This is an excerpt from Frank Elavsky's dissertation on *Tool-making as an Intervention on the Accessibility of Interactive Data Experiences*, which can be accessed in full at this archival link:

http://reports-archive.adm.cs.cmu.edu/anon/hcii/CMU-HCII-26-103.pdf

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Abstract

In this dissertation, we contribute practical advancements in tool-making as an intervention on the accessibility of interactive data experiences. The thesis of this dissertation is as follows: *This dissertation argues that the tools practitioners use to build interactive data experiences are themselves sites where accessibility barriers are produced, prevented, or alleviated for both end users and authors. This work contributes five tools—Chartability, Data Navigator, Softerware, Cross-perception, and Skeleton—that collectively center accessibility work on the empowerment of disabled and non-disabled practitioners across the full arc of evaluation, data navigation, analytical interaction, and personalization.*

Rather than framing accessibility research solely around ideal experiences for end users with disabilities, this thesis investigates why accessibility work is so difficult for the practitioners who build interactive data experiences and what tool-making can reveal about those difficulties. We organize this investigation around four domains where practitioners face the most persistent challenges: evaluation, navigation, interaction, and personalization. *Chartability*, a heuristic framework contributed first and maps the full landscape of accessibility barriers and identified these three latter domains (navigation, interaction, and personalization) as the areas where the most severe gaps remain. *Data Navigator* and *Skeleton* then investigate navigation, finding that practitioners struggle because navigation structure has no visible, manipulable representation in their workflows. *Cross-perception* engages interaction, demonstrating that blind data analysis has been constrained by existing tools and that a new interaction design framework can reshape what analytical work is possible. *Softerware* addresses personalization, revealing that access needs genuinely conflict across users and that meaningful personalization requires system-level infrastructure that does not yet exist in practitioner tooling ecosytems.

Combined, these contributions provide empirical insights and practical advancements in the state of the art for tooling that bridges gaps in current accessibility practices in visualization and data science. Our work ultimately enables people with and without disabilities to better evaluate barriers in, analyze with, design for, develop, and personalize interactive data experiences. We demonstrate that tool-making is a productive intervention that both engages accessibility barriers and elucidates why those gaps exist in practitioner work.

Part I

Introduction

Chapter 1
Introduction

This thesis is a body of research situated within the existing research area focused on making interactive data representations more accessible for people with disabilities. Much of the work in this existing area is situated within the context of making interactive data *visualizations* accessible, particularly (but not exclusively) for people who are blind. My work, contributed here in this thesis, is focused on using *tools* as a specific intervention and sub-area of study for making interactive data *representations* accessible for people with disabilities, broadly speaking. ("Representations" here is an intentionally broader term than "visualizations," which are exclusively visual representations of data.)

Before we begin, two things must be understood up front, or else the rest of this thesis could be interpreted with disruptive assumptions: we must interrogate the phrase "making visualizations accessible" and unpack why *tools* are a meaningful area of study.

1.1 Is "accessible visualization" really an oxymoron?

The first assumption that must be disrupted is perhaps the motivating cornerstone of this research, which is that the phrase "making visualizations accessible," while a noble goal, is not the semantically correct phrasing nor precisely what describes my work. This can be misleading. I do use the phrase "accessible visualization" but will admit that this seems to confuse certain people with very particular opinions about things. We will clear this up.

Villains of our field's past have written incendiary and ableist perspectives on why "no forms of data visualization, not just dashboards jam-packed with graphics, can be made fully accessible to someone who is blind," and that "[a blind man] will never be able to analyze data as I do visually, because many aspects of vision cannot be duplicated by his other senses" [35]. However, this position misunderstands what the goal of accessibility is, and arguably even what the goal of visualization itself is.

Making visualizations accessible *isn't* about the visualization, it's about making the outcomes of the visualization accessible.

Visualizations are ubiquitous and paramount for decision-making. However, the *artifact* that is a visualization is not even the goal of the act of visualizing: developing understanding, insight, confidence, and communication among and between human beings are the goals of visualization. Visualization is about making data easier to use for all kinds of things. Yes, our visual system enables us more than any other form of sensory cognition that we have [13, 41, 126]. But we aren't trying to make sight itself accessible. We are trying to make it possible for people to make meaningful decisions, gain valuable information, build conjectures, and effectively communicate with others.

Many, many people who I've spoken to over the course of my career, even before embarking on this thesis journey, misunderstand this simple fact: making a "visualization" accessible *isn't* about the visualization itself but rather making what the visualization is meant to *accomplish* accessible. It's about equal outcomes, not equal interactions with an artifact.

People with disabilities are no small portion of the world's population. In the United States, 27% of people self-report living with at least one disability that affects their daily lives [97] and all of us will eventually age into disability (if we are lucky to live a long life).

People with disabilities (again, that will be all of us *eventually*) deserve to participate fully in life. They deserve financial independence. They also deserve loving care and interdependence. People with disabilities have a right to make informed decisions, to know about the status of a global pandemic, and to have an understanding of local and national politics [34]. While we use visualizations to navigate all of these domains, the goal is not to make the charts and graphs themselves somehow equally useful to all people. That would be a false measurement of success.

Our goal then, is measured by the success of lives led by people with disabilities [130]. Many other measurements are just metrics along the journey towards that goal. We then ask: Can people with disabilities also use data to live full lives? Can they make *fast* decisions based on data? Meaningful, careful, *slow* decisions? Communicate complex ideas? Crunch and clean data, develop models, find errors, and build hypotheses? Can they have memorable, immersive, beautiful, aesthetic experiences with data too [63]? Making "visualizations" accessible really is a misnomer. We are ultimately trying to make everything about what interactive data experiences *accomplish* for people equitable and accessible.

Again, if the goal of accessible visualization were about visualizations themselves, then the correct course of action would be one framed by the medical model [88]: that there is a normative state of behavior and capability (in this case, it would be "normal" to be able to read a visualization and make a decision) and any deviation from that norm must be corrected. This framing first assumes that the visualization should not be altered or improved. And then this framing puts the burden on the bodies of people with disabilities: that they must be "fixed" and given sight or brought to some equivalent state as someone who is "healthy," normal, and sighted. Plenty of scholars have already discussed why this framing is a problem, not only because it places undue burden on people with disabilities, produces pathologies and hierarchies of disability, but also because it is fundamentally not economically or ethically feasible.

So we then turn to other models of disability, such as the social model. The social model is heavily discussed by disability scholars and is not the end-game or last and total way of thinking about disability [88, 102, 104, 124, 147]. But the core motivation is that society, not medicine, is also a path towards solving problems that people with disabilities face. A few important concepts and concretely actionable things come from the social model that can help motivate the work of this thesis.

