line with Ireland and Pennebaker (2010), for seven selected LIWC categories (ie, personal pronouns, impersonal pronouns, articles, auxiliary verbs, common adverb, prepositions, conjunctions, negations, quantifiers), LSM scores were calculated per individual using the following formula:

$$\mathrm{LSM}_{\mathrm{Category(Individual)}} = 1 - \frac{\left|\mathrm{Category}_{\mathrm{Individual}} - \mathrm{Category}_{(\mathrm{Team-Individual})}\right|}{\mathrm{Category}_{\mathrm{Individual}} + \mathrm{Category}_{(\mathrm{Team-Individual})} + 0.0001},$$

in which $\mathrm{Category}_{\mathrm{Individual}}$ refers to the relative frequency (a percentage) of the use of a category by an individual team member during one of the tasks. $\mathrm{Category}_{(\mathrm{Team-Individual})}$ represents the average relative use of this category by the rest of the group, thus excluding the individual team member. Next, the total LSM score per individual and per task was calculating by averaging the scores for $\mathrm{LSM}_{\mathrm{Category(Individual)}}$.

Acoustic features

Next to LSM, for the fourth research question, changes in pitch were identified for the analysis of acoustic-prosodic entrainment. The individual audio recordings of the participants were reduced to the portion of interest and segmented into the different parts, based on the task within the overall activity. Pitch data was then measured for each of these task segments, using Praat software (Boersma & Weenink, 2022), resulting in time-coded pitch data for each individual per task segment, after which the average pitch per task segment for each individual could be calculated. Next, pitch difference for each individual per segment was calculated by subtracting the average group pitch of a segment ($\mathrm{MPitch}_{(\mathrm{Team})}$) from the individual pitch ($\mathrm{Pitch}_{(\mathrm{Individual})}$) and taking the absolute value of the resulting measure. This is summarized in the following formula:

$$\text{Pitch difference} = \left|\mathrm{MPitch}_{\mathrm{Individual}} - \mathrm{MPitch}_{(\mathrm{Team})}\right|.$$

Data analysis methods

In line with research questions 2b, 2c, 3b and 4b, to analyse the relationships between different measures, correlation analysis was used. More specifically, since all measures are calculated per person and for each of the problems to solve (ie, per phase), multilevel correlation was used to account for differences between persons. This was crucial when using the measures of acoustic-prosodic entrainment, based on pitch difference, since persons' pitch varies a lot.

RESULTS

The share of team functioning aspects, cognitive aspects and task-oriented aspects

Most interactions in the overall exercise are related to establishing, constructing and maintaining shared knowledge and understanding ($M=0.47$, $SD=0.02$), followed by negotiating and coordinating for task completion and problem solving ($M=0.38$, $SD=0.02$). To a smaller extent, utterances were related to maintaining team function and organization ($M=0.11$, $SD=0.03$). Interestingly, differences between teams regarding the relative frequencies of these categories are rather small (see Figure 1), as shown through the standard deviations.

Measuring distribution of participation

For research questions 2a, 2b and 2c, distribution of participation was measured through three indicators: word count, number of utterances and words per sentence. Figures 2 and 3 represent the average individuals' word count per group and the average individuals' utterances count per group. The average word count per individual is 896.78 ($SD=354.88$) and the average number of utterances is 140.97 ($SD=40.51$). Based on the visualizations, clear differences can be seen between and within certain teams. For example, word count is lower in group 5 compared to the other groups (see Figure 2). Standard deviations per team, on the other hand, show the heterogeneity in terms of quantity of participation. For example, the heterogeneity in terms of utterances count is lower in groups 1 and 2, compared to groups 7 and 8.

To further exemplify these differences in participation, the average word count and words per sentence are shown on the individual level for two of the participating teams in Figure 4. The results show a higher level of equality of participation in group 2 compared to group 8.

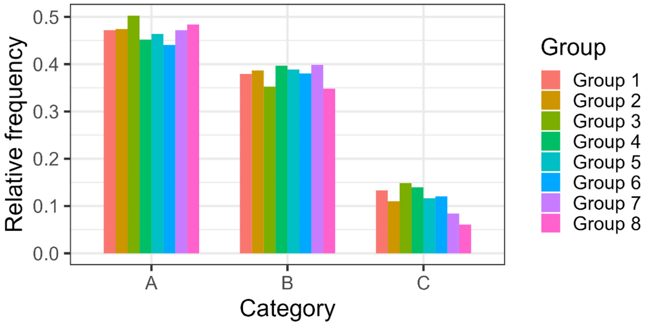

FIGURE 1 Barplots depicting the relative frequency of the main categories of the coding scheme per group. A = Establishing, constructing and maintaining shared knowledge and understanding; B = Negotiating and coordinating for task completion and problem solving; C = Maintaining team function and organization.

