The Elephant in the Room: Expert Experiences Designing, Developing and Evaluating Data Visualizations on Large Displays

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Large displays can provide the necessary space and resolution for comprehensive explorations of data visualizations. However, designing and developing visualizations for such displays pose distinct challenges. Identifying these challenges is essential for data visualization designers and developers creating data visualizations on large displays. In this study, we aim to identify the challenges designers and developers encounter when creating data visualizations for large displays. We conducted semi-structured interviews with 13 experts experienced in creating data visualizations for large displays and, through affinity diagramming, categorized the challenges. We identified several challenges in designing, developing, and evaluating data visualizations on large displays, as well as building infrastructure for large displays. Design challenges included scaling visual encodings, limited design tools, and adopting design guidelines for large displays. In the development phase, developers faced difficulties working away from large displays and dealing with insufficient tools and resources. During the evaluation phase, researchers encountered issues with individuals' unfamiliarity with large display technology, interaction interruptions by technical limitations such as cursor visibility issues, and limitations in feedback gathering. Infrastructure challenges involved environmental constraints, technical issues, and difficulties in relocating large display setups. We share the lessons learned from our study and provide future directions along with research project examples to address these challenges.

CCS Concepts: • **Human-centered computing → Empirical studies in visualization**; **Information visualization**; *Visualization design and evaluation methods.*

Additional Key Words and Phrases: Large Display, Qualitative Study, Design, Development, Evaluation, Data Visualization

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1 Introduction

Large displays (LDs) have been of interest to data visualization designers and developers [18] because they present potential advantages for diverse scenarios. LDs create a cohesive physical viewing space at least the size of the human body and often with considerably higher resolutions than desktop-sized displays [18]. LD environments can facilitate the presentation of multiple high-resolution visualizations [77]. In addition, they can support data exploration by offering ample space to display and compare multiple views generated throughout the exploration process [8]. Also, LDs allow people to use physical movement in place of virtual navigation on the LDs to explore a large data visualization [13, 15, 46] and can facilitate the collaborative exploration of data visualizations [27, 77]. Despite these advantages of LDs in the data visualization field, these technologies are mainly used in research labs, high-profile institutions, and companies [18], and have yet to be widely adopted.

Creating data visualizations for LDs has unique challenges compared to those designed and developed for smaller displays (e.g., desktop-sized displays or mobile devices. These challenges include using the available space and resolution effectively [4, 18], designing appropriate interactions with modalities other than mouse and keyboard [18], and supporting multi-user interaction and collaborative scenarios [27, 77]. Previous studies [4, 18] identified the challenges of creating data visualizations for LDs by synthesizing research findings in the literature. Challenges identified from surveying the literature are valuable. However, we lack an understanding of how these identified challenges are experienced by experts in real-world settings when creating data visualizations, and we need to identify potential challenges that may have been overlooked by previous work. Understanding and identifying these experienced challenges is important since obstacles to working with LDs could restrict the adoption of these technologies and diminish their potential impact.

To address this gap and propose effective support for creating data visualizations for LDs, we need to capture lived experiences in creating data visualizations for LDs. Thus, we conducted a qualitative study using semi-structured interviews with 13 experts with experience creating data visualizations for physical LDs (e.g., wall-sized displays, tabletops, or multi-displays). In this study, we included the perspectives of experts designing, developing, and evaluating data visualizations for physical LDs. Expert interviews allowed us to gather firsthand insights and lived experiences from individuals directly engaged in creating data visualizations for LDs.

Our findings highlight the need for the development and dissemination of resources and tools for the design, development, and evaluation of creating data visualizations for LDs. Additionally, we lay the groundwork for future research and innovation to support experts who create data visualizations for LDs. Our contributions include:

- interviews to gather firsthand insights from experts with experience in creating data visualizations for LDs,
- twelve challenges related to designing, developing, and evaluating data visualizations for LDs and building LD infrastructure, identified through thematic analysis,
- twelve future directions and research project examples to address the identified challenges.

2 Related work

In this section, we review existing literature and previous studies on LDs, highlighting the gaps our work aims to fill. Our focus is on creating data visualizations for LDs, rather than on other applications such as User Interface (UI) design. while LDs can offer advantages for displaying and interacting with UIs, there are challenges in designing UI for LDs, such as space management issues, overlapping zones in multi-user scenarios, and the lack of specific UI design guidelines for LDs [60]. However, creating data visualizations for LDs presents distinct challenges from designing

UIs, as it requires conveying insights through graphical representations of data. Previous studies have identified several data visualization design challenges for LDs through literature review methods [4, 18]. However, the challenges data visualization experts experience when designing, developing, and evaluating data visualizations on LDs remain under-explored, which is the focus of our work.

2.1 LDs Advantages and Building LD Infrastructures for Data Visualization

Compared to desktop-sized displays, LDs offer additional space and more pixels [18], resulting in several advantages for visualizing data. The surplus space offered by LDs can be advantageous for visualizing large datasets [85]. It allows for the display of more data items, variables, views [3, 18, 79, 101], resulting in a more comprehensive representation of the data. Practicing analysts also use additional space offered by LDs as rapid access to external memory while working with massive document collection [3]. With additional space offered by LDs, tasks such as detecting temporal and spatial trends, recognizing spatiotemporal patterns, and performing pattern matching become time-efficient and accurate [100, 101]. The high pixel density on LDs can streamline the presentation of both an overview and detailed information in a single view, eliminating the need for frequent pan and zoom during data exploration [18, 77]. While Jakobsen et al.'s [47] study concluded that display size and resolution had no notable impact on the usability of map visualizations, Ball et al.'s [16] study showed that map visualizations directly benefit from the high resolution of LDs, as they allow a large portion of the map to be visualized at once and interactively at multiple scales. Andrews et al. [3] explored how LDs could enhance sense-making tasks with massive document collections. Knudsen et al. [50] used data from various domains, such as phone log analysis and healthcare policy, to show the potential use of additional space and resolution offered by LDs for showcasing and structuring data visualizations in coherent layouts. Aurisano et al. [8] conducted an observational study of visual data exploration on LDs and found that participants used the display space by creating many visualizations and organizing them in coherent collections based on evolving interests. Reda et al.'s [80] study highlighted that using additional space and resolution for multiple related data visualization views could enhance the number of discoveries during visual exploration. Rajabiyazdi et al. [77] explored the use of LDs across multiple disciplines and showed how additional space offered by LDs aids discoveries during visual exploration.

Compared to desktop-sized displays, individuals can physically move in front of LDs, facilitating physical navigation as an interaction modality [18]. Physical navigation improves individuals' performance, allowing them to explore various regions of the data visualization [15, 46, 63]. Physical navigation allows people to move closer for more details or step back for a broader overview [44]. Research findings indicate that physical navigation can enhance search performance in a map visualization by over ten times [14], and aid search performance in corpus visualizations as well [62]. Physical navigation also enables the use of cognitive resources to improve spatial memory use [74]. LDs allow multiple individuals to view and interact with data visualizations simultaneously. This results in collaborative engagement in data exploration and analysis [27, 77]. LDs have the capability to support various collaboration styles, including parallel work and close collaboration [55, 63, 76]. While LDs have advantages, there are also limitations to consider. For instance, setting up LD infrastructure may entail various requirements, such as the need for increased computational power, need for a cluster of personal computers for driving LDs [96], efficient graphics hardware [18] or custom graphics cards [59] for visualizing massive datasets. Tailored and potentially distributed rendering [28] or middleware [59, 83] for multi-display setups.

Several visualization applications have been developed for LD environments, with a focus on collaboration [2, 23, 55, 64]. Additionally, there are applications tailored for the presentation of substantial volumes of data on LDs [9, 16, 77, 85, 96], the execution of complex tasks on LDs [23, 63, 77, 79], and the integration of 2D and 3D views for LDs [1, 2, 78]. However, the process creating data visualization tools and systems for LDs may pose challenges that need to be addressed to ensure a smooth creation of data visualizations on LDs.

2.2 Designing Data Visualization For LDs

Previous studies have shown that the additional space and large number of pixels offered by LDs present unique challenges in terms of appropriately scaling data encodings [4, 18]. Variations in viewing distances and angles affect the perception of visual variables, requiring different visual encoding decisions for LDs compared to desktop-sized displays [4, 19, 33, 100, 101]. UI elements and interactions with visualization need to relocate to be within reach of the people [10].

