Developing an In-Application Shared View Metric to Capture Collaborative Learning in a Multi-Platform Astronomy Simulation

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ABSTRACT

There has been recent interest in the design of collaborative learning activities that are distributed across multiple technology devices for students to engage in scientific inquiry. Emerging research has begun to investigate students' collaborative behaviors across different device types and students' shared attention by tracking eye gaze, body posture, and their interactions with the digital environment. Using a 3D astronomy simulation that leverages a VR headset and tablet computers, this paper builds on the ideas described in eye-gaze studies by developing and implementing a metric of shared viewing across multiple devices. Preliminary findings suggest that a higher level of shared view could be related to increased conceptual discussion, as well as point to an early-stage pattern of behavior of decreased SV to prompt facilitator intervention to refocus collaborative efforts. We hope this metric will be a promising first step in further understanding and assessing the quality of collaboration across multiple device platforms in a single shared space. This paper provides an in depth look at a highly exploratory stage of a broader research trajectory to establish a robust, effective way to track screen views, including providing resources to teachers when students engage in similar learning environments, and providing insight from log data to understand how students effectively collaborate.

KEYWORDS

Shared view, Log data, Science education, Astronomy education, Immersive virtual reality

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1 INTRODUCTION

Collaborative activities have been established as a strong method for supporting learning [10]. As more advanced technologies developed, there has been more integration of emerging technologies such as immersive virtual reality (VR) (e.g., [9, 28]) and augmented reality (AR) (e.g., [12, 16] for collaborative learning. However, understanding how students use the technologies is challenging as it often requires expensive and elaborate configurations of software and monitoring devices including eye trackers, motion trackers (e.g., Microsoft Kinect), multi-directional microphones, video cameras, and more. These additions can constrain learning inside a traditional learning environment such as a classroom, limiting the number of people who can participate in collaborative learning activities. Even more, emerging technology such as AR and VR headsets can be very expensive, and many educational settings will not be able to afford these devices for every single student.

Multi-player, cross-device learning platforms are gaining in popularity within education and for entertainment. However, to effectively study and understand these environments, it is critical that we develop novel and less intrusive approaches to tracing students' collaborative actions, such as a shared view metric. Providing collaborative spaces is important as it helps students engage in the learning process during inquiry activities; and effective simulations can be supportive for collaborative inquiry learning activities [29]. In many cases of collaboration in technology-enhanced learning environments, tasks often have a single collaborative space (e.g., a large multi-touch display surface, see [17]), or multiple personal devices that provide ways to share with the group [30]. Carefully curated collaborative spaces and tools may help generate the shared space to effectively work together to complete educational tasks. To understand how to facilitate students in developing shared knowledge, research has tracked students' collaboration in multiple ways. Some innovative methods include body posture or gesture tracking [15, 20], and eye gaze tracking [11, 23]. However, there has been little research in investigating students' collaborative behaviors across different device types (e.g., [21]).

As technology becomes increasingly relied upon in educational settings at different scales, exploring novel ways to analyze collaboration in a cross-technology context such as between a tablet and VR headset becomes critical. By establishing a method to track collaborative learning without any additional equipment, it will be possible to offer more effective classroom management resources, just-in-time instruction within the digital learning environment to encourage additional collaboration, and assistance to researchers.

2 RELEVANT WORK

2.1 Importance of Facilitating Knowledge Sharing in CSCL (Computer Supported Collaborative Learning)

Research has shown that the quality of interaction between learners affects learning outcomes in computer supported collaborative learning (CSCL) environments [1, 26]. However, in most cases, collaborative learners do not spontaneously engage in such productive interaction activities; CSCL environments should help learners engage in more productive interactions [14]. Productive collaborative learning requires a process where group members establish shared knowledge [5, 13]. Being aware of each other's knowledge or status among group members in the CSCL environment facilitates collaborative learning and enhances their communication [7]. Shared annotations also improve students' knowledge sharing and collaborative learning [31]. As such, some studies have investigated how shared knowledge can best be facilitated in CSCL environments [6, 8, 19]. However, most of the studies have been done in environments with a single device or platform; there is a lack of research on how students with different perspective from multiple devices can be supported in achieving shared knowledge.

2.2 Joint Visual Attention in Collaborative Learning

A hallmark of collaborative learning is the ability to negotiate shared knowledge related to the tasks at hand [24]. Barron [1] found that successful collaborations on educational tasks engaged in discussion about a proposed idea. This study highlighted that students who work in parallel on tasks, meaning they are in a team but are working to solve the problem on their own, were found to have lower performance on mathematics assessments compared to groups who sustained joint attention and where students were listening and interacting with one another. One such effort for developing shared knowledge is the research around joint visual attention (JVA). JVA was first introduced in early childhood development research [3]. Tomasello and Akhtar [27] operationalize joint attention as the focus on a common reference to build understanding. There are several methods for assessing JVA in digital learning environments. With the development of multimodal data collection techniques, researchers can leverage a variety of tools, such as body posture [20], eye-tracking or gaze tracking [11, 22, 23], and application log data [2, 4]. Specifically, Jermann et al. [11] found that when leveraging eye gaze tracking in collaborative tasks, a dyad that has high quality interactions (based on collaboration flow, sustaining mutual understanding, technical coordination, participation symmetry, and task division) also demonstrated a higher eye gaze recurrence rate than pairs who had lower quality interactions. This finding is also supported by Schneider and Pea [23], where some participants were able to see their team member's eye gaze on a shared screen; results indicated that collaborators who could see their fellow participants' eye gaze in real-time achieved higher quality collaboration and learning gains.

