Mirroring Participation Level During Joint Problem Solving: An Adaptive Approach To Scaffold Collaboration Within Online Groups

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Abstract. This paper presents the findings of a study which explores supporting collaboration within online groups, during Joint problem solving (JPS) activities. We investigated the effect of mirroring the participation level of individual members, on their group's collaboration. We explored existing work in adaptive support for collaboration and the theoretical perspective about the effect of self-performance reflection to improve the performance. Using a controlled experiment, we studied the JPS process of 10 groups (4 members in each group); 5 groups interacted using an adaptive interface (i.e. with mirror of participation level), while the other 5 groups interacted via a non-adaptive interface (i.e. without participation level mirror), in a text-based chat-room for online group interaction. We made a qualitative assessment of the groups discourse and a quantitative analysis to investigate significant differences between the experimental conditions i.e. adaptive versus non-adaptive, using ANOVA. Our findings show that a real-time mirror of individuals' participation improves group collaboration, during JPS.

Keywords: Mirroring · participation level · collaboration level · adaptive support.

1 Introduction and related work

The cognitive benefits of group learning have been well researched [29,16,19,22,27] and literature has established that it helps learners to articulate and construct new knowledge through arguments and coordination during joint problem solving (JPS). In traditional classrooms, group learners benefit from the physical presence of an instructor that manages and guides collaboration during the teamwork; this advantage is not available to online groups.

One of the principal objectives of Computer Supported Collaborative Learning (CSCL) research is to incorporate group learning and its benefits for distance education over the web, in such a way that online groups are supported to have experiences that are similar to what exists for face-to-face groups [10,26]. Findings in existing studies posited that an *effective and efficient system adaptation*, and an *"unobtrusive"* intervention of a remote teacher or a computer agent can provide this kind of support and scaffold collaboration within an online group [17].

Collaboration itself, in the context of learning, is theoretically rooted in *Vygotskys work* and Piagets constructivist idea about "social field"; it was argued that the interaction, shared understanding and joint problem solving (JPS) activities during teamwork propagates cognition. These theoretical conjectures, formed the basis for CSCL research, to pursue leveraging the ubiquity of computing technology to support the *social* and *constructive* element of group learning. Aside the goal to provide an environment that enables group interaction, research in CSCL is also tasked to capture and model group activities, to monitor and determine support needs, and provide efficient and effective support that can optimize collaboration and maximize learning during JPS [17].

1.1 Adaptive support for collaboration

In early work on adaptive support for education via computer supported environments, *adaptive educational systems (AES)* were conceptualized, to adapt key features of a learning system (e.g. *content presentation* or *navigation support*) to suit an individual's need; similarly *intelligent tutoring systems (ITS)* were conceived to individualize support to learners, through an agent model of a teacher in computer based problem solving [10,17].

Most studies on *AES* and *ITS* targeted helping an individual learner in a computer supported environment. Incipient studies on adaptation for group learning environments emerges later in literature. A succinct review of some of the existing studies, with respect to the concepts explored and a summary of their findings are presented in Table 1.

We found that the *adaptive intervention* proposed by most of the studies was based on a *user profile* or/and *data of users' interaction/activities* within the group environment; the adaptation decisions aimed to change the system environment to suit users' (individual or group) preferences or to inform an instructor (agent/remote human) about the most suitable intervention for the current user (or group).

The approach in this study is to *mirror the participation level* of members within the group in real-time back to the group during a joint problem solving discussion. We hypothesize that this reflection will stimulate positive participatory behaviour that can improve interaction within the group. This proposition is in accord with Soller's [26] position, that *reflection of the information about individuals' participation in a JPS*, can significantly influence (stimulate) a positive attitude towards the joint task and in turn scaffold collaboration.