Previous studies have provided general guidelines for both visual and interaction design to aid data visualization designers during the design process. For instance, Munzner [68] introduced a nested model for visualization design with four layers, emphasizing the importance of characterizing the problem domain and abstracting it into operations and data types. Sedlmair et al. [92] proposed a nine-stage framework to enhance the conducting of design studies. McKenna et al. [66] introduced the design activity framework to guide novices through the design process. Sedig et al. [91] presented a pattern-based framework for visualization design, focusing on the thinking processes of designers. These studies contribute to the understanding and improvement of the visualization design process and help data visualization designers through the design process. Additionally, several studies focused on offering design guidelines and considerations for visualizing data effectively in immersive environments [34, 98, 99] and providing insights into designing intuitive interactions for these environments [97]. However, these design guidelines and principles did not specifically address design considerations for physical LDs.

Andrews et al. [4] provided a list of guidelines for designing data visualizations for LDs. Despite the valuable insights and guidelines offered by Andrews et al. [4], data visualization designers may find it challenging to practically apply these guidelines in their design process of creating data visualizations for LDs. Furthermore, advances in technology, changes in user expectations, and the emergence of novel interaction modalities have expanded the landscape of challenges in designing data visualization for LDs. We lack an understanding of how insufficient design support affects the creation of data visualizations for LDs; therefore, we investigated this lack of design support by capturing the experiences and challenges faced by designers in creating data visualizations for LDs.

2.3 Deployment of Data Visualization on LDs

LDs benefit from different interaction modalities for data manipulation and explorations, in addition to mouse and keyboard, and touch [4, 18]. These interaction modalities include multi-touch [55], mid-air gestures [7, 70], eye gaze-based interaction [54], proxemic interaction [31, 45, 49, 58], integration of hand-held devices (like smartphones or tablets) [11, 12, 24, 42, 50, 56], and voice commands [7, 94]. All of these interaction modalities present opportunities for visual data exploration on LDs. However, data visualization developers need tools tailored to the unique characteristics of LDs to effectively implement these interaction modalities.

There is an abundance of tools and libraries available for developing data visualizations, including well-known ones such as D3 [20]. However, when it comes to developing data visualization for LDs, there is a noticeable lack of dedicated tools and libraries. While widely-used libraries such as D3 [20] cater to desktop-sized display data visualization needs and interactions with mouse and keyboard, there are few specialized libraries and tools such as SAGE3 [37], which is the updated version of SAGE2 [83], and DataV [67] that facilitate the development of data visualizations for LDs. The existing tools and libraries, including those specifically designed for LDs, often fail to accommodate the diverse interaction modalities proposed in the literature for LDs and translate these theoretical concepts into practical implementations. We lack an understanding of how insufficient tools and libraries impact the development of data visualizations on LDs; therefore, we studied developer experiences in creating data visualizations for LDs.

3 Methodology

Study Design: To gain a deep understanding of challenges encountered by designers and developers while creating data visualizations for LDs, we conducted 1-hour semi-structured interviews with open-ended questions. The interviews for this study were conducted between May 2023 and May 2024. We framed our interview questions as follows. First, we asked demographic questions from our participants. Then, we started the semi-structured questions, asking questions prepared in advance. The initial set of questions focused on participants' experience in creating data visualizations for LDs, including details about the LDs they have worked on and the work environments where these LDs were located (see Appendix A for the script and the list of questions). We also asked follow-up questions regarding the type of data they worked on and the tools and techniques our participants used while creating data visualizations for LDs. We encouraged participants to elaborate on the processes they followed in each phase of data visualization creation—design, development, and evaluation—and to articulate any challenges they encountered throughout these processes.

Participants: In this study, we specifically looked for individuals experienced in creating data visualizations for various types of large environments, such as tabletops, wall displays, or multi-displays. Our criteria include:

Inclusion Criteria:

- have a background in data visualization, or related fields pertinent to the study of data visualization for various types of physical LDs, such as wall-sized displays, tabletops, or multi-displays,
- actively engage in projects related to data visualization on LDs and have experience in creating such visualizations.

Exclusion Criteria:

- focus only on Augmented Reality (AR)/Virtual Reality (VR) or immersive technologies (e.g., Computer Automated Virtual Environment (CAVE) [30], immersive analytics, immersive visualization) as they have sufficiently distinct challenges, affordances, and visualization creator experiences that are not aligned with our study's focus on challenges of designing, developing, and evaluating data visualizations on physical LDs,
- no experience in designing, developing, and evaluating data visualizations on LDs.

In order to identify potential participants, we used a purposeful sampling technique [73]. We reached out to potential participants, specifically targeting industry partners who worked on creating data visualizations for LDs, staff, and faculty in research labs across various countries with LD research programs. We reached out to these people through email. We also used snowballing [36] to identify more participants. We recruited 14 participants who self-identified as experts in creating data visualizations on LDs. However, one participant was later excluded from the analysis as they fell in our exclusion criteria and were working on data visualization for VR using VR headsets rather than physical LDs, introducing a different set of challenges. We analyzed 13 interview transcripts.

Data Collection and Analysis: We conducted the interview sessions online via the Microsoft Teams platform and audio and video recorded them for transcription purposes. We used open coding [29] and the affinity diagram technique [38] to analyze our data. First, all the authors independently read the interview transcripts multiple times. Second, all the authors coded interview transcripts by extracting relevant quotes and assigning codes to the quotes. Through this process, we gathered a total of 69 codes. We used a Miro board to organize and create a visual representation of the codes and collaboratively grouped sticky notes based on their similarities and relationships. This iterative process enabled us to identify themes that encapsulated the challenges encountered across various stages of the data visualization creation for LDs. In the end, we grouped these challenges into four themes: T1: challenges of designing data visualizations for LDs, T2: challenges of developing data visualizations for LDs, T3: challenges of evaluating data visualizations on LDs, and T4: challenges of building LD infrastructure. By the time we reached P9, we observed that no new concepts or themes were emerging, indicating that thematic saturation was achieved [89]. Appendix B includes details on codes (Miro board), themes and categories, and saturation table.

4 Results

This section contains information about the demographics of participants interviewed in our study and the various types of LDs and interaction modalities they used. The goal of our study is to shed light on the challenges encountered by designers and developers while creating data visualizations for LDs. We are reporting the results of analyzing interviews with 13 participants (2 Female, 10 Male, and 1 non-conforming), with ages ranging from 26 to 56 years. Our participants' experience ranged from less than a year to 30 years, which helped us obtain a comprehensive spectrum of insights and perspectives on the challenges associated with data visualization creation for LDs. The participants represented various roles, including 6 academics (P1, P2, P3, P4, P5, P7), 4 representatives from industry (P6, P9, P12, P13), and 3 graduate students (P8, P10, P11). Each participant was actively engaged in projects related to data visualization for LDs and possessed experience in creating such visualizations. They worked with different types of data and domains, such as earthquake and environmental data, criminal intelligence data, social media posts, and football player profiles (see Table 1 for more details on participants' demographics and their context of work with LDs).