This body of literature, therefore, suggests that collaborative tools that provide ways for individuals to negotiate and identify where fellow collaborators are looking or moving suggests an increase in collaboration, but also potentially learning gains. When developing different collaborative tools and environments within an educational setting, there are many considerations. Collaborative tools should be designed to support effective problem solving with a clear group goal, where group members can exchange ideas, share information, negotiate agreements, and manage relationships [18]. Traditional eye gaze tracking is difficult for calibration, which requires extensive computations to align data, especially when students are free to look around 360 degrees around a room [21]. Typically, research focuses on one device type or another. There is little research in the field investigating how to make sense of collaborative interaction data across different devices with different perspectives.

With the increased use of digital platforms as a means of collaborative learning and emerging technologies integrated into digital learning environments, this study strives to understand how students build "common ground" through viewing the same model from different perspectives using different devices. As a preliminary study, we develop a shared view metric that can represent how students in a group shared a view in solving collaborative tasks across different devices and further help us understand how students engaged in building shared knowledge. Future multimodal analysis ultimately will aim to understand how students build understanding, leverage previous knowledge, and create a common representation to solve astronomy tasks. The purpose of this preliminary study is to explore the following questions:

- How can a shared view metric be developed to capture students' collaborative learning across devices?
- What are the relationships between the shared view metric and students' use of simulation tools explicitly developed to aid collaboration?

We hope the results can inform how the metric can be improved to better represent students' collaborative learning and how tools can be better designed to support collaborative learning in future implementations. In the following sections, we will describe a data transformation and metric development for a digital shared view within an educational context to track potential collaboration across multiple devices.

3 METHODS

3.1 Simulation description

To facilitate collaborative learning of the night sky exploration, a prototype cross-technology simulation platform for VR (Oculus Quest headsets) and tablet (Microsoft Surfaces) was developed using the Unity game engine. Three views are provided within the simulation: horizon view, Earth view, and star view. Horizon view, which is the main view, allows for the observation and annotation of the night sky from a specific location, date, and time.

Each user can control their view to explore the night sky with their own device, but if necessary, students in a group can coordinate their view to share the view. Users can draw annotations in the night sky, and the drawings are shared instantly across the devices so they can be used as a reference for each other. Earth view

Table 1: Group Information: Crash Sites and Devices

Lab Session	Crash Site	Device Type	Number of Students
8 am	Alpha	2 Surface, 1 Quest	3
	Beta	2 Surface, 1 Quest	3
	Gamma	2 Surface, 1 Quest	4
10 am	Alpha	2 Surface, 1 Quest	4
	Beta	2 Surface, 1 Quest	4
	Gamma	2 Surface, 1 Quest	4
Noon	Alpha	2 Surface, 1 Quest	3
	Beta	2 Surface, 1 Quest	4
	Delta	2 Surface, 1 Quest	4

allows both VR and tablet users to observe the Earth from above while dropping pins to change their location and obtain latitude and longitude coordinates. Star view, accessible only to the tablet users, provides an explorable view of the full celestial sphere and catalogued western constellations.

To test the use of the simulation in an applied setting, a multi-step problem-solving task was created in collaboration with the introductory astronomy instructors. The task "Lost at Sea" has students using their observations of the night sky to determine the location of a crewed space capsule that has splashed down at night somewhere on the planet. Groups of students must first identify features of the night sky to determine which hemisphere the capsule is located in (task 1), then identify familiar constellations to use as reference points (task 2), then refine their crash site location estimation through the calculation of both latitude (task 3-1) and longitude (task 3-2) using the night sky.

3.2 Participants

Ultimately, three groups from three different lab sessions data were collected, for a total of nine groups (see Table 1). Within the simulation, there are four preset crash sites (i.e., referred as alpha, beta, gamma, and delta). Groups were randomly assigned a single crash site in the northern hemisphere to follow the tasks. This is to ensure that all groups could solve tasks through a similar process and difficulty level as the process of calculating the crash site's latitude and longitude varies depending on which hemisphere the capsule would be located in.

3.3 Procedure

Each group was provided two Microsoft Surface Tablets, and one Oculus Quest. In addition, each group was provided a worksheet with the three tasks (see 1.1), space for handwritten answers, and an informational packet that contained relevant information to the task at hand, such as calculating latitude and longitude. Prior to the simulation, students were given a brief walkthrough explaining the simulation controls, information about the Quest, and responded to a pre-test asking questions about interest in the subject and general science, science related activities, and beliefs about themselves in relation to science (e.g." During science activities, I prefer to ask other people for the answer rather than think for myself"). Following the simulation, each participant completed a post-test, which asked general questions on device usage during the session, thoughts about the simulation, task difficulty, and how they felt their team collaborated.

3.4 Data source

This study used data collected from videos recorded during the group work, screen recordings from the devices, and simulation (or 'log') data. Table 1 provides the group and participant structure, including assigned crash site. Log data was generated each time a new 'event' occurred, meaning that each time a participant moved to a different location, leveraged a provided simulation tool, or changed the direction their screen faced, a new event was triggered. The number of events generated changed depending on the participant as well as the device used. For instance, the Quest generated much more data as each time a user shifted their head, the simulation registered it as a digital move, whereas a tablet user had to use on screen buttons to shift their view. For each event triggered, the latitude, longitude, UTC date and time, simulation time (as students could manipulate the time around the time of the crash site), heading vector, event name, selected object, and selected star, as well as which view users were on were all collected. During the pilot study, 78,656 rows of data were generated.