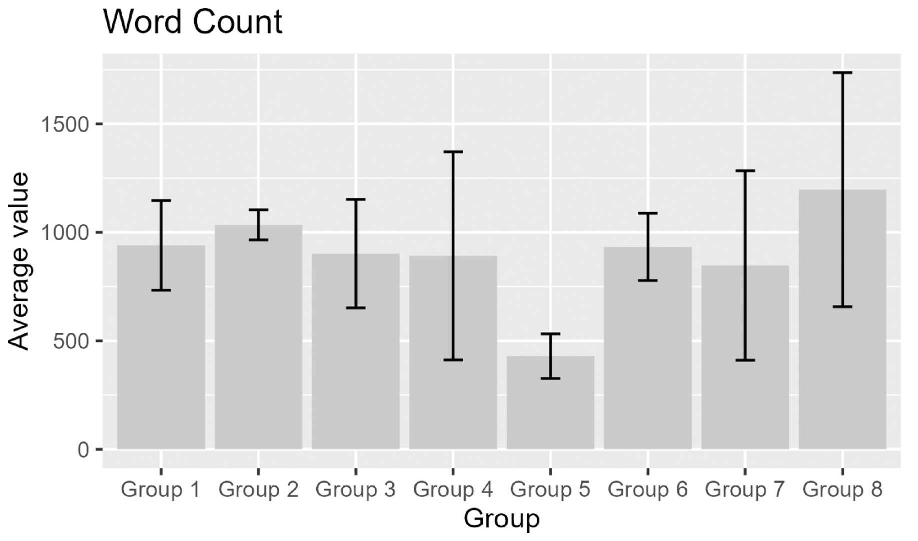

FIGURE 2 Barplot depicting the average word count per group for the individuals. Error bars show standard errors.

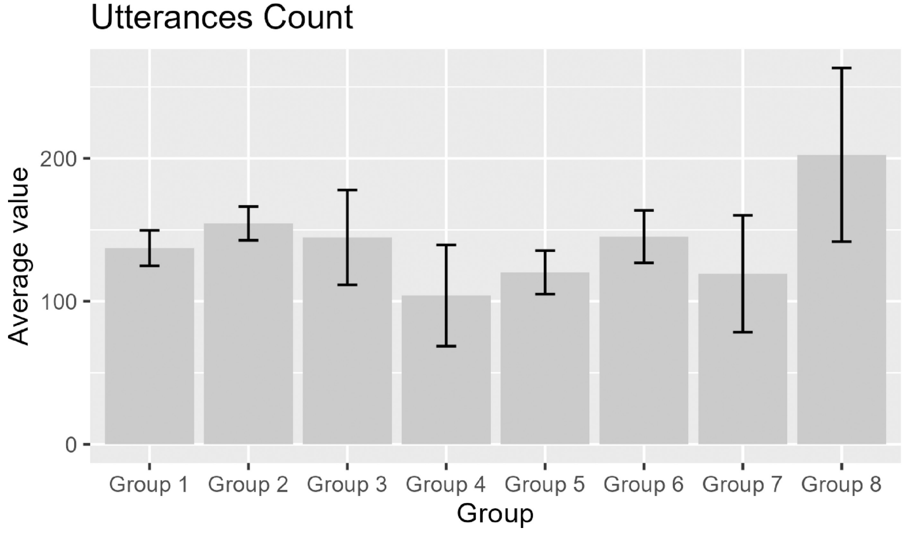

FIGURE 3 Barplot depicting the average number of utterances per group. Error bars show standard errors.

More specifically, in group 8, a great difference in participation, can be observed between Jupiter and Sphynx, based on utterances count and word count.

The average word count per sentence was also calculated using LIWC as an indicator of the length of the contribution. As discussed earlier, this is indicative of the level of detail or depth of ones' contributions. In average, the word count per sentence per individual is 5.56 (SD = 0.85). An overview of the average words per sentence per group is shown in Figure 5. The standard deviation is largest in group 7 (SD = 1.24), which means that the average length of contributions per individual is greater in this group compared to other groups.