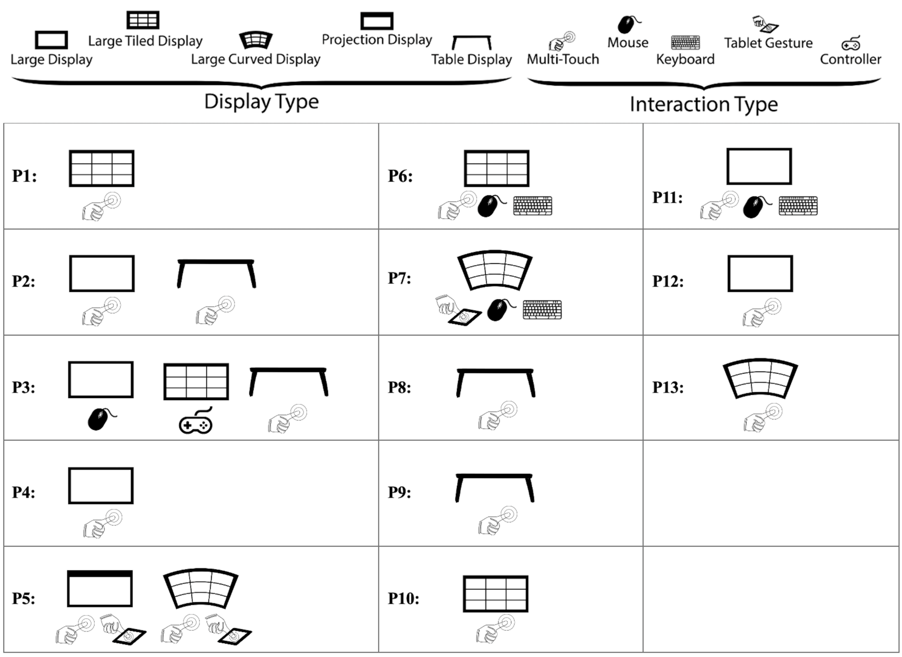
Table 1. Demographic information and expertise of study participants. Demographic variables include age, gender, professional years of experience working with LDs, occupation, and self-defined field of work. Additionally, the table shows participants' type of data and domain of work relevant to their expertise with LDs. *Years of experience creating data visualizations for LDs.

P#	Age	Gender	Experience*	Occupation	Self-defined Field of Work	Type of Data and Domain
P1	37	Female	6	Assistant Professor	Computer Science	Earthquake and environmental data
P2	43	Male	11	Post-doc Researcher	Information Visualization	Science fiction stories
P3	43	Male	15	Assistant Professor	Software Engineering	Criminal intelligence data
P4	40-50	Male	6	Lecturer	Human-Computer Interaction	Image and text data
P5	35	Male	10	Associate Professor	Information and Computing Science	Social media posts
P6	38	Male	14	Computer Scientists at a Tech Company	Computer Science	Scientific experiment data
P7	56	Male	30	Professor	Computer Science	Fluid dynamic simulation data
P8	31	Female	1	Graduate Student	Graphic Design	Health data
P9	26	Male	<1	Software Developer at a Tech Company	Computer Science	Health data and time-series text data
P10	33	Male	4	Graduate Student	Computer Science	Computational notebooks
P11	26	Male	3	Graduate Student	Computer Science	Climate change impact data
P12	32	Male	1	Web Developer at a Tech Company	Information Visualization	Football players profiles
P13	35	Non-conforming	9	Research Scientist at a Tech Company	Information Visualization	Photos and 3D renders of buildings

There are many types of LDs with different physical properties and interaction means. We asked our participants to describe the type of LDs they worked with to ensure that their displays qualified as large displays, providing a cohesive viewing space at least the size of the human body. Our participants worked with various types of LDs, including tabletops, multi-displays, and curved LDs. They used different means of interaction, such as touch, multi-touch, and mouse and keyboard.

Table 2 shows the diverse types of LDs and interaction modalities used by each participant. This table shows that in our study, the most frequently used type of display by our participants is upright LDs and large tiled displays, which is a combination of different numbers of desktop-sized displays. The most commonly used interaction by our participants was multi-touch.

Table 2. An overview of display types and interaction modalities of each participant.



During the interviews, we asked our participants to describe the challenges they encountered in designing, developing, and evaluating data visualizations for LDs and challenges in building LD infrastructures. We coded the interview transcriptions for challenges our participants faced during the data visualization creation process. Table 3 presents the themes and categories of challenges identified in our study. Also, Table 3 shows how often each challenge was mentioned by participants during the interviews. To calculate this frequency, we carefully read the interview transcripts, counting every sentence where participants referred to a specific challenge.

5 Challenges and Future Directions

This section contains detailed descriptions of 12 challenges (C) identified, each accompanied by quotes from participants and corresponding future directions (FD), along with research project examples to address the identified challenges. In this study, our goal is to shed light on the challenges of creating data visualizations on LDs. Our findings revealed challenges associated with creating data visualizations for LDs. By "creating data visualizations", we refer to the design, development, evaluation, and deployment processes involved in crafting visual representations of data for LDs.

Table 3. Coding results: the numbers in each cell represent how many times each participant mentioned the challenge (code).

Themes	Categories	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13
T1: Challenges of Designing Data Visualization for LDs	C1: Difficulty Scaling Visual Encodings		1	1		2						1		
	C2: Limited Design Software and Tools								8					
	C3: Difficulty Adopting Design Guidelines								3					4
T2: Challenges of Developing Data Visualization for LDs	C4: Developing Away from LD	1	2	2			2		1	4		1	4	6
	C5: Limited Development Tools	1	1	3			5						1	1
	C6: Limited Learning Resources				2			1					1	1
T3: Challenges of Evaluating Data Visualization for LDs	C7: Unfamiliarity with LD			1		2	2	2	1		1		1	2
	C8: Interrupted Flow of Interaction		3	5	2			3			2	3	3	1
	C9: Limitations in Feedback Gathering During Evaluation			1					1				2	
T4: Challenges of Building LDs Infrastructure	C10: Environmental Factors and Space Constraints	2	1	1		1			1				2	1
	C11: Technical Issues and Lack of Technical Support		3				4				2	2	1	1
	C12: Difficulty Relocating LDs		1	1										

5.1 T1: Challenges of Designing Data Visualizations for LDs

The most important characteristic of LDs is their size and resolution, which can also present the challenge of effectively using this additional space and number of pixels without overwhelming individuals with too much information [18, 82], while variations in viewing distances and angles also affect individuals' visual perception [4, 19, 33, 100, 101]. While additional space and high resolution of LDs can enhance visual encodings like the number, size, and color of data marks [82], determining the appropriate parameters for these marks remains a challenge for data visualization designers [4]. In addition to this, our participants pointed to challenges for designing visualization on LDs, such as limited design tools and the difficulty of adopting design guidelines, which we will discuss here. Notably, we observed that while a few participants actively discussed designing data visualization challenges, the majority of our participants mentioned that they either skipped the design phase entirely or rushed through it quickly, often due to time constraints.

C1: Difficulty Scaling Visual Encodings. Sketching and paper prototyping are necessary steps in the design process [17, 32, 35, 52]. Designers often use paper of comparable size to the intended screen dimensions when creating data visualizations or interfaces [32, 35, 52, 93]. However, sketching and paper prototyping for LDs can be challenging due to the unique characteristics of LDs. These displays come in diverse sizes and aspect ratios, which are different from the commercially available papers used for sketching. Due to this disparity, 4 of our participants encountered challenges sketching their data visualizations and layouts with the appropriate visual encoding size, spacing, aspect ratio, and layout. P2 said *"There's always that situation of you think it works. The aspect ratio is right and all that, but until you actually come in and see what it looks like, are your thought sizes too small or too big? Is the spacing nice? . . . It's hard to kind of exactly predict and be happy with."*

This underlines the need for practical strategies to bridge the gap between sketching mediums such as pen and paper and the distinct requirements to design visualizations for LDs. Lischke et al. [60] demonstrated the use of a yardstick on a desk to get a feeling for the size of their LD while sketching. Similarly, in our study, P3 highlighted the need for flip-charts to create a fake wall in the size of their LDs to sketch on it and noted *"What we did, which would just get the flip-chart paper, corresponding to what we had in the screen wise for one screen. So you could then tape, so we could take the whole wall with it and we had the wall that was big enough to simulate [the LD] ... So later, we had a wall and 4 flip-chart stands as well. It looked pretty silly, but it was actually very effective."* Furthermore, individuals' proximity to LDs can change during their use compared to desktop-sized displays, which maintain consistent proximity of arm's reach [19]. P11 mentioned this challenge and said *"One of the main challenges of designing was trying to make everything viewable from a comfortable distance because I don't know how far away the users are going to be from display, and if you make it too big, then you can't fit a lot on there and if you make it too small, then you can't see it."* Jakobsen et al. [45] introduced a solution which adjusts visual encoding size and aspect ratio by tracking the position and distance of individuals relative to LDs. Another solution to address this challenge could be responsive data visualization [5, 40, 41]. Responsive data visualization is adapting visualizations to the characteristics of the display device [5]. The data visualization community investigated responsive data visualization from desktop-sized displays [5, 40] to mobiles and tablets [41]. Yet, few studies have considered responsive data visualization for LDs [75] and none of these solutions were adopted or mentioned by our study participants.

