Can Analytics of Speaking Time Serve as Indicators of Effective Team Communication and Collaboration?

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ABSTRACT

People with effective teamwork skills, such as collaboration or leadership, are highly demanded in the workplace. In turn, educational providers have adopted active learning methodologies, such as collaborative problem-solving. However, the objective evaluation of collaboration at scale still is a challenge. This paper explores the relationship between quantitative measures obtained from automated transcriptions of speech and qualitative indicators of effective collaboration. An omnidirectional microphone and an artificial intelligence algorithm were used to collect speaking data from 20 triads of students discussing and building a concept map. The study focused on validating the potential value of speech recording devices to quantify the dynamics of communication networks by comparing quantitative metrics obtained from them with an established rating scheme for measuring the extent of collaboration. Results showed a relationship between the standard deviations of the speaking times of the participants in each group and the evaluation obtained from the qualitative rubrics of communication and interpersonal relationships. Thus, the extent to which all group members contribute to the discourse can potentially serve as an indicator of effective group work.

CCS CONCEPTS

• **Applied computing** → **Collaborative learning**; • **Human-centered computing** → **Collaborative and social computing**.

KEYWORDS

multimodal, learning analytics, teamwork, collaboration analytics, CSCL

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1 INTRODUCTION AND RELATED WORK

Professionals with effective teamwork skills, such as collaboration or leadership, are highly demanded in the workplace [14]. For this reason, educational institutions have adopted active learning methodologies, such as collaborative learning and team-based problem solving [11]. However, the objective evaluation of collaboration at scale still is a challenge, especially in face-to-face, domain-specific situations [9]. Collaborative learning supported by new emerging technologies facilitates the design of collaborative activities, in addition to collecting relevant information that allows determining whether a group is collaborating efficiently [1]. Previous work has investigated how simple measurements of symmetry (i.e., the Gini index) of speech events [5, 7] and turn-taking patterns [6] can be used as a potential indicator of effective collaboration in an experimental group setting. More recently, Noel et al. [10] investigated the application of metrics based on social network analysis (permanence and prompting) to identify potential relationships with the performance of groups in a collaborative writing task. Other researchers have considered the speaking time, along with other digital traces of activity, as potential metrics of different qualities of collaboration [e.g., 2, 12, 13].

The closest work to ours was performed by D'Angelo et al. [3] who performed a semi-automated analysis of low-level features from speech data and related them with high-level indicators of quality of collaboration. However, although the works presented above aimed at automating the analysis of speech data (at least to some extent), the authors did not compare such data with any established score of collaborative learning.

In this paper, we explore the relationship between quantitative measures obtained from automated transcriptions of speech and qualitative indicators of effective collaboration according to a well-established rating scheme to assess the quality of collaborative learning [8]. An omnidirectional microphone and an artificial intelligence algorithm to perform automated speaker detection and transcription were used to collect speech data (verbal interactions and speaking times) from 20 triads of university students discussing and building a concept map about a nutrition topic at an interactive tabletop. The rating score by Meier et al. [8] was applied to assess the quality of collaboration of the groups.

2 STUDY

This study delves into the data collected in [4]. In the original study, 60 undergraduate engineering and science students at an Australian university had to answer the question, "What kinds of foods should we eat to have a balanced diet?" Students were required to create concept maps after studying the Australian Dietary Guidelines. First, each student developed a concept map individually, using an interactive multi-touch digital tabletop and the Cmate application (see Figure 1). Then, they were asked to carry out the same activity but in trios. For our research, we consider the data collected from the 20 collaborative groups.

Each group session lasted around 30 minutes and was video recorded. Each interactive tabletop was augmented with an omnidirectional microphone, which can enable speaker identification. The audio signals were then pre-processed using the Otter.ai[1] web application to perform an automatic transcription.