1.2 Theoretical Perspective and Study Justification

Performance feedback (Mirroring) is connected to *"social cognitive theory and self-regulated learning behaviour"* [24], which argues that reflection about learners' capabilities can positively influence their behaviour in a learning process/context. According to Schunk [24] (as depicted in Figure 1), *human functioning* involves a two-way interaction between *behaviour change*, *environmental variables* and *cognition*; with cognition including the awareness of their performance level.

Table 1: Relate work: Adaptive support for group learning.

Literature	Adaptation, method/mechanism & aim	Adaptation effect metric
Tsovaltzi et al. [28]	Prompts and scaffolds using *collaboration scripts*, to guide students to collaborate in a virtual chemistry laboratory.	* Feedback from participant, * Speed and efficiency of solving learning task (between *scripted* & *unscripted* groups of two member learners).
Chen [11]	* Agent-based monitor and visualization of collaborative process based on contribution messages and update on learners *webTop* which in-turn update the *knowledge building module*. * The aim was to provide an adaptive rule-based update on *knowledge building module* to provide automated, effective and efficient intervention that will aid the groups' collaboration	Feedback from teachers versus agents' performance as regards effectiveness and efficiency of intervention to groups
Marcos-Garca et al. [18]	* Interaction analysis with *Role-AdaptIA* using social network analysis method, to characterize and detect changes in learners' role in during JPS. The aim was to inform teachers about emergence of roles and undesired interaction patterns, to aid regulation and support to JPS process within a computer supported learning groups	Qualitative comparison social representation of groups before and after teachers' intervention
Adamson et al. [2]	* Conversational agent is employed to instill adaptive scaffolding of collaboration within online an online group, * this approach termed *"Academically productive Talk" (APT)* provides a generic prompt to encourage learners to articulate and expand their line of reasoning, * the agent provide positive feedback to learners when they apply APT facilitation moves in their interaction during JPS	* ANOVA measure of learning between pre- and post-test, - measure of this learning as it differs between conditions using ANCOVA, * process analysis to measure improvement in interaction with APT intervention
Rumetshofer & W [21]	* User-centric approach to improve usability and acceptance, * Integrating psychological factor into the system, transforming general object into personalized learning object based on user profile and adaptation rules. * system layout and navigation is also adapted to learners' preference	

Self-awareness of one's performance can encourage actions to attain a "designated performance level", influence achievement behaviour, "persistence, effort expenditure and skill acquisition" [24]. Feedback on a learner's performance level can provide the motivation for continued learning [7].

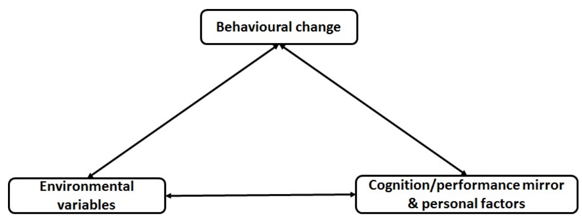


Fig. 1: Human functioning as reciprocal interactions between behaviors, environmental variables, and cognition/reflection about performance and other personal factors [24]

An *agentic socio-cognitive view* perceives an individual as proactive, self-reflecting and self-regulating, rather than as "an organism shaped and shepherded only by external events" [8] (such as a prompt, scripted interaction, agent-teacher intervention, or change in system environment), as considered in existing studies on adaptive group learning systems [2,11,18,21,28].

It is hypothesised in[13] that humans are driven to evaluate their own "opinion and ability; that a person's cognition or reflection about the context in which he exists and his appraisal of what he is capable of doing will together have bearing on his behaviour" [13]. Also, the measure of individuals' participation levels based on a relative comparison within the groups [5,4] is corroborated by Festinger's [13] hypothesis, that, in a social context, reflection on self-performance is in comparison with the performance of others within the context.

1.3 Mirroring participation to scaffold collaboration

DiMicco & Bender [12] investigated the effect of the awareness of participation activities on the goal(s) of JPS; real-time feedback on individual participation was provided during JPS discussion and its effect was evaluated through participants' self-report, as regards to how well the *provided feedback* has informed, stimulated or regulated their activity during the meetings.