> **FD#1:** Future research needs to continue investigating responsive design for adapting visualizations from desktops to LDs and develop proxemic interactions to scale visualizations based on individuals' viewing distance. Also, future research could focus on the development of prototyping tools tailored for LDs to streamline the design process.
> **Example**: Future research could investigate how different types of visualizations (e.g., bar charts, scatter plots, heatmaps) scale when transitioning from desktop-sized displays to LDs. There are opportunities for further use of proxemic cues and technologies, such as depth-sensing cameras to assist designers in designing interactive visualizations that seamlessly adapt to users' changing proximity to the LD.

C2: Limited Design Software and Tools. In addition to paper prototyping, designers also use digital design software or tools, such as Adobe Photoshop, for sketching. Digital design tools have the potential to facilitate the design of complex data visualization and offer flexibility in making changes and the ability to easily edit and transform sketches [53, 90]. These benefits of digital design tools have led to the development of new tools and frameworks specific for designing data visualizations, such as Visualization-by-Sketching approach [90], and SketchStory digital whiteboard [57]. However, none of these tools and frameworks are tailored for LDs. There is a pressing need for specialized digital design tools that facilitate designing data visualization for LDs. P8 noted that design software did not work on the LD they had in their work environment and said *"Initially, I thought that it might be a good idea to try to sketch the original designs, or at least the basic ideas on the display itself ..., but Photoshop is not working on the display. That was a little bit disappointing ... so during the sketching process, what I had to do was sketch on my tablet or my computer and then copy those sketches to the tabletop to see if the scale of what I was doing actually made sense. I wouldn't describe it as a seamless process."*
Another possible solution to sketch visualization for LDs is to create a large canvas using a graphic design tool like Photoshop on a personal computer. However, designing on such a large canvas using a personal computer can be tiring and associated with a high cognitive load, as it requires

a considerable amount of panning and zooming. Another solution to address this challenge is using design emulator tools. Design emulators are tools that facilitate the creation of functional prototypes and support iteration in the design process [43]. While numerous design emulators, such as Figma and Adobe XD, are available for desktop-sized displays, mobiles, and tablets, there is a lack of such tools for LDs.

> **FD#2:** Future research needs to continue developing tools and emulators for sketching to simulate the LD environment and demonstrate how visualizations will appear and function in LDs.
> **Example**: Future researchers could develop a specialized emulator tool designed to create prototypes of data visualizations for LDs. This tool should provide a simulated LD environment, allowing designers to preview how the visualization will appear on LDs.

C3: Difficulty Adopting Design Guidelines. The scarcity of design guidelines and principles for the unique characteristics of LDs compounded the challenges faced by designers in creating data visualizations for LDs [79]. In contrast to mobile and desktop-sized displays, design guidelines available to designers working with LDs are limited [60]. Andrews et al. [4], Braseth et al. [21], and Mayer et al. [65] highlighted the need for tailored design principles and guidelines when creating visualizations for LDs. Similar to these findings, 2 of our participants (P8 and P13) highlighted the need for design principles specifically tailored for LDs when creating data visualizations. P8 noted *"But what we found was that, sadly, many of the studies were listed as design principles that could be understood as basic user experience . . . that when you went back to the basic UX/UI design bibliography would be redundant. So it was extremely hard to find something that would actually add to that and that would be specific to the displays. . . . I guess having references [that provide design guidelines for LDs] could help us design for the tabletops. . . . Right now, the available bibliography is very limited."*

> **FD#3:** Future studies need to provide more practical and actionable design guidelines derived from translating perceptual findings.
> **Example**: Future researchers could conduct comprehensive literature reviews, such as systematic reviews, meta-reviews, scoping reviews, or narrative reviews to elucidate design patterns and guidelines used by visualization designers while creating data visualizations tailored for LDs.

5.2 T2: Challenges of Developing Data Visualizations for LDs

Developing data visualization refers to the implementation of the data visualization designs [6]. This includes the coding and programming required to bring the designed data visualization to life, allowing individuals to explore, understand, and analyze data, identify patterns, unravel the important and useful insights from data, and support better decision-making [6, 39, 69]. Our interview results showed that most of our participants had to develop data visualizations away from LDs due to limited access to LDs. Also, participants shared their concerns about the limited development tools and learning resources available for developing data visualizations for LDs.

C4: Developing Away from LD. Developers need to check the development results on LDs after implementing the data visualization. When developers use their personal computers and implement data visualizations away from LDs, testing the results of implemented data visualizations becomes challenging. A study by Lischke et al. [60] underscored the necessity of using simulators because of the absence of LD setup during the data visualization creation process. Similarly, (9 out of 13) participants noted that they had to develop data visualizations away from the LDs due to

certain constraints, such as limited direct physical access to LDs. They often had to rely on post-development adjustments based on outcomes and constant back-and-forth checks between personal computers and LDs. P9 said *"I'm working remotely, I upload the content and it looks like it's working, but I'm not really sure if it's working or not. That's a problem. We don't have a way to look at it. I usually have to ask one of my colleagues: Hey, can you go into the room and actually check that things are being displayed as they should, or if something is broken?"*
Also, as we discussed in Section 2, the literature introduced different modalities for interacting with LDs. In our study, the primary interaction modalities implemented by our participants were touch and multi-touch, which posed challenges, especially for developers who are creating data visualizations remotely and away from the LDs. P9 said they could not imitate touch behavior during development *"I don't have a touch screen at home ... so I couldn't fully imitate the touch behavior. ... Let's say for drag and drop interactions, the mouse works and the touch events on the large display do not work. I think this is why I need to go there and see it myself."* This challenge becomes more complex when developers need to test interactions such as mid-air gestures or multiple devices. For example, P1 used multiple devices LDs, mobile devices, and augmented reality headsets to display and interact with data visualizations. Emulating this diverse ecosystem of devices away from the LDs and refining interactions through trial and error can be challenging, if not impossible.

FD#4: Future studies need to further develop and deploy accessible tools and emulators tailored for LDs that replicate the LD environment on desktop platforms and enable interactions beyond a mouse and keyboard.
Example: Future researchers could create intuitive and accessible software simulations that mimic the functionality of LDs, allowing developers to test their data visualization and applications intended for LDs without the need for physical prototypes. This could involve emulating the multi-touch capabilities and gesture controls typically associated with LDs.

C5: Limited Development Tools. There are limited tools, software, libraries, and toolkits specifically tailored for LD to aid data visualization developers [18, 93]. Developers often find themselves in the position of having to adapt or modify existing tools to meet the requirements of LD prototyping. Previous literature introduced tools and libraries that developers of data visualizations for LDs may be able to adapt. Recently, Harden et al. [37] presented SAGE3, which is the updated version of SAGE2 [83], to create and deploy data visualizations on LDs collaboratively and interactively. Mei et al. [67] introduced DataV, a Software-as-a-Service visual deployment tool that facilitates the creation of interactive visualizations on LDs. These tools support LD visualization development for multi-device, multi-user interaction, and remote collaboration. While these tools are useful, they are not commonly used in practice. Robust visualization libraries widely used in the data visualization field, such as D3 [20] and Vega-Lite [88], are not designed for LDs and do not work on LDs. They lack support for LD interactions, often assuming a single interaction focus without support for multi-touch or other interaction modalities. In our study, 6 participants mentioned the lack of development tools for LDs. P6 said *"[Developers] have their tools. [When they] go to [large] display, tools that they were working with are not working anymore."* Also, P3 mentioned *"We did not have any emulators in process, so like you know, sometimes you can have hard phone emulators, mobile phone emulators and you can test [your application] ... but there weren't any good libraries or frameworks for doing that on large displays."*

FD#5: Future studies should further suggest and create tools that cater to the unique requirements of data visualization development for LDs.
Example: Future researchers could facilitate the adoption of existing tools, software, toolkits, and libraries (e.g., D3) for LDs or introduce extensions (e.g., LD-D3) tailored to LDs' unique requirements. These extensions might include support for diverse interaction modalities beyond traditional mouse and keyboard input, such as multi-touch gestures, voice commands, or eye-tracking interactions.