Although in this paper we do not report on the content of the conversation, this step enabled to obtain the fine-grained information about the duration of the speech interventions by each group member. In sum, the dataset included information about the speaking time and the number of interventions that each student performed, in addition to the moments of silence. Figure 2 (left) illustrates an example utterance by Participant 1 of Group 1 at the beginning of their session and (right) the exact duration of that intervention as processed by Otter.ai.

3 ANALYSIS AND RESULTS

3.1 Qualitative analysis

The video recordings of the 20 groups were evaluated based on the 8 rubric items in the rating scheme for assessing the quality of computer-supported collaboration processes [8]. Each rubric item is measured with a number ranging from -2 (very poor) to 2 (very good). These items, enumerated from 1 to 8, quantify different dimensions of the collaborative process, including quality of communication (items 1 and 2), joint information processing (3 and 4), group coordination (5, 6, and 7), and interpersonal relationships (8). More specifically, item 1 (*mutual understanding*) assesses if individuals made understandable contributions, avoiding incomprehensible technicalities; and if listeners focused their attention on what other speakers were saying saying, giving verbal feedback. Item 2 (*dialogue management*) assesses if time was not wasted on assumptions or confusion. Item 3 (*information sharing*) assesses if the group members collected the most information for the solution. Item 4 (*reaching consensus*) evaluates the ability to make collective decisions between different alternatives to achieve the final solution. Item 5 (*tasks division*) assesses whether group members carried out their tasks in a systematic way. Rubric 6 (*time management*) evaluates how the group members controlled the time of their interventions. Rubric 7 (*technical coordination*) assesses whether individuals mastered basic technical skills to use the tools to their advantage. Item 8 (*reciprocal interaction*) assesses how individuals encouraged each other to contribute with their opinions and perspectives. The qualitative assessments were performed by two investigators independently, following the scoring scheme. After this, they met to discuss disagreements and agree a mutual assessment for each of the groups. The first eight columns of Table 1 present the results from this assessment.

3.2 Quantitative analysis

From the information collected in the previous step, we can identify the following metrics: speaking time, number of interventions and silences time. From those, we used speaking time for our experiment as this metric was already used and explored in a previous investigation (see [10]). The last six columns of Table 1 show the speaking times performed by the users, and the following statistical measures: mean, median, and standard deviation. In what follows, we focus on the statistics and rubrics that deliver the most significant findings, namely, the standard deviation of speaking time and rubrics R1 and R8.

3.3 Correlation analysis and results

Table 1 shows a correlational analysis of the variables. To guarantee the multivariate normality required by the coefficient, the Henze-Zirkler (hz) test was applied. The main findings were obtained for the standard deviation of the speaking time of the groups (SD) and the evaluations of rubrics 1 (R1) and 8 (R8). The variables SD and R1 have a normal distribution, with a value $hz = 0.694$, p-value < 0.1; for SD and R8, normality is also observed, with $hz = 0.633$, p-value < 0.1. Hence, we apply the Pearson correlation coefficient (ρ). As a result, a high inverse correlation was found between R1 (maintaining mutual understanding) and SD ($\rho = -0.87$, p-value < 0.001). The above means that the greater the similarity in the conversation times of the participants, the greater their mutual understanding. Also, an inverse correlation was found between R8 (reciprocal interaction) and SD ($\rho = -0.6$, p-value < 0.01). Similarly, the greater the similarity in the conversation times between the students, the greater the reciprocity in their interactions.

4 DISCUSSION AND CONCLUDING REMARKS

The automated analysis of speech data can complement qualitative studies focused on the evaluation of group work and effective communication. Some statistically significant results were obtained from the analysis of correlation between the quantitative and qualitative indicators of speaking time and collaboration, respectively. The importance of using equitable speaking time in collaborative activities is highlighted. However, it is important to point out that equitable speaking must be coherent to the discussion topic. This group behavior can enable equal participation in the generation of knowledge and in the search for solutions. In addition, the rubric item makes the contributions understandable by the users of each

