Investigating Hackathons with Collaboration Analytics

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Abstract

Hackathons, collaborative events where individuals form teams to address specific problems, have gained significant traction across various domains since the early 2000s. Due to their time-bound nature, these events present unique challenges, necessitating the rapid establishment of collaboration methods and diverse support from hackathon organizers and mentors. Studying these events offers insights into emerging group work patterns, but tracking all teams during a hackathon is challenging. Traditional methods like surveys and log file analysis provide limited insights into team interactions. To address this, the following paper introduces a comprehensive data collection approach, encompassing detailed observations, speech transcripts, and wearable badges. Furthermore, it explores using Multimodal Collaboration Analytics (CA) and Sociometric wearable devices (SWDs) to study human behavior in hackathons. The primary research aim is to understand collaboration in absentia, leading to questions about designing technologies to capture collaboration and visualize group interactions. The paper discusses the iterative design approach for a collaboration analytics platform. The paper presents initial findings, challenges, and questions related to the study of collaboration in hackathons and how such tools can support the events and offer insight into collaboration.

CCS Concepts

• **Human-centered computing** → **Collaborative and social computing devices**; **Collaborative interaction**; **Interaction design process and methods**; • **Social and professional topics** → **Computer supported cooperative work**; • **Applied computing** → *Collaborative learning*; • **Multi-modal Learning Analytics, Human-centered computing, Open Learning Analytics Tools, Scenario-based design**;

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Keywords

Collaboration Analytics, Iterative Design, Sociometric Wearable Devices, Prototyping, Hackathons, CSCW

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1 Introduction

Hackathons and similar time-bounded collaborative events have become a global phenomenon [5]. The largest hackathon league supports more than 300 annual events in Europe and the US alone [1]. Since their inception in the early 2000s, hackathons have proliferated into various domains, from science [15], entrepreneurship [2], and corporations [27], to non-profit organizations [36] and education [29] with the aim to create (innovative) technology [26], tackle civic, environmental and public health issues [14, 26, 34], spread knowledge [7, 9] and create and expand communities [15, 24].

Studying teams during hackathons, however, is difficult. Most existing approaches utilize qualitative means of data collection, such as interviews and observations [23, 24, 27]. These approaches either do not scale well — in the case of observations — or rely on participant memory — in the case of post-event interviews. Moreover, they do not allow for real-time or close to real-time analysis of collaboration, which could provide valuable insights for hackathon organizers. Quantitative data collection approaches, such as surveys and archival analysis of communication and collaboration traces (code repositories, document histories, and chats) [19, 21, 33], also do not allow for on-the-fly analysis and only provide narrow insight into what happens between team members.

We aim to add to these methods by providing additional sources of information about how teams collaborate. Our overall research aim is thus: *How do we study collaboration when we are not there through analytics?* Drawing on approaches developed in Collaboration and Multimodal Learning Analytics (CA & MMLA) [30, 31]. Specifically, we are developing an open system incorporating diverse data sensors that connect to systems to capture a range of interaction modalities between people. This paper raises questions

[1] source: Major League Hacking, https://mlh.io/about

Set Up	Sess. 1	Sess. 2	Sess. 3	Sess. 4	Sess. 5
Devices	5 Vision Badges and 5 Voice Badges	5 Regular Badges and 5 Voice Badges	5 Regular Badges and Jabra Microphone	5 Vision Badges and 5 Voice Badges (no mentor)	5 Regular Badges and 5 Voice Badges
Environment	Square tables, fixed chairs	Square tables, fixed chairs	Square tables, fixed chairs	Round tables, movable chairs	Round tables, movable chairs

Table 1: The different sessions of group work for the hackathon that show the different equipment setups

on ways to explore research approaches to design and rapidly prototype a collaboration analytics platform for collecting, analyzing, and making sense of data for group work in hackathons and similar settings. The paper presents the different technologies and approaches we are investigating through different iterative steps to explore what happens in the teams at hackathons. The initial results intend to raise challenges and questions for the community to discuss, what is important to capture with these systems, and how to provide information from the system for different stakeholders, including researchers studying collaboration.

This paper is organized as follows: the next section provides a brief background. It then describes our design approach and introduces the context of the hackathon we investigated, the platform used, and data collection. We present some initial findings from the hackathon results, followed by discussions and challenges.