C6: Limited Learning Resources. The shortage of robust and widely adopted data visualization development tools for LD often prompts developers to create their own solutions. Consequently, developers rely on support or any documentation resources that have been created for these custom tools or libraries. In contrast, when a vast community spanning multiple institutions uses common data visualization development libraries or toolkits, developers focus on their support and dissemination and have access to a broader range of support avenues. The lack of developing data visualization for LDs' learning resources not only impedes the development process but also hinders the overall advancement of LD data visualization development. This challenge results in a burden on developers, who must expend additional effort to seek out scattered learning resources or rely on a trial-and-error process during the development process. In our study, 4 participants highlighted the need to create dedicated learning resources, P4 said *"I didn't get too much help from … because this is like a very specific platform that I needed."* Similarly, P7 mentioned *"It was harder because [of] the whole way I was working. I was a student … and everybody was working in the lab. So you just leaned over to the guy sitting next to you. Hey, have you seen this before? There were no books or I mean, everybody was inventing it."*

FD#6: The LD research community should establish more easy-to-follow and accessible repositories of learning resources and collections of materials to support the development of data visualization for LDs.
Example: Future researchers could create online platforms where researchers, developers, and educators can access a curated selection of tutorials, case studies, design guidelines, and best practices specifically focused on developing data visualizations for LDs.

5.3 T3: Challenges of Evaluating Data Visualizations on LDs

Evaluating data visualizations aims to ensure the data visualizations effectively communicate a comprehensive understanding of the represented data and enhance individuals' understanding of the data [26, 87, 95]. Our study result showed that due to the specific characteristics of LDs, evaluating these visualizations can be challenging. These challenges included people's unfamiliarity with the technology, interrupted flow of interaction, and limitations in feedback gathering during the evaluation phase.

C7: Unfamiliarity with LD. People's unfamiliarity with LDs can affect the evaluation of data visualizations, as the general public is more accustomed to working with desktop-sized displays rather than LDs [93]. Individuals might feel uncomfortable interacting with unfamiliar devices such as LDs in front of other people due to social embarrassment, such as the concern about seeming foolish [22, 81] and uncertainty regarding potential interactions [48, 72]. Most of our participants (8 out of 13) mentioned this challenge as an obstacle for evaluating data visualization on LDs. P10 noted *"It takes a little bit of work for people to get used to using it … most people are very used to a smaller display and when they have all this space, sometimes they don't know what to do with it."* This challenge could relate to concerns about causing damage to LDs and difficulties in interacting with the technology, as P5 highlighted *"We grew up with this thing that you don't want to break the TV. It's expensive and I kind of feel that this is a kind of cultural thing that people are afraid to [touch] them, right? And I think this is a challenge now [but it will not be a challenge] 20 years in the future."*

FD#7: Future researchers need to incorporate familiarization tasks in their studies to foster participants to become comfortable with LDs and interaction techniques before participating in the evaluation studies.
Example: Future researchers could design preliminary sessions where participants are introduced to LDs. Before the evaluation sessions begin, participants could engage in guided exercises, such as performing zooming and panning tasks on a sample data visualization. These sessions could result in participants becoming more comfortable with LDs, reducing the learning curve and ensuring that the focus in evaluation sessions is on performance and interaction with the data visualizations rather than on learning how to use the LD.

C8: Interrupted Flow of Interaction. The user experience in the evaluation phase of creating data visualizations for LDs can be interrupted by technical limitations such as keyboard-to-screen workflow and cursor visibility issues [18, 84]. Most of our participants (8 out of 13) mentioned that evaluating data visualizations with people was impacted by an interrupted flow of interaction. P2 mentioned that in their evaluation studies when individuals needed to interact with the LD using a keyboard, they had difficulty switching between the keyboard and the screen, expressing, *"There's kind of that jumping back and forth from the keyboard to the screen, that's kind of another challenge, that they couldn't focus on the study."* In another case, P2 noted that their study participants frequently experienced difficulties in keeping track of the cursor during the evaluation process and said *"It's really easy to lose the cursor and even though we've increased the mouse pointer size and changed the contrast and stuff, people still struggle with that."*
Another set of evaluation challenges are related to multi-display setups. LDs can be created by combining multiple desktop-sized displays. Bezels and navigating multi-display setups using a mouse posed additional challenges during the evaluation process. Robertson et al. [84], Lischke et al. [61], and Belkacem et al. [18] emphasized the increased physical strain experienced when navigating the mouse cursor across LDs. Similarly, our participants highlighted that navigating across multiple displays using a mouse required frequent hand movements, which was cumbersome for individuals involved in their evaluation studies. P2 said *"When you have to drag something, dragging it across like 5 displays with the bezels, that's a challenge when you're using mouse."*

FD#8: Future studies need to continue developing and deploying more robust and suitable middleware for LDs, addressing challenges such as interrupted interaction during data visualization evaluation sessions.
Example: Future researchers could develop middleware which supports diverse evaluation requirements, including customizable mouse pointer sizes to accommodate different users' preferences and needs. Additionally, middleware should offer adaptable layout configurations to ensure the interface can be tailored to various evaluation scenarios.

C9: Limitations in Feedback Gathering During Evaluation. Collecting data during evaluation studies on LDs refers to gathering relevant information and observations to assess the effectiveness, usability, and user experience with data visualizations [86]. In our study, 3 participants mentioned the limitations of collecting data during the evaluation phase due to the unique characteristics of LDs. Participants said that they needed to video record their evaluation sessions to observe user interactions with data visualizations. They put the recording device on one side of the display, which limited the individuals' access to that part of the screen. P3 said *"So the tabletop was about a*

50-inch screen and [participants] had to move physically. . . . one side of the screen wasn't available for use because we were doing recording devices and it was a bit cumbersome." Participants mentioned that they had multiple recording devices to gather data during their evaluation sessions, and synchronizing them was challenging. P12 said *"I think we did like a clapping to synchronize [cameras] because we had to turn on one camera, then walk through the other one and turn it on and make sure that we can look at all videos simultaneously."* Participants also mentioned the display's brightness affected video quality and impacted the reliability and usability of the recorded data. Furthermore, to gather feedback from all interaction modalities and LD angles, researchers need to synchronize data and analyze them, which can be demanding.

> **FD#9:** Future research needs to further develop tools to support data gathering and analysis for evaluating visualizations on LDs.
> **Example**: Future researchers could develop tools to support data gathering which seamlessly integrate and synchronize multi-camera and multi-screen footage to provide a comprehensive view of individuals' interactions during the data visualization evaluation sessions. These tools should also automatically generate detailed transcripts of user actions and verbal responses to save time when analyzing the evaluation sessions.

5.4 T4: Challenges of Building LD Infrastructure

Building LD infrastructure involves setting up the environment and technical aspects. Building these infrastructures can face several challenges, such as spatial limitations, lack of technical support, and difficulty in relocating LDs [93].

C10: Environmental Factors and Space Constraints. Individuals need to be able to move freely in front of the LDs and interact with the data visualizations. This physical navigation enhances individuals' performance and enables them to move closer to see finer details or step back for a broader overview [15, 46]. Additionally, LDs are sometimes located in public spaces or busy rooms, which can pose challenges when working with confidential data. Our participants (7 out of 13) indicated that environmental factors and space constraints presented challenges when working with LDs. P2 noted *"It's the room is 20 feet by 20 feet. The room is totally windowless, there's people who want to work with confidential data in there, so there's no way for people to walk by and see what you have on display."* P1 also noted *"Sometimes the room is busy. Sometimes people take classes in the same room or other people do research in the same room."* Another environmental challenge mentioned by our participants was inadequate ventilation or cooling systems. Prolonged use of LDs can lead to increased heat buildup, which could result in an uncomfortable working environment. P5 said *"The room was just too hot. Getting stuck in this warm room and just waiting for this to compute whatever we made, was frustrating back then."* Although building up these infrastructures can be expensive, it is necessary to allocate sufficient funding and space and install proper ventilation.

> **FD#10:** Future studies should further investigate developing low-cost LD hardware, including computing devices, displays, and interaction tools. These advancements should prioritize suitability and ease of maintenance.
> **Example**: Future researchers could explore advancements that include using cloud technologies that eliminate the need for expensive computing devices. Projectors or foldable displays can be used to create low-cost displays.

