Real-Time Feedback for Enhancing Team Collaboration: A Comparative Analysis of Collaboration Metrics with a Production Line Scenario using Virtual Reality

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ABSTRACT

Effective collaboration is essential in high-stakes environments where poor teamwork can lead to critical errors and adverse outcomes. This Work in Progress aims to contribute to research by providing real-time feedback to prevent critical situations arising from inadequate collaboration. We are developing an experiment to compare seven indicators of collaboration for their effectiveness in real-time context. Using a collaborative virtual environment, we can control the situation and environmental effects, allowing for precise and reliable assessment of each indicator. The goal is to identify the most efficient indicators for real-time assessment of collaboration, thereby enhancing team performance and preventing critical failures. This research will contribute to optimizing teamwork and operational success in critical fields, such as industrial applications, where collaboration is crucial.

CCS CONCEPTS

• **Human-centered computing** → *Collaborative interaction*; • **Virtual reality**;

KEYWORDS

Collaboration, Virtual reality, Teamwork, Indicators

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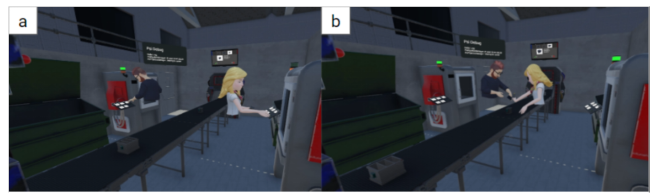

Figure 1: Individuals collaborate to build a battery. Left figure (a) presents a situation where each participant interacts with their parts generator to create battery modules and right figure (b) presents the participants collaborating around the battery to complete it with the previously generated modules according to the plan displayed on the assembly line screen.

1 INTRODUCTION

In critical systems such as surgery for example, the successful execution of complex operations depends heavily on the effective collaboration and communication of the interdisciplinary medical team [10]. Inadequate collaboration can result in adverse events that potentially endanger patient safety [5]. Observations and techniques such as debriefing are recognized methods to provide teams feedback and improve their effectiveness [1]. Thanks to the advance of some technologies such lidar cameras, oculometers or algorithms to process their data, an increasing number of research projects are looking into real-time measurements of team activity: Schneider et al. [12] investigated the use of multimodal signals to capture some aspects of collaboration and called this method Multimodal Collaboration Analytics (MMCA). Synchronous multimodal signal processing, where the many sensors available (eye-tracking device, lidar camera, etc.) and advances in artificial intelligence enable automatic measurement of some indicators, eases the hard interpretation of data (verbal analysis, movement analysis, etc.),

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but above all opens new research possibilities by the amount and speed of interpretation achieved. In this context, real-time feedback opens new perspectives to address declining collaboration within teams. But to accurately assess the quality of team collaboration, it is essential to select appropriate indicators for measurement. The objective of our study is to evaluate the effectiveness of various collaboration indicators referenced in existing literature and identify those best suited for assessing collaboration. Using a virtual reality collaborative task (Fig. 1) presented in section 3, we aim to collect precise behavioral data and create a meticulously controlled environment for evaluating each indicator

2 RELATED WORK

There are several approaches aimed at evaluating the collaboration process during a collaborative activity. Literature reviews of Praharaj et al. [9] and Schneider et al. [12] underline indicators of the collaboration process for collaborative activity in the Computer Supported Collaborative Learning (CSCL) field. Based on previous literature review, Léchappé et al. [6] tested four indicators based on these literature reviews. These indicators include speaking time distribution between collaborators, turn-taking with overlap, presence of joint visual attention and mutual gaze. Another approach in the Computer-Supported Cooperative Work (CSCW) field is that proposed by Jouanne et al. [4], employed three distinct indicators: Adaptation, Closed-loop communication and emotional expression between team members.

1. **Adaptation:** Derived from Piaget's work [8], adaptation involves modifying current actions to address disturbances or solve problems. Piaget categorized adaptation into:
   - **Alpha regulation:** persisting with current actions despite repeated failures.
   - **Beta regulation:** acknowledging failure without knowing how to proceed.
   - **Gamma regulation:** understanding failure, analyzing why, and adjusting actions
2. **Closed-loop communication:** Proposed by Mathieu et al. [7] as a marker for shared mental models. The concept involves:
   - **Simple closed loop:** receiver acknowledges sender's message.
   - **Enriched closed loop:** receiver acknowledges and expands upon sender's message.
3. **Emotional expression between team members**: this indicator focuses on the display of emotions among team workers during collaboration.

By comparing these sets of indicators, the study aims to evaluate and identify the most effective metrics for assessing collaboration within team dynamics. Each indicator offers unique insights into communication patterns, adaptive behaviors, shared mental models, and emotional dynamics crucial for effective teamwork. The comparative analysis will enhance our understanding of real time collaboration assessment methods in virtual reality.