The relationship between these variables was investigated using multilevel correlation. Data included individuals' values for each of these measures per phase. Results show that

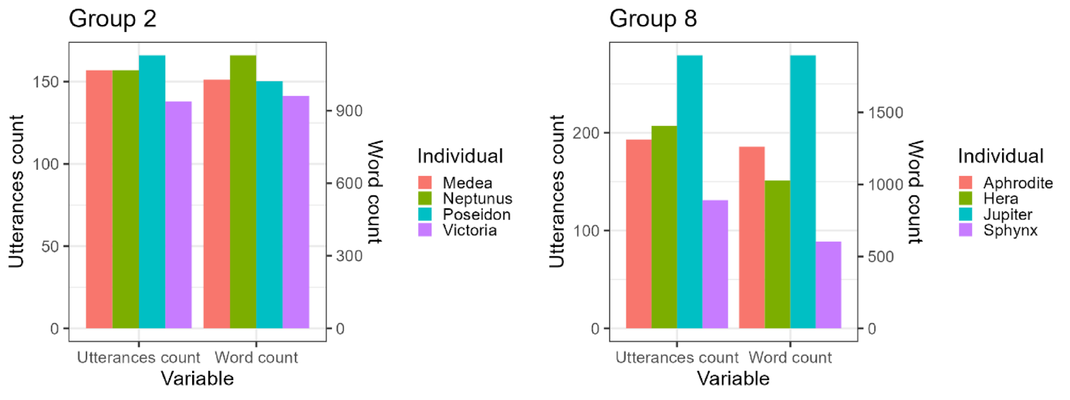

FIGURE 4 Barplots depicting the absolute word count and number of utterances per group member. Each of the plots in this figure consists of two *y*-axes.

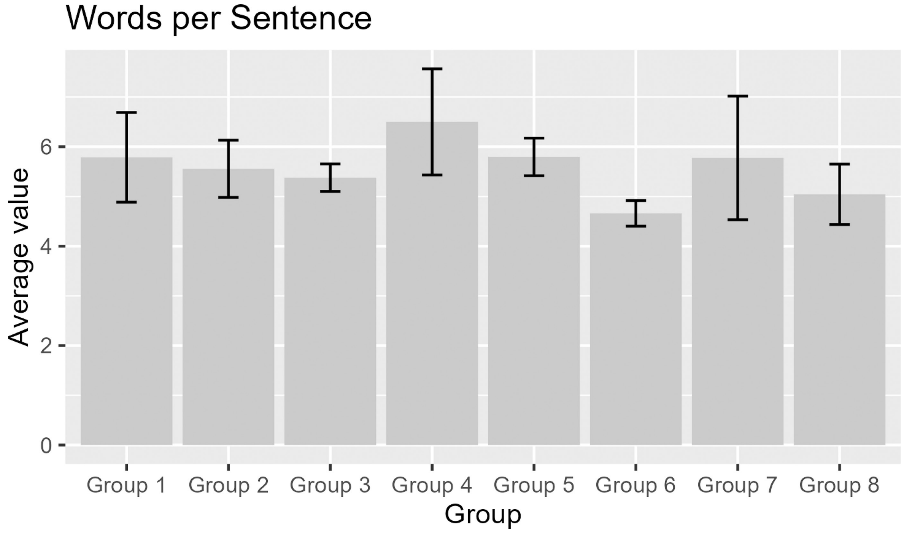

FIGURE 5 Barplot depicting the average words per sentence per group. Error bars show standard errors.

word count and the number of utterances per individual are strongly positively correlated ($r=0.79$, $p<0.001$). Looking into the relationship between words per sentence and (a) word count ($r=0.42$, $p<0.001$) and (b) number of utterances ($r=-0.15$, $p=0.028$), respectively, a rather moderate and weak correlation were found.

Personal pronoun use as an indicator of positioning and status

Regarding the personal pronoun use, in average the most frequently used personal pronoun is the first-person singular ($M=3.50$, $SD=0.41$), followed by the second person singular ($M=2.56$, $SD=0.30$) and the first-person plural ($M=2.50$, $SD=0.58$). To a smaller extent, participants used the third person singular and plural pronouns.