C11: Technical Issues and Lack of Technical Support. LDs can require complex technical setups, which can introduce multiple points of potential failure, including server crashes, the difficulty of implementing multi-touch on LDs, and glitching out of one display in a multi-display setup, which leads to disruptions in the workflow. In our study, 6 participants highlighted these difficulties and discussed how these challenges affect working with LDs. P6 noted *"You know the hardware. It's always a challenge. ... infrastructure in the back end requires a lot of servers, if one of those components has a problem then the whole thing kind of like collapses and you don't really know what's working and what's not, and now you need to start rebooting things until you can get them operating again. So those are some hardware challenges that we face."* A lack of dedicated technical support to address these issues could result in extended periods of non-productivity and frustration for data visualization designers and developers for LDs. P11 said *"We didn't have any tech support ... the bad thing is that we don't have anyone to maintain [it], so we have to maintain it ourselves."*

> **FD#11:** Future research needs to demonstrate the LDs' need for technical support due to the evolving nature of these technologies. This will create further opportunities for LDs' adoption and usage in the long term.
> **Example**: Future researchers could provide comprehensive video tutorials or documentation that offers detailed instructions and troubleshooting guidance, individuals can gain the knowledge to overcome challenges when setting up LDs or doing troubleshooting, even in the absence of direct support.

C12: Difficulty Relocating LDs. Infrastructure typically involves fixed hardware configurations, such as multi-displays that are hung and fixed on the wall and cannot be easily relocated [71]. Sharing the data visualization systems developed for LDs with the scientific community and the public is another challenge mentioned by our participants. Since moving LDs for demoing purposes is not easily possible and data visualizations developed for LDs cannot be easily demonstrated on a desktop-sized display, these demos are often shared in video format, which limits their presentability. The inability to easily relocate LDs and their associated infrastructure presents additional challenges when changing institutions. Two participants mentioned the difficulty in relocating LDs. They lost access to LDs and technical and infrastructure-specific knowledge they had developed over the years when they changed their institutions. P3 elaborated *"So the hardware is stuck in the lab, so that didn't exist outside the lab, and because it was massive, you had the installation costs. Displays are really prohibitive to be able to move from different areas and it just wasn't possible."*
As our study revealed, building infrastructure for LDs presents challenges. However, these challenges should not detract from the importance of pursuing research in this field. The difficulties in LD infrastructure development should be seen as opportunities for inventive problem-solving. Fostering innovative strategies to overcome these barriers is key to advancing LD research.

> **FD#12:** Future research needs to further investigate ways of recreating portable LDs to demo data visualizations; these need to use inexpensive and accessible devices and materials.
> **Example**: Future researchers could use lightweight projectors, foldable displays, and low-cost sensors to recreate LDs that can be easily transported and set up for demonstrations in various environments.

6 Discussion

In this study, we delved into the challenges experienced by experts in creating data visualizations for LDs. We identified challenges in designing, developing, evaluating, and building infrastructure for LDs. Issues such as difficulties in scaling visual encodings, limited availability of design software and tools tailored for LDs, and challenges in adopting design guidelines were mentioned when designing data visualizations for LDs. The design process in the field of data visualization and HCI has focused on understanding individuals' needs, catering to diverse domains, and managing the transition between designers and developers to ensure user-friendly systems and applications [66, 68, 91, 92]. However, our study results highlight specific design challenges that have not been considered when designing visualizations for LDs and should be further explored. We believe addressing these challenges in design process models and guidelines is important, especially considering there is increasing diversity in display types and interaction modalities.

When it came to developing data visualizations for LDs, challenges identified from our study include the need to work away from LDs, and insufficient development tools and learning resources. While toolkits such as Sage3 [37] and VegaLite [88] exist, their adoption is not universal and they are not specifically designed for LD interaction modalities. Many research labs working with LDs have created effective custom, in-house development tools to address the specific needs and challenges LDs pose during the development process. However, these tools require continuous updates as technology evolves and rely on internal and undocumented knowledge. Our study results emphasize the need for introducing platforms to share these solutions within the community that can be a catalyst for the wide adoption of LDs in the data visualization field.

Evaluating data visualizations on LDs can be challenging. People's unfamiliarity with LD technology, interruptions in interaction with data visualizations on LDs, and limitations in feedback-gathering processes were some of the issues faced by experts in the field. Several evaluation methods exist in data visualization and HCI to assess designed systems or applications with potential users [51]. However, these evaluation methods may not be suitable for LDs due to their portability and accessibility issues. We believe our community needs to introduce creative ways to simulate or emulate LD environments for evaluation purposes or propose alternative evaluation methodologies that could meet LD's unique challenges. These solutions could be useful not only for evaluation purposes but also for effectively demonstrating data visualizations on LDs.

Building LD infrastructure also presented hurdles for experts creating data visualizations; these hurdles include environmental constraints such as the need for additional space and cooling systems, technical issues including server crashes, implementing multi-touch on LDs, and display glitches, as well as difficulties in relocating LD setups for demonstration purposes. Several solutions for building LDs infrastructures were suggested by previous literature, including clusters of personal computers for driving LDs [96], or middleware for multi-display setups [59, 83]. However, we believe our community needs to invest in additional robust hardware and software to mitigate technical issues and develop portable, flexible configurations for easy relocation and setup, which can collectively address the challenges of building and demonstrating LD infrastructure.

Lastly, we believe that to catalyze the widespread adoption of LDs for data visualization purposes, it is important to integrate the experiences and needs of designers, developers, and users throughout the entire process of creating data visualizations for LDs, rather than only focusing on user needs.

6.1 Generalizability of Future Directions

In our study, we provided Future Directions to address the challenges of creating data visualizations for LDs, and pinpointed areas that need further investigation and innovation in data visualization for LDs. However, it is important to acknowledge the limitations of these proposed FDs in relation to the diversity of LDs. For instance, in FD#1, FD#2, FD#3 FD#4, FD#5 FD#8, and FD#9, we proposed that prototyping tools, design guidelines, emulators, development tools, middleware, and tools for data gathering and analysis tailored for LDs could help overcome challenges in designing, developing, and evaluating data visualizations for LDs. However, tools and guidelines designed for one type of LD may not be suitable for other types of LDs due to their differences in screen sizes, aspect ratios, ideal viewing distances, and screen orientations. In FD#6 and FD#11, we discussed the need for future research to provide learning resources and technical support. However, these resources and support should also be tailored to the specific type of LDs, as each type of LDs has different hardware, software, or configuration requirements to function properly. In FD#7, we highlighted the need for future researchers to incorporate familiarization tasks in their studies to foster participants to become comfortable with LDs before participating in evaluation studies. However, these familiarization tasks should be tailored to the types of LDs used in the research, considering factors such as the LDs' interaction modalities. In FD#10 and FD#12, we discussed that low-cost foldable displays could serve as a potential option for recreating LDs. However, low-cost foldable displays may not replicate the full range of functionalities and experiences provided by different types of LDs. Therefore, practitioners and researchers should be mindful of these differences when applying the recommended solutions, recognizing that not all recommendations may be universally applicable to all types of LDs.

6.2 Study Limitations

Our study was designed to capture various perspectives from different fields, roles, and years of experience. The participants were selected through purposeful sampling from our network, which may not be representative of all experts with experience in creating data visualizations for LDs. Additionally, our study size was 13 participants, which is consistent with standards in HCI where the average sample size is 12 and studies with limited samples are common [25]. We acknowledge some limitations in generalizability due to the sample size. Despite this, our study provides a strong foundation for future work.

We excluded experts who primarily worked on creating data visualizations for AR/VR or immersive technologies (e.g., CAVE, immersive analytics, immersive visualization) from our study. This decision was made because these experts fell beyond the scope of our research objectives, and we anticipated that their experiences would be sufficiently different. Therefore, their perspectives on the challenges of data visualization creation might not be reflected in our findings. Although these experts may still face similar challenges, this limitation underscores the need for future studies to explore this specific domain comprehensively.

Another limitation of our study is the gender imbalance among participants, with 2 out of 13 individuals being female and 1 being non-conforming. This disparity may impact the diversity of perspectives represented in our findings, particularly regarding gender-related experiences and viewpoints. However, the motivation and protocol for the study were developed through discussions that incorporated input from both male and female researchers.

