Supporting Collaborative Exploratory Visual Data Analysis in Multi-device Environments

by

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THESIS

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Computer Science
in the Graduate College of the
University of Illinois at Chicago, 2021

Chicago, Illinois

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“Dedicated to my father Abdullah and my mother Muslaha.”. iii

ACKNOWLEDGMENT

Despite all the challenges along the way in writing this dissertation, writing this acknowledgment is the most difficult, in a sense. Many people influenced me to reach the end of this journey, the start of a brighter new chapter. First, I would like to thank my advisor professor Andrew Johnson for his continuous support and valuable feedback that helped to better shape my research. His continuous appreciation of whatever small effort I make kept me motivated. From him that I learned how to explore the path as a researcher and see things in new and unexpected ways. I could not have asked for a better advisor. I would also like to thank my committee, professors Steve Jones, Joseph Michaelis, Wei Tang, and Khairi Reda for their time in reading my dissertation and providing valuable critique and feedback.

Special thanks go to my friends and colleagues at the Electronic Visualization Lab. I was particularly fortunate to be surrounded by wonderful people like you, who are always ready to provide help, advice and inspiration. Many thanks to Arthur. He never hesitated to help and even to find solutions for my technical problems. Thanks to Juan for all the good times in the hard days. Thanks to Jillian, Sai, Lance, Luc, Dana and everyone at EVL who were always willing to help. Keep the good and creative work and I will always remain a member of the EVL family.

Thanks to Azmi, for his uncompromising support, love, and patience in the last two years, for understanding stressful times, and for always managing to encourage me.

Lastly, my heartfelt thanks go to my family, my first supporters since the beginning. With my papa, it is all started that afternoon when we left to Riyadh. I know I cannot pay him back for all of the sacrifices he has made for his family. Thank you mama for keeping me in your prayers, my source of tranquility. It's time to spend more time with you my old good friend after being living overseas for more than eight years. Thank you my brothers, Naif, Saleh, and Abdulrahman (may your soul rest in peace) for your endless love and support. I will always remember how you were believing in me and motivating me to take the challenge. I always see in your eyes that I can do it. Thanks to Abdulmjjed for sharing this journey with me. Seeing your success as well nicely seasoned the accomplishments. With love, I dedicate this to you.

AA

CONTRIBUTIONS OF AUTHORS

Chapter 1 introduces the thesis problem and presents the main research questions addressed by this dissertation. Some of these research questions were framed in a poster (Alsaiari and Johnson., 2019) for which I was the primary author. Chapter 2 presents background, related work, and design principles for this research. Some of these related work and design principles appeared in a published paper (Alsaiari and Johnson., 2019) for which I was the primary author. Copyright © 2019 IEEE. Chapter 3 represents a designed framework for multi-device visual data analysis. This chapter appeared in a published paper (Alsaiari and Johnson., 2019) for which I was the primary author. Copyright © 2019 IEEE. Chapter 4 describes a user study to understand collaborative visual data analysis in multi-device environments. Addressed research question and used methodologies appeared in a poster (Alsaiari and Johnson., 2019) for which I was the primary author. Used software and data sets were previously appeared in a published paper (Alsaiari and Johnson., 2019) for which I was the primary author. Parts of this chapter appeared in a published paper (Alsaiari et al., 2020) for which I was the primary author. Data sets were provided courtesy of http://service.iris.edu/ and http://www.occeweb.com/. Chapter 5 presents the design of visualization tool to visualize dimensions search space. Chapter 6 presents and evaluation study to evaluate the effects of visualizing the dimensions search space on exploratory visual data analysis. Krishna Bharadwaj and Arthur Nishimoto helped in video coding. Chapter 7 concludes the dissertation and summarizes the main contributions of this research.

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SUMMARY

There is a steadily growing interest in leveraging ecosystems of digital devices that go beyond a single desktop for collaborative visual data analysis and exploration. This new thrust of multi-device interfaces supports new models for complex collaboration scenarios, and have great potential to support analysts in their data analysis by utilizing each device's capabilities. However, there are some challenges inherently associated with visual data analysis in multi device environments (MDE). This dissertation investigates how the analytical process occurs in multi-user multi-device environments to provide a theoretical understanding of collaborative exploratory visual data analysis and better inform the design of visualization tools. First, I touched on the challenges of designing cross-device visualization tools by introducing the design and implementation of a multi-device system for collaborative visual data analysis that enables cross-device visualization sharing and simultaneous interaction. Then, through an exploratory user study, I evaluated strategies of exploratory visual data analysis in a collaborative multi-user multi-device environment. I synthesized a two-level characterization of the analysis structure from observed analysis behaviors. I observed that subjects navigate the data space in three identified exploration patterns and the analysis was primarily depth-oriented. In addition, the cost of deciding what to explore next "Gulf of Goal Formation" is higher in collaborative settings due to short-term memory and the recency effect. I hypothesized that visualizing the dimensions search space would increase the breadth of the analysis and reduce the decision cost. Using a between-groups study, I evaluated the effect of revealing information about what

dimension's data space coverage(s) were investigated and what were left. The results indicate that visualizing dimensions search space increases the breadth of the analysis and reduces the decision cost by positively affecting the rate of views generation.

CHAPTER 1

INTRODUCTION

Parts of of this chapter were previously published as: Alsaiari, A. and Johnson, A.

(2019). “Towards Understanding Collaborative Visual Data Analysis in Multi Device Environments”. In *2019 IEEE VIS*.

Visual Analytics, as defined by Cook and Thomas in their Research and Development Agenda, is “the science of analytical reasoning facilitated by interactive visual interfaces” (5). The analytical reasoning is an iterative process that involves cycles of visualization creation, interaction and refinement. Therefore, Visual Analytics tools facilitate the human reasoning process by the means of technological support and analytical techniques.

With the increased amount of data that comes from different sources and domains, visual analytics became rarely a solitary activity. Analysts from different backgrounds need to work together to contribute their contextual knowledge and create a better understanding of their data. The integration of visualization and collaboration into a new direction of research imposed new challenges for designers and generated new prospects for researchers to expand the state of art design and evaluation of visualization tools. Designing for collaborative visual data analysis requires special considerations to fully support the sense making process (6).

As shown in Figure 1, collaborative visualization can occur in four different scenarios clas sified over time and space. Co-located collaborative systems involve a shared workspace such

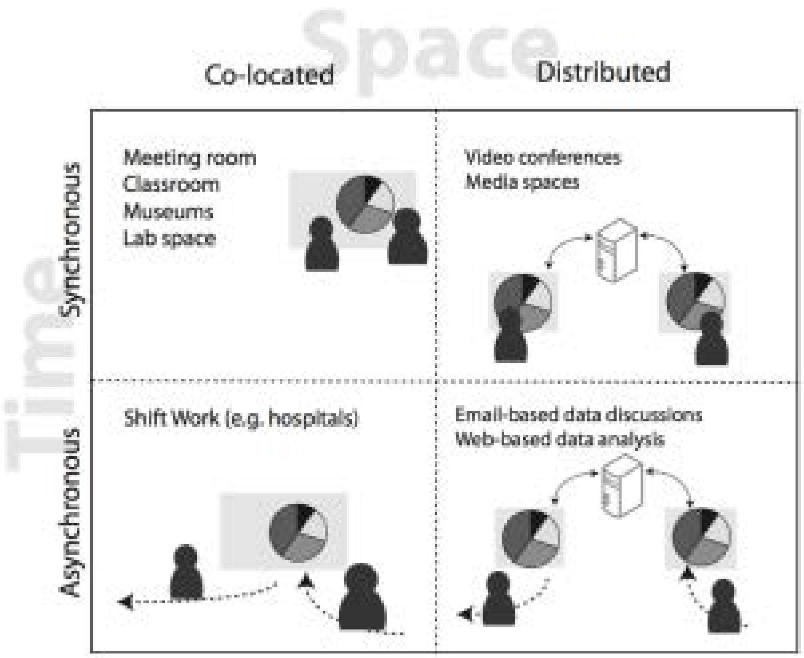

Figure 1: Different scenarios of collaborative visualization classified over time and space (1)

as large displays or tabletops, while distributed systems involve a shared virtual workspaces for remote collaboration.

Visual data analysis tools should support suitable social interactions according to the type of the collaborative environment. A rich body of research investigated the design of visualiza tion tools for co-located (7) (8) (9) and distributed collaboration (10), each of which required unique design principles derived from the visualization and computer-supported cooperative work (CSCW) communities. Besides the technical aspects, a vast majority of past research has focused on more human-centered questions to address issues regarding work coordination, sharing, and groups' awareness in co-located and distributed settings.

With the popularity and availability of various types of devices with different input and out put modalities, a new thrust of research has emerged to explore the potential of these display technologies in supporting analytical reasoning and sense making. Multi-device environments (MDE) have great potential to support analysts in their data analysis by utilizing each de vice's capabilities. However, little is known on how to design visualization tools for multi device environments to support efficient visual data analysis. This research investigates the design of visualization tools for collaborative exploratory visual data analysis in multi device environments.

1.1 Motivation

Recently, there has been an increased interest in leveraging ecosystems of multiple devices for collaborative visual data analysis (11) (12) (13) (14) (15) (16) (17) (18), imposing the need to rethinking the design and evaluation of visualization tools for these environments.

This new thrust of leveraging multi-device environments for visual data analysis supports new models for complex collaboration scenarios and provides the means for users to immerse themselves in their data by creating flexible and mobile exploration territories. However, there are some challenges inherently associated with visual data analysis in multi-device environments.

First, as the analytical process is underway, many visualizations become scattered among different devices and displays. Building a mental model of the analysis flow can render the analytical process more challenging as it would be difficult to track many visualizations. There fore, it's difficult for analysts to keep track of all the prior analyses and the cost of deciding what to explore next can be even higher. Analysts in collaborative settings need to understand

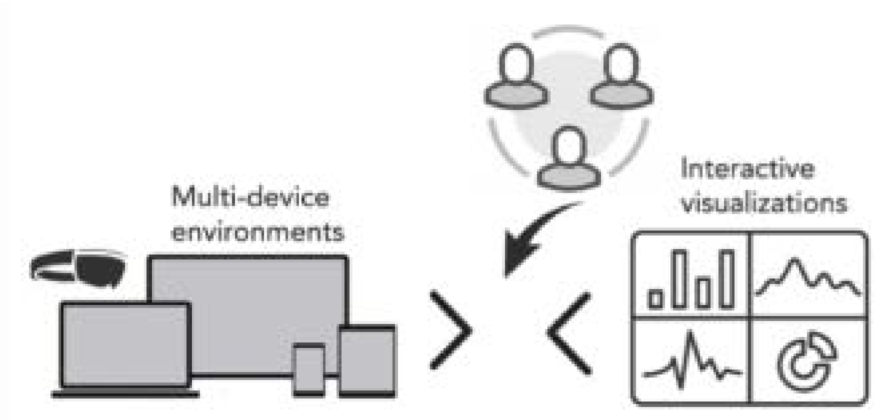

Figure 2: This research investigates the design of visualization tools for collaborative exploratory visual data analysis in multi device environments.

what courses of analysis were investigated by team members and what were left. Therefor, supporting exploratory visual data analysis is essential especially when multiple analysts work together in a setting beyond the single desktop.

In addition, with factors such as the recency effect and the short-term memory, they tend to remember the most recent exploration. This can affect the breadth of the analysis. The tendency to recall the most recent items encourage a depth-oriented exploration. Therefor, visualization tools should promote a breadth-first analysis.

1.2 Thesis Problem

Motivated by the above-mentioned challenges, this research explores the collaborative visual data analysis in multi device environments. The goal is to investigate how the analytical process occurs in this multi-user multi-device environment to provide a theoretical un-

derstanding of collaborative exploratory visual data analysis and better inform the design of visualization tools.

This dissertation investigates the following research questions:

RQ1: In the first phase of this research, I started with an exploratory study to address the question of what is the complex picture of users' experience during a collaborative visual data analysis in a multi-user multi-device environment?

Activities in multi-device environments can be complex. It is important to understand aspects around tools, users, and tasks, and how these aspects shape the analysis process. Un derstanding the analytical strategies and their associated challenges will help us to identify important design considerations and requirements that support some of these challenges.