First, we look to the historical birth of the social model of disability: in the 504 sit-ins that took place in the United States in 1977. Cities had curbs and curbs are a barrier for people who use wheelchairs. So protests happened because decisions were being made without people with disabilities at the table. In this instance, people acknowledged that political power was an exclusive club and fought to ensure their cry "nothing about us, without us!" materialized.

And this leads us to the first and most-foundational philosophical framing for this thesis: that our *artifacts*, these things we've created from curbs to data visualizations, can become *barriers* for people with disabilities. And it is then the artifact, not the body of the person with a disability, where disability is produced in this model. Rather than a comparison to a normative state as a way to frame disability (the medical model), we instead must observe and evaluate material outcomes based on human-made problems.

So, the social model is framed around society "solving" inequities: we get involved and make political and legal change tangible. But a second model also emerges from within the social model: one where we can now frame *who is first responsible* for repair: the curb designers and implementers.

And knowing who is first responsible for access leads us into the moral and ethical imperative that motivates this thesis: the builders and makers of visualizations are ultimately the ones who provide exclusive value for only a subset of people: those *without* disabilities. **We must first change how builders and makers do their work.**

So the phrase "accessible visualization" is really about recognizing that visualizations produce barriers for people. That means that it is our ethical imperative, as builders and makers, to fix them. And that act of fixing barriers leads us away from mere visual representations of data into a wide variety of other senses and interaction modalities. There are many paths forward towards fuller and more-equitable lives led by people with disabilities.

1.2 On *tools*, *tool-making*, and *human-tool* interaction

Then the act of making becomes immensely important: we, the builders and makers of our world, need to get things right; there is a risk involved when making things that we will exclude people with disabilities. We need to make sure that we build a better world than the one we have now. We must care for new things we create and tend to the repair and maintenance of what we've already made. And this ethical imperative leads us to the topic of *tools* and *tool-making*.

So the second thing that must be understood before we embark on this thesis is that *tools* are not the same as *solutions* or *applications*. Sometimes tools can be used to *solve* things and are certainly, in ideal circumstances, *applied* in various contexts. But understanding the role of the "tool" in human-tool interaction is paramount for engaging in the work of making anything accessible for people with disabilities.

We use tools to shape our world, break old things, and make new things. But a tool, like the hammer (as an example), does not inherently *solve* something like homelessness. But a hammer can be used to build homes if there are social policies in place and proper resources allocated. This means that for the success of tooling, there is often a larger material, social, legal, and policy reality that supports and necessitates those tools. This thesis will not be focusing on changing the upstream dependencies, but optimistically operating as if they were true (or will be true in time).

However, in some cases, tools can *destroy*. The hammer has a claw and can easily pry apart boards and tear down homes. So tools carry potential to do all kinds of things, both good and bad, and how a tool is used is often open-ended, variable, and heavily dependent on socio-technical realities. Tools participate in personal and political agendas [141] and are sometimes, for this reason, regulated or made proprietary and controlled by powerful entities [45, 139].

So tools are not without any sort of ethics. We cannot just blame tool-users for outcomes when much of a tool depends on these larger systems and structures. Technologies (tools included) encode the assumptions and biases of their *creators* as much as, if not more than, their users. Tools that build things for others to use can be loaded with assumptions about what people are *able* to do [142] and also rules and guardrails about what anyone downstream from that tool's design *should* do [45, 138]. These assumptions, biases, and rules *limit*, *enforce*, *magnify*, *exclude*, and *enable* what a tool-user is capable of.

Tools for visualizing data are a perfect case study in this problem: virtually every major data visualization library, application, or software ever made was made entirely with the assumption that data should be transformed into visual representations. This is a reasonable assumption, since virtually all of the tool-makers are sighted and visualization is incredibly helpful to our cognition of and communication with data [38].

So data visualization, as a field, has focused its tool-making efforts on reducing the difficulty involved in visualizing data. Some visualization tools are concise [109], others are lower level but much more expressive [8]. Tool-making in visualization has focused on making it easier to scaffold a wide variety of interactions both with the visualizations as well as with their underlying data models [54].

However, as time has moved on, people began to speak out about color-vision deficiency in data visualization. Some people, primarily those with X/Y chromosomes (largely men) who are of European ancestry, have a deficiency in their ability to perceive certain colors. Then a plethora of research arose that began to look into the barriers that folks who are colorblind face in data visualization. As a result, our practices and tools improved. We began to educate practitioners, develop new color palettes, researched new methods for testing our designs, and built new systems for handling automatic color encoding. Our tools evolved.

But now data visualizations have arguably become ubiquitous in daily life. By comparison, we have far more tools now for making visualizations quickly and easily than we do for representing data in non-visual ways. We also have far more research, relatively speaking, into how sighted end users interact with visualizations.

So this thesis engages gaps that arise in this space: Practitioners face immense challenges when crafting accessible data experiences. We first need to educate practitioners on what accessibility barriers actually are in interactive visualizations. Then, we must help them engage the hardest barriers in this work and create building blocks that help them to construct navigable data experiences, build design frameworks that can inform entirely new kinds of data interaction, and develop software systems for end-user personalization and agency. Our research seeks to advance the state of the art in tools that assist in accessible data interaction while also using tool-making as an intervention that helps us to better understand and characterize *why* and *how* data practitioners face barriers themselves in this work.

Chapter 2
Background & Related Work

2.1 Practitioners and Tools

2.1.1 Understanding Builders, Makers, Designers, and Developers

Research investigating the practices and experiences of individuals who create with computers employs a range of high-level methods. Ethnographic studies, case studies, and design ethnographies are common approaches, allowing researchers to immerse themselves in communities such as the DIY/maker and assistive technology spaces [62, 65]. These methods capture the nuanced challenges practitioners face when engaging in new and unfamiliar work, including the transition from traditional to digital fabrication, coding, and tool creation [64]. By observing and interviewing practitioners in naturalistic settings, researchers uncover the social, cultural, and technical factors that shape how makers adapt and evolve their work practices.

Participatory design and co-creation are also central to this field [125]. These approaches encourage collaboration between researchers and practitioners or end-users, enabling a deeper understanding of the cognitive and creative processes behind design and development [49]. Such collaborative sessions reveal how designers shift their thinking when encountering novel challenges, embracing iterative processes that blend experimentation with reflection. Similarly, developers often modify their applications, tools, and even programming languages through feedback loops and community-driven innovation, highlighting a dynamic interplay between individual creativity and collective knowledge.