Similarly, Janssen et al. [14] studied the impact of *visualizing participation level* on the collaboration within computer supported learning groups; they showed that there is evidence of a positive effect on collaboration, when the participation level of members is reflected back to them.

In this study, we extend the previous investigations [12,14] about the effect of *the mirroring of participation level* on collaboration. First, we study online groups that interact via a text-based environment, rather than face-to-face verbal interaction as studied in [12]. Also, we evaluate this effect through a controlled experiment (*with* versus *without* the *mirroring of participation*), rather than judging it from the perception of participants as in [12]. Our study resembles the study in [14]. Our proposed *mirror of participation level* is based on the same aspects of participation as their *participation tool* [14]. The difference is with the visualization perspective; we used *bar-charts* instead of the *network-like spheres* representation used in [14] (see Figure 2).

In a deeper contextual comparison, the participation level measure in this study is based on the *Word-count/Gini-coefficient measure of symmetry* (WC/GCMS); a metric model presented in Adeniran et al. [5] that evaluates individual's participation/group collaboration based on textual discourse. The *WC* component of the *WC/GCMS* model computes individuals' participation level; a relative measure within the group. *WC* combines the *number of learner contributions* (synonymous to the *distance of each sphere from the center* in [14]) and the *length/word-count* of each contribution [5] (synonymous to the *size of the sphere* in [14]) to compute the level of participation within a text-based group discourse. This feature is a modification of the *participation tool* in Janssen et al. [14], to present a more compact *feedback on participation level* that is easier to interpret and presumably more effective in context (see the chat-room interface illustrated in Figure 5).

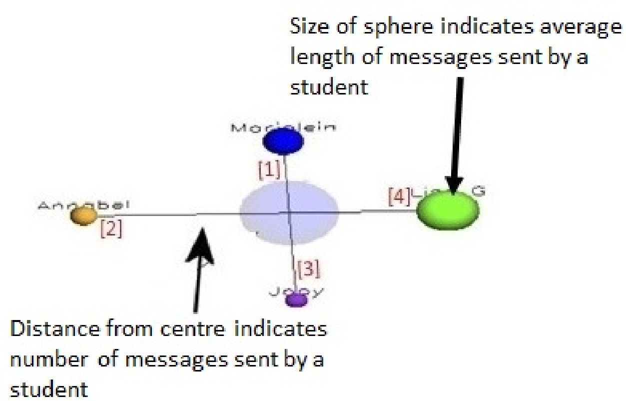


Fig. 2: Janssen et al's visualisation of learners' participation within a group [14]

Furthermore, the *mirroring mechanism* that we propose is this study is *unobtrusive*. While the group interacts via a joint problem solving discourse (JPSD) chat-room presented in [5], this chat-room is enhanced to provide seamless feedback of *the participation level* within each group at a regular interval (see Figure 5). Participants do not need to "zoom the participation tool" in order to view *their own* or *an other member's* participation level during the JPS, as designed in Janssen et al. [14].

Also, the JPSD chat-room is designed such that *feedback* is limited to the *within-group* view, the extended inter-group view (see Figure 3) in Janssen et al. [14] is considered extraneous and will increase the *cognitive load* demand for the JPS [15,23]. Our ***within-group*** *mirror of participation level* is sufficient and efficient for our investigation as we aim to scaffold collaboration within *autonomous* groups.