3 METHODOLOGY

Based on the literature, several hypotheses are advanced:

- **H1** Compared to other indicators, mutual gaze, emotional expression, speaking time distribution between collaborators and closed-loop communication demonstrate higher efficiency to measure collaboration states.
- **H2** Adaptation and closed-loop communication provide a better assessment of actions coordination [11] between users compared to other indicators.
- **H3** The efficiency of the indicators to measure a collaboration state depends on the step of the collaborative activity.

3.1 Material and Software

The experiment will take place in a virtual environment using two Meta Quest Pro headsets equipped with features to track facial expressions and oculometers monitoring users' gaze. We developed a virtual reality dyadic collaborative task with Unity. Regarding audio, we capture conversations between the two participants, using a wireless Go II receiver/transmitter kit and two lavalier microphones. The setup includes two computers: one acts as a server responsible for receiving and analyzing data, while the other manages the Microsoft Kinect Azure motion tracking system. This configuration ensures efficient data handling and synchronization during the experiment.

3.2 Data acquisition

Dataset are recorded using the framework Microsoft PSI [2], developed by Microsoft Research, which serves as a comprehensive framework for handling multimodal, temporally streaming data: PSI facilitates real-time visualization of collected data and offers the unique capability of replaying recorded sessions as if they were occurring in real time. The sensors, software components with PSI and computers used enable the realtime recording of events, and their realtime analysis over a twenty seconds time frame window [6].

The specific data collected includes recordings of:

- `Video` as first-person views of users,
- `Postures`, based on the Skeletons collected using the Kinect Azure camera,
- `Audio`and speech-to-text transcription,
- `Discussions` etween subjects: logging conversations and interactions among participants, including dialogue contents and patterns observed during collaborative tasks,
- `Task Logs` for recording interactions such as UI interactions, module generation, module retrieval, and module placement within the virtual environment,
- `Users' Gaze` for tracking users' eyes direction towards objects, specific areas, and other users, allowing for analysis of joint visual attention and mutual gaze behaviors,
- `Users' Movement` for capturing users' positional data, rotation data, and areas of interest (AOI) within the virtual space.

This approach using PSI ensures a comprehensive collection of data across various modalities, enabling detailed analysis of user behaviors, interactions, and collaborative dynamics during the virtual reality experiment. The real-time visualization and session replay features provided by PSI enhance the study's analytical capabilities, supporting the assessment of collaboration indicators and team effectiveness within our experimental context.

3.3 Task Scenario

For this study, a team of two participants takes on the roles of two workers in a battery manufacturing factory. The chosen task is based on a real-world assembly line, but with simplified activities so participants recruitment can be made within a large scope. Their objective is to correctly assemble the maximum number of batteries within a limited time. The study involves two phases:

1. **Tutorial Phase:** during this phase, participants go through a tutorial to learn how to assemble a battery and how to address any potential incidents that may arise. This tutorial is designed to ensure that participants are well-prepared for the main experiment and to prevent any negative emotional repercussions.
2. **Main Experiment Phase:** in this phase, participants are required to collaborate effectively to assemble all batteries correctly within the given time constraints. This phase serves as the main focus of the study, assessing teamwork, problem-solving abilities, and task completion under pressure.

3.4 Environment and Scenario

The co-located participants navigate through a shared virtual and physical space, divided into two areas by a conveyor belt in the virtual environment and by tables in the physical space, with each area designated for one subject. The batteries appear at the start of the conveyor belt (Fig. 2.b). On the screen at the end of the conveyor belt (Fig. 2.c), the participants can visualize how to complete the batteries. Each participant must use the module generator (Fig. 2.a) placed in his area to produce the different parts necessary for the battery. The generators produce 5 types of parts, where one of them is unique to each generator — forcing the participants to work together for a specific model of battery. Regarding the collaborative activity, the battery frequency of the production line and the complexity of the batteries increase through the activity. The participants can regulate the speed of the conveyor belt by constantly pulling a stick at the beginning of the conveyor belt. If the participants become too overwhelmed, they can use the emergency button present on each side at the end of the conveyor belt (Fig. 2.e) to stop it. The number of failed and successful (completed correctly) batteries is displayed on the monitor.

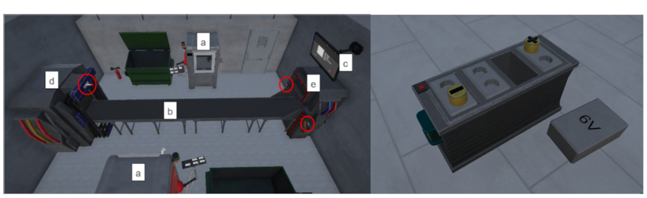

Figure 2: Figure 2: previsualization of the virtual environment volumes (left figure) and an example of a battery model (right figure). (a) module generator, (b) conveyer belt, (c) information panel, (d) entry of the conveyer belt, (e) exit of the conveyer belt.