Additionally, design-based and case-study research methods explore how new practices can augment the existing work of practitioners [18, 68]. This involves not merely filling gaps or solving isolated problems but reimagining the possibilities for creative and technical expression. Researchers in this space envision systems that support continuous learning, adaptation, and innovation [47]. The focus is on enabling practitioners to extend their capabilities—providing scaffolds for experimentation, fostering environments where unconventional approaches are encouraged, and integrating new technologies in ways that amplify creativity and intelligence rather than simply addressing deficits [72, 132, 142].

Overall, the research methods used in this area are multidisciplinary, combining qualitative insights with iterative design practices to offer a holistic picture of the challenges and opportunities of builders, makers, designers, developers.

2.1.2 Approaches to Tool-making in Human-Computer Interaction

In human-computer interaction, tool-making research spans both the creation of entirely new capabilities and the enhancement of existing systems. One prominent approach involves piggybacking on current systems—leveraging their established functionalities to introduce improvements that streamline workflow or unlock new interactions [46]. This method often focuses on integrating with widely used platforms to amplify their usability, enabling users to perform tasks in more intuitive or efficient ways. By building on existing infrastructures, researchers can demonstrate how small, targeted modifications have the potential to transform user experiences.

Another significant approach centers on the notion of appropriation [25, 26, 107, 129]. Here, research examines how users adapt tools for uses beyond their original intent. Studies in this vein explore the creative processes behind such re-purposing, uncovering the latent functionalities and opportunities that emerge when practitioners modify systems to suit their unique needs. This perspective often leads to the development of modular, extensible tools that encourage experimentation and user customization, fostering a more personalized interaction with technology. In some cases, theory has been developed from the study of emergent and generative tool-use [4, 6], broadly informing future tooling projects as well as general theories of creative human interaction with technology.

Beyond these, tool-making in HCI also includes the development of systems designed to empower users by providing entirely new capabilities, sometimes explicitly named "toolkits" and other times generally just referred to for their ability to enable novel interaction and outcomes [77, 99, 108, 117, 117]. These projects may range from novel software environments that facilitate rapid prototyping and live programming to innovative hardware devices that bridge the gap between digital and physical interactions [57, 59, 99]. The emphasis is not solely on problem-solving but on enabling creative exploration, new possibilties, and even hacking the potential of technologies towards new ends [58]. Such projects often present their contributions through demonstrative prototypes and case studies that reveal potential applications, even if they are accompanied by minimal formal evaluations [30].

This body of work reflects a balance between novelty and practicality. While some projects aim to introduce groundbreaking new ways to interact with data and systems, others refine existing practices to improve efficiency and accessibility. Together, these approaches underscore a commitment to enhancing human capabilities, allowing users to not only solve problems more effectively but also to unlock new avenues for creativity and innovation.

2.2 Data, Accessibility, and Data *and* Accessibility

2.2.1 Advancements in Interactive Data Visualization and Data Science

Recent years have witnessed significant advancements in interactive data science and visualization, driven by innovations that enhance both the performance and usability of data tools. Crossfiltering, as a subtype of cross-linked interaction, has emerged as a powerful technique, enabling users to interact with multiple data dimensions simultaneously [5, 53, 80, 136]. By linking various filters, analysts can quickly build hypotheses and isolate patterns, trends, and anomalies in complex datasets, leading to more informed decision-making. Stress has been placed in recent years on developing fast systems that are optimized showing more and more data at once while reducing latency in user interaction as much as possible [54, 80, 144].

Automated data processing and cleaning have revolutionized workflows by reducing the time spent on manual data wrangling [32]. Sophisticated algorithms now automatically detect inconsistencies, fill missing values, and transform raw data into usable formats. These improvements enable researchers and practitioners to focus more on analysis rather than preparation.

Faster tooling has further accelerated data exploration. Enhanced computational frameworks and optimized libraries allow for real-time data manipulation, making interactive visualization more responsive [54]. Coupled with easier-to-use grammars and scripting languages, these tools lower the barrier to entry, empowering users with limited visualization, geometry, trigonometry, data, and graphics coding experience to generate complex, interactive, visual representations of data [109]. New visualization types and techniques—ranging from dynamic dashboards, faceting, to immersive 3D visualizations—offer novel ways to explore and interpret data [144].

Despite significant breakthroughs, current advancements have largely neglected the needs of people with disabilities. Innovations in data science and visualization have focused on sighted user populations, prioritizing visual clarity and interaction speed using direct pointer techniques (such as with touch or a mouse) [89]. This focus often overlooks accessibility requirements for individuals who are blind, have low vision, experience cognitive or vestibular challenges, or possess motor disabilities that limit traditional pointer use [140].

2.2.2 Accessibility and Assistive Technology in Research versus Practice

2.2.2.1 Research: Focus on Blindness and Computer Output

Research and standards are both somewhat limited by a strong bias towards visual disabilities. In *Chartability*, 36 of the 50 criteria related to accessible visualization considerations involve visual disabilities [29, 34]. Marriott et al. also found that visual disability considerations are the primary focus of data visualization literature [89], leaving the barriers that many other demographics face unstudied. Accessibility research broadly has traditionally concentrated on the experiences of individuals who are blind, investigating how they perceive and interpret computational output [84]. Studies in this area explore alternative modalities for conveying data, such as auditory representations (through synthesized speech), tactile interfaces, and sonification techniques. Researchers focus on identifying effective methods for transforming visual data into formats that blind users can easily comprehend. This body of work not only examines the perceptual challenges but also delves into cognitive processing differences, aiming to optimize the accessibility of complex information and interactive systems for users with visual impairments.

While research has made strides in converting visual outputs into auditory or tactile forms for blind users, interactive input methods remain underdeveloped. Most efforts have concentrated on optimizing screen reader navigation and information retrieval, leaving text entry and command execution cumbersome. Screen readers, as they currently exist, offer limited support for efficient input, making it challenging for users to perform complex interactions. Although tactile interfaces hold promise for providing more intuitive input methods, they are still in the experimental stage and have not been fully integrated into mainstream accessible computing solutions, perpetuating a critical gap in effective user interaction.

2.2.2.2 Practice: Focus on Standards and Specialization

In contrast, practical accessibility efforts are often centered on the implementation and adherence to established standards and guidelines, such as WCAG [133]. There has been a growing interest in developing guidelines for practitioners [28, 29] and even applying guidelines as a method of validation alongside human studies evaluations and co-design [34, 82, 83, 150]. Existing accessibility standards bodies like the Web Content Accessibility Guidelines do stress the importance of accurate, functional semantics in order for screen reader users to know how to interact with elements [135]. For interactive visualizations this means that button-like or link-like behavior should expressly be made using elements that are semantically buttons and links.