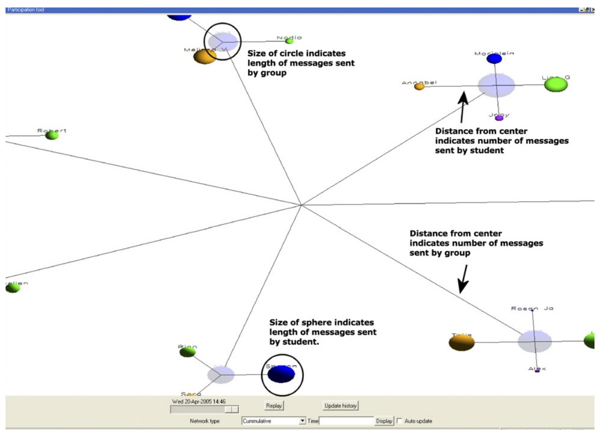


Fig. 3: Measure of learner's participation extended view between groups [14]

Considering the differences with related work discussed, we extend the context and modify the collaboration feedback mechanisms that exist to explore *online group* interaction, via the JPSD chat-room, to address the following research question:

Research question: Can the *mirror of members' participation level* as provided by the JPSD chat-room [5] (see Figure 5) stimulate participatory activities within groups and scaffold collaboration during JPS?

The exact hypothesis is explained in the Results section, as it is easier to explain the concepts in it using the data from the study.

In the remainder of this paper, we discuss the study design and procedure, visualization, observation and analysis of group JPS activity data (i.e. textual discourse of groups) and a summative evaluation [20] of the effect of *mirroring participation level* within online-groups, during JPS.

2 Conceptual Framework and Study Design

Our framework for investigating and characterizing interactive activity within online-groups and the adaptive approach we conceive to support collaboration is illustrated in layers [9,20], as shown in Figure 6. *Layer 1.1* captures JPS

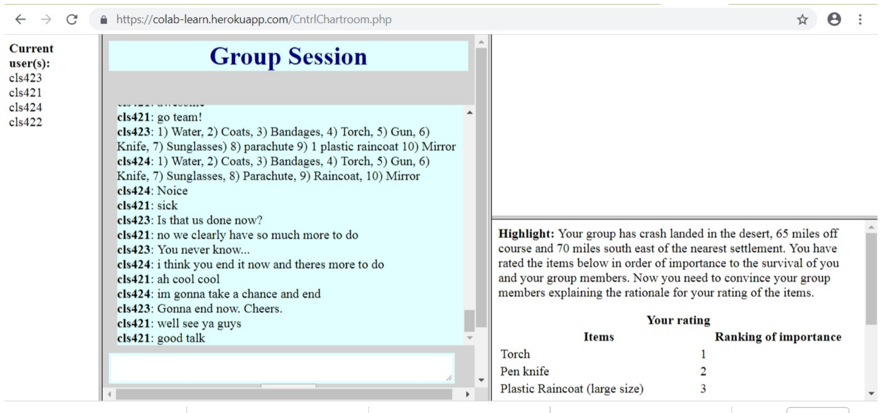


Fig. 4: Control groups' non-adaptive JPSD chat-room interface

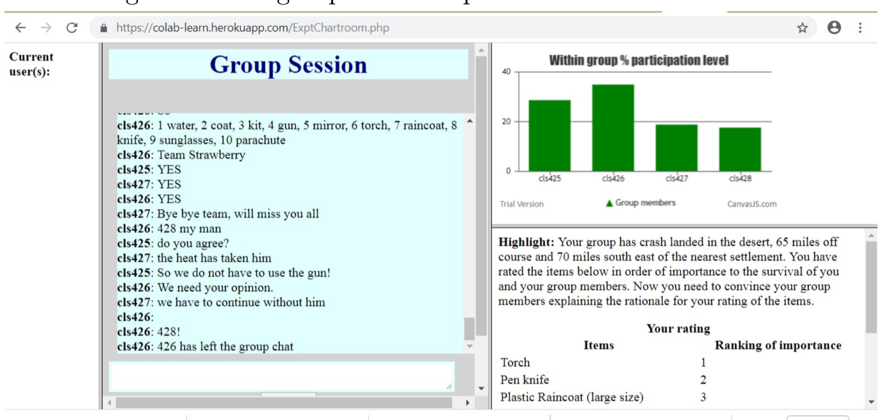


Fig. 5: Experiment groups' adaptive JPSD chat-room interface

activities that indicate and inform the measure of collaboration [3,6], *layer 1.2* takes its input from *layer 1.1* (i.e. indicators of collaboration) and applies partly the WC/GCMS metrics [5,4] to compute the within-group participation levels, and *layer 1.3* computes the between-group collaboration level with WC/GCMS, the *between-groups* comparison is visualized as shown in Figure 7b.