3.4.1 Data Cleaning. To answer our research questions, we first considered how the data was initially recorded. As a new row of data was generated based on an event, this led to "time gaps" where students may have been discussing tasks with their peers, referencing help sheets, or otherwise considered idle. More time gaps were found in tablet logs than the VR logs, as each time the VR user shifted their head generated new data, whereas tablet users had to actively manipulate the screen to shift location or view despite looking at the screen. The initial transformation considered the time gaps; for example, if a VR user moved from London to Los Angeles, and the other team member did not trigger an event in that second, then the data from their previous event was carried down. This allowed the research team to compare the devices at a second granularity when each second at least one device triggered a new event, which we predetermined to be relevant to answering when students were "looking" at the same thing within the simulation. Future work will generate all seconds between first and last event per group.

To make these comparisons across devices (note we only compared devices, rather than participants as participants were free to

Table 2: Data Dictionary: Features and Descriptions

Variable	Description	Example
Session-group	Descriptor variable indicating which session and which crash site the group evaluated.	10am-alpha
Device pairing	Indicates which two devices are being compared. This is not the username assigned to the device, rather, the Quest device was always assigned "VR" and then the other two devices were assigned Tablet 1 or Tablet 2 arbitrarily based on descending alphabetical order.	{VR-Tablet 1, VR-Tablet 2, Tablet 1 - Tablet 2}
Task	Indicates which task the event occurred in.	{Task 1, Task 2, Task 3}
Scene indicator	If students were both in the same "scene" (earth view, star view, horizon view) available in the simulation. This feature was assigned a 1 if they were in the same scene, 0 if not.	{0,1}
Same location	If the latitude and longitude distance equal 0, then it was said to have the pair co-located (a value of 1, 0 for non-colocation). This was found to be appropriate as students typically used the drop-down menu to explore other locales or dropped a pin from Earth View to make dramatic changes in location.	{0,1}
Simulation time difference	Participants are able to adjust the time within the simulation to any given time or date to observe how the stars move. The absolute value of the difference in the simulation time between two devices is given in minutes for this feature.	800 minutes
Events Occurred	Given as an ordered pair of (Device 1, Device 2), events occurred provides insight on event types that occurred at this moment in time.	(drawmode started, annotation added)

rotate devices and many groups did not have a 1:1 device participant ratio), and different simulation usage patterns in collaboration, comparison at the pair level (between different devices) was thought to provide more insight onto collaboration. Data was excluded prior to all three group devices initiating the "connected" event, indicating that they had full access to the simulation. This allowed for intragroup and intergroup comparisons. Further, internal time (UTC with datetime) the simulation recorded was joined with video time stamps. This helped interpretability of findings when students moved on in their tasks as determined by watching the videos and marking when students transitioned to the next or previous task and to leverage qualitative analysis of collaboration from the videos. Relevant features are discussed in Table 2

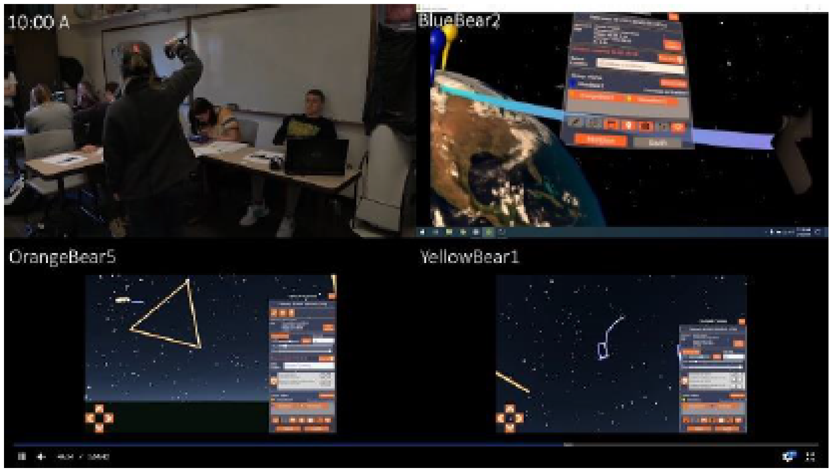
3.4.2 Shared View Metric. Shared view (SV) metric was developed to track when two device's screens overlapped. SV metric allowed us to set parameters for overlap, based on simulation data. As the first exploratory stage, we limited some conditions to generate SV metric. That is, to determine if there was a screen overlap, device users had to be at the same location, at the same simulation time, and had the same scene loaded. If this logic was not met, then we considered students were not looking at the same view, equaling an overlap of 0. If the logic was met, then we took the heading of each device, provided as (up/down degrees, left/right degrees). Through investigation with the simulation, it was found that the view screen was approximately 60 x 60 degrees for the VR user, which was the smallest field of vision within the simulation. The top left corner coordinates were calculated by adjusting up and left 30 degrees respectfully. As the simulation is a sphere, the distance between a heading of 1 and 3 is the same as 358 and 1. This was considered in the upper left coordinate calculation. By calculating the upper-left coordinate, we were then able to calculate the overlap of the two squares using trigonometric principles. The overlap ranges from 0 to 3600, the total squared area possible. Finally, to calculate SV metric, we took this overlap and divided by 3600. SV therefore ranges from 0 to 1, where 1 is a perfect shared screen, and .5 represents that two screens share about fifty percent of the same content. To check our metric, we observed several 20 second clips from the videos with the associated screen captures and found that the metric was accurate in the context.

This calculation method also affords future devices to be incorporated, and the ability to change the potential overlap based on device screen ratios. However, this preliminary study only considered the narrowest screen range. In addition, we will consider time differences at the same location to identify if two devices are viewing the same celestial objects in the night sky in our follow-up study.