Accessibility professionals, who typically possess specialized expertise, act as intermediaries between the design and development of digital products and the strict requirements of accessibility standards. Their role involves translating abstract guidelines into concrete design solutions, ensuring that websites, applications, and services meet regulatory benchmarks. By focusing on a standards-based approach, practitioners help organizations navigate the complexities of legal and technical requirements, thus ensuring that accessible design principles are integrated into mainstream technology development. This dual focus on rigorous standards and specialized expertise ensures that accessibility is both technically sound and legally compliant across diverse digital environments.

However, accessibility standards are inherently reactive, often lagging behind rapid technological advancements by five, ten, or even twenty years (or more). This delay occurs because developing, vetting, and formalizing standards requires consensus among diverse stakeholders and extensive testing to ensure compatibility and compliance. In contrast, cutting-edge interfaces and computational capabilities evolve swiftly, driven by dynamic market forces and user innovations. Consequently, accessibility guidelines tend to reflect outdated technologies, creating a persistent gap between modern interactive systems and current best practices in accessibility.

2.2.3 Data and Accessibility

In parallel to Mack et al.'s "What do we mean by Accessibility Research?" [84] nearly all topics of study at the intersection of accessibility and data are focused on visualization and vision-related disabilities [140]. Largely, access issues other than vision that affect data visualization (such as cognitive/neurological, vestibular, and motor concerns) are almost entirely unserved in this research space. Kim et al. found that 56 papers have been published between 1999 and 2020 that focus on vision-related accessibility (not including color vision deficiency), with only 3 being published at a visualization venue (and only recently since 2018) [76]. Marriott et al. found that there is no research at all that engages motor accessibility [89]. We have found 2 papers that engage cognitive/neurological disability in visualization and 1 student poster from IEEE Vis, which are all recent (specifically intellectual developmental disabilities [146] and seizure risk [122, 123]). We found no papers that engage vestibular accessibility, such as motion and animation-related accessibility. We also found that there is no research specific to low vision disabilities (not blindness or color vision deficiency) unless conflated with screen reader usage in data visualization. Blind and low vision people are often researched together, but in practice may use different assistive technologies (such as magnifiers and contrast enhancers) and have different interaction practices (such as a combination of sight, magnification, and screen reader use) [128].

Since the 1990s, the most prominent and active accessibility topic in data has been color vision deficiency in data visualization [16, 78, 91, 96, 98]. Research projects that explore tactile sensory substitutions to charts have been a topic in computational sciences dating back to the 1983 [112], with tactile sensory substitutions being used for maps and charts as far back as the 1830s [48]. Sonification used both in comparison to and alongside visualization and tactile methods for accessibility dates as far back as 1985 [10, 22, 37, 87, 92, 149]. Some more recent work has explored robust screen reader data interaction techniques [42, 121], screen reader user experiences with digital, 2-D spatial representations, including data visualizations [110, 114], dug deeper into the semantic layers of effective chart descriptions [82], and investigated how to better understand the role of sensory substitution [17]. Jung et al. offer guidance that expands beyond commonly cited literature that chart descriptions are preferably between 2 and 8 sentences long, written in plain language, and with consideration for the order of information and navigation [71].

A wide array of emerging research projects investigate screen reader users needs, barriers, and preferences, and offer guidelines, models, and considerations for creating accessible data visualizations [17, 34, 82, 114]. Jung et al. offer guidance to consider the order of information in textual descriptions and during navigation [71]. Kim et al. collected screen reader users' questions when interacting with data visualizations, which could open the door for more natural language data interaction [75].

Data visualization accessibility has come far in recent years. But little work has been done to explore what disability scholars call "access friction" - a tension that arises when access must be negotiated [50, 63]. This friction is often a result of static barriers in shared spaces: one artifact or approach designed to include some people may end up excluding others.

Yet despite these resources, making data visualizations more accessible remains a difficult task for practitioners [70, 115]. Some accessibility guidelines even conflict, for example on the topic of patterns and textures used in charts. One side stresses that patterns are harmful to cognitive and visual accessibility [111] while another stresses that redundant encoding strategies are necessary [29].

These difficulties point to a deeper problem: the tools practitioners use to build data experiences were not designed with accessibility in mind, and the resulting gaps are not evenly distributed. Even in an ideal state where guidelines agree, the hardest remaining challenges cluster in three domains: navigation, interaction, and personalization. In these, practitioners lack the structural, technical, and infrastructural means to reason about accessible design and act on those considerations.

Chapter 3
Overview of Contributions

In this dissertation, we contribute practical advancements in tool-making as an intervention on the accessibility of interactive data experiences. The thesis of this dissertation is as follows: *This dissertation argues that the tools practitioners use to build interactive data experiences are themselves sites where accessibility barriers are produced, prevented, or alleviated for both end users and authors. This work contributes five tools—Chartability, Data Navigator, Softerware, Cross-perception, and Skeleton—that collectively center accessibility work on the empowerment of disabled and non-disabled practitioners across the full arc of evaluation, data navigation, analytical interaction, and personalization.*

Rather than framing accessibility research solely around ideal experiences for end users with disabilities, this thesis investigates why accessibility work is so difficult for the practitioners who build interactive data experiences and what tool-making can reveal about those difficulties. We organize this investigation around four domains where practitioners face the most persistent challenges: evaluation, navigation, interaction, and personalization. *Chartability*, a heuristic framework contributed first and maps the full landscape of accessibility barriers and identified these three latter domains (navigation, interaction, and personalization) as the areas where the most severe gaps remain. *Data Navigator* and *Skeleton* then investigate navigation, finding that practitioners struggle because navigation structure has no visible, manipulable representation in their workflows. *Cross-perception* engages interaction, demonstrating that blind data analysis has been constrained by existing tools and that a new interaction design framework can reshape what analytical work is possible. *Softerware* addresses personalization, revealing that access needs genuinely conflict across users and that meaningful personalization requires system-level infrastructure that does not yet exist in practitioner tooling ecosytems.

We engage each domain below with the questions: "Why does this work matter?", "Why is it hard?", and "What has tool-making within this domain showed us?"