Earlier studies that aimed to understand the collaborative process of visual data analysis focused on a few elements (display use, processes, work styles, etc.) as they address group's work around a single display. To capture the complexity of collaborative visual data analysis in a multi-user multi-device environment, I presented an Activity-Centered approach that identifies the network of actors that make the activity takes place in this environment: users, tools, and task. As presented in Chapter 4, these activity actors were identified based on the visualization reference models, and used to apply appropriate empirical methods in terms of each aspect for analysis. I believe that these three aspects (users, tools, and tasks) shape the complex picture of user experience in this environment. In Chapter 4, I discuss the study and the application of the hybrid analysis approach. I synthesized an overall understanding of the process and identified a set of observed challenges.

RQ2: The second important aspect is to derive an understanding of what is the char acterization of the analysis process in this environment. After multiple passes of qual itative coding, I found that the analysis proceeds at two levels. Within each level, I further observed a set of exploration patterns. At the higher level, participants were taken along a set of exploration paths, and along each analysis path, I observed a set of view-to-view exploration patterns that occur within the larger cycles of the analysis. In Chapter 4, I present a struc tural categorization of the analytical process in such a complex environment and discuss how this categorization corresponds to the current structural assumptions of exploratory visual data analysis. I also discuss research implications and touch on the potential value of augmenting visualization tools with supportive mechanism for efficient exploration.

The presented characterization of the analysis flow revealed patterns of how participants searched the space of data. I identified three patterns of navigating the dimensions data space as will be discussed in Chapter 4. However, participants relied on their mental model on navigating the data space. They were blocked form how much, and what, of the data space they have covered. As the analysis proceeds, it was hard to keep track of prior analyses due to many visualizations. Therefor, the exploration was oriented towards limited dimensions' space coverage. We need an approach that increases the awareness of the group and individual exploration of the data search space, and that can facilitate the exploration process. This led me to explore how to augment the design with a visualization of dimensions search space and what are the effects on the analysis.

RQ3: What are the effects of visualizing the coverage of the dimensions search space on exploratory visual data analysis? I hypothesized that explicit visualization of dimensions search space would improve the performance of the exploratory task. In chapter 5, I presented the design and the implementation of visualizing the dimensions search space. In chapter 6, I evaluated the design in a between-groups study. I tested three hypotheses in the presented study. I hypothesized that visualizing the dimensions search space will reduces the decision cost, increases the breadth of the analysis, and increases formed questions and observations. The results from the study supported the first and the second hypotheses. The results showed that the visualization of the dimensions search space reduces the cost of decision and increases the breadth of the analysis.

1.3 Research Scope

This research focuses on supporting visual data analysis in co-located settings where a small group of collaborators work together using multiple devices to make sense of their data. The focus on this direction was motivated by the benefits that co-located collaboration offers in many disciplines. Co-located collaboration reduces communication barriers that appear in other settings, as collaborators communicate directly at the same time and in the same place. With direct interaction, collaborators can easily assess their team’s need and adjust the team’s work. Especially in the case of using multiple devices, collaborators can easily switch roles and change the analysis strategy without the need for the cumbersome installation of additional instruments.

Furthermore, the exploratory nature of visual data analysis requires social interactions for discussion, ideation, etc. which can be handy in co-located settings.

In addition, in co-located settings, collaborators can employ multiple devices at the same time taking advantageous of offered opportunities. As I will discuss in the next chapter, multi device settings have great potential for collaborative visual data analysis. In this research, I employ a workspace with a large display integrated with portable devices. Specifically, the large display is integrated with tablets, laptops, and an AR headset (See Chapter 3 for more details). Earlier studies on large displays have shown that their physical affordances result in the emergence of different kinds of collaboration that have been used in many domains. The presence of portable devices would allow for different collaboration styles. As reported by Isenberg et al.(2011b), collaborators tend to branch from the group work which emphasizes the importance of supporting different work styles in groupware applications (8). In this research, I investigate the geoscience application domain. A few reasons motivated the selection of this domain. First, geoscience domain data typically has spatial and non-spatial features. The large scale exploration of these types of data benefits from the emergence of solutions that go beyond a single desktop. For example, large displays offer a large-scale exploration of spatial 2D representation, while AR headsets offer a spatial 3D representation. In addition, the analysis of heterogeneous spatiotemporal data has been emerging recently.

1.4 Methodological Approach

Empirical study approaches have been widely adopted by visualization research for visualiza tion evaluation, and for understanding the behavior of individuals using the visualization tools.

Tory (19) provided a categorization of user study methods applied to visualization research based on their goals of conducting. She stated that user studies are performed in visualization not only for ”*evaluation*” but also for ”*understanding*” the context of use. After specifying the study goals, researchers should delineate their research questions and objectives and iden tify appropriate empirical methods. This categorization helps the study designers to articulate their goals and narrow down their choices of appropriate empirical methods. Empirical ap proaches common in visualization research include the quantitative experiment, the qualitative observational study, and the usability study. Qualitative methods are widely used to answer exploratory questions using collected qualitative data. However, it has become common to use a mixed method to offset the shortcomings of each empirical method.

The study conducted in chapter 4 falls into the category of user studies for ”*understanding*”. The goal is to understand the context of use to enhance the tool design. More specifically, my goal was to observe the collaborative process of visual data analysis to inform the design space. Therefore, I designed the user study by paying attention to methods appropriate for this goal of empirical studies. As I discuss in Chapter 4, I used the exploratory user study method by applying a mixed methods employing both qualitative and quantitative analysis. The study conducted in chapter 6 falls into the category of user studies for ”*evaluation*” to evaluate the context of use.

CHAPTER 2

BACKGROUND AND RELATED WORK

Parts of this chapter were previously published as: Alsaiari, A., Johnson, A., Nishi moto, A., “PolyVis: Cross-Device Framework for Collaborative Visual Data Analy sis", In the Proceedings of *2019 IEEE International Conference on Systems, Man, and Cybernetics* (IEEE SMC 2019), October 6-9, 2019, Bari, Italy.

2.1 Collaborative Visualization

Collaborative visualization as defined by Isenberg et al. (20) is ”the shared use of computer supported, (interactive,) visual representations of data by more than one person with the com mon goal of contribution to joint information processing activities”. It lies at the intersection of two areas, visualization and computer-supported cooperative work (CSCW). Each of these areas has a long history of research, and specific challenges and requirements. Therefore, col laborative visualization brings its unique challenges to the intersection of these areas.

During the last twenty-years, many frameworks were proposed to support collaborative visualization for small groups to internet scale users. For example, Lark (9) is a visualization tool that support co-located collaboration for small groups around tabletops. In contrast, Many Eyes (10) is a web-based framework proposed to support a large-scale data visualization and asynchronous collaboration at the internet-scale.

Hence, collaborative visualization is classified into different scenarios based on the setup and the style of collaboration. According to the space-time matrix shown in Figure 1.1., there are four scenarios of collaborative visualization. Each setting requires specific design considerations and requirements.

Both synchronous and asynchronous visual analytics need special considerations due to the unique requirements for each setting. Work partitioning across space and time in asynchronous collaborative settings provides scalability yet introduces new challenges. Heer and Agrawala (6) defined a set of design considerations that identify important aspects for achieving effective collaboration in visual analytics settings. Those aspects with regards to asynchronous collab oration are important to increase the collaboration awareness and work engagement during asynchronous visual analytics. However, asynchronous visual analytics is out the scope of this research, therefore, I focus here on some design principles for co-located synchronous visual data analysis. Other efforts have been made to identify the requirements and design consid erations for specific settings such as collaboration around tabletops (21) and collaboration in multi-display environments (22).

Petra et al. (20) presented an overview of collaborative visualization scenarios and their associated challenges. They pointed out that designing for each of these settings should handle specific technical and social challenges. The technical challenges arise from the designing and the implementation of the physical and the digital environment. It should address and differentiate appropriate aspects of group work. The physical environment brings addition challenges unique to the type of the environment, either a large-display, tabletop, or multi-device environment.

2.2 Interactive surfaces for Information Visualization

Analyzing data that comes from different sources and domain requires multiple analysts from different background to work together in order to understand data and derive an insight. Therefor, there has been an increased interest in developing frameworks that go beyond a single desktop for visual data exploration and analysis. Petra et al. (23) , in their research agenda on visualization and interactive surfaces, stated the advantages and opportunities that multi-device environments offer for visualization. These include:

- Analysts have larger space than what one device can offer, to visualize and work on more data.
- It allows the distribution of the data to the appropriate device for visualization. •

It allows different collaboration styles by enabling individual and group work.

2.2.1 Literature Themes

A rich body of research investigated different aspects of designing visualization tools for multi-device environments. In the beginning of this research, I surveyed the recent research articles about visualization tools in multi-device/interactive surfaces. After a closer look at these publications, I found that they fell into few categories. The majority of these publications address the development/comparison of interaction techniques for interactive surfaces. The second research focus is the development of specific physical setups for visualization tools or applications for specific domains. Few publications addressed aspects of users' collaboration around interactive surfaces.

2.2.1.1 Interaction beyond mouse and keyboard for InfoVis

Different interaction mechanisms were proposed to facilitate exploration of visualization on interactive surfaces. Instead of using traditional mouse and keyboards, natural and direct interactions were used. Chegini et al. (24) presented a set of touch-based interactions for collaborative exploration of scatter plots on large displays. It enables multiple people to interact with visualization at the same time using different techniques for manipulation.

Figure 3: Themes of Interaction for information visualization.

Cross-device interaction examines the design and the development of interaction techniques that leverage the combination of different devices. Due to their popularity and portability, tablets, mobile phones and smart watches have been integrated with large displays and tabletops to steer the interaction and the visual exploration. By leveraging each device's display and input

modalities, they provide fluid interplay between them to support the visual data analysis tasks (16). Langner et al. (25) examined interaction techniques for multiple-coordinated views on large displays. They found that interaction from distance using mobile devices offer flexible movements, which is essential for collaboration and perception of many visualization at the large display.

Due to the physical nature of large displays and other devices, many approaches considered the space in front and around interactive surfaces for interaction. An interesting possibility for that is the use of proxemics. Jakobsen at al. (26) studies the possibility of using body movements to drive interaction with visualizations. They developed proxemics-based interac tion techniques as input for visualization manipulation. In their approach, they used the spatial relations among people and visualization as an input for visualization exploration. In VisTiles presented by Langner et al. (27), they instead used the spatial relations among devices to steer interaction. VisTiles utilized the portability and dynamics of mobile devices to enable flexible layout and distribution of coordinated multiple views. Therefore, it aids a user-friendly inter face. The coordinated multiple views can adapt to the spatial arrangement of devices enabling new visualization composition and exploration of multivariate data.

2.2.1.2 Setups development beyond a single desktop for InfoVis

Other frameworks investigated the composition of multi display environments to utilize the capabilities of heterogeneous devices, and extend the visual space for visual data exploration. Towards this goal, Badam et al. (11) presented the software of Munin that was developed to unify the composition of multi device environments through a service-based model. It envisions

the anytime and anywhere visual data analysis. Through the service-based model, a user can specify the physical setup, input, output, and visualization services for the assembled devices.

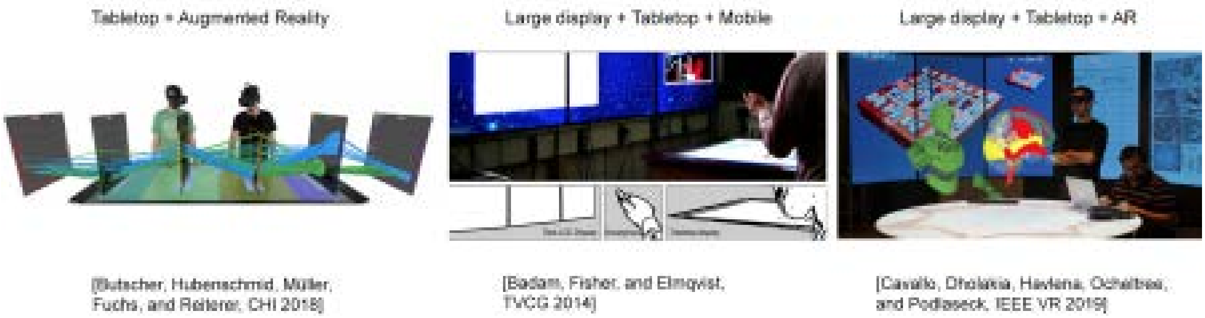

Figure 4: Examples of setups beyond a single desktop for information visualization.

Other physical setups were presented in the literature for the visual exploration of multidimensional data. These systems investigated the opportunities that the new technologies offer for visualization. Butscher et al. (17) and Cavallo et al. (28) presented new design spaces for visual data analysis through the use of immersive technologies. These systems enable an immersive collaborative analysis of multidimensional data where users can immerse themselves into the data.