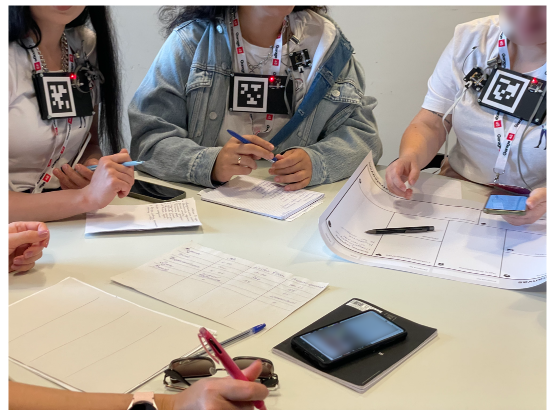

Figure 1: The participants working with vision and audio badges.

2 Background

Hackathons are time-bounded, participant-driven events that are organized to foster specific goals or objectives. The goals and objectives of hackathons often relate to innovation [8], learning [32], networking [24], or to addressing specific issues [14]. During these events, participants form teams to work on projects that are of interest to them with the goal to create an artifact [5]. Hackathons can thus serve as a great means to study teams while they ideate, conceptualize, and build the first versions of an artifact [10]. Moreover, hackathon teams often consist of individuals who have not collaborated, these events also provide the opportunity to study how teams form and establish means of communication and collaboration [3, 4, 23].

To foster the goals of a hackathon, organizers create a scaffolding for their event that unfolds over the allotted time. Generally, people participating in the event have different backgrounds, expertise, and goals [6]. The motivation to participate in these events is interest-driven to work on a shared project; however, additional incentives like prizes, networking, and community can also be strong drivers [22]. Hackathons also encourage innovation and novelty and push the participants to learn outside their expertise with big ideas [16, 28, 35]. Researching these events is complex, and since they span multiple domains, it is challenging to combine the different research.

There are diverse systems employed in Collaboration CA and MMLA, spanning research, commercial, and physiological platforms [18]. However, these specialized systems, platforms, and tools demand specific hardware and software. Sociometric wearable devices (SWDs), gaining traction since the early 2000s, have been instrumental in analyzing human behavior patterns in real-life settings, including corporate and healthcare environments [17, 38]. These devices, especially in hackathon contexts, offer the advantage of enhanced privacy controls and minimal reliance on facial recognition technologies. Therefore, there is a need to develop a more open system that can incorporate diverse data sensors that can connect to systems to capture a range of modalities that are easier to deploy and more accessible.

3 Methodological Approach

3.1 Design Approach

The development of the system is guided by a broad design science approach that uses pragmatic approaches to sketching with technology and agile development [1, 13, 37]. We started by identifying the different requirements for the platform [12], following the iteration of cycles 1) Awareness of the problem, 2) Suggestions, 3) Development, and 4) Initial reflections on the different outputs and the interplay between approaches. We use the fourth step of this process to provide an initial evaluation of the system and the data collected. Additionally, we use a qualitative approach to the observation data collected by trained observers and the dialogue transcripts (from the system) to provide a rough “ground truth” and a mixed approach to provide insights[20].

This paper presents the current state of the platform and its application in a real hackathon setting. This version of the platform has been the fourth iteration, and more details can be found about the iterative cycles in previous research [18].