The 4 domains of work that I engage in this thesis start first with **evaluation**. In work contexts where someone is designing and developing interactive data experiences, the practitioner must have the knowledge, tools, and resources available to systematically identify how their interfaces produce barriers for people with disabilities. A significant portion of professional accessibility work (arguably most, if not all) is founded on auditing and evaluating barriers to access. This work is pre-dominantly done through a standards-based approach [133], although in more robust evaluation work, people with disabilities are actively involved in the process [100].

Evaluation is difficult work because much of it is contextually defined by the author themselves, and most tasks at this intersection require careful, non-automated processes and methods [24, 100]. To make matters more difficult, no comprehensive guidelines, tests, and tools exist in any singular location. Practitioners often must gather these resources themselves, which tend to be situated towards accessibility in general or are high-level and provide minimal usefulness in practice. Additionally, practitioners themselves often have little knowledge about the veracity or quality of any given bit of information they gather [70, 115], and often do the work themselves to synthesize this disparate space of information into a usable format they can apply to their own evaluation work.

To engage this, our first main chapter focuses on *Chartability*, a heuristic framework that enables designers, developers, and auditors to systematically evaluate data visualizations and interfaces for a wide range of accessibility barriers, considering people with visual, motor, vestibular, neurological, and cognitive disabilities. In this project, we did the hard work for other practitioners and contributed our collection of synthesized accessibility resources in a single workbook. We had practitioners try out our resource in real environments, in-situ, in order to learn more about the challenges and barriers they themselves faced in evaluation work. With *Chartability*, practitioners, especially those with limited accessibility expertise, gained more confidence and clarity in assessing and improving their work. Additionally, *Chartability* has since become widely applied as a framework that isn't just used for evaluation but also as design guidance in many contexts, internationally, including policy organizations, governmental groups, and more than 100 companies and businesses.

Chartability then opened up a significant landscape of new projects and research directions. From a combination of my existing expertise as a visualization designer and engineer, in addition to continued application of *Chartability* in the wild, we began to identify the trickiest and most-difficult domains of work for practitioners. Chartability has 50 total heuristics, or tests, each organized under one of 7 principles. But 3 larger domains began to emerge as the areas where the most severe and dramatic accessibility barriers remained unaddressed: on data *navigation*, analytical *interaction*, and interface *personalization*.

So the next section of this thesis engages the first of these three: **navigation**. Navigation is a fundamental type of interaction that is leveraged by modern software-based assistive technologies. Screen readers, the primary tool used by people who are blind to interact with computers, navigate content. Additionally, many other assistive technologies, such as a sip and puff device (like the "POSSUM" from as far back as '63 [86]) also navigate. Navigational technologies are leveraged by people with a significant array of disabilities, yet tend to be entirely ignored by existing data visualization tools, which are pre-dominantly built to support direct input (using a computer mouse).

Empirical work has already demonstrated that structural navigation is actually good [150], even when regular alternative text (image descriptions) exist. This is both because people who are blind can gain both a high level understanding (from the description) as well as lower-level sense of the data's structure and arrangement, in addition to the fact that discrete, structural navigation exposes interactivity that may exist on any visualization elements (such as they can be hovered or clicked with a mouse in order to perform some action). So, if good empirical work exists: *why haven't practitioners put this research into action? What makes this work hard to do?*

We first built *Data Navigator* to provide the building blocks we needed in order to address the technical and conceptual gaps that were required to make any visualization or visualization tool provide a navigable, interactive structure. *Data Navigator* is a low-level toolkit which can be used to construct accessible navigation structures such as lists, trees, and diagrams from an underlying graph structure. We leveraged graph theory for an applied HCI problem: nodes and edges represent any relationships within the data as a structure, which then supports rich expressiveness of data navigation experiences. Users can navigate discrete marks in a visualization, clusters, groupings, and more. In addition to its structural scaffolding, *Data Navigator* also supports a wide array of input modalities leveraged by people with disabilities (screen readers, keyboards, speech, and gestures).

Data Navigator provided a substrate, but this contribution alone wasn't enough to engage the question *why is navigation so hard, in practice?*. So the chapter following *Data Navigator* introduces *Skeleton*, a data navigation authoring tool built on top of *Data Navigator*. Our novel approach in *Skeleton* involves visualizing and making manipulable the nodes, edges, and textual data that comprise non-visual end user experiences. *Skeleton* visualizes the building blocks that comprise *Data Navigator*. Additionally, *Skeleton* provides expressive, rapid scaffolding capabilities that leverage data visualization rendering engines. This scaffolding engine helps practitioners quickly create common configurations for non-visual data navigation structures that retain visual congruence to the underlying structure.

But most importantly, *Skeleton* serves as a framework that shapes designerly consideration. Our conjecture was that because sighted practitioners cannot *see* navigation building blocks, they will not treat those elements as iterable design materials. We conjectured: Navigation is hard in practice because sighted designers face barriers to iteration and understanding. We conducted an empirical study with sighted practitioners and found that making non-visual elements visual helped practitioners shift from treating accessibility as a compliance task to treating it as a design problem, re-iterating on the visual aspects of their design, and engaging in the complex and nuanced components that comprise data navigation experiences.

Now, **interaction** becomes the next area we wanted to engage. Existing accessible data interaction for people who are blind, including our previous work on navigation (which is a form of interaction), predominantly seeks to expose information. This is what we call *access-oriented interaction*. In terms of low-level analytical tasks, most are then made feasible through navigation, sonification, or summarization-based and question-answering approaches: retrieving values, filtering, computing derived values, sorting, determining ranges, clustering, and finding outliers. What remains are analytical tasks that, despite being "low level" (understood as *unable to be reduced into more fundamental tasks*), are cognitively highly complex: finding correlations and characterizing distributions [3]. These tasks require complex hypothesization and exploration, rather than a system that simply encourages surfacing what is known or what is already present in the data: it requires combining, remixing, restructuring, and dividing data.

But blind *analytical interaction* isn't just important to engage because it is understudied, it is important to engage because many of interactive information visualization's most impactful tools for data science enable it [37, 54, 95, 136]. In visualization, *cross-filtering* is one example of an interaction that enables a user to filter one visual space while seeing a coordinated change in another visual space simultaneously and near-instantaneously. The speed of input interaction and perception of output also matters: even a small bit of latency changes the quality of a user's data exploration activities [80]. We conjectured that a screen reader, the most-used tool leveraged by blind people when interacting with computers, may be insufficient for engaging this task.