7 Conclusion

We have presented the findings from our qualitative interview-based study conducted to gather firsthand insights from 13 experts experienced in creating data visualizations for LDs. We analyzed the results of our interviews using thematic analysis. We identified 12 challenges in designing, developing, and evaluating data visualizations on LDs as well as building LD infrastructure. We proposed 12 future directions and research project examples aimed at addressing the identified challenges. Our results serve as a catalyst for further exploration and innovation in creating data visualizations for LDs. By bringing attention to the specific challenges faced throughout the data visualization creation for the LDs process, we aim to encourage researchers to contribute to the development of resources and tools that facilitate the design, development, and evaluation of data visualizations for LDs. By pointing out the challenges faced by designers and developers working on creating data visualizations for LDs, we hope to inspire continued research efforts that contribute to the advancement of effective and impactful data visualizations for LDs.

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Appendix A

Appendix A.1 Interview Script

Thank you so much for participating in this interview. We are going to ask a series of questions about your experiences creating visualizations for large display environments or tabletops. We want to learn about your experiences and challenges so that we can help inform practices for future researchers. We want to identify challenges and understand your process of working with the large display. Our goal is to better understand your experience making visualizations for large displays, and the differences between making visualizations for desktops versus large displays. We are more interested in hearing about your experiences with design, development, and evaluation- what it was like, and where you faced challenges- and less interested in the result of your project. As we mentioned in the consent form, your information will be anonymous, and we will protect your identity. We also will take care to ensure that your project and lab are not identifiable in our reporting of results, so feel comfortable telling us about your experiences.

We will be recording this interview. You can choose to keep your camera on or off. You can share examples through screen-sharing, and this will be included in the recording.

If any of our questions were unclear, please feel free to let us know. We have a number of people here (2-3). We will have one person conducting the interview with others asking follow-up questions and taking notes. Let's do an introduction.

Now, I am going to start the recording, please turn off your camera if you are uncomfortable.

Appendix A.2 Interview Questions

1. Demographic questions:
   a. Age: How old are you?
   b. Gender: What is your gender identity?
   c. Academic Background: What is the highest level of education you have completed?
   d. Job Title: What is your current job title or occupation?
   e. Experience: How many years of experience do you have working with large displays?
2. Can you please tell us a bit about your background/expertise working with large displays or tabletops?
3. Can you give us an overview of your large display, so we have some context for your experiences: the properties of the large display and the physical context of your large display?
   a. Can you tell us about the environment in which the display is located (classroom, library, research lab)?
   b. How easy was it to access the technology and how often could you access the technology?
   c. Can you describe the size of your large display (width vs. length)? Is it reachable with hands?
   d. Can you describe the orientation of your large display (wall vs. tabletop)
   e. Can you describe the shape of your large display (flat vs. curved)?
   f. What interactions were set-up for this display, for you to use? Did it have a touch system, a mouse and keyboard, sensors/tracking, input server for devices?
4. When you first started working on this platform, how did you learn how to use it (e.g., other students, Faculty, Personnel, or Resources)?
5. Thank you for telling us about your display. Now, think about the projects you did on a large display. Can you please describe your 1-2 [significant, most challenging, most recent, most comfortable discussing] projects done with this large display in short? We are more interested in knowing about your experience in the process of doing your project with this display.
   a. What was the goal of your project?

b. What was the domain of the project (e.g. medical, or environment)?
c. Who were the target users of your project?
d. What types of data do you use for your projects (e.g. text, geographical, or temporal)?
e. Who were your collaborators if you had any (students, supervisors, industry, gov, medical, artists)?
    i. Can you elaborate on the process of collaborating with them?
f. What interactions were set-up for this display, for you to use? Did it have a touch system, a mouse and keyboard, sensors/tracking, input server for devices?

6. Do you think most of your work falls under design, technical development, or evaluation?
    a. Could you please describe your **design** process?
        i. Did you sketch for the full display? How? Accounted for the large space and resolution?
        ii. How did you choose font/visual encoding, and aspect ratio while you sketched?
        iii. How did you make the sketches (e.g. pen and paper or whiteboard)?
        iv. What software or tools did you use for design (e.g. Photoshop)?
    b. Could you please describe your **development** process?
    i. Can you describe what your developed application or visualization looked like, and how it worked?
    ii. Were you developing the prototype away from the display? Were there any challenges with this setting? What proportion of the time were you working on the display itself vs the personal computer?
    iii. What programming languages were you using?
    iv. How do you utilize your screen size (e.g. single view, small multiples, or distributed)?
    v. How are you developing/simulating the touches/interactions if you are developing on your laptop?
    vi. Size for font/visual encodings for large displays/laptops - how did you account for it?
    vii. How did you develop your prototype accounting for this on your laptop considering your laptop has a different size screen?
    c. Could you please describe your **evaluation** process?
        i. Which one of these study types best describes your evaluation studies? User performance, user experience, communication through visualization, etc.?
        ii. What was unique about doing this evaluation study on a large display vs a laptop/PC? What were the challenges?
        iii. Did you have to make any preparations before the evaluation session starts? What was it?
        iv. How did you capture the study data/recording?

7. Could you please tell us about challenges and additional opportunities opened by using these display probes?
    a. How comfortable were you working with your display?
    b. Were you always comfortable? Did you become more comfortable?
    c. What were the challenges of working with large displays in your projects?
    d. If something broke, did you have tech support to help with the display?
    e. Certain hesitant/difficulties working with the technology?
    f. Did you have any challenges with working with end-users or collaborators? How did the display help your end-users with their tasks?

8. Any final thoughts to share about the challenges you faced working with large displays?

9. Final thoughts and tips for future researchers who will work on large displays?

Appendix B

Appendix B.1

Please see our Miro board for the codes: https://miro.com/app/board/uXjVMBRYOaU=/

Appendix B.2

The first table shows the themes, categories, description of each category, and a representative quote from our participants; second table shows that we do not have new codes introduced after P9 and reached saturation.

Themes	Categories	Descriptions	Representative Quotes
T1: Challenges of Designing Data Visualizations for LDs	C1: Difficulty Scaling Visual Encodings	LDs' increased size, resolution, and varying user distances complicate the selection of appropriate visual encodings, such as the number of data marks, the size of data marks, and their color.	"There's always that situation where you think it kind of works. The aspect ratio is right and all that, but until you actually come in and see what it looks like, are your thought sizes actually too small or too big? Is the spacing nice? It's hard to kind of exactly predict and be happy with". (P2)
	C2: Limited Design Software and Tools	Existing design software and tools, such as Photoshop, lack specific adaptations to facilitate designing data visualization for LDs.	"Photoshop is not working on the [large] display. That was a little bit disappointing ... I think it's not because of the display, it's just because Photoshop doesn't support this kind of hardware yet ... So, during the sketching process, what I had to do was sketch on my tablet or my computer and then copy those sketches to the tabletop to see if the scale of what I was doing actually made sense. I wouldn't describe it as a seamless process ... it would have been nice to be able to do [it] on the [large] display". (P8)
	C3: Difficulty Adopting Design Guidelines	The absence and pressing need for design principles specifically tailored for LDs when creating data visualizations.	"But what we found was that, sadly, many of the studies were listed as design principles that could be understood as basic user experience ... that when you went back to the basic UX UI design bibliography would be redundant. So, it was extremely hard to find something that would actually add on to that and that would be specific to the [large] displays. I guess having references [that provide design guidelines for LDs] could help us design for the tabletops. Right now, the available bibliography [that provides design guidelines for LDs] is very limited". (P8)
T2: Challenges of Developing Data Visualizations for LDs	C4: Developing Away from LD	Not having access to LDs during the data visualization development results in developing data visualizations away from LDs, making the development process challenging for developers.	"I'm working remotely, I upload the content, and it looks like it's working, but I'm not sure if it's working or not. That's a problem. We don't have a way to look at it. I usually must ask one of my colleagues: Hey, can you go in the room and actually check that things are being displayed as they should, or if something is broken"? (P9)
	C5: Limited Development Tools	The availability of tools, software, libraries, and toolkits specifically tailored for LD to aid data visualization developers is limited.	"[Developers] has their tools... [When they] go to [large] display, tools that they were working with are not working anymore". (P6)
	C6: Limited Learning Resources	The lack of learning resources for developing data visualization for LDs makes the development process challenging and time-consuming for developers.	"I didn't get too much help from ... just in that because this is like a very specific platform that I needed". (P4)
T3: Challenges of Evaluating Data Visualizations for LDs	C7: Unfamiliarity with LD	Individuals are more accustomed to working with desktop-sized displays rather than LDs, resulting in challenges when evaluating data visualizations on LDs with the public.	"We grew up with this thing that you don't want to break the TV. It's expensive and I kind of feel that this is a kind of cultural thing that people are afraid to [touch] them, right? And I think this is a challenge now [but it will not be a challenge] 20 years in the future". (P5)
	C8: Interrupted Flow of Interaction	The users' experience in the evaluation phase of creating data visualization for LDs is interrupted by technical limitations such as keyboard-to-screen workflow and cursor visibility issues.	"It's really easy to lose the cursor and even though we've increased the pressure size and changed the contrast and stuff, people still struggle with that". (P2)