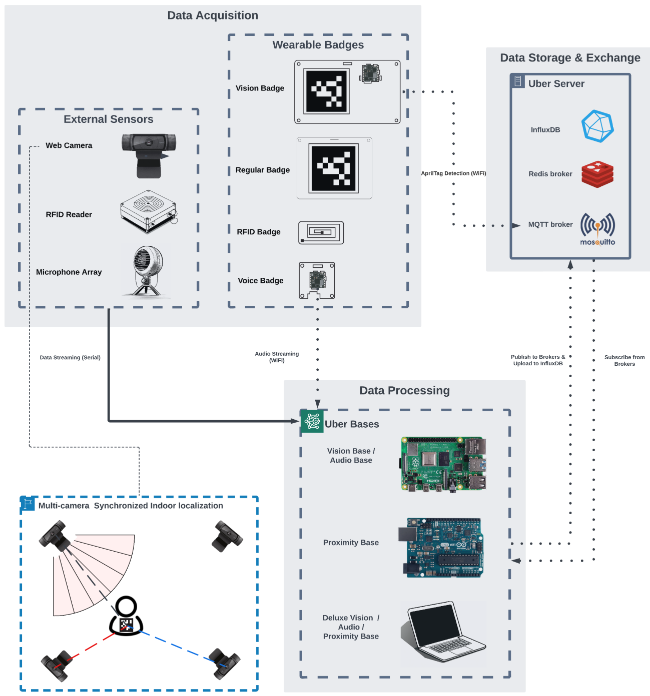

Figure 2: mBox system architecture

3.2 Hackathon Setting

The research was conducted during the *Empowering Women Estonia 2023*, organized by Garage48 in collaboration with the Estonian Refugee Council. The event occurred on September 9-10, 2023, in Tallinn, Estonia. No prizes were awarded in this hackathon. It was a part of the longer program where Ukrainian refugees were helped to rebuild their lives in Estonia through entrepreneurship—the hackathon aimed to develop business ideas and value propositions via teamwork sessions and mentorship. Professional mentors from different fields supported the participants. Figure 1 illustrates the working environment for the team of participants.

3.3 Participant Selection

The hackathon was medium-sized, with over 50 participants. From 35 candidates who consented, 15 individuals were selected for the study. Teams with full participant consent were chosen, resulting in four multilingual teams. Two teams spoke Russian/Ukrainian, one team spoke Persian/English/Russian, and the fourth team spoke English/Russian. The teams had 4, 6, 3, and 2 members, respectively. Teams formed around similar ideas, such as a cone-pizza restaurant, an online design company, and an Indian food restaurant. Some participants had expertise in these fields, while others did not. Most participants were adult women.

4 Collaboration Analytics in Hackathon

4.1 Collaboration Analytics Platform

The architecture of the CA platform revolves around multifaceted badges for on-person data collection and specialized base stations for data processing and synchronization. The badges come in four different types, each serving a specific purpose. The Vision badge is equipped with Nicla Vision Arduino boards [2] and AprilTags [25], facilitating AprilTag onboard detection that aids in the construction of a participant network graph. Voice Badge, also utilizing Nicla Vision, is designed to stream audio data to the audio base station for speaker and speech recognition. The Regular Badge features a basic AprilTag to provide essential data on location and orientation. The RFID badge equipped with an RFID tag provides basic proximity information. Figure 2 presents the system architecture.

The sensors & badges collect and send data to base stations; these hubs are specialized units designed to handle specific data types. The Vision Base Station, powered by either Raspberry Pi 4 or high-performance computers, processes visual data captured from the web camera that detects the AprilTags on badges to pinpoint their location and orientation. At the same time, Vision Badges contribute additional AprilTag data, enhancing the base station's grasp of badge-to-badge spatial relationships. The AprilTag detection results from base station webcams and badge onboard cameras are synchronized every second to form a network graph, capturing the participant spatial relationships. Similarly, the Audio Base Station, utilizing Raspberry Pi 4 or high-performance computers, handles audio data from either Voice Badges or the Jabra (video conference microphone array speaker). The Audio Base synchronizes the recognition results from different Voice Badges to identify the most dominant speaker in each segment.

The Uber Client (UC) is the system's dashboard, providing two key visualizations. Real-Time Visualization is achieved by subscribing to MQTT/Redis topics or InfluxDB for instant insights, while Post-Time Visualization offers retrospective analysis based on archived InfluxDB measurements. Lastly, the Uber Server (US) acts as the data backbone. The US utilizes InfluxDB to retain time-series measurements and manages data traffic through MQTT and Redis brokers, ensuring a seamless flow of information across the system.

4.2 Data Collection

A team of 4 (native language speaking), as shown in Figure 3 part B, was selected to be monitored using the developed platform technology. Observations and interviews provided ground truth for the technology above. Each team was assigned an observer who followed a semi-structured observation guide. Observers took time-stamped notes to facilitate the correlation of this information with sensory logs and visualizations.

The hackathon took place over two days and we collected data during five teamwork sessions. We deployed different technologies and shifted room environments between the sessions, as displayed in Table 1.

The hackathon provided an experimental stage for exploring the different types of data the Platform collects. Therefore, we tested different configurations of the vision badges and audio devices. Raw data were collected individually using external sensors and wearable badges. The data communication infrastructure utilized WiFi for audio streaming from voice badges to audio bases, while serial (USB) was used for data transfer from camera/Jabra to bases.