3.5 Analysis

As a preliminary study, we employed an exploratory approach to develop a metric to be used in future work. By calculating the overlap, as described in the above section, we were then able to develop a more foundational understanding about the relationship between the shared view, tool use, and the potential relationship with a quality of collaboration. Figures 1a and 1b demonstrate what a low SV metric may look like during the lab session (Figure 1a) and a highly considered SV metric (Figure 1b).

First, descriptive analysis was completed on the developed metric (see Table 3). Given the small sample size of the current study, key visualizations were developed as the primary vehicle to drive understanding. Finally, we focused on the groups in 10 am session to better understand the relationship between SV metric and quality collaboration. This is our preliminary efforts in identifying association between SV and quality collaboration. Only three groups had a maximum of 1, and standard deviations range from 0.05 and 0.21.



(a)

(b)

Figure 1: (a) SV of 0. Different scenes and looking different directions result in students not looking at the same thing. (b) High SV and overlap across all three devices.

Table 3: SV Descriptive Statistics for the Simulation

Group	Count[a]	SV_Min[b]	SV_Avg[c]	SV_Max[d]	SV_Std[e]
8am-alpha	7293	0	0.1082	1	0.2082
8am-beta	5244	0	0.0077	0.9009	0.0537
8am-gamma	6603	0	0.0178	0.9867	0.1003
10am-alpha	10317	0	0.0634	0.985	0.1786
10am-beta	9876	0	0.0308	0.9086	0.1291
10am-gamma	7728	0	0.0645	1	0.2056
Noon-alpha	7467	0	0.0111	0.9884	0.0846
Noon-beta	8610	0	0.0496	1	0.1681
Noon-delta	6555	0	0.0243	0.9967	0.1326

[a] The number of instances that occurred in the log data, [b] Minimum of SV, [c] Average of SV, [d] Maximum of SV, [e] Standard Deviation of SV

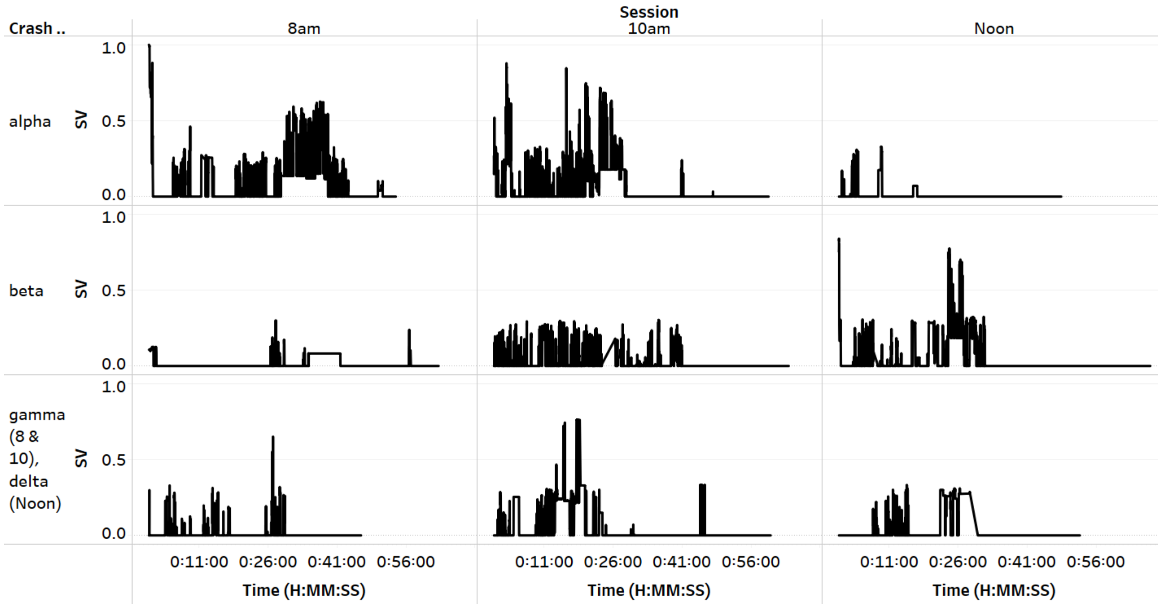


Figure 2: Group average shared view (SV; y-axis) metric across time (x-axis) partitioned by crash site (y-partition) and lab session (x-partition)