To engage this, this thesis introduces *Cross-perception*, an approach for building analytical interactions that support perception in one space of input interaction with simultaneous, non-competing perception of output in another space of data representation. We first formalized a design framework for producing *cross-perception* experiences and then built a novel prototype device, the *cross-feelter*, that enables blind *cross-perception* of a cross-filtering data exploration interface. In an empirical study with blind users (with and without existing data expertise), we found *cross-perception* speeds up analytical exploration by 90% and helps blind users consider vastly more questions of their dataset (+188% computational queries, +54% spoken aloud) compared to a screen reader-driven interaction.

Beyond performance, we found that our input modality itself shaped the character of analytical engagement: participants didn't just work faster, they considered more dimensions of their data and asked qualitatively different questions. The *cross-feelter* also reduced anxiety and substantially increased enjoyment, particularly for participants without prior data expertise, suggesting that the barriers blind practitioners face in data work are not only functional but affective. Additionally, we had our blind practitioners imagine new interaction possibilities that *cross-perception* could enable including and beyond our *cross-feelter* device.

Our final domain of work is the most difficult for visualization practitioners to engage: **personalization**. While *navigation* demanded better software tooling and visual support and *interaction* required new hardware, *personalization* completely re-orients how software authoring takes place. Personalization matters because of *access friction*, which is a design challenge where one design or interface configuration that might be accessible for one person or group of people turns out to create barriers for someone else [50, 63]. In existing work on personalization and accessibility, studies have demonstrated that end-user control is great to have and can alleviate friction [69, 145], but little work has been done to explore what personalization looks like for an existing data visualization library and how practitioners should build and maintain their existing systems to support it.

Our final chapter introduces *Softerware* to address the tension between standardized accessible design and the diverse needs of real users with disabilities. In the wild, *access friction* exists in every design that reaches a public audience; it is inevitable. This tension ultimately means that some users have a worse experience, and may even face exclusion, with any particular design configuration. So for this work, we conducted our research in-situ with visualization software engineers and designers and worked to build a scalable, flexible software system dubbed "softerware" that enables end users to manipulate the appearance and functionality of the charts and graphs they encounter according to their own preferences. We conducted empirical research to inform our collaborators, as well as other visualization system authors, with guidelines and considerations for building *softerware* systems. In our study, no two participants chose the same preference configuration and participants with the same diagnosed condition sometimes needed opposite design treatments. Practitioners, meanwhile, immediately raised ethical concerns about whether personalization would let designers off the hook for poor defaults. These findings revealed that the real barriers to personalization are not at the level of any individual chart but at the level of system infrastructure: without persistence, cross-system interoperability, and shared standards, the effort required of end users exceeds the value they receive.

Combined, these contributions provide empirical insights and practical advancements in the state of the art for tooling that bridges gaps in current accessibility practices in visualization and data science. Our work ultimately enables people with and without disabilities to better evaluate barriers in, analyze with, design for, develop, and personalize interactive data experiences. We demonstrate that tool-making is a productive intervention that both engages accessibility barriers and elucidates why those gaps exist in practitioner work.

Part IV

Interaction: Exploring New Possibilities for Blind Data Science

Chapter 7
Cross-perception: Rethinking Input Design Towards Blind Analytical Interaction

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This chapter was adapted from my paper, currently under review with IEEE VIS:

> F. Elavsky, Y. Li, J. Jang, L. Nadolskis, P. Carrington, and D. Moritz, '*Cross-Perception*: Rethinking Input Design Towards Blind Analytical Interaction', *IEEE Transactions on Visualization and Computer Graphics*, 2026.

7.1 Abstract

Interactive visualization research has produced a rich repertoire of interaction techniques (brushing, linking, and cross-filtering chief among them) that accelerate exploratory data analysis for sighted users. And accessible visualization research has made substantial progress on making data perceivable and navigable for blind users. Yet what remains largely unaddressed is the *analytical* tier of blind interaction: the capacity to actively filter, conjecture, and test hypotheses through direct data manipulation. In existing systems that accomplish interactive, analytical tasks, users predominantly query text or sequentially navigate across discrete units of information, paradigms which focus the user on one piece of information at a time. These experiences limit a user's ability to rapidly explore and interrogate multiple dimensions within a dataset simultaneously. To target this analytical gap, we introduce *cross-perception*, an interaction technique that adapts cross-filtering for non-visual, tactile interaction. *Cross-perception* enables coordinated tactile brushing over one data space to produce perceptible computational output in a separate, linked space, without requiring serial navigation between them. We instantiate *cross-perception* in the *cross-feelter*, a prototype hardware device with dual motorized faders, and evaluate it against screen reader methods in a within-subjects study with 15 blind participants, 7 of whom have professional data expertise. Cross-feelter substantially improves exploration speed (+90%), query generation (+188% computational, +54% spoken), enjoyment, and reduces anxiety (particularly for participants without prior data expertise). We discuss implications for interaction design in accessible visualization and propose *cross-perception* as a framework for a broader class of non-visual, analytically-oriented data interaction techniques.

7.2 Overview

The visualization community has spent decades formalizing interaction techniques for sighted users: brushing scatterplots [5], linking coordinated views [12], and cross-filtering aggregated data to rapidly surface relationships across dimensions [1, 136]. These techniques are not only conveniences. Empirical work has shown that fast, direct manipulation of data fundamentally

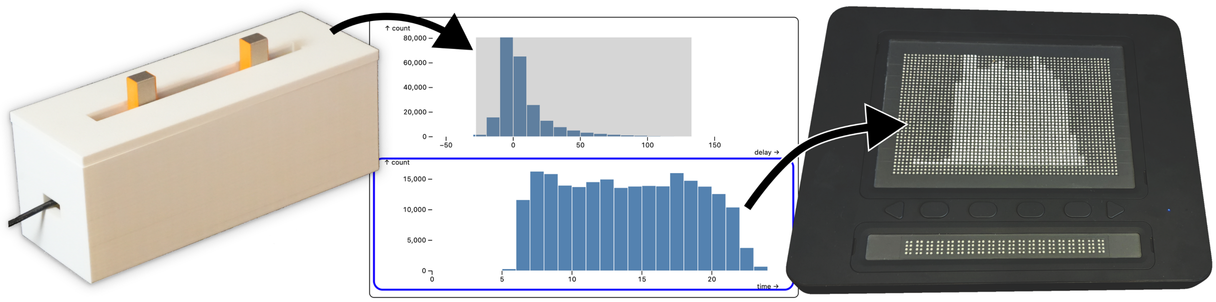

Figure 7.1: Interaction and perception in one space while being able to perceive output in a separate space is the cornerstone of cross-filtering. Our prototype *cross-feelter* (left) can manipulate a visual cross-filter on one visualization (middle) in order to produce output in a separate visualization, as a tactile graphic (right).

changes the speed and character of hypothesis generation, and that even small increases in interaction latency measurably reduce the quality of exploratory analysis [36, 80].