Our *adaptive decision* [9,20] is illustrated by *layer 2* in Figure 6, the feedback path *reflects the level of participation* (output from *layer 1.2*) back to participants in real-time during JPS; this is a design enhancement to the JPSD chat-room discussed in Adeniran et al. [5] (See Figure 5). The goal of this study is to show that this feedback path positively stimulates participation and hence aids collaboration (output from *layer 1.3* in Figure 6) within the groups during JPS.

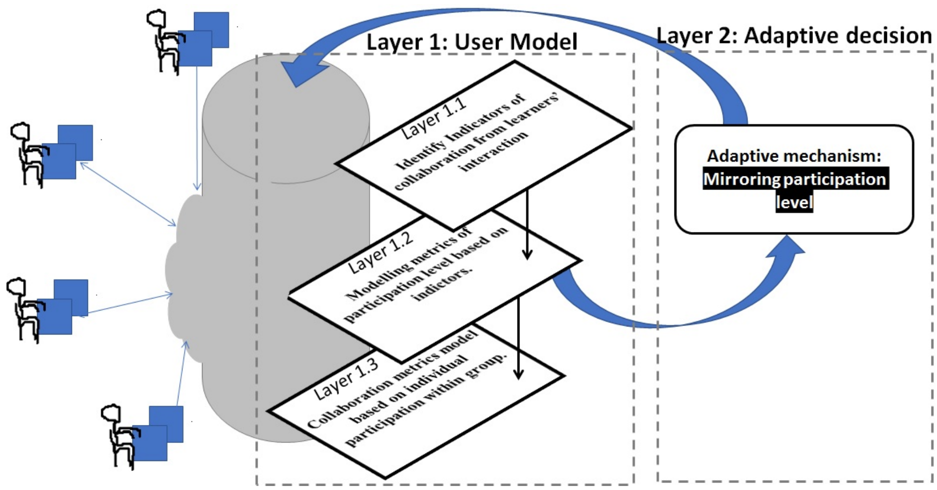


Fig. 6: Framework of Study.

2.1 Experimental Design and Participants' Demographics

We used a between-subject controlled experiment design with two treatments: Feedback-treatment (adaptive) and Control-treatment (non-adaptive). A convenience sample of 40 undergraduate students participated in this study, all within the age 18-25 (9 female, 28 male, 3 undisclosed). Groups G1, G4, G5: 1 female, 3 male; G2, G3, G6, G10: 4 male; G7: 3 female, 1 male; G8: 2 female, 1 male, 1 undisclosed; G9: 1 female, 1 male, 2 undisclosed.

Participants were randomly assigned to each group, and the groups were also randomly allocated to either treatment, so that we have 5 groups for each of the treatments. The study was conducted completely online; members of the same group interacted via the JPSD chat-room [5,4]. For the Feedback-treatment groups, the JPSD chat-room was enhanced with *feedback on the participation level* within the groups (see Figure 5). The chatroom for the Control-treatment groups did not provide this feedback (See Figure 4).