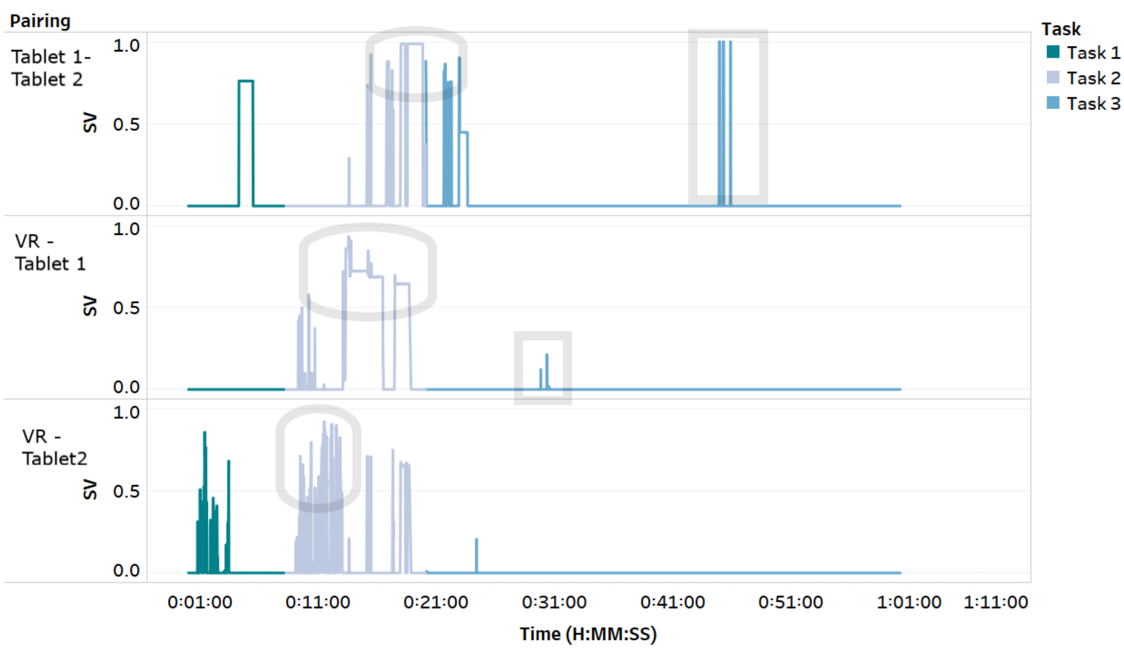


Figure 3: Shared View of 10 am gamma group on the dyad level. Note: Ovals highlight consistent, high levels of SV, whereas the rectangles highlight more sporadic SV. Color and opacity indicate which task the group is working on.

Count is the number of instances that occurred in the data. Recall that the data is for each second an event was triggered for at least one device in the group, with three dyad combinations per group (i.e. VR - Tablet 1, VR - Tablet 2, Tablet 1 - Tablet 2). If you take 8 am alpha's count at 7293, divide by 3 dyads, and then divide by 60, the result is approximately 40.5 minutes' worth of data. Minimum, maximum average, and standard deviation are also provided.

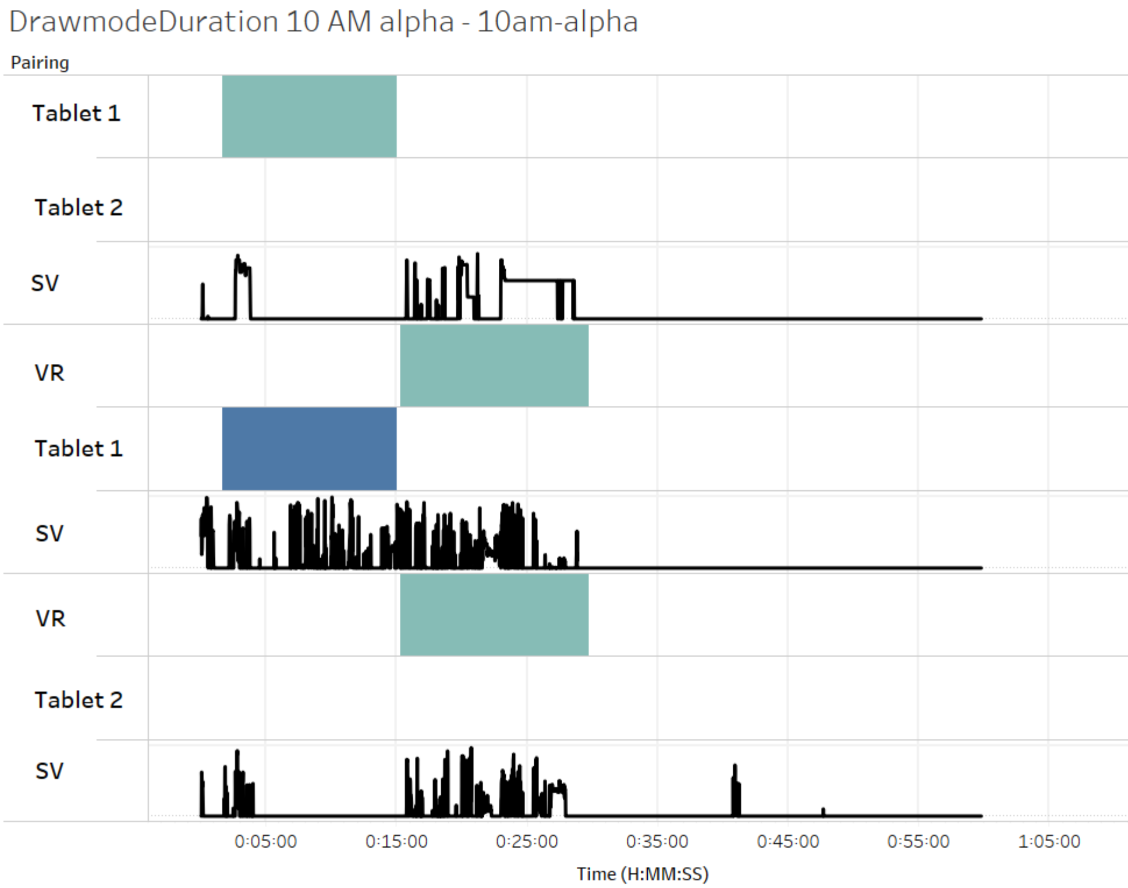


Figure 4: Draw mode activations and SV metric trend: 10 am alpha. Notes. Boxes within device bands indicate draw mode activation for each device, with the SV between the two devices as a line in the SV band for each device pairing