Accessible visualization research has made substantial and genuine progress in recent years. Blind users can access data through rich text descriptions [71, 82], sonification [61, 74, 151], and tactile representations [14, 60, 89, 90, 120, 127]. Increasingly, this work extends beyond rendering to *interaction*: screen readers support structured traversal of chart elements and their relationships at varying levels of granularity [30, 93, 150], and multimodal systems pair conversational agents with tactile displays to support rich data exploration [103].

What existing work addresses is, broadly, the question: *what is here?* A blind user can navigate a data representation to understand its structure, locate specific values, extract summary statistics, ask descriptive questions, and build a mental model of what the data contains. This is *access-oriented* interaction, and current tools support it with increasing sophistication.

What remains largely absent from accessible visualization is a different kind of interaction entirely: the *analysis-oriented* kind, in which a user not only reads a dataset but actively operates on it: filtering subsets, conjecturing relationships, testing hypotheses, and generating new knowledge through iterative manipulation. These are the fundamental activities of interactive data science, and they have a different character from access-oriented interaction. Questions shift from "*what is here?*" to "*what happens to Y when I constrain X?*" According to taxonomies of analytical tasks, existing work has largely not addressed "characterizing distributions" and "correlating" tasks, which are fundamental to hypothesis-construction [3].

We propose *cross-perception*, an interaction technique that adapts cross-filtering for non-visual contexts while preserving the simultaneity that makes it analytically useful. Cross-perception is defined by two properties. First, *coordinated tactile brushing*: the user manipulates a persistent tactile input in one interaction space, selecting a range across a data dimension. Second, *linked perceptual output*: the computational result of that manipulation is immediately perceivable in a separate space, without requiring serial navigation between them. Together, these properties support not only access to data but active analytical engagement with it: the capacity to ask iterative questions through direct manipulation.

To evaluate cross-perception and explore its design space, we built the *cross-feelter*: a prototype device with two motorized linear faders that maintain persistent, absolute tactile position for brush handles, paired with a refreshable braille display for tactile output. We conducted a within-subjects study with 15 blind participants, comparing the cross-feelter against a screen reader baseline on structured and open-ended data exploration tasks.

In our work, we address four research questions:

R1 **(Exploratory):** How might we formalize a tactile interaction approach that enables coordinated, non-visual interaction and perception across multiple spaces?

R2 **(Quantitative: Objective):** In what measurable ways can we observe improvements to blind data interaction using our approach, in terms of speed, accuracy, precision, and quantity of data queries?

R3 **(Quantitative: Subjective):** What are the self-reported effects on stress, cognitive load, anxiety, and enjoyment when using our approach?

R4 **(Qualitative):** In what ways do blind data practitioners imagine extending our approach and its instantiating hardware to new contexts?

This paper makes three contributions. First, we formalize *cross-perception* as an interaction technique for non-visual *analytical* data interaction; one that equips blind users to actively filter, conjecture, and test hypotheses through direct tactile manipulation, not only to access and navigate data (Section 7.4). Second, we provide an empirical evaluation demonstrating that cross-perception yields substantial improvements in exploration speed, query generation, and user experience relative to screen reader interaction, while maintaining comparable accuracy and precision (Section 7.5–7.7). Third, we argue that accessible visualization has made significant progress at the access-oriented tier of interaction, and that our field's frontier has shifted: the work now should be to give blind users *analytical agency*: the ability to interrogate data, not only to read it (Section 7.8).

7.3 Related Work

This paper sits at the intersection of two bodies of work: research on cross-filtering and analytical interaction in data visualization, and research on making data accessible to blind users. We review each in turn, then characterize the specific gap that cross-perception addresses.

7.3.1 Cross-Filtering and Interactive Visual Analysis

A note on terminology. *Brushing* is the direct manipulation gesture of selecting a contiguous visual range across a data dimension [5]. *Linking* propagates that selection across coordinated views [12]. *Cross-filtering* applies the linked operation as a filter on shared underlying data, constraining what is visible across views rather than merely annotating selections [1, 136].

What makes cross-filtering analytically valuable is not that users can manipulate the interface, but that the gesture and its computational consequence are perceived simultaneously. Even 500ms of additional latency measurably reduces the rate at which users generate observations and formulate hypotheses [80], and providing partial results incrementally reduces but does not eliminate this cost [36]. Temporal coupling between input and output is the mechanism by which direct manipulation supports hypothesis generation, not an implementation detail [53]. Recent work on scalable cross-filtering has continued to optimize this coupling through improved architectures [54], including pre-computed aggregates [95]. This distinction, between analytical interaction that constructs new information through manipulation and navigational interaction that locates information already present, motivates the core design challenge of cross-perception.

Previous work establishes that cross-filtering supports *analytical* interaction, in which the user constructs and tests hypotheses through rapid, iterative, direct manipulation, rather than navigating toward information that is already present. The value of this analytical interaction is that the user, not a system, gains new insights, questions, and understanding [118].

7.3.2 Non-Visual Data Representations

Accessible visualization has produced many systems for making data perceivable to blind users across text, audio, and tactile modalities [31, 43, 71, 74, 82, 101, 127]. We position cross-perception as complementing this work: many rendering and representation problems have made significant advancements in recent years; but analytical interaction problems, comparatively, have not.

Sonification. Sonification, mapping data variables to auditory properties such as pitch or timbre, is a distinct and sophisticated field with its own tooling, theory, and evaluation methodologies [56]. Recent work has formalized sonification as a first-class rendering approach with grammar-level expressiveness, enabling mappings comparable in richness to visual encodings [74]. Some work has explored data-centric approaches that treat sonification and visualization as parallel co-equal representations [151].

A note on auditory perception is warranted: the human auditory system is capable of parsing concurrent streams and segregating them into distinct perceptual objects [9]. However, the relevant constraint for blind and low vision users working with data is more specific: in task-driven contexts, synthesized speech from a screen reader competes with data-representing audio in the same channel, increasing cognitive load of the user and providing complex challenges for authors when designing speech audio and sonification interfaces [40, 74, 131]. Dual-task and multi-task operations become difficult or impossible, which is a design challenge for cross-filtering specifically, where the filter state and its output must be perceived simultaneously.