Within the groups, clear differences in members' personal pronoun use can be observed. This is further exemplified in Figure 6. This figure shows, for example that, in group 1, Rheia

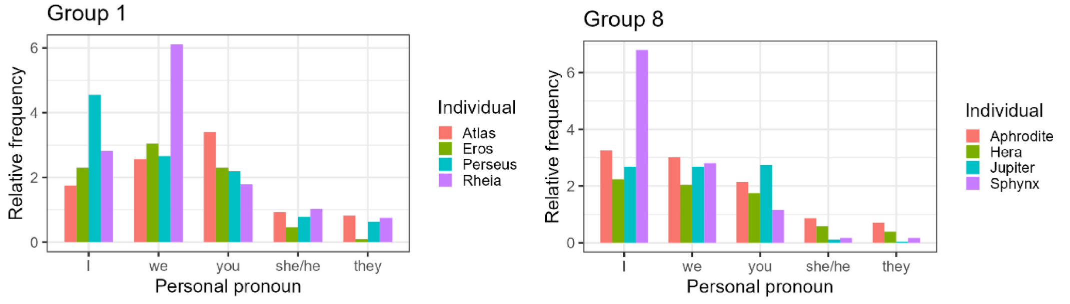

FIGURE 6 Barplots depicting the pronoun use of each member in groups 1 and 8. The relative frequency represents the use of one personal pronoun compared to the total use of personal pronouns.

seems to be more collectively oriented compared to the other group members, whilst Perseus seems to be more self-oriented than compared to the others. In group 8, Sphynx seems to be mostly self-oriented.

The relative frequency of category A was negatively correlated with the pronoun "we" ($r=-0.18$, $p=0.007$), but not significantly correlated with the pronouns "I" ($r=-0.06$, $p=0.422$), "you" ($r=0.07$, $p=0.279$) or "she/he" ($r=-0.02$, $p=0.784$).

The relative frequency of category B was positively correlated with the pronoun "we" ($r=0.23$, $p=0.001$), but negatively correlated with the pronouns "I" ($r=-0.19$, $p=0.005$) and "you" ($r=-0.06$, $p=0.365$) and not significantly correlated with "she/he" ($r=-0.01$, $p=0.855$).

The relative frequency of category C showed no significant correlation with the pronoun "we" ($r=0.02$, $p=0.729$), but was positively correlated with "I" ($r=0.32$, $p<0.001$) and not significantly correlated with "you" ($r=-0.02$, $p=0.742$), and was positively correlated with "she/he" ($r=0.15$, $p=0.030$).

Lexical and acoustic-prosodic entrainment during the CPS exercise

The average overall trend of the LSM over the first six phases, for all of the participants, is shown in Figure 7. To see what trend can be observed for the lexical entrainment, a linear mixed model was used to assess the relationship between task and LSM, while accounting for the differences between participants. Results show that, in average, participants had lower LSM scores in Task 4 ($B=-0.08$, $SE=0.02$, $t=-3.47$, $p<0.001$) and Task 5 ($B=-0.05$, $SE=0.02$, $t=-2.05$, $p=0.042$) compared to Task 1. No other LSM scores were significantly different between Task 1 and the other remaining task.

A linear mixed model was fitted to investigate whether participants' pitch difference, the difference between the average pitch per group and a member's pitch, significantly differed over the phases. Results show that the pitch difference in Task 4 ($B=-3.45$, $SE=1.54$, $t=-2.24$, $p=0.027$), Task 5 ($B=-4.83$, $SE=1.54$, $t=-3.13$, $p=0.002$), Task 6 ($B=-4.63$, $SE=1.61$, $t=-2.88$, $p=0.004$) and Task 7 ($B=-5.45$, $SE=1.94$, $t=-2.81$, $p=0.006$) is significantly lower compared to Task 1, indicating a downward trend. The other tasks did not significantly differ from the reference task.

Next, to assess the relationship between lexical entrainment and acoustic-prosodic entrainment, multilevel correlation was used. Adjusting for the individual factor, a rather weak positive correlation between LSM and the absolute pitch difference was found ($r=0.24$, $p<0.001$).

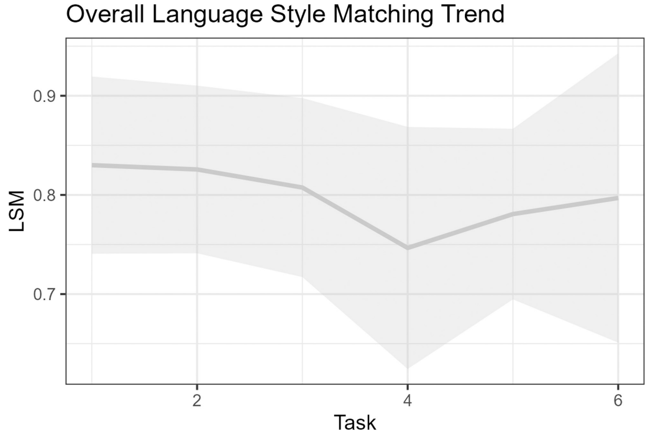

FIGURE 7 Graph depicting the LSM trend.