2.2.1.3 Collaboration beyond a single device for InfoVis

The last theme of work addressed aspects of users' collaboration such as collaboration styles, territoriality, processes, and coupling and decoupling of work. I conducted a search-

based survey on publications that their main research focus was around collaboration. I chose the major visualization and interactive surfaces venues such as IEEE VIS, EuroVis, ACM CHI, ACM ITS, CoVis, and IV.

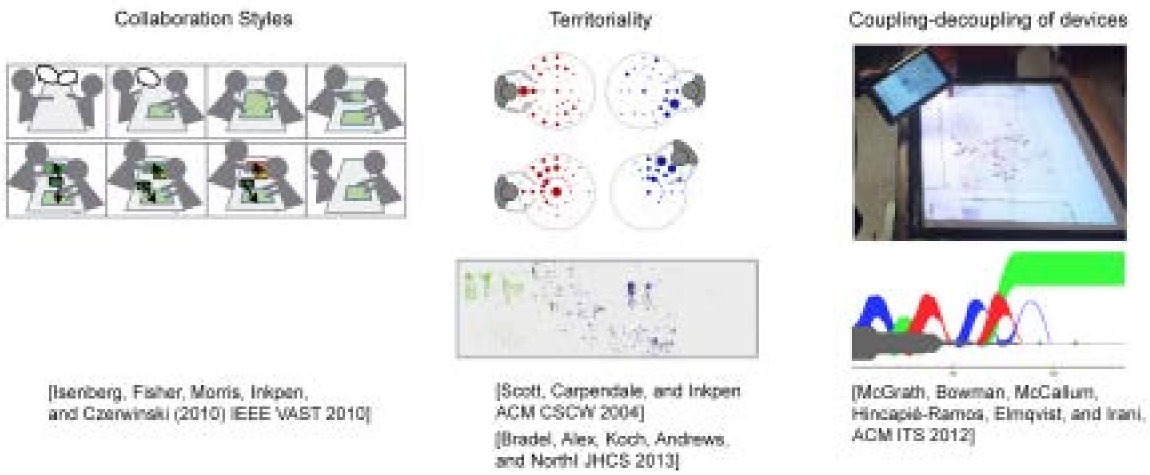

Figure 5: Studying collaboration beyond desktop environments.

Figure 6 lists the surveyed publications, their setup, and research focus. This theme of work is the most related to the work presented in this research, although the goal of this research is not only to understand the collaboration in multi-device environments but also to provide tools support that enhance this collaboration. The work presented here differs from the work presented in the literature in two aspects. First, we address the flow of the analysis process from the dimension of analytical flow and structure with regards to the use and formation around

multiple devices. Second, we study this problem in a dynamic environment of multiple devices including large display, laptop, tablets, and AR headset.

			Physical setup					Visualization type				
Author	Year	Group's members	Mobile	Tablet	Laptop	Tabletop	Large display	Map	Charts	Graphs	Other	Research Focus
Mahyar et al.	2009	3				■	■		■			Note taking
Mahyar et al.	2010	3				■	■		■			Processes and note taking
Isenberg et al.	2010	2				■					■	Collaboration styles
McGrath et al.	2012	3		■		■		■				Pattern of coupling and decoupling
Wallace et al.	2013	4		■		■			■			Breadth vs. depth sensemaking
Bradel et al.	2013	2					■				■	Territoriality
Chung et al.	2014	3		■		■	■			■		Collaboration and cross-device sharing
Mahyar and Tory	2014	3			■					■		Communication and coordination
Mahyar et al.	2016	4-5		■		■	■	■				Public engagement
Langner et al.	2018	2	■				■	■	■			Movements and distant interaction

Figure 6: Publications that their main research focus is collaboration around visualization tools and interactive surfaces.

Mahyar et al. (29) (30) studied the collaborative visual data analysis around large displays with the focus on the record-keeping activity. They identified how and when users keep notes and charts during the analysis. They analyzed the use and the contents of those saved items. Then, they classified the analysis activities into five categories. The presented framework of the analysis activities encompasses the record-keeping as a main activity that takes place along

with all other activities. As their work focused merely on the analysis task, this research studies the analysis task and its structural characteristics that was shaped by the dynamic social and digital interaction. This structural definition informs the further support of the analysis process.

Isenberg et al. (31) performed an exploratory study to observe collaboration styles of pairs around a single large display. They identified eight collaboration styles of team's work around the tabletop. These styles classified as close and loose collaboration. Their work investigated the styles of collaboration around single device where multiple devices bring more dynamic collaboration as we observed in this work.

McGrath et al. (15) proposed Branch-Explore-Merge protocol to support the coupled and decoupled visual data exploration in an environment of tabletop and tablets. Portable devices, i.e. tablets, allowed for private exploration and merging of results onto the shared space, and hence, the branching and merging protocol facilitates flexible levels of exploration territories. Chung et al. (18) studied the sharing and organization of information entities across devices through gestural interaction. Their work addressed users' collaboration around devices and the organization of information entities while the work presented in this research addresses the task flow from the dimension of analytical flow and structure with respect to the use and formation around devices.

Understanding territoriality on interactive surfaces is essential for collaboration and com munication. Some studies focused on the collaborative use of devices and territoriality on large displays (32) and tabletops (33). Bradel et al. (32) explored how pairs of participants used the large display during a collaborative analysis task of textual data. They observed that the large

space offered by the large display allowed participants to construct different spatial schemas.

Users used areas on large display to non-verbally communicate space ownership. They created territories for private and shared use, in addition to territories for storage. This highlights the importance of supporting the individual and group work on collaborative interactive surfaces. Lngner et al. (25) tracked the movements pattern and interaction from distance with the large display to understand territoriality of individual in the physical space. The territoriality in this research requires different evaluation metrics as it is scattered across physical and digital spaces. However, I save the investigation of physical and digital boundaries for future work.

Wallace et al. (34) investigated different displays configurations and how each setup affected the sensemaking and equity of participation. All three setups designed around a single tabletop which implies different considerations for the task and social interaction.

Other aspects of collaborative visualization for multi-device were investigated. Mahyar and Tory (35) studied the effect of linking individuals work in a virtual space using an office setup with personal desktop computers. Related to collaboration, Mahyar et al. (36) studied the iterative design of multi-device urban planning environment that engage a broad range of stakeholders. Sarvghad et al. (37) presented the notion of dimension search space visualization.

Briefly, this research differs from previous work by addressing the analysis process from the dimension of analytical flow and structure with regards to the use and formation around multiple devices. The resulted characterization of the analysis process informed the design of the proposed approach of visualizing the dimension search space. The novelty of the proposed approach is identified by two features. First, the differentiation of individual and group search space. Second, the guiding of the analysis process through the realization of the analysis paths patterns.

2.2.2 Roles of Devices

The goal of utilizing heterogeneous devices for visual data analysis is to leverage their different capabilities and strengths during analytical activity. Here I review their potential roles in supporting visual data analysis.

2.2.2.1 Portable Devices

Portable devices such as phones, tablets, and smartwatches are small personal devices mostly used privately by their users. Portable devices have been adapted to serve as a secondary dis plays for different needs. They were used as a controller for interaction in front of large displays (25) allowing multiple users to interact with the large display form distance. In addition, they can take the role of a private display in collaborative settings. Users can branch from the pub lic work to due their analysis and merge finding later (15). Smartwatches are special type of portable devices and they are in fact lightweight and wearable devices. They are non-intrusive devices allowing users to be hands free and able to interact with other devices. Due to their limited display capabilities, they require special considerations for visualization design (38).

2.2.2.2 Personal Computers

Personal computers have been widely used in offices and homes. Their input capabilities using mouse and keyboard are familiar by the majority of users. In fact, traditional visualization tools were mainly designed for the desktop setup, supporting its input and output capabilities. Personal computers are beneficial for personal visual exploration of data.

2.2.2.3 Large Displays

The large space offered by large displays serves as a canvas to visualize multiple visualizations and juxtapose them for analysis. They have been demonstrated to positively affect the visual data exploration by providing a large ”space to think” (39). In addition, the large space enables multiple analysts to interact with them at the same time. They serve as a shared display that is accessible to everyone. Large displays also support natural an intuitive interaction metaphors such as touch and speech interactions, increasing their interactivity and support for multi user interaction.

2.2.2.4 Immersive Displays

The notion of immersive displays are more broader than Augmented Reality (AR) and Vir tual Reality (VR) displays. For example, very large displays with large field of view qualify as immersive displays. Nevertheless, for simplicity, here I refer by immersive displays to AR and VR displays. Big Data characteristics required non-traditional means to support the limited human ability to extract information and gain knowledge from the data. AR and VR are one of promising techniques to support the challenges of big data. They are suitable for the limited perception capabilities of the human brain. VR displays showed better exploration of data that holds spatial dimensions. They have been used as an interactive and collaborative plat forms for scientific visualization (40) and visual data exploration (41) moving from traditional visualization of 3D data on 2D screens.

2.2.3 SAGE2

SAGE2 (2), the successor of SAGE (42), is a middleware developed using web-browser technologies to take multiple displays and unify them as one high-resolution workspace. It enable users to collaboratively share and display their contents on the large display (Figure 2.5).

Figure 7: User collaborating during a SAGE2 session where they share digital contents (i.e. PDFs, images, etc.) on the large display. (2)

Display clients provide information of the corresponding viewport in the workspace via their URLs. Any number of displays on different systems can be joined to form a unified view of the SAGE2 workspace. SAGE2 native applications are written in JavaScript using SAGE2 API. Applications open simultaneously on the large workspace enabling users to collaboratively interact with them. Users interact with the workspace through UI clients running on their devices using a SAGE2 pointer, which is an html element that collects the native mouse events and propagates them to the corresponding display client for handling. Due to its distributed application and event model, all users input events are passed to the head node server which in turn distributes them to display clients for handling. Each display client has its own instance of running applications and receives events to handle them consistently. In this system, I integrate the SAGE2 large display with portable devices of different modalities like tablets and AR headsets to create additional visual exploration territories. Coupling and coordinating with different devices requires middle modules for data sharing, translation and synchronization due to different platforms inter-dependency. To tackle this issue, I developed the PolyVis framework based on declarative visualization design and operation transformation (OT) for seamless migration of visualizations and their interactivity between devices.

2.3 First Set of Design Principles for MDE

2.3.1 (D1) Device agnostic visualization sharing

Generally, there are two ways to develop visualizations. One is a native development for a specific platform, and the other is a web-based development. Unlike native applications, web-based applications can be deployed to any device using web technology. Many frameworks and toolkits were developed based on web technology like D3 (43) and JavaScript InfoVis Toolkit (44) to support information visualization applications. PolyChrome (12), Vistrates (45) and Visfer (46) are all web-based frameworks developed to support the collaborative visual analysis. However, sometimes, going natively cannot be avoided when working with devices like AR/VR headsets. In addition, native applications are essential to take the full advantage and

support of the target device. Going with one way is not enough to support all applications and user requirements. To close this gap, solutions for cross-platform infrastructures are essential (47). Grammar-based representation of visualizations has been introduced in many works with various levels of abstraction. They provide a mechanism to define visualization interdependently from rendering platforms. Examples of these declarative languages include Vega (48), Vega Lite (49), ggplot2 (50), and ggvis (51). In addition, PolyChrome (12) adapts a centralized server to maintain concurrent web-based visualization exploration by pushing DOM events between browsers. DOM Events are wrapped into a global space and inverted on the target display to support different display sizes and configurations. This mechanism is called Operation Transformation (OT) and it is originally developed to maintain concurrent use and consistency in text editing tools (52).

2.3.2 (D2) Support of parallel and joint activities

The style of collaboration between participants is affected by the display setup, the prob lem under investigation and the analysis metaphors. Studies showed that collaboration around interactive surfaces for information visualization in co-located settings takes the forms of com pletely independent, partially independent and joint (coupled) work (9)(53). Other studies by Isenberg et al. (54)(31) identified the styles of collaboration as a spectrum that varies from loosely coupled to tightly coupled. These findings emphasize the importance of supporting indi vidual and group work, and efficient transitions between styles. Another aspect that is related to the style of collaboration around interactive surfaces, is the use of the space. Territoriality, which is the spatial coordination of collaborative work, also takes three forms as identified by Scott et al. (33). Users use the space for personal work, group work and for storage. 2.3.3 (D3) Fluid cross-device interaction

Spreading visualizations and the analysis tasks to multiple devices requires intuitive cross device interactions. Information sharing and management should not distract users from the actual analysis. Embodied interactions (55) leverage the proximity of devices to develop in teractions that carry out these operations. Badam and Elmqvist (46) presented a cross-device interaction technique for data sharing in ubiquitous environments based on a design elicitation study. The interaction technique leverages the physicality of the devices, to effortlessly share visualizations across devices using a built-in camera and embodied QR codes. In VisPorter (18), gestural interaction was utilized to transfer information across displays in an intuitive and direct way. Their approach was based on the concept of physical references of shared information, rather than using symbolic references such as IDs and URLs.