[2]https://www.arduino.cc/pro/hardware-product-nicla-vision/

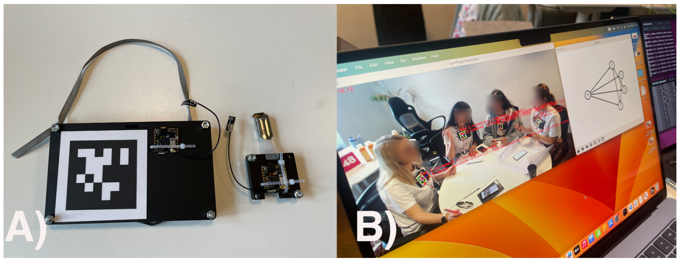

Figure 3: The Audio and Vision Badges in part A) and the badges in action during the hackathon in part B)

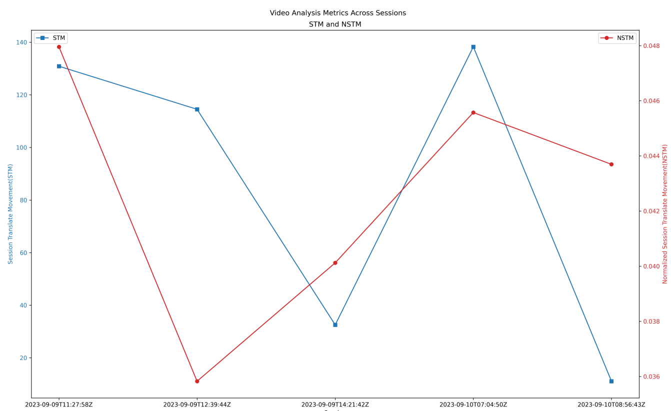

Figure 4: Video Analysis Across Session: Comparing the average normalized movement levels reveals that sessions with stationary furniture (0.0413 m/s) had lower movement than sessions with movable furniture (0.0446 m/s). This indicates that participants moved more when the furniture was flexible. Specifically, there was an 8.06% increase in translational movement when the chairs and tables were movable compared to when they were stationary.

Besides the vision badge's onboard AprilTag detection, processing for other data modalities was conducted at their specialized base stations. Messaging services based on MQTT and Redis broadcast the processed results for each badge across the IoT network. A synchronizer coordinated the badges' results, generating synchronized measurements for each 1.5-second segment.

5 Initial Results

5.1 Quantitative Analysis from System Logs

The platform performed without major issues and generated several measurements for each session based on the real-time raw data. Measurements are speaker & speech recognition, participant location, rotation, and relation stored in InfluxDB. We derived some further analysis results based on these measurement logs, which are as follows:

5.1.1 Video Analysis. To determine the position and location of the participants through the mBox system, we used computer vision to recognize the individual badges. We tracked the location and orientation of each participant relative to a single webcam, thereby quantifying their motion activity. We measured two key metrics for each session: the total movement in meters and the normalized movement in meters per second. All sessions used the same technical setup, with the webcam connected to the Vision Base, ensuring consistency in data collection. As shown in Figure 4, comparing the average normalized movement levels reveals interesting insights. For sessions 1-3, conducted in a setting with stationary furniture, the average normalized movement level is 0.0413 m/s. This is lower than the average of 0.0446 m/s observed in sessions 4-5, which took place in an environment with movable chairs and round tables. This represents an 8.06% increase in translational movement when the furniture was movable.

We also calculated the body orientation of each participant by deriving the normal vector from the rotation vector of the badge they wore, as detected by the webcam. We computed the cosine of the angles between their orientations to ascertain whether participants were facing each other. For vision badges, the onboard camera's detection function offered supplementary data to identify the orientation of the badge relative to others. To gauge activity levels in various environmental setups, we compare session 1 with session 4 (both featuring vision badges) and session 5 with sessions 2 and 3 (all using regular badges). Our observations indicate that session 4 exhibits a higher level of interaction among participants than session 1, as evidenced by the number and thickness of the edges representing interactions in Figure 5.

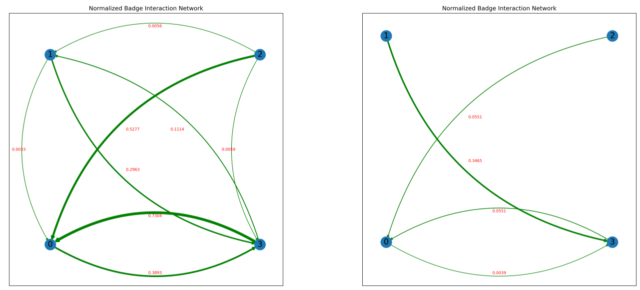

Figure 5: Normalized Badges Interaction Network: Session 4 (left) shows a higher level of interaction among participants compared to session 1 (right), as indicated by the greater number and thickness of the edges representing interactions. This suggests more frequent and stronger communication between participants in session 4.