DISCUSSION

This study explores the use of verbal and non-verbal data modalities, specifically content analysis, LIWC-based semi-automatic analysis, LSM and acoustic data analysis. The first research question aimed to explore the relative share of different aspects of team communication during group performances in CPS. Building on previous research (Staarman et al., 2005; Sun et al., 2020) that highlighted the low presence of team functioning aspects in team members' discourse within CPS, the study hypothesized that there would be fewer utterances related to team functioning aspects compared to cognitive and task-oriented aspects. The results of this study support this hypothesis. In addition, it was found that, overall, the relative frequencies of the types of interactions were relatively consistent across different teams. The relatively low frequency of utterances related to maintaining team function and organization could indicate that team members give only limited attention to team dynamics and task division, although previous research has claimed the importance of social regulation for effective team functioning (Kreijns et al., 2002). This could have implications for teams' efficiency.

Second, earlier research indicated the importance of equality of participation for the quality of CPS group behaviour (eg, Baltzersen, 2022). However, there was unclarity on how this could best be measured. Therefore, the second research question aimed at exploring three measures of proportion of contribution in CPS (ie, including word count, words per sentence and number of utterances) and investigating the relationships among them. Clear differences in participation patterns both between and within certain teams were identified. Our findings suggest that team members differed in their levels of engagement and contribution during the exercise (Tausczik & Pennebaker, 2010), which may have implications for team performance and outcomes (Fransen et al., 2013; Weinberger & Fischer, 2006). Next, our findings showed that team members who contributed more in terms of word count also tended to have more utterances. Team members who contributed more in terms of word count tended to have longer contributions in terms of words per sentence. However, the relationship between words per sentence and number of utterances was weak and negative, indicating that team members who had longer contributions in terms of words per sentence tended to have little less utterances. This result supports earlier research, identifying words per sentence as an indicator of the depth of one's contributions (Tausczik & Pennebaker, 2010), which is rather distinct compared to the other two quantifiers (ie, word count and utterances count). Based on these results, it could be argued that the most valuable insights for the quantity and equality of participation could be drawn from a combination of utterances count and words per sentence.

Third, earlier research suggests that personal pronoun use can serve as an indicator of how individuals position themselves towards other individuals and the group as a whole during group interactions (Tausczik & Pennebaker, 2010). The third research question therefore aimed at exploring pronoun use during the CPS interactions. Our results indicate that the most frequently used personal pronouns were the first-person singular, followed by the second-person singular and the first-person plural pronouns which was hypothesized based on previous research (Atabek & Yildiz, 2010). In some of the groups, clear differences between participants could be identified regarding the use of the first person singular pronoun and the first person plural pronoun. Furthermore, the results demonstrated a relationship between personal pronoun use and the relative frequency of interactions. Specifically, when individuals used more first-person plural pronouns, they seemed to be less focused on the cognitive aspects of CPS discourse and there was higher focus on task-oriented aspects in their CPS discourse. When individuals used more first-person singular pronouns, there was less focus on task-oriented aspects and more focus on team functioning aspects in their CPS discourse. These findings suggest that the pronoun use of a person is to some extent related to the types of CPS interactions being made.

Fourth, looking into the evolution of lexical and acoustic–prosodic entrainment, as measured with LSM and pitch difference, throughout the CPS task, significant differences were identified. Overall, there was no clear upward or downward trend for LSM, but the LSM value was significantly lower in two of the phases. This could be due to the nature of the exercises in these phases, including, among others, verbal reasoning. For pitch difference, on the other hand, an overall decreasing trend was identified, meaning that, as the CPS task evolved, people converged in terms of acoustic–prosodic entrainment. Next, as hypothesized, a rather weak relationship was found between the two entrainment measures. This suggests that lexical entrainment and acoustic–prosodic entrainment are indicative of unrelated aspects of the social interactions in CPS processes.