2.2 Procedure

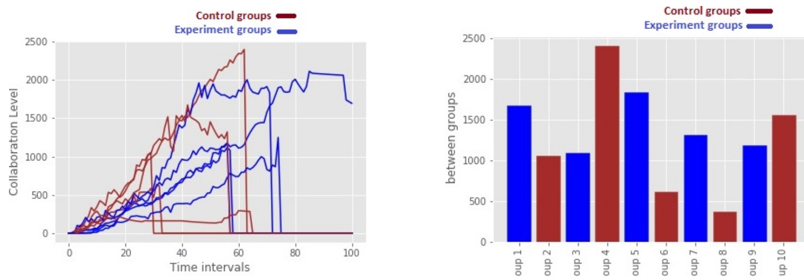
We applied a problem-based learning concept. Each group was asked to solve a task jointly; we adopted the "*desert survival*" group task [1] where a scenario was painted that the group crash landed in the desert, 65 miles off course and 70 miles south east of the nearest settlement. The group members were to rate some items left with them in order of importance to their survival [1]. Members were tasked to explain the rationale for their item-ratings and reach a group decision. The participation procedure was as follows:

1. Participants provided their consent to participate by agreeing to the statement in the consent page of the study web application.

2. They filled out a collaborative attitudes/skills questionnaire.
3. They studied the task and rated the items individually.
4. They joined the chat-room where they took part in a group discussion to agree on a group rating of the items.
5. The study took about 45 minutes to complete.

3 Study Results

We visualize the relative level of collaboration between the ten groups, applying the WC/GCMS metric [5]. A time-series visualization is shown in Figure 7a and the same measure based on the overall group discourse in JPS duration is illustrated in Figure 7b.



(a) Time series simulation of real-time measure of collaboration using the WC/GCMS metric [5]

(b) WC/GCMS measure of collaboration [5] based on whole discourse content

Fig. 7: Visualizing Collaboration Level:Relative measure between-groups

3.1 Observation

From Figure 7a, we can observe that the *Feedback-treatment* groups spent more time discussing in the chat-room, compared with the *Control-treatment* groups. Also, Figure 7b shows that the Feedback-treatment groups (shown in blue) collaborated relatively better than the Control-treatment groups. Although *G4*, one of the groups in the Control-treatment shows to be the most collaborative group; this observation is understandable, because there are other factors that come-into-play to affect individuals' participation and consequently collaboration within a group; for example *knowledge level with respect to learning context*, *personality of individual group members*, *language use*, *coordination*, *leadership* etc. [6,25].

The transcript extracted from the discourse of *G4* shows more of the positive indicators of collaboration and team-work skills highlighted (see Table 2). This explains the group's higher measure of collaboration as shown in Figure 7b. As well for all the groups that measure relatively well as visualized in Figure 7b, the qualitative assessment of their discourse content validates the measure (and similarly the reverse: the qualitative analysis and participation level measurements of groups that collaborated badly were also aligned). The complete discourse of all groups can be viewed online[1].

Table 2: Extracted transcript from G4's discussion: [2]

Coordination:

```
cls421: Hey
cls423: I think we are still missing someone.
cls421: it seems like it
cls424: yeah, lets wait a little longer
```

Leadership

```
cls423: I take it we now need to rationalise the ordering of our items?
cls424: yes
cls422: I guess
cls424: Okay, what does everyone have for number 1?
```

Argue/agree/disagree

```
cls421: not me
cls423: But they were just involved in a plane crash an  although there are no
        injuries they will still need some medical items following the crash.
cls424: Youre not going to be able to do anything with heatstroke too
cls424: You can die within 3 hours without shelter
cls421: water would help with heatstroke surely
cls421: would one plastic raincoat help more than one coat per person
cls423: Very valid point. Both equally important, personally i chose the bandage
        stopping infections and bleeding will be more useful then providing some
        shade during the day.
cls424: i would argue that the sun is a more immediate enemy to us than the
        possibility of infection
cls424: we know that the sun and the cold are going to come
```

However, despite G4 being in Control-treatment and shown to be relatively the most collaborative group, the visualizations from Figures 7a and 7b attest that Feedback-treatment groups collaborated relatively better than the Control-treatment groups. To substantiate this position, we define a simple quantitative *groupsOfTreatments* (gOT) measure. We score each group based on the number of groups below its level of collaboration, e.g. G4:=9 as it is the most collaborative group shown in Figure 7b). The score for all groups within either treatment is given by: Feedback-treatment (G1:=7, G3:=3, G5:=8, G7:= 5, G9:= 4), Control-treatment (G2:= 2, G4:= 9, G6:= 1, G8:= 0, G10:= 6). The average score for the *Feedback-treatment* is 5.4, while that for the *Control-treatment* is 3.6, which supports our position.