2.3.4 (D4) Exploiting the physical space

Utilizing physical space is essential in scalable visual data analysis. Andrews et al. (39) showed that analysts exploit the spatial affordances of large displays to serve as an external memory and as a semantic layer for spatial data layout and organization. In collaborative settings around tabletops, users frequently move and organize information to approach their analysis tasks (54). Multi device ecologies enable users to carry information and form dynamic exploration territories across displays that populate the physical space. The view and the analysis process can be extended to span multiple exploration sites across the physical space.

The affordances of the physical space enable the flexible configuration and coordination of devices to approach the task. In addition, physical space is essential to embody information and immerse users in their data.

2.4 Modeling of Visual Data Analysis

Neumann et al. (56) presented an information visualization framework describing collabo rative activities in information visualizations context. The presented framework is derived from an exploratory study that was designed to understand the process of collaborative visual data analysis around tabletop display. They contributed an evolving understanding of this process and informing earlier models of information visualization. Brehmer and Munzner (57) reviewed the literature on visualization tasks and derived a multi-level typology of visual analysis tasks. The typology comprises why and how a task is performed, and what are the input and output to complete it. It helps to express high-level tasks as sequences of low-level tasks. Lam et al. (58) presented a framework based on a review of 20 design study papers to describe the high-level analysis goals and how they can be achieved with low-level tasks identified from the review. As in (57), the high level context of analysis goals helps to interpret the low level actions.

Several studies modeled the behavior of users during exploratory visual analysis as a set of states. Reda et al. (59) used a Markov chain to model the transition between different cognitive and computational processes. The weighted transition between processes states help to understand user analytical behavior and predict future interaction. Sarvghad et al.

(60) defined the analysis states during the analysis session as newly created visualization with new set of attributes. The same definition of analysis state is used in Voyager (61) and Voyager2

(62). Unlike other categorization of the analysis, they defined the analysis as a navigation of the dimension space where the analysis state changes by the change in the data dimension space. The previous representations of the analysis as sets of states captures the complex flow of the analysis but it doesn’t provide a full understanding of the analysis structure. Battle and Heer (63) reviewed the literature on exploratory visual data analysis and identified a set of assump tions regarding analysis performance, goals, and structure. After evaluating those assumptions through analytic provenance in Tableau, they synthesized a definition of exploratory visual data analysis contributing an understanding of it structure. We further add to this definition by presenting a two level categorization of analysis structure synthesized from observations of collaborative visual data analysis sessions.

CHAPTER 3

POLYVIS: DESIGNING FOR VISUAL DATA ANALYSIS IN MULTI-DEVICE ENVIRONMENTS

Parts of this chapter were previously published as: Alsaiari, A., Johnson, A., Nishi moto, A., “PolyVis: Cross-Device Framework for Collaborative Visual Data Analy sis”, In the Proceedings of *2019 IEEE International Conference on Systems, Man, and Cybernetics* (IEEE SMC 2019), October 6-9, 2019, Bari, Italy.

3.1 Introduction

Visual analytics encompasses a large amount of data that comes form different sources and domains. Therefore, collaborative visual data analysis has wide application across domains to enable multiple users (often called analysts) to work together to collaboratively contribute their contextual knowledge and deepen their understanding of the data. The heterogeneity of datasets and the need for multiple analysts to work together demanded solutions that go beyond the single desktop (64) (65). There has been a shift to big and multi-surface interfaces for visual data analysis. Tiled wall displays have been shown to increase the performance of visualization tasks (66) and the productivity of exploratory visual analysis (67). In recent years, spreading to multi-device settings for co-located collaborative visual data analysis has emerged to leverage different devices capabilities (17) (27).

Designing multi-display interfaces that combine multiple devices for collaborative visual data analysis faces multiple challenges. They should support key principles for effective collab oration. First, the ability to share visualization between collaborators and devices is important to support different collaboration styles. Collaborators should be able to share visualization between different devices. However, cross-device visualization sharing requires the development of flexible visual representations that can seamlessly migrate between devices regardless of the rendering platform. In addition, cross-device collaborative systems should allow simultaneous interaction with visualization. Cross-device simultaneous interaction can be a grand challenge due to platforms disparity. An interaction (e.g. touch) on a specific device should be interpreted in other synced platform to execute the same action (e.g. click).

This chapter addresses the above mentioned challenges by introducing the design and im plementation of a multi-device system for collaborative visual data analysis that enables cross device visualization sharing and simultaneous interaction between devices. I integrate SAGE2 large display with portable devices (laptop, tablets and augmented reality headset) for co located visual data analysis. The system implements a front-end multi-display user interface and a networked communication and coordination protocols for visualization sharing and si multaneous interaction between clients devices. Each device plays specific roles according to its display modality as described in section 3.2.2. Back-end protocols for communication, sharing, interaction synchronization are described in sections 3.2.3 and 3.2.4.

3.2 PolyVis System

Below, I discuss the primary features of the framework. I refer to the design principles discussed in the last chapter (D1-D4) in the description of the framework and how the choice is made to meet these principles.

3.2.1 Overview

The proposed framework is specifically designed to seamlessly support collaborative visual data analysis that can span multiple devices of different modalities. The framework is built on top of SAGE2 middleware that drives tiled wall displays and unifies them as one high-resolution display. PolyVis integrates portable devices with SAGE2 display to compose a heterogeneous visual data analysis environment enhanced with further exploration capabilities.

Earlier studies of collaborative visualization emphasized on the importance of supporting individual and group work for different collaboration styles. While the large display is a pri mary display, tablets enable different exploration styles. They allow users to branch from the main analysis to conduct a local exploration or to conduct a coupled exploration with other collaborators (D2). PolyVis users can join the analysis session using their tablets or phones to pull and push visualizations from the large display and do further analysis activities as will be described below.

The integration of AR/VR devices enables a different display modality. However, PolyVis only support the HoloLens AR headset for 3D immersive visualization. This choice can be justified by the fact that VR display modality requires additional considerations to be integrated

effectively. Unlike VR, AR headsets can enable collaborators to exploit the physical space as an additional exploration territory without blocking them from their surrounding environment. The system is a server/client based system where SAGE2 server handles the communication with and between several clients applications for the laptop, tablet, SAGE2 app, and HoloLens. Figure 8 shows an overview of each device capabilities. Users can iteratively filter data, specify the visual encoding, and create visualization. They can pull/push visualizations and change their visual representations using portable devices.

As users can pull/push visualization, they also can sync interaction on a view between the wall and the tablet displays. Any changes are made on the tablet will update the synced view on the wall and vise versa. The simultaneous interaction approach is described in 3.2.3. To share visualizations between devices (pull/push), PolyVis adapts the visualization declarative design as described in section 3.2.4.

Developing visualizations can be a tedious process for users with no programming skills, such as data analysts. Therefore, visualization authoring systems and toolkits have been widely adapted in recent years. The presented framework enables the rapid construction of visualiza tions by a visualization authoring UI following the flow of the information visualization reference model (68) in which users filter the data, specify the visual encoding, and create the visualiza tion. Here, users play a major role in the visual mapping task that maps each data attribute onto a single visual channel.

As will be described in the next chapters, groups of three participants used the system to perform exploratory visual data analysis of geoscience data sets.

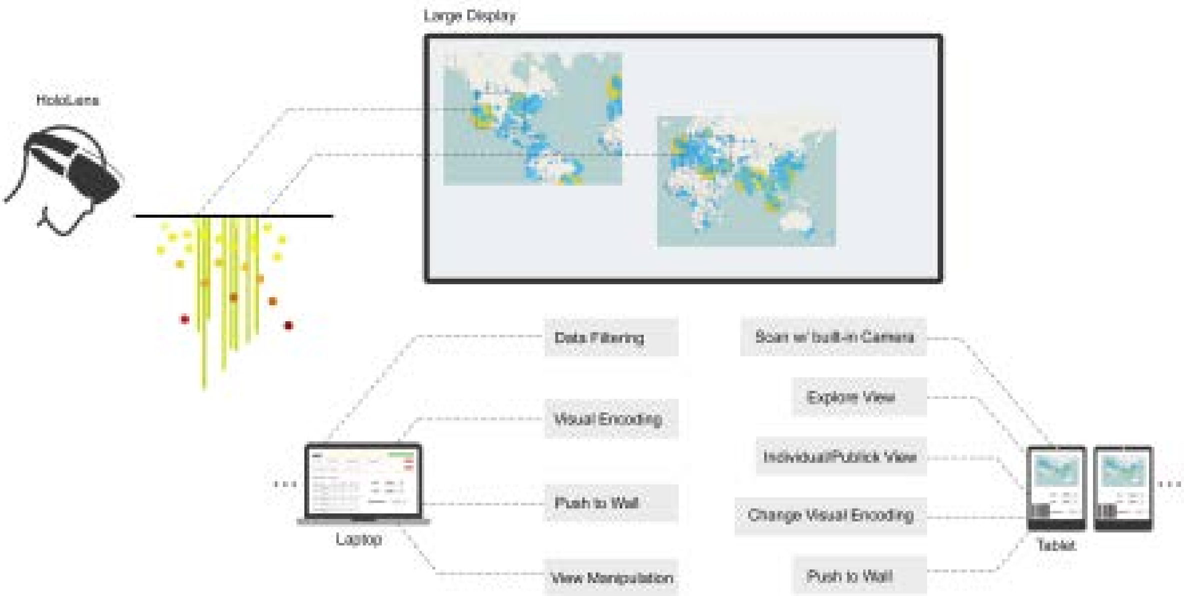

Figure 8: An overview of each device capabilities.

3.2.2 Physical Environment

Different devices like smart-watches, phones, tablets, laptops, large displays, AR and VR headsets became common display metaphors for information visualization. Some of these de vices like smart-watches and VR headset require unique design considerations due to their field of regard either a very small or a very big. Therefore, I limited my scope to support the integra tion of portable devices that vary in between like tablets and the HoloLens AR headsets. Any number of mobile devices with a built-in camera and web browsers (i.e. tablets and phones) can be joined to pull and push visualizations from and to other devices (D3). The HoloLens client device extends the exploration into the third space. Each distinct HoloLens client should run

on a separate machine. While theoretically the system can support a larger number of devices clients, I used one laptop, two tablets and one HoloLens in the conducted studies.

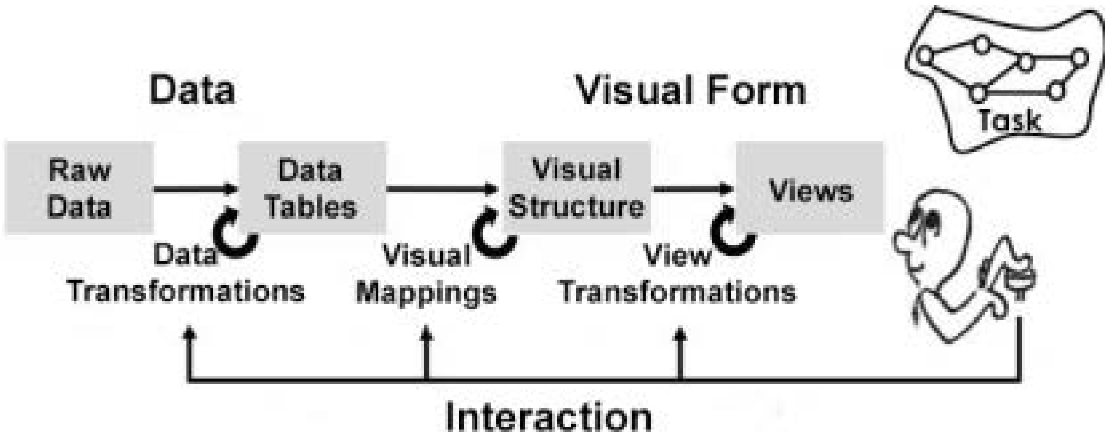

Figure 9: Visualization reference model (3).