5.1.2 Audio Analysis. Using different audio analysis techniques, we analyzed who was talking (speaker diarization, the amount of talk time per person, who was talking, and then compared these metrics across the sessions.

For our initial analysis of the audio logs, we examined Speaker Alignment for All, Speaker Distribution by seconds, and Speaker Distribution by segments as shown in Figure 6. Across the five sessions, we analyzed four metrics of session conversation: the average duration of pauses, turn-taking count normalized by session duration, whether the participants talked equally, and the silences

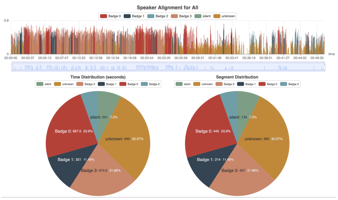

Figure 6: Speaker Diarization, sessions 1 and 4 : Session 4 (left) shows a higher level of interaction among participants compared to session 1 (right), as indicated by the greater number and thickness of the edges representing interactions. This suggests more frequent and stronger communication between participants in session 4.

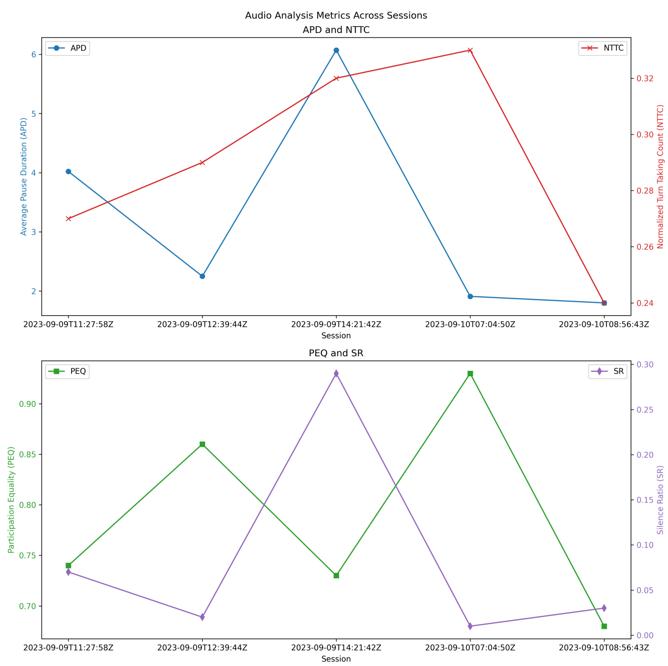

Figure 7: Audio Analysis Across Sessions: Between the two sessions, speaker alignment shows different patterns of diarization. In session 1, the mentor is registered as unknown, with noticeable periods of silence and unbalanced talk durations, while in session 4, there is less mentor involvement and more equal participation among the participants.

ratio. The upper plot of Figure 7 compares the Average Pause Duration (APD) and the Normalized Turn-Taking Count (NTTC). The lower plot shows Participation Equality (PEQ based on Gini coefficient) and the Silence Ratio (SR). Based on the metrics, session 3 is geared more towards individual work, characterized by fewer turn-takings and longer pauses, indicating less active conversation. In contrast, session 4 demonstrates a lively discussion with more frequent speaker changes and higher participation equality.

Conversational Patterns. In Figure 6, we compare sessions 1 and 4 to illustrate the emerging conversational patterns. Looking at the

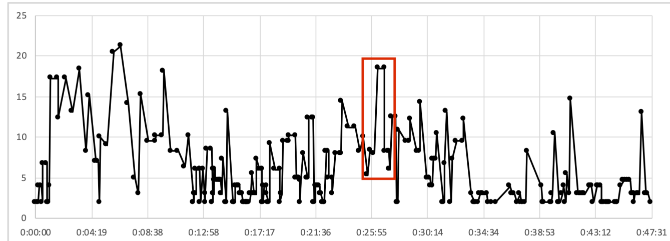

Figure 8: The degree centrality score in Session 1: degree centrality of nouns and proper nouns in each utterance.