In conclusion, the results presented, and the methods used in this paper, provide innovative ways and insights for mapping group dynamic processes in CPS. These findings have implications for informing the design of learning scenarios. Specifically, given the limited presence of team-related interactions in CPS, the integration of supporting roles, also known as group-building roles (Mudrack & Farrell, 1995), into CPS learning scripts could elicit interactions pertaining to team function and organization. Furthermore, other types of learning and teaching support could be designed using the learning analytics described in this study. These types of support could include the use of dashboards to aid in detecting and interpreting the quality of students' interactions. For example, Stewart et al. (2023) describe how intelligent CPS feedback can be given to students focusing on different types of interactions. An earlier example is the reflect table, described by Bachour et al. (2008), which focuses on the quantity of participation. Several levels of aid exist, to which van Leeuwen et al. (2019) refer to as mirroring, alerting and advising. Mirroring allows the teacher to review information independently, alerting provides notifications or categorizations for groups that require attention and advising offers additional guidance for interpreting the alerted information. Yet, it was not within the scope of this study to research on which level the support to teachers and learners should best be provided. More research is needed to make the incorporation of such data sources in learning dashboards meaningful to these stakeholders.

In addition, further research on MMLA of verbal interactions in CPS could, for example, investigate how the measures used in this study relate to task outcomes or the perceived quality of collaboration of the learners. Next, it could be further identified how learners' personalities or roles within the team relate to their interactional behaviour in CPS contexts. For example, it could be assessed whether someone who is perceived as a leader in a team has distinct interactional patterns (eg, through pronoun use). This is partially in line with earlier research of Dowell et al. (2019), who designed a framework for group communication analysis. Their work offers educational stakeholders a scalable and domain-independent approach to examine the construction and maintenance of roles in CPS interactions, focusing on the dynamic sociocognitive processes involved (Dowell et al., 2020). Next to the measures used in the current study, additional measures could be taken into account, focusing more particularly on the semantic content of learners' interactions. Furthermore, to enable the use of these data sources, research should invest in automatic speech recognition and (semi-)automatic content analysis across contexts and languages. Especially in our Flemish research context, automatic speech recognition is underdeveloped.

Several limitations of this research should be pointed out. First, many of the measures are dependent on the quality of transcriptions. Although manual transcription has been shown to reduce word error rates, some errors may still be present. Similarly, the coding was not done automatically, which could influence the obtained results. Second, the data set used is limited and is related to one specific CPS context, with participants selected through availability sampling. More specifically, this research solely focused on adult learners in professional settings and does, for example, not take into account students in K12 or higher education. Third, the selected problems in the CPS task used for the data collection needed to be suitable for learners from multiple backgrounds. This may not fully capture the complexity and dynamics of real-life CPS scenarios related to peoples' professions or education and it may not fully reflect participants' natural communication patterns. These limitations have an influence on the generalizability of the results. In response, it is advisable to replicate this study in multiple contexts (eg, cultures, professions and age groups), both with homogenous and heterogeneous groups, in terms of, for example, educational backgrounds.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to disclose.

DATA AVAILABILITY STATEMENT

Research data are not shared.

ETHICS STATEMENT

This study received ethical approval from the Ethical Committee of KU Leuven (G-2022-5202).

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ANNEX A

CODING SCHEME FOR COMPUTER-SUPPORTED COLLABORATIVE PROBLEM-SOLVING CONTENT ANALYSIS

Category	Sub-category	Item
A: Establishing, constructing and maintaining shared knowledge and understanding	A1: Sharing knowledge and understanding of problems and solutions	Proposing appropriate solutions or introducing new appropriate information related to the problem Talking about givens and constraints of a specific task Building on others' ideas to improve solutions
	A2: Establishing common ground	Asking for further clarification Giving feedback on the understanding of what the other is saying and asking questions Eliciting feedback from the one who is listening Clarifying any information needs and responding to questions Evoking turn taking by means of explicit handovers Repairing misunderstandings
B: Negotiating and coordinating for task completion and problem solving	B1: Responding to others' ideas or proposed solutions	Providing reasons to support a potential solution Questioning, correcting or pointing out others' mistakes Confirming to support a potential solution
	B2: Monitoring execution	Talking about or discussing the results
	B3: Time management	Monitoring time
	B4: Technical coordination	Using the technical tools
	B5: Discussing strategies	Discussing the general group strategies
C: Maintaining team function and organization	C1: Taking initiatives to advance collaboration processes	Asking if others have suggestions Asking to take action before anyone on the team asks for help Complimenting or encouraging others Apologizing for one's mistake(s) Proposing to ask or asking for help outside of the group
	C2: Coordinating task division	Defining (sub-)tasks and talking about the adoption of these tasks