[1] https://otter.ai/

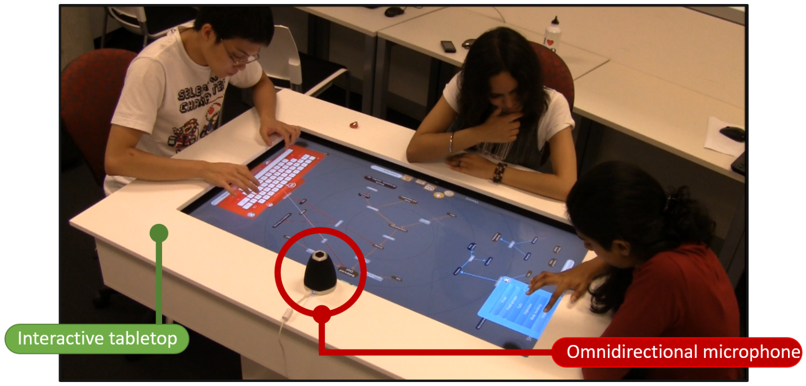

Figure 1: Example utterance by one participant (P1) in Group 1

Figure 2: Example utterance by one participant (P1) in Group 1

Table 1: Comparative table of qualitative and quantitative variables

	Group rubrics items evaluation								speaking time					
Group	R1	R2	R3	R4	R5	R6	R7	R8	User 1 [s]	User 2 [s]	User 3 [s]	Average	Median	SD
1	2	2	2	2	-1	0	1	2	289.50	209.7	345.9	281.70	289.50	68.43
2	2	1	0	0	1	2	0	1	314.40	405.0	317.7	345.70	317.70	51.38
3	0	1	0	-1	-1	-2	-2	-2	585.80	186.0	483.8	418.53	483.80	207.74
4	0	0	-1	0	-1	-2	-1	-1	516.60	96.9	567.2	393.57	516.60	258.16
5	2	2	1	1	2	2	1	1	180.80	515.3	263.3	319.80	263.30	174.26
6	1	1	2	0	1	-2	-1	-1	203.10	160.3	728.8	364.07	203.10	316.59
7	2	1	1	0	-1	1	-2	-1	277.80	370.5	233.2	293.83	277.80	70.04
8	2	1	1	-2	0	-2	-2	1	249.57	157.5	460.5	289.19	249.57	155.34
9	-1	1	1	1	1	-2	0	-2	33.60	262.5	722.9	339.67	262.50	351.07
10	2	2	2	2	0	2	1	-1	334.00	407.6	369.2	370.27	369.20	36.81
11	2	-1	2	2	2	-1	2	1	280.60	335.3	538.2	384.70	335.30	135.72
12	0	0	0	-2	1	-1	-1	-2	324.00	281.3	577.9	394.40	324.00	160.34
13	-1	-1	1	0	-1	1	-1	-2	759.40	108.7	352.5	406.87	352.50	328.74
14	2	2	2	2	1	1	2	1	365.00	245.0	471.1	360.37	365.00	113.12
15	-2	0	0	-2	-1	0	0	-1	221.00	870.3	108.1	399.80	221.00	411.36
16	2	1	1	2	1	1	2	1	421.70	315.4	340.3	359.13	340.30	55.60
17	0	0	-1	0	-1	0	-2	0	484.10	347.8	109.1	313.67	347.80	189.82
18	1	2	2	1	-1	-1	-2	-1	732.70	343.0	417.8	497.83	417.80	206.81
19	2	2	2	2	2	2	1	1	448.30	415.5	327.8	397.20	415.50	62.30
20	1	1	1	1	-1	2	-1	-1	621.20	225.3	402.6	416.37	402.60	198.31

group. Finally, this study allows a first internal validation of speech recording devices as useful tools to quantify the dynamics of communication networks. This kind of tool has been used to develop multimodal prototypes. However, it had not been tested with an established rating collaboration scheme [10, 15].

As future work, it is expected to expand the correlational analysis of variables, using other centrality measures based on the number of interactions between participants and also consider the content of the conversations. For the development of more inferential explanatory methods, however, additional analytical techniques are required.

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