4 FINDINGS AND DISCUSSION

The SV metric was developed as a way to capture students' view sharing across devices in response to our first research question. We first examined the evolution of SV across time (see Figure 2). Time in this case, along the x-axis, is represented by a standardized time, where 0 minutes, 0 seconds was determined for each group at the first data point present in the cleaned dataset. As noted in *Participants*, three lab sessions occurred at 8 am, 10 am, and noon. Recall that SV is calculated on a dyad level to understand how different groups leveraged different platforms. In addition, SV was generated at a device dyad level to provide further exploration of device use to be capitalized in the next stages of the study. To review a group's SV patterns, an average between the three dyads' SV values was calculated. Table 3 shows the overall SV pattern of each group accordingly. Consider that the overall average overlap between all devices across sessions is 0.04 ($\sigma = .115$); 8am alpha group shows the highest average (0.11) then, 10am gamma (0.06) and alpha (0.06), and then 12pm beta (0.05). However, visualizing the SV trends observed over time further provides additional detail. As such, Figure 2 demonstrates the variation in group averages across SV at a given moment in their lab session. There does not appear to be any relationship between session and crash site on the overlap of the digital shared view. This is expected as each group dynamic should not be influenced by the crash site and lab session. Examination at the dyad level was also conducted to see if any combination of devices might show different patterns. Figure 3 shows differences within dyads of a selected group, 10 am gamma, as an example. Two patterns of high SV were identified visually. First, devices show high (above .5), prolonged SV, where there is little to no change in screen view overlap (see the middle of Figure 3 between VR – Tablet 1 as highlighted by the oval). Additionally, as seen in VR – Tablet 2 there is a case without a constant SV, but rather has a variable high SV. This appears to be an intentional shared view, with one of the devices looking around a similar vicinity, perhaps searching for an object before returning to the groups view. If SV does drop below .5, then it is only for a few seconds before returning to the similar vicinity. In contrast, sudden spikes of SV with return to little or no SV soon after suggests that the SV may be unintentional as it occurs briefly with no reoccurrence. Sustained SV shows more potential for meaningful collaboration

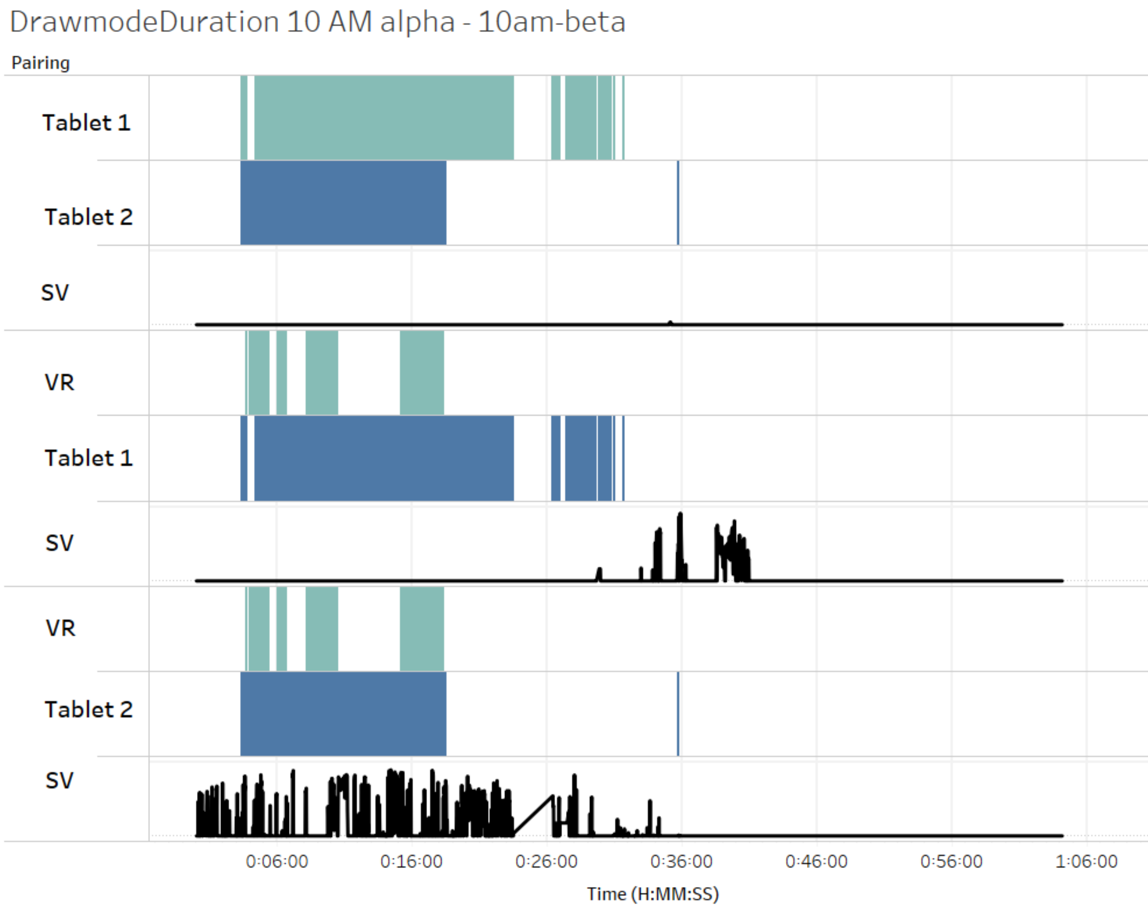


Figure 5: Draw mode activations and SV metric trend: 10 am beta group. Notes: Boxes within device bands indicate draw mode activation for each device, with the SV between the two devices as a line in the SV band for each device pairing

whereas times or dyads that have more sporadic SV could be more accidental or not meaningful [21].