	C9: Limitations in Feedback Gathering During Evaluation	LDs' different characteristics impeded comprehensive data collection and evaluation study.	"So, the tabletop was about a 50-inch screen and [participants] had to move physically … one side of the screen wasn't available for use because we were doing recording devices, and it was a bit cumbersome". (P2)
T4: Challenges of Building LD Infrastructure	C10: Environmental Factors and Space Constraints	Not having enough space and effective cooling systems makes data visualization evaluation studies on LDs difficult.	"The room is 20 feet by 20 feet. The room is totally windowless, there's people who want to work with confidential data in there, so there's no way for people to walk by and see what you have on display". (P2)
	C11: Technical Issues and Lack of Technical Support	Technical challenges, including server crashes, the difficulty of implementing multi-touch on LDs, and glitching out of one display in a multi-display setup led to disruptions in the workflow. A lack of dedicated technical support to address these issues results in extended periods of non-productivity and frustration for data visualization designers and developers.	"We didn't have any tech support … the bad thing is that we don't have anyone to maintain it [large display], so we have to maintain it ourselves, and that was hard". (P11)
	C12: Difficulty Relocating LDs	Moving LDs for demoing purposes is not easily possible and data visualizations developed for LDs cannot be easily demonstrated on a desktop-sized display.	"So, the hardware is only stuck in the lab for that project, so that didn't exist outside the lab, and because it was massive, you had the installation costs for these large visualizations. Displays are prohibitive to be able to move from different areas and it just wasn't possible". (P3)

Categories	**Codes**	**P1**	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**
C1: Difficulty Scaling Visual Encodings	1. The size of the charts is uncertain because the distance from which the user will stand is unknown.		■									■		
	2. Need to create a wall of paper to design on it.					■								
C2: Limited Design Software and Tools	3. Software similar to Photoshop doesn't function well on LDs.								■					
	4. The process of sketching on a tablet and checking it on LD is not seamless.								■					
	5. The process of sketching on a tablet and then checking it on an LD is time-consuming.								■					
	6. There's a need to start the sketching process directly on LD during the initial phase.								■					
	7. There's a need for sharing and opening a link of the design on the display to adjust.								■					
	8. The inability to design directly on LD itself due to limited design tools.								■					
C3: Difficulty Adopting Design Guidelines	9. There are no specific design principles or guidelines tailored for LDs.								■					■
	10. There are no references available for screen element placement specific to LDs.								■					
C4: Developing Away from LD	11. Testing the system is arduous and time-consuming.			■									■	■
	12. Differing lighting between your room and the LD room impacts colors.									■				■
	13. The challenge lies in not knowing the exact font size before system development and having to adjust it on the LD after seeing it.								■					
	14. Hard to anticipate and evaluate the size, aspect ratio, spacing, and color.	■		■									■	■

	15. Need for using touch devices for interaction testing.		■											
	16. Requesting a colleague to visit the LD room and check your development work.						■							
	17. Need for utilizing Zoom or Teams to view the results of development on LDs.									■				
	18. Need for using VPNs when working remotely.						■							
	19. Not being able to fully imitate the touch behavior.									■			■	
	20. There's a need to download the code onto another PC for testing purposes.									■		■		
C5: Limited Development Tools	21. There's a need to implement new development tools.	■											■	
	22. The desktop operating system isn't functioning properly on LD.		■											
	23. The UI of the tools is not optimized for LDs.						■							
	24. the lack of useful tools discourages people from using the system, and without users, there's no incentive to develop useful tools.						■							
	25. The absence of software packages and libraries for LD development presents a significant challenge.			■										
	26. Developers prefer using their laptops or developing browser-based systems when tools are incompatible with LDs.						■							■
	27. There are no development visualization tools available specifically designed for LDs.						■							
	28. There are no emulators, akin to Figma for mobile app design, available for LDs.			■										
	29. Choosing the best interaction for LD visualization tools remains uncertain because of limited development tools.						■							
C6: Limited Learning Resources	30. Limited learning resources necessitate seeking assistance from colleagues during development, googling it, or doing trial and error.				■			■					■	■
	31. Supervisors might offer limited assistance due to the use of a new platform.				■									
C7: Unfamiliarity with LD	32. People engage less with LDs because LDs aren't widely available.			■									■	
	33. It requires some effort and time for people to become accustomed to LD.					■					■			■
	34. People are hesitant to touch LDs because they don't want to damage them.					■								■
	35. Non-techy individuals may struggle with using LDs.						■							
	36. People still don't find LDs natural to use.							■						
	37. Elderly individuals are more unfamiliar with LDs.								■					
C8: Interrupted Flow of Interaction	38. Need for using the mobile phone to interact with LDs.				■									
	39. There's continuous switching between the keyboard and the screen.		■											

	40. Losing track of the cursor is common and enlarging it doesn't resolve the issue.		■									■		
	41. Dragging the cursor across multiple displays requires a lot of hand movement.		■											
	42. Details are missed due to the presence of bezels in multiple displays.			■								■		■
	43. The grid pattern on multiple displays poses a challenge for users when interacting with them.							■						
	44. Conducting evaluation studies in real-world settings with LDs and capturing people's attention and encouraging interaction with our system.				■									
	45. There's a need for a custom app for eye-tracking users due to the size of the LDs.					■								
	46. Manipulating the data becomes challenging when users stand very close to LDs.			■										
	47. People need to crouch down to interact with and view items at the bottom of the display.			■										
	48. False touches occur frequently.			■										
	49. Interacting with LDs using the body instead of a mouse and keyboard.							■						
	50. User interaction experiences within 3D environments and LDs are limited to point-and-click actions							■						
	51. Creating space for multiple users and the necessity for a tool to facilitate interaction with LDs when several individuals are utilizing data visualization on LDs.				■						■			
	52. Hard to have multiple users interacting with LDs at once and users need to take turns and multi-touch does not function perfectly.			■								■	■	
C9: Limitations in Feedback Gathering During Evaluation	53. Setting up cameras to record data needed synchronization and caused blocking of one side of the screen and data recording.			■									■	
	54. The LD's brightness causes issues during video recording.								■					
C10: Environmental Factors and Space Constraints.	55. There's a need to replace sensor-based lights with switch lights, as the solitary lighting affects experiencing the full quality of the LDs.								■					
	56. Natural light impacts how screens are perceived.			■										
	57. Need for furniture relocation for space management.	■												
	58. High traffic in large display rooms.	■												■
	59. A small room poses challenges in moving in front of LDs and for maintaining data confidentiality.		■										■	
	60. Need for allocating appropriate cooling systems.					■								
C11: Technical Issues and Lack of Technical Support	61. Need for using GPUs or heavy computers and challenges associated with working with them.		■											■
	62. The lack of 3D rendering capabilities in computer systems and did not support GPU.		■											
	63. There's a need for middleware suitable for LDs due to the challenges posed by using Windows in LDs.						■					■		

	64. Scanners generate custom file formats that are incompatible with the LDs, rendering them unopenable.						■							
	65. The lack of support to maintain the LD exacerbates hardware challenges.						■				■	■		
	66. Servers crash down frequently, and LDs often experience glitches.						■				■			
	67. Multi-touch functionality on LDs is not functioning properly and there is a need for installing extra drives.		■										■	
C12: Difficulty Relocating LDs	68. It's impractical to transport the large display to conferences for demo purposes.		■											
	69. The LD remains confined to the lab due to its immense size.			■										

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