3.5 Commitment

A critical aspect of our experimentation's success is inducing time pressure on the subjects. Simply imposing a time limit for the assembly of batteries might not sufficiently instill a sense of urgency among the participants. To truly immerse the subjects in the environment and intensify their engagement, we added storytelling elements that involve them in their roles so they can be committed to the task: sounds, noises, and lights similar to a factory. This storytelling approach aims to enhance their emotional investment in the task, thereby heightening their perception of time pressure during the experiment [3].

3.6 Breaking point

Ultimately, we identify a team's lack of collaboration through a critical breaking point. We use two types of batteries: regulated batteries, which pose no issue and can be assembled independently, and non-regulated batteries, which require both collaborators to work together synchronously to assemble the elements. If the collaborators fail to assemble the non-regulated battery properly, it will begin malfunctioning. At this stage, the participants must trigger the emergency procedure, demonstrating that their collaboration has failed. This action serves as a distinct marker of the breakdown in teamwork.

4 COLLABORATION CODING

In our study, we will adopt the coding methodology outlined by Léchappé et al. [6] for sessions' analysis. The recorded sessions will be segmented into specific time windows, and each segment will be annotated by collaboration experts. The annotation process by the human experts will provide detailed insights into the dynamics of collaboration exhibited during the experimental sessions, and give a ground truth so automatic metrics can be evaluated. This structured coding approach allows for nuanced characterization of collaborative behaviors and facilitates comparative analysis across different experimental conditions.

5 COMPUTING COLLABORATION INDICES

In our study, we employ specific metrics derived from the referenced paper to assess collaboration indicators. Here's how each indicator is computed based on the described approach:

Speaking Time Distribution is calculated by dividing each participant's talking time by the total speaking time of all participants in the time window. An index ranging from 0 to 1 is then computed, with values closer to 0 indicating more equitable speaking time distribution.

Joint Visual Attention and Mutual Gaze can be computed based on the data collected by the headset occulometer (e.g., object or users looked). Joint Visual Attention is identified when both users look at the same object within a 4-second time window. If user A gazes at an object and user B also gazes at the same object within the last 2 seconds, it is considered a joint visual attention event.

Mutual gazes are recorded when users look at each other.

Active Participation (Turn-Taking and Overlap), Turn-taking patterns are analyzed with and without overlap. Turn-taking with overlap occurs when user B starts speaking while user A is already speaking, and user A stops speaking before user B finishes. Turn-taking without overlap happens when user B starts speaking within 3 seconds after user A finishes speaking. Overlap is recorded when user B speaks at the same time as user A but finishes before user A.

Adaptability is derived from users' gaze, movements and actions measurements in the environment. As defined by Piaget's work, [8] adaptability can be differentiated into three distinct categories:

- **Alpha** regulation is characterized by the cognitive denial or disregard of a situation, manifested in the maintenance or repetition of actions without modification.
- **Beta** regulation involves the acceptance of an unsuccessful course of action, with modifications occurring via trials and errors without anticipation of difficulties or planning ahead.
- **Gamma** regulation is characterized by the immediate implementation of effective solutions, or by an understanding that the initial action is ineffective. In these instances, an individual will attempt to discern why this is the case, subsequently developing a novel solution that proves to be highly successful due to the understanding and anticipation of potential solutions to the problem.

We used specific patterns to distinguish the type of adaptability. For example, alpha regulation is detected when a user repeatedly tries to insert a motor module into a car battery until he succeeds. If we detect a pattern where users switch and replace modules in a battery one after the other, we define it as beta regulation. As for gamma regulation, it is detected when the user realizes that he has made a mistake, verbalizes his thought to his partner and changes or replaces a module in the battery.

Communication loops are derived from user verbalization transcribed during the activity using a speech-to-text tool, and from turn-taking detection information. Then, they can be classified into four different types. If the sender initiates a message without receiving an acknowledgment, it's classified as an open loop. If the sender receives a relevant response from the receiver, it's a simple closed loop, and if the receiver provides additional relevant information along with the response, it's classified as an enriched closed loop. However, if the receiver provides a partial or ambiguous response, making it unclear whether the message has been understood, it's classified as an incomplete loop.

6 FUTUR WORKS

When the PSI application development ends, we will be able to collect all experimental data in real time. This application will integrate advanced hardware, such as Quest Pro headsets for immersive VR experiences and Kinect Azure motion trackers for precise body motion monitoring, into a Unity-based software environment. The PSI application will enable real-time synchronized data, comprehensive behavioral coding and secure data storage. Once the environment is finished, we will run the experiment using the PSI application to ensure seamless data collection. The final step will be to analyze the collected data to gain valuable insights into team dynamics and collaboration effectiveness. This approach will significantly enhance our research capabilities and lead to a deeper understanding of effective collaboration through the identification of efficient real-time indicators.

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