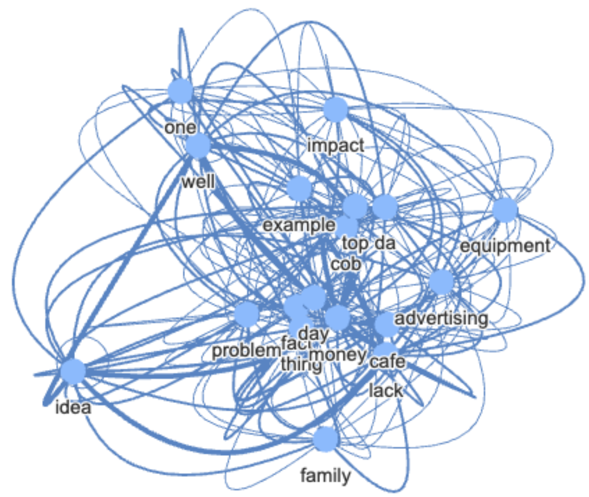

Figure 9: Semantic network graph at the highest score after the mentor entered the conversation highlighting the nouns.

Speaker Alignment for All between the 2 sessions, we see different breakdowns of speaker diarization. In session 1, we see the mentor registered as unknown in the system. We see that periods of silence and unbalanced talk durations between the participants are seen in the pie charts. In session 4, there is less mentor involvement and more equal participation between the participants. Furthermore, Figure 8 shows the sum of the degree centrality of nouns and proper nouns in each utterance in Session 1 by time. The semantic network analysis based on speech transcription (Fig.9) shows many key phrases, such as cafe, family, advertising, and impact, were used. Figure 9 illustrates how, in response to the mentor's question, the participant presented her concept of a family cafe as a solution to a social problem. The score of degree centrality increased (Fig.8) after the mentor came in at around 25:25, aligned with the moment shown in the following qualitative analysis in Figure 10. Note that due to space limitations, we have not included the transcript based on the audio and the observational notes of the researchers.

5.2 Qualitative Analysis with Observation Reports

Audio and visual badges are valuable tools to address the challenge of scaling research and enhance our understanding of team collaboration. However, they cannot establish ground truth without verification between what the sensors and the humans capture. Therefore, comparing and analyzing both quantitative and qualitative aspects is important. To achieve this, we cross-referenced our observations with audio logs and visualizations. As a result of this approach, we discovered that sensors can provide a complementary dataset to observations. Nevertheless, they may not align with the ground truth in certain rare instances. In this paragraph, we present some noteworthy findings from our investigation.

In Figure 10, it is evident that an *unknown* speaker joined the conversation during session 1. Additionally, our observations indicated that the mentor took charge of the discussion by posing questions like, "What is the problem you're trying to solve?" In response, A2 told a story about her existing café, while three other participants actively took notes. The visual evidence presented in Figure 10 confirms this scenario, as no other respondents were present.

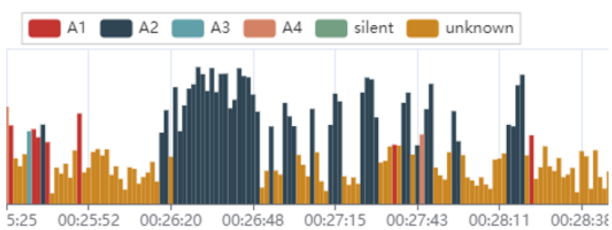

Figure 10: Mentor joining Team A's discussion

A similar pattern could be observed in other sessions as well. For instance, in session 3, we observed a case where A2 shared their idea with a mentor, but A3 further developed the problem. The mentor chipped in some comments to A3 development. This pattern is visible in Figure 11, in which we can see A2 starting the conversation with the mentor and later followed up by A3 and the mentor development.

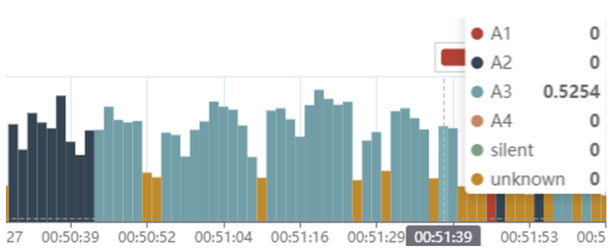

Figure 11: A2 shares an idea, which A3 develops

Quantitative data sometimes gives more information about the situation than observations. For instance, in session 2, according to observations, A1 had an active discussion with a mentor while the mentor was trying to explain via explanations *(e.g., "Well, I don't have that problem")*. Furthermore, observations note that *"Everyone else is listening"*. Figure 12 shows this was not the case. As A3 was paired with A1, she also chipped in some comments. The raw video analysis proves the same fact. Although A3 had little speech fragments, she still participated in this conversation and didn't listen as it was observed in the first place.