3.2.3 Cross-device Visualization Coordination Approach

PolyVis can enable coupled exploration style by coordinating views between two devices (D2). That is, users can link a local view on the tablet with a global version on the wall and interact with them simultaneously. To allow coupled exploration styles between devices, the views on both devices should be synchronized. When it is needed to maintain visualization co ordination, the system should synchronizes visualization state between client devices, regardless of rendering platform, to ensure that collaborators see the same data.

In this section, I discuss the choice of the selected coordination approach. To understand how to support cross-device visualization synchronization, we need to analyze the structure of visualization applications in order to specify the possible places for synchronization in different platforms.

According to the visualization reference model (Figure 9) , the ”*view transformation*” con verts the *”visual structure”* into a *”view”*. To maintain the same view across all clients, one possible way is to synchronize the view itself. However, it is difficult to sync the view itself (and its rendering components like SVGs) due to different rendering environments across platforms.

Another way to coordinate views across all clients is through interactions. As shown in Figure 9, the user can control the parameters of the views through *interactions*. User interaction with the view triggers an action (program logic) that updates the view. Therefore, interactions will trigger the view transformation cycle that updates the view. So any interaction triggers an action that updates the visualization should be triggered in all coordinated views. Synchronizing interaction is more generic than synchronizing the view itself.

Nonetheless, synchronizing interaction is not straightforward. Low-level interaction events can be variant in different platforms. Click event for example corresponds to pinch event in HoloLens. While they differ in their representation, they posses a similar activity semantic. Gotz and Zhou (69) characterized user’s visual analytic interactions into a multi-tier activity model based on their semantic richness. The bottom tier of their 4-level model is the low-level interaction events which have little meaning without context such as click, mousemove, etc. The second tier is the actions tier. Actions are meaningful units that can be achieved by one

or more low-level events such as brush, filter, inspect, etc. While they posses a richer semantic than low-level events, they are generic in visualization tools (69).

3.2.3.1 Interaction Synchronization

The interaction synchronization approach presented in this chapter is based on the actions tier. All interactions are wrapped into predefined rich semantic visualization actions and shared with peer clients for synchronization. The interaction synchronization API interprets and exe cutes (triggers) the action in the target device for coordination.

The representation of rich semantic action captures its properties and parameters. Similar to (69), a rich semantic actions are defined as:

Action =< Id, Type, Parameters[value, valueType, deviceId, timestamp] >

Where the type represent the type of the action and the parameters hold the values to execute this action.

Similar to PolyChrome (12), the server is used to maintain the global state between all clients. Low-level events are wrapped into a global space (actions) and inverted on the target display. The framework encapsulates coarser interaction operations instead of low-level events, so they can be shared and inverted by the target device. There are four types of actions that are supported for synchronized interaction. These are inspect (details-on-demand’ for a visual object), brush (highlighting a subset of visual objects), pan (scrolling a visualization), and zoom (scaling a visualization). Although the tablet client is written in JavaScript similar to

SAGE2 applications, the coordination layer is necessary due to the difference in interactivity handling between SAGE2 applications and other JavaScript-based applications. 3.2.3.2 Visualization Persist State

The second challenge that PolyVis addresses is sharing visualization between devices as will be described in the next sub-section. However, it is especially important in collaborative settings to share visualizations in their current state. Therefor, PolyVis maintains visualization state after interaction.

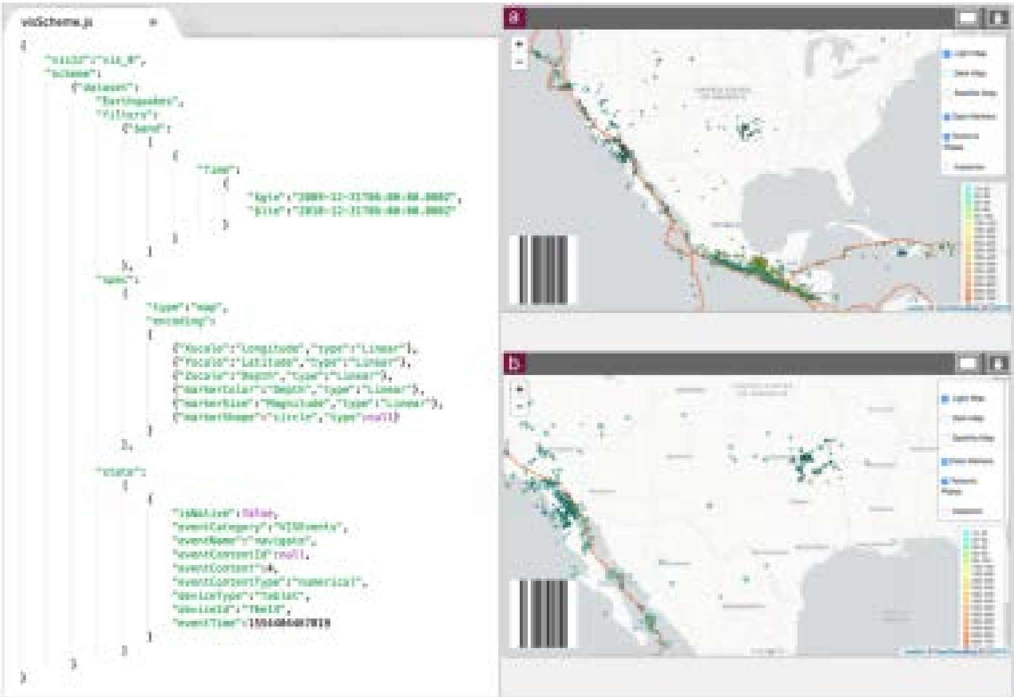

Figure 10: An example of a visualization scheme structure. (a) visualization at initial state. A new visualization state is pushed to the scheme after an exploration event occurred in (b).

Most visualization frameworks lack the ability to capture the visual exploration state and the path that led to it. The most challenging aspect is how to capture the visualization state. From the visualization task perspective, interactions in visualization can include a set of low level events, such as brushing interaction which is composed of the events: mouse-down, mouse move and mouse up. Do we consider the visualization state after each low-level event or after a richer semantic interaction that is composed of a set of low- level events?

Figure 11: The visualization declaration scheme can span different devices for rendering: (a) large display, (b) tablet, and (c) HoloLens.

The state definition needs to be identified first before any effort to capture it is made. As discussed in the last section, I define operations as interaction-centric operations. To en able consistency between different platforms, I chose to define the visualization state based on semantic rich interactions. I enable client side maintenance of a persist state. The state is recorded as the user interacts with the visualization. I defined an intermediate layer to record and push the state to the visualization scheme. When the visualization is shared, the state is recovered according to the device-dependent interactivity and visual channels encoding.

3.2.4 Visualization Sharing

As I discussed in the previous chapter, visualization development can be either native to a specific platform like AR/VR headsets or it is web-based application that can be deployed to any device using web technology. Grammar-based representation of visualizations (i.e Vega Lite(49)) has been introduced in many works with various levels of abstraction. They provide a mechanism to define visualization interdependently from rendering platforms. For visualization sharing between different devices, I treat visualizations as user-configurable semantic units (D1). I use a grammar-based representation of visualization to represent the visualization semantic.

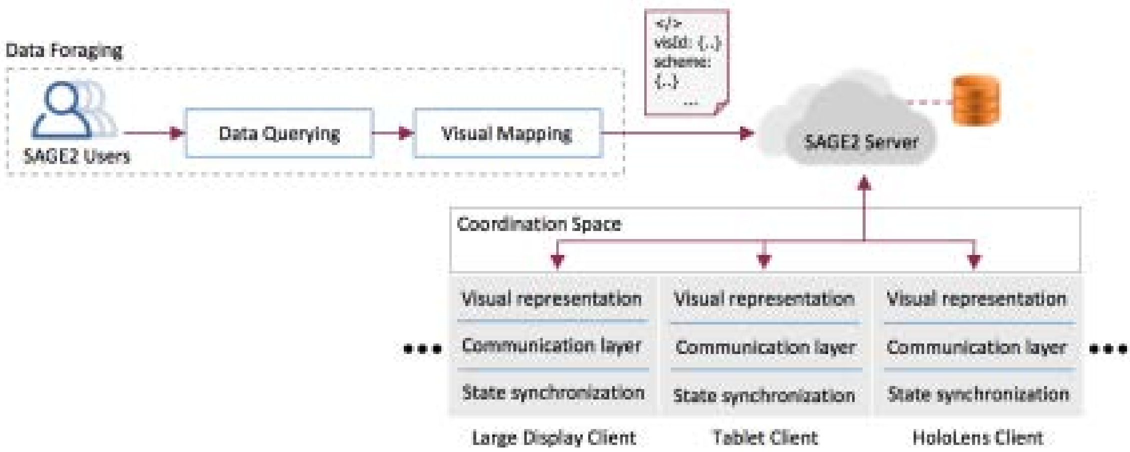

Figure 12: An overview of the system components. A visualization scheme is defined by the user through a set of filtering and visual encoding specifications. The server coordinate the spanning of the scheme to the target device and coordinate the event wrapping and sharing between devices.

Unlike other grammar-based applications, I assume a dynamic visualization scheme that gets updated with user interactivity with the visualization. I employ an all-in-one JSON format to declare three main components of the visualization in our framework.

These components are: query specification for data retrieval, visual encoding channels, and interactivity state. I capture those components during user composition of visualization. The interactivity state is captured automatically using our persist state mechanism and update the scheme accordingly. Figure 10 shows an example structure of these components. Decoupling the visualization semantic from its view transformation process enabled a seamless migration of visualizations across devices (D1).

Using this approach of declarative visualization design, visualization can be shared between devices regardless of the rendering platform. To share a visualization, the application shares the visualization scheme with peer client. The view transformation is delegated to the target device for rendering (Figure 11).

3.3 Evaluation

To evaluate the use of the prototype system for the visual data analysis of real world datasets, I conducted a collaborative session with two visualization researchers. Here, I outline the data analysis scenario and discuss feedback from experts.

3.3.1 Collaborative Scenario

Two researchers with a background in visualization, one has additional experience using immersive technologies, conducted a visual data analysis of two geosciences datasets. For ref erence, I will refer to the users as U1 and U2. The users performed a visual analysis task

to ascertain the relationship between injection volume, the pressure of fracking wells and the frequency of earthquakes in Oklahoma State. The first dataset contained information about earthquake incidents in Oklahoma and California from the years 2000 to 2010 (Appendix C). The Wells dataset contained information about the fracking activities in Oklahoma and Califor nia also from the years 2000 to 2010 (Appendix C). The earthquake dataset consisted of 24555 records and 12 attributes while the Wells dataset consisted of 5138 records and 9 attributes. These datasets have attributes with similar meaning such as the location, the time, and the depth. The earthquake dataset was provided courtesy of http://service.iris.edu/ and the Wells injection dataset was provided courtesy of http://www.occeweb.com/.

The users started with the question: Is there any correlation between the injection volume of wells and earthquake events? U1 began by mining the data for all earthquake events during 2010 and then he visualized them on a large display map. He also created a map of the locations of active well during 2010. U2 captured the barcode attached to the map of earthquakes by using the camera of the handheld device to pull the map visualization and performed analysis of the mapped data. He created a line chart to plot the frequency of earthquake events over the year and pushed the chart to the wall. They observed an increase in the number of earthquake incidents during the month of December.