Second, we examined the relationship between shared view and students' use of simulation tools explicitly developed to aid collaboration. One of the simulation tools allows students to "draw" or "annotate" certain celestial objects or area of night sky in the horizon scene (see the examples of annotation in Figure 1a). Draw mode is highlighted as this is a tool that is ripe for collaboration. When students activate draw mode and make subsequent annotations (i.e., "drawing" connections between two or more stars or constellations), this information is then shared simultaneously with the group. It is expected that students draw to encourage other team members to also look at similar items to generate a shared understanding during solving the tasks. To leverage the annotation tool, students must start and end 'draw mode'. To explore the potential relationship between SV and the use of this built-in tool, we provide two examples. Figure 4 shows the trends of the group 10am alpha. When draw mode is activated, there is more sustained SV overall, but especially within one device having activated draw mode between VR and Tablet 2 (bottom row) and initially after draw mode is activated between Tablet 1 and Tablet 2. This may be an indicator of intentional use of technical coordination (see [11]). In contrast, 10 am beta group (see Figure 5) shows heavy activation of draw mode, see Tablet 1 and VR users activation patterns, but does not have any change of behavior. There are no sudden peaks, no change in SV sustainment, and little to no SV pattern change within active draw mode. Where this is a tool provided to communicate ideas, draw attention to, and "sketch" out findings, we would expect its intentional use to be associated with higher levels of joint attention, which is a future application of SV in our study. However, we find that draw mode does not appear to be associated with increased or change in SV behavior of 10 am beta group at the present time. Potentially, more explanation or explicit scaffolding on the different tools is needed in future studies to encourage students to use the tool.

Last, we investigated how the metric can be improved to better represent students' collaborative learning and how tools can be better designed to support collaborative learning in future implementations. To do so, we specifically selected 10 am session (alpha,

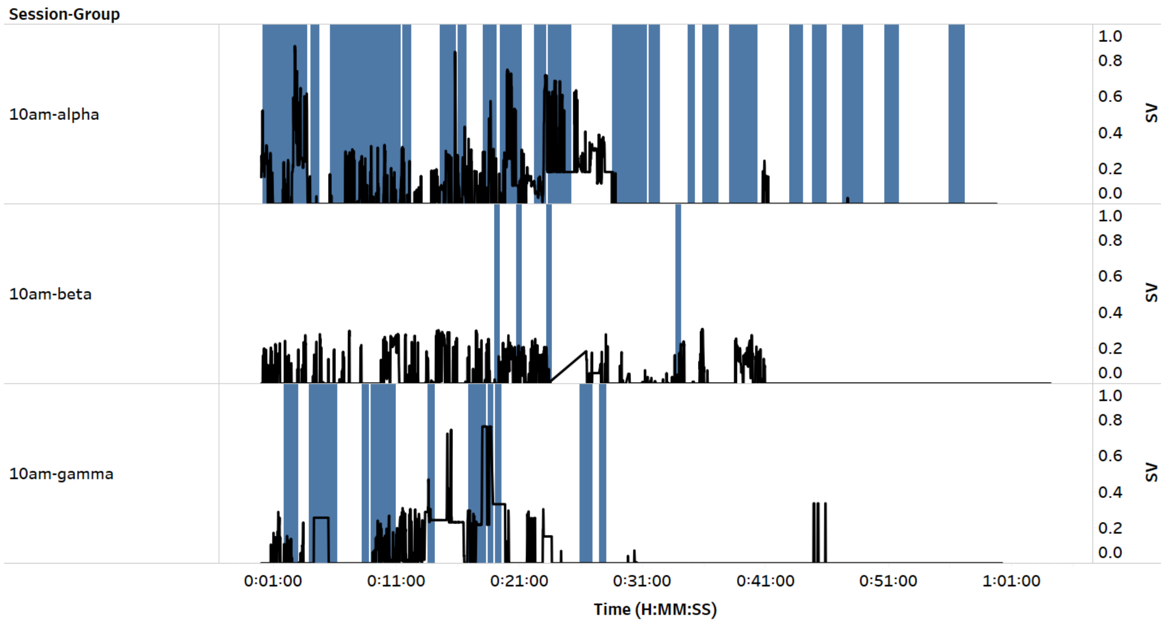


Figure 6: 10 am conceptual discussion (blue background) and group averaged SV overlayed (line graph, right y-axis)

beta, and gamma groups) to further investigate the students' collaborative behaviors. We developed the coding scheme to observe the groups' collaborative behaviors defined in Sheb and Mercier [25] in which different forms of collaboration in problem solving are identified. We focused on two types of behaviors to review with SV, including (1) conceptual discussion and (2) facilitator intervention. Conceptual discussion does not focus on whether the conversation or information presented between group members was correct. Rather it highlights moments where group members are introducing, identifying, clarifying, and negotiating information relative to the tasks. Facilitator intervention documents when group members sought outside help, whether it was technical assistance, clarification on task, or had questions surrounding knowledge required for the task. The research team watched the group work videos of 10 am session to mark when each type of collaborative behaviors was observed, and the Cohen's k between two researchers was 0.817 which indicates almost perfect agreement.