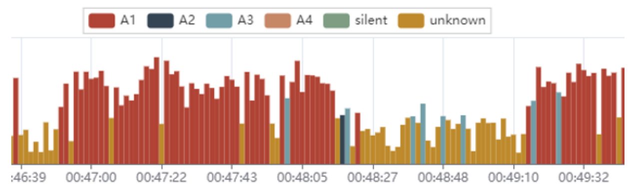

Figure 12: A1 discuss with mentor, while A3 chips in some comments

While we identified numerous use cases and patterns in which quantitative data accurately reflected the actual collaboration during the sessions, there were isolated instances where they did not align. For example, during session 3, speaker alignment and distribution indicated clear signs of the mentor being present as 37.21% was detected as *unknown* speaker in the conversation. Still, according to observations noted, it wasn't the case. Furthermore, raw video analysis showed that the actual speaker was one of the team members and not just a random background noise. Upon analysis, it became apparent that this discrepancy might be linked to using Jabra instead of audio badges in this particular session. Jabra, equipped with a single conference microphone rather than dedicated microphones on every badge, may not be suitable for this type of research now and needs further improvement as a part of the platform.

6 Discussion & Challenges

This paper reported on the developed collaboration analytic platform, intending to use and combine different ways of investigating what happens at hackathons and how we can capture data through a collaboration analytics system, which formed the main research aim of *How do we study collaboration when we are not there through analytics?* We can see from the quantitative and qualitative results that collaboration at hackathons is complex and that developing a system that captures this richness is challenging. For instance, the data from Figure 4, badge data, tells movement patterns that the nature of activities and the physical environment impact movement and that notions of ecological psychology [11] could play an essential role in understanding different patterns of physical interaction in teams. Conversation patterns also point to the different phases of work that highlight the different types of dialogue that unfold during collaboration. Figure 5 shows how the vision and regular badges perform, and we can see the vision enables badges to track some interpersonal connections between the people. Cooperation and collaboration are complex, and multiple modalities are needed to capture the nuances of social and cognitive interactions between participants. Additionally, the different comparisons between the analytics platform, the transcripts, and the observations illustrate the challenges of combining data from sensors and humans.

Our exploratory approach aimed to generate ideas from these analyses, visualizations, and dashboards to support exploring how aspects of collaboration unfold during a hackathon. We use these visualizations to give insight into the physical and conversational patterns. If they match what we observe and extract from the transcripts and video, we begin to have more confidence in the automatic collection of data on a larger scale. The visualizations are also seen as sketches and ways for researchers to understand what the sensors are collecting and create common ground for our work. Combining qualitative and quantitative analysis provides insight into how the platform performs and the challenges of building systems that can automatically provide accurate data from multimodal sensors. The insights from our different approaches to data utilization illustrate differences between how the sensors in the platform capture human cooperation and how we, as people, perceive collaboration. Integrating sensor data with human observations can be challenging, especially when aligning quantitative data with qualitative insights. However, creating various data visualizations highlighting physical and conversational interaction patterns can give us a more comprehensive understanding of collaboration. At the same time, the paper provides valuable insights and shares the platform with the community.

The challenges presented in this paper are severalfold and are focused on collaborative and cooperative aspects of software engineering. First, we are investigating how iterative prototyping, akin to sketching with technology, can be used to investigate what we can measure in group work. What makes sense to measure if we want to understand and improve these cooperative experiences? How does the hardware and software perform? Since the aim is to create socio-metric wearable badges and other tracking technologies, what does this mean for the participants? Do we want to create events where we need to track the participants?

By creating different data visualizations, we see physical and conversational interaction patterns. However, we presented some visual findings showing clear patterns, cross-reference audio logs, and observation notes; we are currently verifying the ground truth and assessing the potential for future technology adoption. Although the paper provides insights into collaboration analytics with the community, the next steps to investigate cooperation and collaboration in hackathons require a more systematic approach to software development and creating interventions to verify human interaction. The developed platform can thus provide input for research on such events but cannot fully replace human observers.

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