To investigate the temporal relationship with injection volume, he moved to the map of wells and captured the attached barcode. Then, he created another line chart of total volume injection per month. A pattern is observed, so he pushed the chart to the wall and started to discuss with U1. They observed an increase of volume injection during the month of November, which

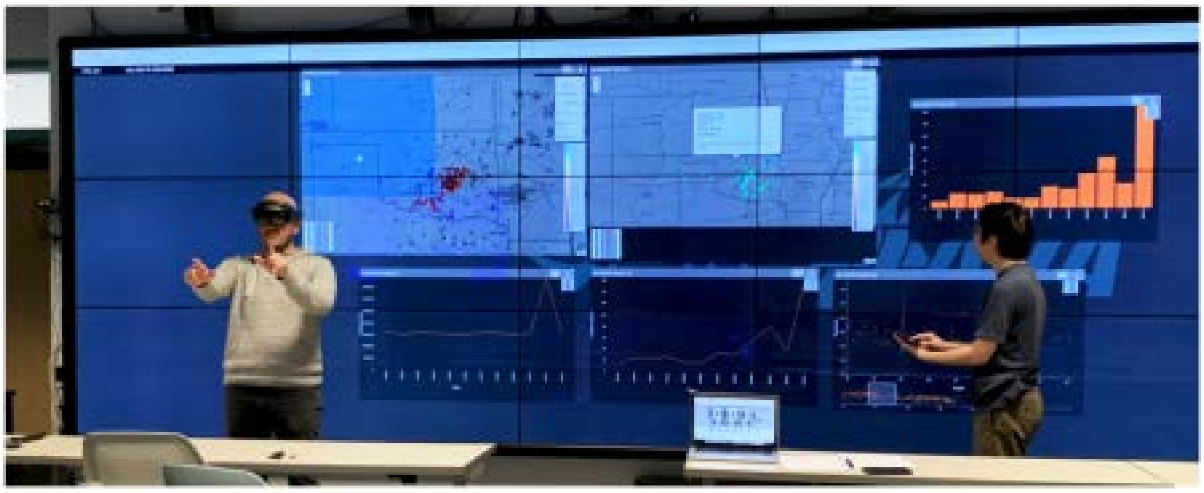

Figure 13: In a collaborative session, the user on the left is examining data in 3D using a HoloLens device. Data points (Wells) within the blue rectangle on the left map are viewed in 3D via HoloLens. The other user on the right is using a tablet (with linked visualization) to inspect specific areas on the right map.

has no temporal relation with the increase in earthquake events, but they made a hypothesis: can a high volume injection cause an increase in earthquake frequency for the next month? U2 used the HoloLens to examine the relative depth of the wells compared to the depth of the earthquakes. They concluded that an additional investigation of the observed pattern is needed for different years and probably for different states to test their hypothesis.

3.3.2 Expert Feedback

I collected feedback from the experts regarding the usage of the system for visual data analysis and the benefits of integrating different devices into the process of visual data analysis. U1 mentioned that the use of the tablet gave more freedom of movement, obtain the data they want, process it and push it back. He also believes that this will allow different people to focus on different things of the analysis process. Because of the affordance of portability, both users mentioned that it would be beneficial to use the portable devices as a controlling metaphor to control visualization on other devices (i.e. tablet to control a visualization on large display or on the HoloLens). Controlling here is different than coordinating or linking visualizations. In this context, it means moving visuals around, minimize or maximize them, etc. U2 mentioned that it is useful to view datasets in 2D on the large wall and in 3D on the HoloLens, but the hardest part is to determine what the HoloLens user is seeing. As U1 used the HoloLens to view the data in 3D, he added that it also needs a kind of representation on the large display or any mechanism that would increase the awareness. Experts gave good feedback on how the devices are complementary to each other.

3.4 Conclusion

In this chapter, I presented the PolyVis framework for the building and promoting of visual izations in multi device environments. It supports visual data exploration by utilizing multiple devices of different modalities. The primary goal was to maintain consistent sharing and inter action with visualizations across different platforms. To achieve this, I relied on the declarative visualization design and the operation transformation paradigms. I treat visualizations as se mantic units (in the form of grammar) to migrate to and render by different devices. SAGE2 users assume a major role in the composition of visualization grammar without any need for programming skills. The interactivity with the visualization is captured and stored in a global space for consistent representation. Therefore, the state of the visualization will be maintained as the data analysis proceeds regardless of the processing device. There are a few areas that

I plan to improve in the future. First, the visualization layers at each device only support few visualization types. I plan to extend that to support more advanced types of visualization such as multi lines, stacked bars, parallel coordinate, node-link, etc. I plan also to support the 3D version of these types on the HoloLens client. In addition, as suggested by experts, I would like to implement a mechanism for cross-device multi-coordinated views. With multiple visualizations at a time, it would be beneficial for the visual exploration to connect data points across scattered views.

CHAPTER 4

UNDERSTANDING COLLABORATIVE VISUAL DATA ANALYSIS IN MULTI-DEVICE ENVIRONMENTS

Parts of this chapter were previously published as: Alsaiari, A., Johnson, A., Nishi moto, A., “PolyVis: Cross-Device Framework for Collaborative Visual Data Analy sis”, In the Proceedings of *2019 IEEE International Conference on Systems, Man, and Cybernetics* (IEEE SMC 2019), October 6-9, 2019, Bari, Italy. AND as: Al saiari, A. and Johnson, A. (2019). “Towards Understanding Collaborative Visual Data Analysis in Multi- Device Environments”. In *2019 IEEE VIS*.

4.1 Introduction

The work of this chapter addresses the questions: what is the complex picture of users’ experience during a collaborative visual data analysis in a multi-user multi-device environment? and what is the characterization of the analysis process?

Collaborative visual data analysis is a complex process. There are several factors add to this complexity. As I discussed in Chapter 2, users and tools influence one another in system-user interaction. Therefore, the complexity of the analysis process is not influenced only by the respective task, but also by users and tools. The goal of this chapter is to understand this process based on involved factors, and identify challenges that shed light on requirements to improve the design. To achieve this goal, I conducted an exploratory study to observe how 44

users approach the analysis task in a multi-device environment, and how this differs from one display settings. In the first phase of the study analysis, I decomposed the problem into three dimensions. I performed a hybrid analysis approach with mixed methods to analyze these dimensions. Specifically, I analyzed the usage of the tools, the analytical activities, and the strategies of collaboration around devices. In the second phase of the analysis, I performed an in-depth qualitative analysis and provided a structural categorization of the visual data analysis process. This categorization was influenced, on abstract level, by the three dimensions of the analysis environment. The findings and observed challenges highlighted the importance of a supportive tool that unites the scattered effort. I envision this through a hybrid model of a visualization recommendation tool that cast the analysis process as an assignment problem based on the different aspects of the environment: the tasks, the tools, and the users. This motivated the future work of this research. In Chapter 5, I provided a set of design guidelines to enhance visualization tools with recommendation system that steer the analysis process in flexible and efficient way. In Chapter 5, I discussed the current designs of visualization recommendation systems and their building metrics. In contrast to previous work, my proposed model frames its recommendation metrics based on the different aspects of the environment. The design, implementation, and evaluation of this model is the core of the next phase of this research and will be investigated in more detail.

4.2 Exploratory Study

The study presented in this chapter falls into the category of user studies for ”*understanding*”. The goal of this type of user studies is to build a rich understanding of user experience

and context of use by observing the user-system interaction. Then, this understanding can help informing the design space of such systems. Within a multi-device environment, collaborators employ different tools to perform different kinds of activities in approaching the respective task. The main question is: what are the flow patterns that collaborators follow in approaching the task? I believe that the flow of the data analysis is shaped by the following sub-questions: How do users use the tools? What types of activities do they perform? And how do they collab orate? Each question corresponds to one aspect: tools, tasks, and users. I aim to synthesize the flow patterns of the analysis process by quantitatively and qualitatively analyzing the three aspects. Subsequently, I target the categorization of how the analysis process unfolds. Through this analysis, I can define further requirements on how to provide tool support for collaborative use and coordination of analytical components. This chapter contributes a better understand ing of the visual data analysis process and provides the directions for further development of information visualization tools around interactive surfaces.

4.2.1 Participants

I recruited 18 subjects, 6 groups of 3, from a pool of undergraduate and graduate students at the electronic visualization laboratory and computer science department of the University of Illinois at Chicago. Participants comprised of 13 male and 5 female students between ages of 18 and 34. They participated in the study for the duration of 45min-1.5hrs. Participants had varied experience in visual data analysis, ranging from moderate to advanced. EVL affiliated students had advanced background in visualization while participants who were not affiliated with EVL, had taken at least one EVL course and had moderate experience with visualization.

4.2.2 Software

For these studies, I used a cross-device framework that I developed for collaborative visual data analysis, PolyVis (70). In PolyVis, I integrated SAGE2 (2), a large display collaborative application, with portable devices for co-located, multi-device visual data analysis. Portable displays can vary from smartwatches to the fully immersive VR headsets. Due to the unique requirements of integrating devices from these categories for information visualization, I limited my scope to support the integration of portable devices like tablets, laptops, and HoloLens AR headsets. Specifically, PolyVis integrates SAGE2 large display with laptops, tablets and the HoloLens AR headset. It provides users with an environment for visualization compositions and sharing across displays. PolyVis also offers the capability to utilize each device for specific tasks. Some of these tasks include data filtering, visual mapping, visual representation, visualization construction and sharing. This environment allowed analysis across different devices and many visualizations with the ability to move and share them.

PolyVis usage scenario: Using a laptop or a tablet, users can start by mining the data for all earthquake events during 2010, and then specify their visual representation (i.e. map) to visualize them on the large display. Any user with a tablet can capture the barcode attached to the map of earthquakes using the camera of the device to pull the map visualization to the portable device. Analysis charts like scatterplots, line or bar charts can be created for the pulled map for analysis and then they can be pushed back to the wall. Using the laptop, the user can select a specific area on the map to view data points in 3D using HoloLens. PolyVis was developed based on a declarative visualization design like Vega-lite (49) and the paradigm of

operation transformation for seamless migration of visualizations and their interactivity between devices.

4.2.3 Datasets and Tasks

Each group performed visual analysis tasks using two geoscience datasets. The first dataset contained information about earthquake incidents in Oklahoma and California from the years 2000 to 2010. The Wells dataset contained information about the fracking activities in Ok lahoma and California also from the years 2000 to 2010. I collected, cleaned, preprocessed and stored datasets in NoSQL database using MongoDB. The earthquake dataset was pro vided courtesy of http://service.iris.edu/ and the Wells injection dataset was provided courtesy of http://www.occeweb.com/. The earthquake dataset consisted of 24555 records and 12 at tributes while the Wells dataset consisted of 5138 records and 9 attributes. These datasets have attributes with similar meaning such as the location, the time, and the depth. Earthquakes dataset has other attributes like magnitude while Wells dataset has other attributes like well status, well type, injection volume, and injection pressure. Tasks were designed to ascertain the relationship between injection volumes, the pressure of fracking wells and the frequency of earthquakes in Oklahoma and California states.

Each group completed two tasks, with focused and open questions. In the first task, the subjects were given focus questions that can be answered by creating one or two visualizations. The focus question is designed in a way that helps subjects learn how to use the system and be familiar with the datasets. For example, “how does the injection volume on Oklahoma compare to California in 2010?” Subjects were then asked an open exploratory question to determine

the correlation between earthquake events and wells’ volume injection of two states, California and Oklahoma, from the years 2000 to 2010. They were asked to create as many visualizations as they needed with no restrictions regarding using devices or moving in the space. 4.2.4 Setup and Data Capture

The study was conducted in a room space of approximately 10.61 by 5.59 meters, equipped with a high-resolution large display. Overall display size is approximately 7.3 by 2.05 meters at a resolution of 11,520 by 3,240 pixels. Other portable devices were placed on a table in the middle for use during the study: one MacBook Pro (macOS Sierra, 2.4 GHz Intel Core i5), one 8” Samsung - Galaxy Tab A (32GB, Android 9 (Pie)), one 10” Samsung - Galaxy Tab A (64GB, Android 9 (Pie)), and one Microsoft HoloLens 1 (Windows Mixed Reality OS, Intel 32-bit (1GHz) CPU, 2 GB RAM). There were no chairs provided in the working area as shown in Figure 14. Each of the portable devices was attached with Mocap markers for tracking. In addition, three caps with attached Mocap markers were provided to the users.

The whole room was tracked using the OptiTrack Mocap system. The position and ori entation of devices and users were streamed from the OptiTrack Mocap system to a Unity application depicting a 3D model of the physical space. We sampled the captured data at a rate of one frame per second. The unity application was running on a separate machine in the corner of the room. Systems usage logs were collected from all deployed devices. I wrote a script to capture all interaction events with the system. Each log included the device id and type, the action type, and the timestamp. System logs will be used in my quantitative analysis of the device usage. The study was video and audio recorded using two cameras, one showing

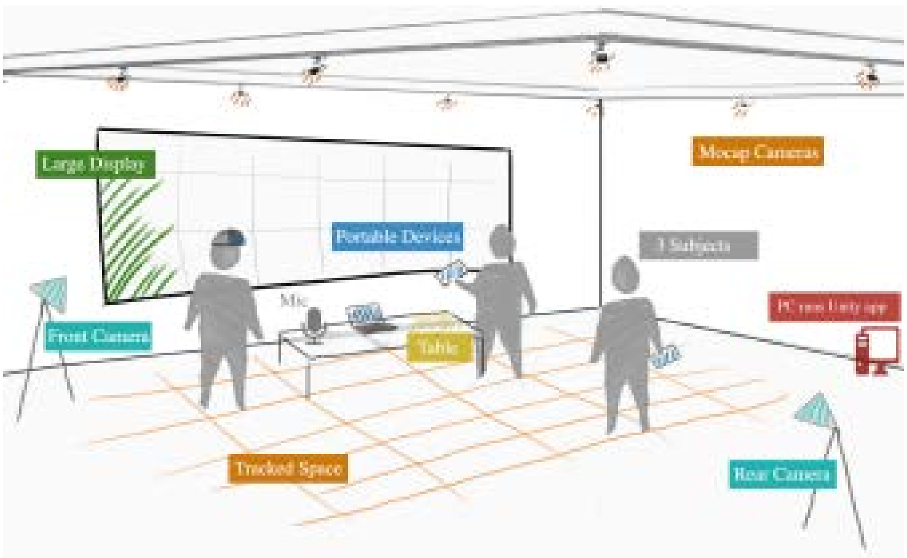

Figure 14: Illustration of the study setup.

the full room from behind and one showing the subjects' interaction with the large display from the front. The setup is pictured in Figure 14.