To understand the relationship between the types of collaborative behaviors and SV metric trends, we overlayed the group SV average with the occurrences of conceptual discussion (Figure 6) and facilitator intervention (Figure 7). Figure 6 shows that the 10 am alpha group had many more instances of conceptual discussion (166 instances), compared to beta (6 instances) and gamma (36 instances) groups. When looking at dyad SV, as seen in Figure 3, we note there are prolonged instances of high SV, and other instances of spontaneous, yet very brief, high SV. Jermann et al., [11] found that dyads who had higher levels of gaze reoccurrence, which would be comparable to SV in our study, was correlated with higher, quality interactions. Schneider et al. [21] identified higher learning performance as students increased in joint visual attention on a tangible surface. As noted in Table 3 and Figure 6, 10 am alpha group had much higher SV not only on average, but over time. In line with the literature, this is therefore a promising first step at establishing SV as a metric that can be used to identify signals of quality collaboration. It is worth noting that this study is still descriptive by nature and needs more consideration and analysis to validate the claim.

Next, we evaluated the role of the facilitators on SV. As shown in Figure 7, 10 am beta (middle) required much more facilitator interaction from teachers or researchers (green shaded background) than other groups. Figure 7 interestingly shows a lower or decreasing SV prior to many of the interventions, which then sees some increase after the interaction across the three groups (i.e. see around minute 11 in 10 am beta (middle), and minute 15 in 10 am alpha (top)). After further investigation, it was found that the gamma group retired one of their devices after 21 minutes. While their facilitator intervention occurs less frequently than beta's, the gamma group shows longer durations requiring help up until they reduce the amount of time spent with the VR, at which time they have the same number of instances (facilitator intervention) as the alpha group. Therefore, difficulty using the devices could be a factor impacting collaboration and potentially learning. If similar patterns are found in future work with students who struggle with the VR or simulation, this information can be helpful in providing in simulation cues to reduce technology frustration and enable students to focus on the task at hand.

5 CONCLUSION AND FUTURE WORK

Literature points to increased eye-gaze reoccurrence as having a positive impact on quality collaboration and learning gains. Continuing to learn and develop methods to assess such behaviors while also providing educators and learners the affordance of using readily available technology as well as emerging technology may prove beneficial in additional contexts. Effective collaboration is key in scientific inquiry; by providing the scaffolding through learning

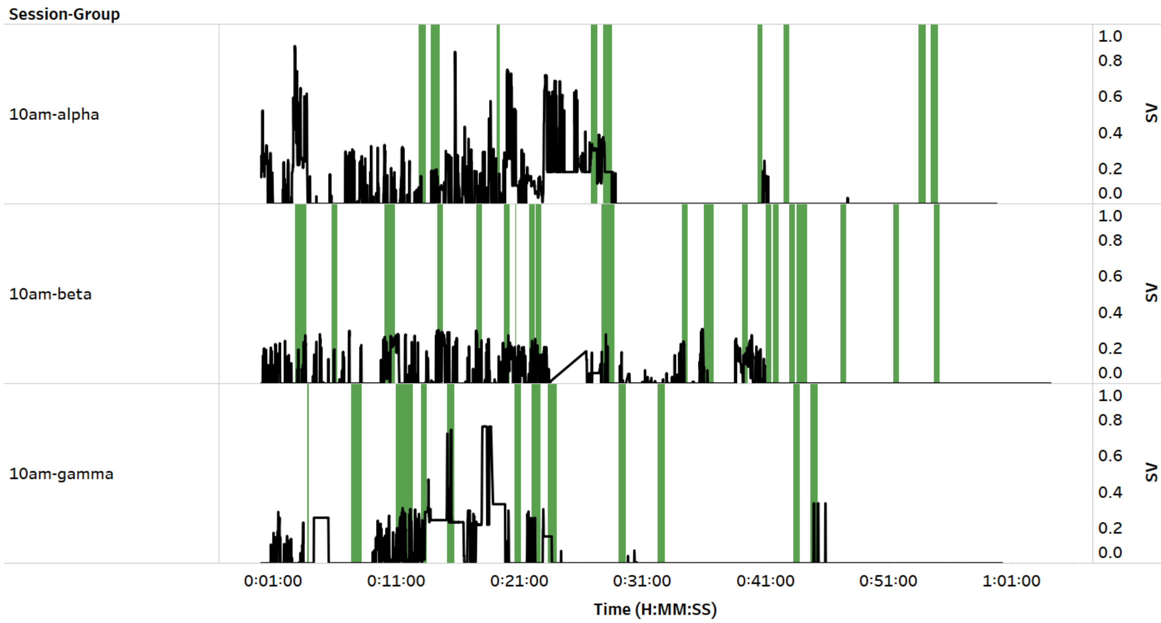


Figure 7: 10 am facilitator interventions (green bands) and group averaged SV (black line graph) overlayed.

activities, students can learn from each other and build a shared knowledge to solve tasks. This paper provided a methodology for tracing shared view across different device types when using the astronomy simulation in 3D, multiplayer, cross device simulations.

Future work will focus on including a larger sample to validate the metric. Currently, such a small sample is a significant limitation on the generalizability of this work. With an increased sample size and additional data collection including demographics, information on group work, and increased participation across institutions will allow for a more fruitful conversation around data bias and impact on generalizability. This will include the incorporation of the quality of collaboration derived from additional qualitative analysis and provide further insight into the relationships between the SV metric, built-in tool use, and quality of collaboration, as well as validating the metric on a larger scale. Such validation can provide the foundations of just-in-time instruction embedded within simulations or to notify an educator when students may need help with the technology or seek additional instruction to solve the tasks. As students "look" around the simulation, either in a VR environment or navigate via keys on a tablet, the log data was able to be leveraged to create a metric that distinguishes when and how much students are viewing the same scene. We offer this method as an applicable alternative to eye-gaze tracking in a similar context, particularly 3D simulations across multiple devices and device types.

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