3.2 Statistical Analysis

We assume that the adaptive *mirror of participation level* stimulates learners' participation rate [8,13,24] and consequently scaffolds the collaboration level. We seek a more quantitative evidence for this assumption by analyzing for variance (ANOVA) in the rate of learners' participation, between the Feedback-treatment and the Control-treatment. The database that drives the JPSD chat-room had

[1] http://colab-learn.herokuapp.com/s4groupX.php, X=3 for *G1*, 4 for *G2*, 5 for *G3*, 6 for *G4*, 7 for *G5*, 8 for *G6*, 9 for *G7*, 10 for *G8*, 12 for *G9* and 15 for *G10*

been structured such that we are able capture the *current-time* that every contribution to the group discourse was made (see Figure 8). We extract the *sequence of times* that a member contributes within the group, $\{t^i_{c_1}, t^i_{c_2}, ..., t^i_{c_{m_i}}\}$, $t^i_{c_1}$ is the time that the first contribution was made and m_i is the total number of contribution made by member i, m_i varies with i, for example $m_i = 3, 1, 3, 5$ for $i = cls421, cls422, cls423, cls424$ respectively (based on the discourse data extract shown in Figure 8). From the *contribution time-sequence* collection, we compute intervals between contributions; let the period before the first contribution $t^i_1 = 0$, then the period (in seconds) between successive contributions by member i within a group is given by Equation 1:

	id	message	time	username	Word Count
0	1	Hello	24:03.8	cls423	1
1	2	yo	24:10.6	cls424	1
2	3	Hey	24:15.8	cls421	1
3	4	I think we are still missing someone.	24:42.0	cls423	7
4	5	it seems like it	24:57.7	cls421	4
5	6	yeah, lets wait a little longer	25:02.3	cls424	6
6	7	so....	25:41.6	cls424	1
7	8	There we go!	26:07.1	cls424	3
8	9	team!	26:15.9	cls421	1
9	10	I take it we now need to rationalise the ordering of our items?	26:49.4	cls423	13
10	11	yes	26:56.8	cls424	1
11	12	I guess	27:03.4	cls422	2

Fig. 8: The Database that drives the JPSD Chat-room: G4's data

$$t^i_k = t^i_{c_k} - t^i_{c_{k-1}} \forall k > 1, k \in \{1, 2, ..., m_i\} (Seconds) \tag{1}$$

Now, we have a collection of periods between contributions made by member i, $\{t^i_1, t^i_2, ..., t^i_{m_i}\}$, the mean of this collection represents member i's *time-interval* of participation in the groups' JPS, given by Equation 2:

$$T^i_m = \frac{t^i_1 + t^i_2 + ... + t^i_{m_i}}{m_i} (Seconds) \tag{2}$$

Finally, the participation rate (frequency of contribution) of member i during the JPS is given by Equation 3:

$$f^i_m = \frac{1}{T^i_m} (Hertz) \tag{3}$$

f^i_m for members within the groups were computed as shown in Table 3 for the Feedback-treatment groups and Table 4 for the Control-treatment groups. We analyze for a significant difference in f^i_m between the treatments (i.e. Feedback-treatment, Table 3 data and Control-treatment, Table 4 data) and between the Groups (i.e. G1, G2,...G10), applying a one-way ANOVA to test the following hypotheses:

1. H1: there is a significant difference in f^i_m (i.e. rate of members' participation) between the Feedback-treatment and Control-treatment.
2. H2: there is no significant difference in f^i_m between the 10 groups.