4.2.5 Procedure

First, participants were greeted and provided with consent and media forms. Then, they spent 2-5 minutes to read and fill out forms. Once participants finished completing forms, I started with a 5-minute introduction to give the users an overview of the software and tools. Next, participants were given the first task of multiple focus questions that could be solved by creating one or two visualizations to familiarize them with the software and tools. I opted for this approach as a practical tutorial on how to use the system. They were told to feel free to ask for a clarification or instruction at any time during this task. They spent 20-30 minutes on this task. Next, they started the main task of an open exploratory question to find the correlation

Figure 15: Subjects examining a set of created visualizations while using different devices. Position and orientation of subjects and devices are streamed from OptiTrack Mocap system to a Unity application depicting a 3D model of the physical space.

between earthquake events and well's volume injection in two states, Oklahoma and California. Participants were told to work on the task in any way they preferred and to create as many visualizations as they wanted. I left it to the participants to find their own way for completing the task. This task was exploratory in nature and took between 25 to 70 minutes to complete. Upon completing the main task, participants spent 2-5 minutes to fill out surveys about their experience in the study.

4.2.6 Coding and Data Analysis

I collected data in the form of recorded videos, system logs, tracking data, and question naires. About 420 minutes of videos were collected (an average of 70 minutes per session, 41 minutes for the main task). I divided the analysis into two parts and in each part I performed multiple coding passes. In the first part, I focused on analyzing tools usage, analytical activ-

ities, and user collaboration styles around devices while in the second part the focus was on the flow of the analysis process. The main goal of this study is to identify how we can provide supporting tools to facilitate the collaborative analysis process; therefore, it is crucial to under stand how the analysis flowed. In addition, revealing aspects of the tools usage, the performed activities, and the users' collaboration styles shed light on requirements that should be taken into consideration when designing a tool.

For the first part of the analysis, I created an excel sheet with 5-second intervals. For each time interval, I coded from the videos the users' formation styles around devices, the tools used, and the type of use. Then, each formation style of user collaboration was classified as close, moderate, or loos. By this, I created 5-second interval logs of the collaboration styles, the tools usage, and performed activities. I converted these log files into timeline visualizations as shown in Figure 17 and Figure 18.

I started coding the analysis flow by creating a second excel sheet and then for every created visualization, I documented how it was created, its relation to previous visualizations, and why it was created. Then, I drew a flow diagram of the created visualizations in chronological order with arrows indicating the first set of visualization relationship codes. After multiple coding passes, I identified a categorization of the analysis flow as will be discussed below.

4.3 Findings

In this section, I present findings from the two major analyses conducted on the collected data. In the first part, I present results from analyzing three aspects of the analysis sessions to

provide an understanding of users' activities and collaboration. In the second part, I present a categorization of analysis strategies observed in the study.

4.3.1 Understanding User Activity: A Hybrid Approach

Previous work examined three factors (users, tools, and tasks) independently. In this study, I focus on the synthesis of these factors. To do this, I adopted a hybrid analysis approach that focused on three different aspects: users, tools, and tasks. We believe these findings will help us identify associated challenges and better inform design goals in developing multi-device tools for visual data analysis.

In their book ”*Acting with technology*” (71), Kaptelinin and Nardi discussed the develop ment of Activity Theory as an approach and theoretical foundation for research in the fields of HCI and CSCW. They discussed its use in ”interaction design” to understanding the hu man interaction with technology and using this understanding to better design technological systems. Interaction design was defined by Winograd (72) as ”the design of spaces for human communication and interaction”.

They ultimately framed the contribution of activity theory to HCI field as: ”Activity theory provides a coordinated description of the use of technology at several hierarchical levels at the same time, and thus opens up a possibility to combine, or at least coordinate, analyses of different aspects of the use of technology, such as physical interaction, conceptual interaction, and social “contextual” interaction”. The adapted approach presented in this paper was mainly motivated by their framing of activity theory in HCI field.

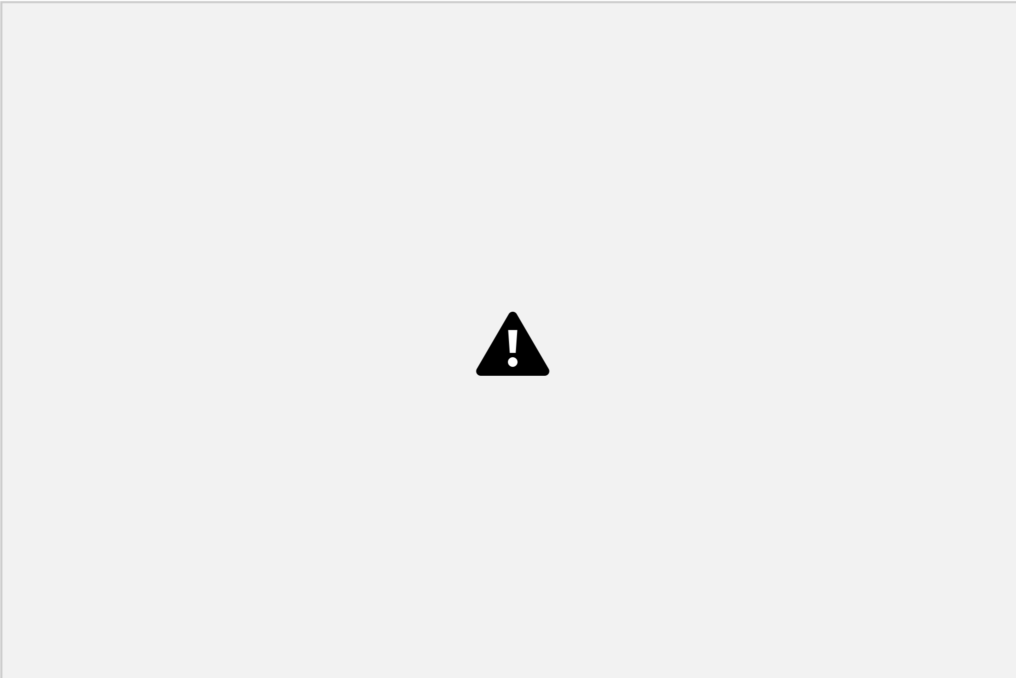

Figure 16: The traditional reference model for InfoVis (above) is redefined for multi-user multi device environments (below). The activity-centered approach maps this definition into activity actors: tasks, users, and tools. For each actor, we apply appropriate empirical methods to present a structural analysis of group's activity in this complex environment.

The ”activity system” triangle proposed by Engestrom (73) is one of the main model that was developed based on the concept of activity theory. It has been considered by several researchers as a theoretical framework for the analysis and evaluation of system-user interaction. This model describes actions through six elements: the objective of the activities, subject engaged in the activities, social context, tools or the artifacts, division of labor or roles, rules or guidelines regulating activities. Therefore, Kaptelinin and Nardi argued that the most leverage from this model are complex systems with multiple subjects and objects, as the focus here changes from single user-system interaction into collaborative uses of technology with mixed virtual and physical settings and set of activities. The activity system model has been applied to many HCI research to inform the design and analysis of technologically mediated activities. We framed an approach in terms of the components of this framework that facilitates the selection and application of appropriate analysis methods.

As defined by the activity system, the activity relies on network of actors to make it possible. Actors are the people, tools, rules, social context, etc, that interact to make the activity hap pens. Therefore, we need to define the network of actors. As shown in Figure 16 (above), the traditional visualization reference model illustrates the iterative process of the visual analysis task. Badam (74) redefined this model (Figure 16 , below) for multi-user multi-device environ ments where multiple users utilize multiple devices to perform the iterative process of visual data analysis. This new definition included two additional actors to the earlier definition: group of users and set of devices. So beside the process of the analysis task, users and devices com pose the network of actors that make the activity takes place in this environment. These three working actors map onto the top components of the activity system triangle. The approach uses these dimensions to apply appropriate empirical methods within each one. Therefore, this structural analysis provides an overall understanding of group's activity in complex visual analytics environments.

4.3.1.1 Tools Usage

Each device has specific capabilities to serve users in the analysis course. We were interested in capturing the usage frequency of each device and how they contributed to the analysis flow.

Some devices like large displays naturally offer a public usage to multiple users at the same time while tablets and laptops tend to be privately used. However, participants were not restricted to use devices in specific ways. Rather, I left it to the users to decide how and when to use the tools. I aimed to capture the dynamic of using devices in parallel, in conjunction, etc. and the patterns of how users utilized them. As shown in Figure 17, I coded the use of devices from videos and system logs at 5-second intervals. I considered a device as under use if one or more participants are interacting with it. That includes direct interaction using touch, click, etc., or indirect interaction like looking at and discussing information. The view exploration task as discussed below encompasses a direct and indirect interaction with devices. In the next subsections, I discuss the types of activities and the styles of user formations around a device. A complete list of tools usage timelines for all trials is presented in Appendix A.

Utilization of devices affordances. Participants used the large display to share and arrange the many visualizations they created through the analysis session. This came naturally from the bigger area offered by the large display. Although users were able to create many visu alizations privately on portable devices, they shared publicly what they thought was important to their analysis.

The large space was also used to lay out visualizations. The layout was important to indicate implicit relationships between visualizations. As I discuss in the next section, participants were taken different analysis paths and in some cases layout was used to differentiate paths. Tablets along with the large display offered different analysis styles as suggested by (15). This was important to allow participants to try different analyses on their own and then share with

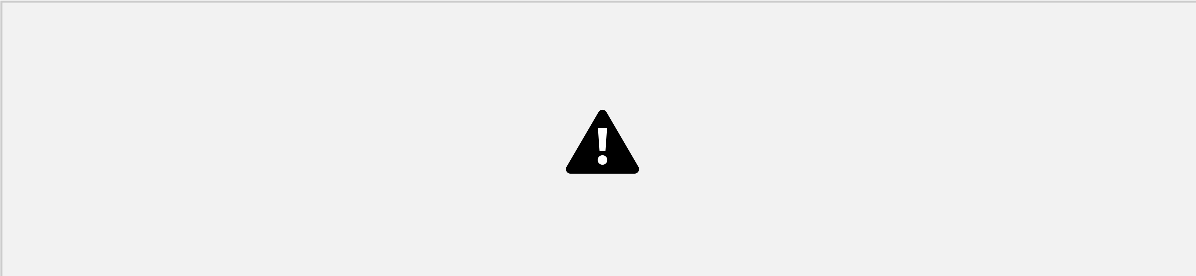

Figure 17: Logging of tools usage during the analysis session. The large display was the most used device.

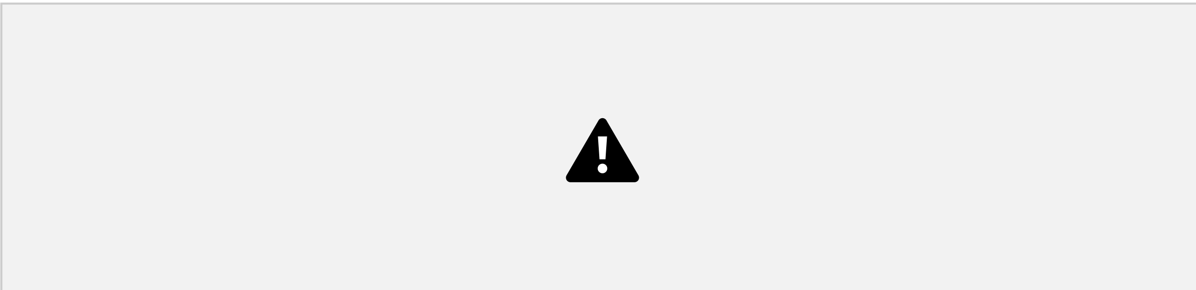

Figure 18: In session 2, participants loosely collaborated by engaging in individual analyses using tablets. See Figure 24.

others. Unlike stationary devices like laptops, tablets also offered some mobility to users by enabling them to move within the space while working on their analysis. In three out of six sessions, participants used the Hololens to compare the depth of wells and earthquakes in 3D. The 3D view offered a quick comparison of depth. In the other three sessions, participants used 2D charts to find a depth relationship, which required them to create many visualizations.

Frequency of use. In five out of six sessions, the large display was the most used device. This can be explained by the fact that users use the large display as a public canvas to plot

and arrange all created visualizations and conduct their discussion and analysis around it. In addition, the large display offers a better space for collaboration than other devices, which align with the current assumptions in the literature (75). In an exceptional session, users used tablets most of their time analyzing visualizations individually, which led to loose collaboration for around 34% of their analysis time. This highlights the importance of supporting communication and work coordination in these systems to enhance collaboration. We need to develop guidelines to better design visualization tools that can utilize the affordances of multiple devices and overcome the communication and coordination challenges.

Joint and parallel use. I observed a frequent presence of coupling styles between devices. In the case of coupling, participants mostly used a large display along with one or two portable devices. While the large display served as a canvas to place visualizations, other devices were used to further analyze these visualizations. Participants were engaged in cycles of creating visualizations and analyzing them (i.e. filter, change representation, aggregate data). Although participants had two tablets, in most sessions they used one of them more than the other one. There were some cases where participants divided tasks and worked on both in parallel. Here, I stress on the importance of a guidance mechanism that can help users to better utilize devices of same capabilities to divide work.

4.3.1.2 Analysis Activities

In this section, I report the common high-level activities I observed among all groups. First, I coded all analytical processes performed by users; then, I classified them into four high-level

TABLE I: Percentage of time spent in using each device.

	Session 1	Session 2	Session 3	Session 4	Session 5	Session 6	Avg.
Task time	43 min	42 min	66 min	28 min	22 min	48 min	42 min
Large display	55%	29%	41%	37%	34%	60%	44%
Laptop	9%	11%	19%	15%	15%	11%	13%
tablet A	35%	47%	12%	18%	14%	47%	29%
tablet B	0%	51%	4%	28%	15%	13%	17%
HoloLens	24%	1%	23%	11%	0%	13%	14%

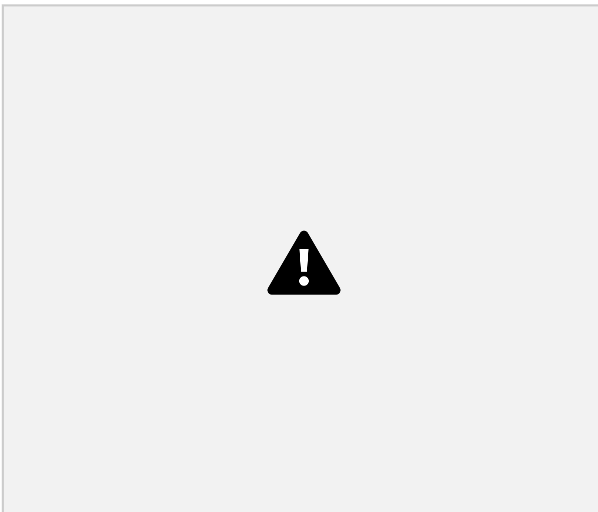

Figure 19: Average percent of time spent in using each device.

activities as shown in Table II. These high-level activities are: creating new views, exploring views, manipulating views, and analyzing views. Table II shows all the micro processes under each of these high-level categories. This categorization has similarity to some visual analysis processes described in (76) (54) which suggests that micro processes within the characterization can occur in settings outside the context of this study. Previous works (76) (54) characterized

users' activities from the perspective of the visual analysis task. In the case of multi-device settings, the affordances of the devices influence the analytical task activities. For example, changing a visual representation into an immersive view is a cross-device analytical activity. Therefore, the characterization of groups' activities is based on our focus on the problem from the different dimensions of the environment. I coded these activities from video recordings and system logs. In this categorization, I focused on "actionable processes". Actionable processes are the type of processes when users directly or indirectly interact with analytical components (visualizations, filters, data subset, etc.) using one or more digital media (devices). In addition to actionable processes, I identified two other non-actionable processes: discuss observations and form hypothesis.

Creating new view. This activity comprises processes such as browsing data attributes, applying filters to datasets, and mapping attributes to visual channels. As the goal of these processes is to produce a new visualization, I identified them as an activity of creating a new view. The final product of these processes is a new visualization that is not derived from an existing one. I classified deriving visualization from an existing one as an activity of analyzing a view. Created new visualizations have no direct ancestors but they mostly have implicit relationships with other views along the historical paths of the analysis. I will discuss the explicit and implicit relationships of views in a later section.

TABLE II: The four activities I observed in the study. Micro processes are performed for the goal of the corresponding high-level activity

Exploring views. The exploring views activity captures all the processes where partici pants aim to derive information individually or collaboratively from visualizations. I noticed participants most of the time share private visualizations on the public wall display to explore information with others. In other cases, participants share their portable devices with others to explore visualizations. Participants explore by reading the information about the visualizations. This process is usually followed by a discussion or forming a hypothesis activity. Participants also interact directly or indirectly with visualizations to explore information. Direct interactions are the direct zooming, navigation, selection, etc., on the visualization while indirect interaction is through another device (i.e. tablet to wall, wall to HoloLens) or merely through the looking at and discussing information.

Manipulating views. I noticed a few processes where participants arrange views on the large display for different purposes. In some cases, participants position views in specific layouts for comparison. In other cases, they resize and position views to create clusters of views.

Analyzing views. Through their analysis, participants derived many views from existing ones. The goal is to render a further analysis of the current subset of data. Further analyzing the view comprises the changing of the visual representation. For example, changing a 2d map into a 3d representation, or into a scatter plot to correlate the distribution of specific attributes. Analyzing view activity also comprises the aggregation of data points using an aggregation functions.

Non-actionable activities. There were some activities where participants do not directly interact with the system. I identified those activities as common non-actionable. Under this definition, I considered when participants discuss observations they found and formulate hy potheses.

Non-linear Temporal Order . I noticed that these activities have no linear temporal order as participants switched between them frequently. To reveal unseen patterns and temporal relationships, I coded the time interval of each activity for all groups. These activities can temporally overlap when performed simultaneously by multiple users. Therefor, I charted each activity in a separate timeline as shown in Figure 20 and Figure 21.

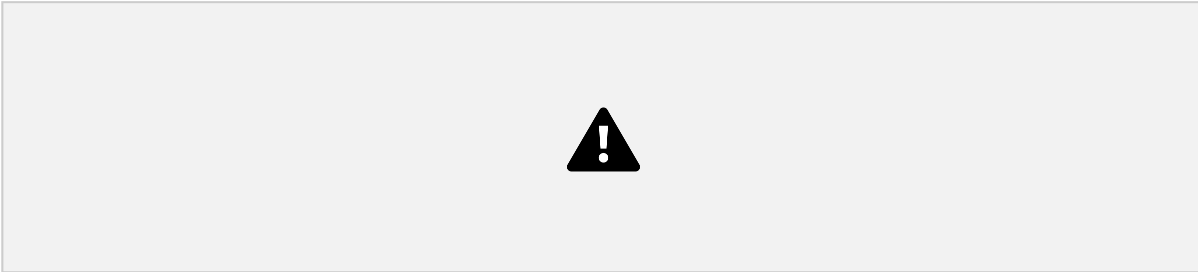

Figure 20: Logging of activities during the analysis session.

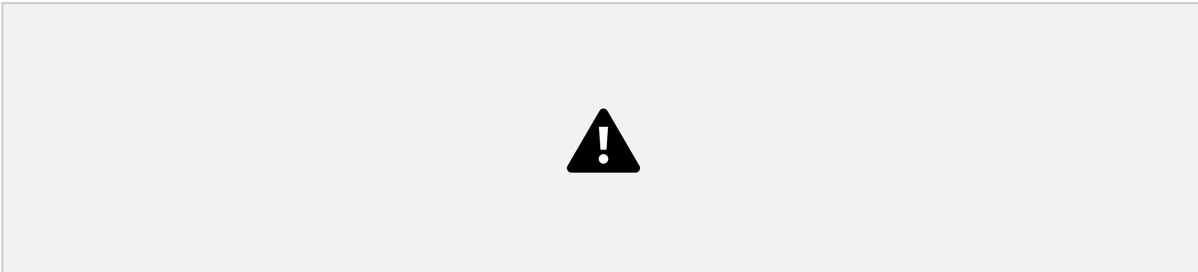

Figure 21: Logging of activities during the analysis session.

Figure 20 and Figure 21 show timeline visualizations of performed activities during two sessions. A complete list of timeline visualizations for all trials is presented in Appendix A.

The Analysis Outcome. The task was exploratory in nature to infer any correlation between the provided datasets. There were no correct or wrong answer. In all sessions, partici pants came to one or two observations. They wrote down those observations, mostly at the end, on the task paper that was given. I didn't observe that they wrote down any other information during the analysis either regarding what dimension space they are working on or other related

TABLE III: Percentage of time spent in performing each activity.

Session	1	2	3	4	5	6	Avg.
Task time	43 min	42 min	66 min	28 min	22 min	48 min	42 min
creating new vis	17%	21%	19%	15%	25%	8%	17%
exploring views	67%	24%	58%	34%	21%	66%	49%
manipulating views	4%	6%	4%	19%	9%	7%	7%
analyzing views	26%	56%	12%	23%	14%	43%	30%

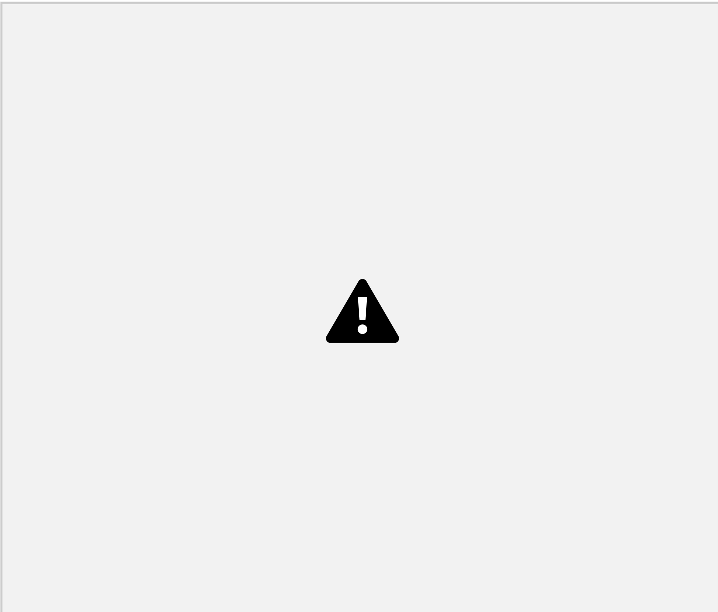

Figure 22: Average percent of time spent in performing each activity.

information. In most sessions, participants started with a dimension space of the data specified by time, location, depth, etc., and then they went broader or deeper in the exploration. At this time, I saved the analysis of the dimension space coverage to be investigated in the future work. Analyzing how they explored the dimension space helps in designing recommendations.

4.3.1.3 Collaboration Styles

Unlike the case of a single display, the presence of multiple devices arises the question of how closely or loosely participants have worked. This also requires us to redefine the close and loose coupling of work. Petra et. al. (31) discussed the close coupling around tabletop display. Several aspects were used to define the range of close to loose coupling. From the most to the least influencing factor, these were the engagement in the discussion, the working on the same information, and the working on the same view.

Having multiple devices to complete the analysis task, I was interested to observe how they would work together. So I envisioned the collaboration as how they would engage in discussing the task, working on the task, as a group or individually, on one device, or using multiple devices. Similar to Petra et. al. (31), I used a few aspects to rate the collaboration as close or loose collaboration. These are the engagement in discussing the task, working on same information or same view, either using one or multiple devices. So in this environment, I consider the collaboration is close in cases where all participants are engaged in a discussion about the task and looking into one or multiple views using one or multiple devices. As shown in Figure 23, there are a few cases were observed in the study in which they can be considered as close collaboration. In all four cases, all participants were engaged in the task. In cases when one participant detaches himself from the group to work individually or to not engage in the work, these are considered to be medium collaboration as the two other participants will still be working as a group in different ways.