Table 3: Feedback-treatment: group member's username and f_m(Hz)

G1	G3	G5	G7	G9
cls412—0.014	cls417— 0.038	cls425— 0.028	cls433— 0.027	cls445— 0.023
cls411—0.028	cls418— 0.012	cls426— 0.037	cls434— 0.019	cls446— 0.021
cls410—0.028	cls419— 0.034	cls427— 0.028	cls435— 0.041	cls447— 0.033
cls409—0.035	cls420— 0.026	cls428— 0.028	cls436— 0.024	cls448— 0.007

Table 4: Control-Treatment: group member's username and f_m(Hz)

G2	G4	G6	G8	G10
cls414— 0.010	cls421— 0.028	cls429— 0.018	cls437— 0.032	cls457— 0.020
cls415— 0.019	cls422— 0.021	cls430— 0.015	cls438— 0.011	cls458— 0.013
cls416— 0.018	cls423— 0.021	cls431— 0.000	cls439— 0.014	cls459— 0.009
cls413— 0.025	cls424— 0.029	cls432— 0.020	cls440— 0.021	cls460— 0.027

Between treatments (H1). There was a significant difference in the f_m^i value for participants between the Feedback-treatment and the Control-treatment (ANOVA, $F(1,38)=9.24$, $p<.005$). This result provides enough evidence of a significant difference between the frequency of participation within the groups considering the treatments as a factor. We thus accept our hypothesis 1 that the *mirror of participation level* stimulated the participation rate within groups.

Between groups (H2). There was no significant difference of f_m^i for participants between the groups (i.e. between Groups 1 to 10) (ANOVA, $F(9,30)=1.70$, $p=0.133$). This implies that group membership did not significantly affect the rate at which the members participated. We therefore cannot refute hypothesis H2. Statistics cannot prove that no difference exists, but the fact that there is not significant difference provides reassurance that the difference we found between the treatments is due to the treatment and not a side effect of the groups.

4 Conclusion

The qualitative assessment of groups' discourse and the visualized relative measure of collaboration between the groups shows that the Feedback-treatment groups collaborate better than the the Control-treatment groups; the gOT measure that we defined above attest to this observation. More, an ANOVA between-treatments shows a significant difference in the rate of members' participation within their group, while an ANOVA between-groups shows no significant difference in members' participation rate. These observations and analysis results reinforce the conjecture that the real-time *mirror of participation level* during JPS is an effective adaptation method that can scaffold collaboration within online groups. Whilst we understand that other factors exist that impact individuals' participation and collaboration within a group, given that all other factors are randomized between groups, *mirroring participation level* as observed in this study is potent to motivate participation and improve group collaboration.

In future work, we will like to investigate this concept on a larger scale with more participants and groups, to study how this *mirroring* affects other characteristic features of the group interaction and how these evolve to affect or indicate collaboration within groups; also considering knowledge gain by learners through the JPS process compared to the within-group participation level and the between-group collaboration level measures. It is also important to our goal to evaluate how much the between-group measure with WC/GCMS agrees with the perception of remote teachers when they assess the discourse content of the group. This will further reinforce or point to improvement directions for our goal to provide real-time monitoring and support for online-group learning.

Furthermore, we will investigate other adaptive support for online group collaboration. For example, we will explore the patterns of members' attributes (e.g., *knowledge levels*, *inclination to participate*) between collaborative and non-collaborative groups; we presume that this can inform an algorithm that automatically forms groups that will collaborate optimally. Also, we conceive an automatic detection of collaborative activity-states of contributions [3] (e.g. exploring sentence openers) and observe patterns of transitions between these states to inform appropriate prompts or instructor's interventions (agent/human) that will efficiently scaffold interaction within an online learning groups.

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