Tactile and haptic output. Research on tactile data representation spans several decades, from foundational work on tactual perception [112] to recent studies formalizing tactile alternatives to common chart types [31, 101]. More recent work has explored simultaneous tactile-and-audio output [14], slide-tone and tilt-tone haptic encodings for shape characteristics of graphs [33], comparative studies on tactile vs audio output [19], and design guidelines for multimodal touchscreen-based graphics that inform both resolution and tactile landmark placement [43].

7.3.3 Access-Oriented Data Interaction

In parallel with rendering advances, accessible visualization has developed increasingly sophisticated interaction techniques for blind users, such as serial and multi-directional navigation across data structures using a screen reader [30, 150]. However, screen reader traversal is sequential and discrete, which impacts a blind user's ability to extract information from visualizations, impacting accuracy by 61% and costing 210% more time doing so [114]. Empirical work has engaged "questions" that everyday blind folks have of data representations [75], and most recently, conversational agents have been paired with refreshable tactile displays to support question-based exploration combining voice input with tactile output [103].

These systems share a common character: they support *access-oriented interaction*, attempting to bridge the gaps that exist between sighted and blind access to information. However, the activities that remains unsupported requires constructing information through manipulation rather than locating it through navigation; the work of professional data science. In analysis-oriented interaction, the question is not merely lookup or query tasks such as *what is the value at this position* but along the lines of *what is the joint distribution within this subrange*, an answer that does not exist until a filter is applied (and a question that may not even exist unless within a system that supports direct interaction and iteration with the data).

7.3.4 Tactile and Haptic *Input*

Tactile and haptic input for data interaction has been explored in immersive contexts (not related to accessibility or blind interaction). For example, Cordeil and colleagues' *embodied axes* allow manipulation of data axes as physical objects in augmented reality [21], and the *MADE-Axis* extends this to motorized dual-axis faders for AR/VR data environments, demonstrating a cross-filtering use case [119]. Both leverage tactile input and motorized output, though both presuppose sighted users in visual contexts.

Within accessibility-specific work, a touchpad-based brush interface showed 1D filter selection feasibility but provides no queryable positional state when the user's hand is lifted [116]. And a non-motorized slider within an accessible smartphone interface shows the principle of persistent tactile state [148] but cannot be programmatically positioned, which cross-filtering requires for two-way synchronization.

The gap that remains is specific: persistent physical state and simultaneity of input and output perception are both necessary for analytical interaction, and no existing accessible system combines them.

Cross-perception is our attempt to address this gap. Our design is informed by the principles reviewed above: the temporal coupling of cross-filtering, the persistent-state affordances of motorized tactile input, and the insights from prior work on non-visual data interaction regarding the importance of simultaneity, spatial memory, and multi-channel perception. The following section formalizes these into a set of design goals for the interaction technique.

7.4 Formalizing Cross-Perception

Cross-perception is a tactile interaction technique defined by two properties. First, *coordinated tactile brushing*: the user manipulates a persistent tactile input in one interaction space, selecting a range across a data dimension. Second, *linked perceptual output*: the computational result of that manipulation is immediately perceivable in a separate space, without requiring serial navigation between them. These properties directly instantiate the simultaneity requirement established in Section 7.3: brush state and its consequence are perceived together, in the same moment, supporting the rapid inference cycles of analysis-oriented interaction.

In this section, we formalize cross-perception by deriving six design goals from the principles reviewed in the related work. We begin with a design vignette with our co-designer and co-author [REDACTED], that illustrates how the same cognitive mechanisms that underpin our goals appear in naturalistic blind interaction with physical documents.

7.4.1 A Design Vignette: Fuzzy Search and Dual-Task Comparison in Naturalistic Blind Reading

The following vignette, shared with permission by our blind co-designer and co-author [REDACTED], illustrates two tactile interaction strategies that correspond directly to our design requirements formalized below. We present this vignette as both grounded in the cognitive science and visualization literature reviewed in Section 7.3 as well as evidence that the principles we derive from that literature describe real, expert-level behavior in the wild.

[REDACTED], a blind neuroscience engineer, was reading an embossed academic paper and explaining a particular equation to the primary author as the equation recurred and evolved across multiple pages. The embossed format provides high-resolution tactile rendering at up to 100 dots per inch, and [REDACTED] interacted with it using two strategies we have named *fuzzy tactile search* and *dual-task comparison*.

Fuzzy tactile search is a spatial indexing strategy. [REDACTED] picked up the stack of pages and thumbed to an approximate location based on tactile position in the stack, touched near the top of the page, immediately recognized from the local texture pattern that he was one page off, flipped to the next page, and navigated directly to the spatial region where the equation began. He then repeated this process to locate the equation's recurrence later in the paper. The strategy relies on two cognitive functions reviewed in Section 7.3: spatial memory, encoding the approximate location of content within a document's physical structure, [11, 20, 23] and *object-location memory*, the ability to retain and retrieve the position of objects without continuous visual or tactile contact [39, 79, 81]. Both functions require that objects *have* a stable spatial position to encode: they cannot operate on a system where position is reassigned or meaningless.

Dual-task comparison is a simultaneous spatial reasoning strategy. Having located the same equation in two places, [REDACTED] placed one hand on each and skimmed both simultaneously, stopping when his hands detected the point of divergence between them. He explained the evolution of the equation by reference to that divergence. This strategy demonstrates exactly the interaction character that cross-filtering supports for sighted users: two data regions perceived in parallel, with relational structure emerging from simultaneous contact rather than sequential reading. It also demonstrates the additional requirement of *simultaneous multi-location tactile interaction*: a user resting a pinky on a known reference point while exploring relative to it with another finger, a pattern documented in prior empirical work on tactile interactive systems [43].

Together, these strategies illustrate a key observation: skilled blind readers of physical documents are not limited to sequential access. The constraint is architectural: the medium must maintain a persistent, meaningful spatial state so that object-location memory can operate, and it must allow simultaneous multi-point contact so that comparison can occur. Our design goals operationalize these requirements for computational, analytical interaction with tactile interfaces.

7.4.2 Design Goals

We derive six design goals from the principles established in Section 7.3 and illustrated by the vignette above.

G1: Maintain and reflect system state through tactile location. Object-location memory requires objects with stable, queryable positions [39, 81]. Tactile input elements must therefore have absolute, persistent positional state: the knob must remain where the user or system last placed it and be readable by touch without performing an action. This also enables motorized two-way synchronization, where the system sets knob position as output and the user sets it as input.

G2: Allow for multiple simultaneous channels of perception. Synthesized speech competes with data-representing audio under cognitive load [40]. Cross-perception routes data manipulation to a tactile input channel, eliminating this competition. Audio output via ARIA-live announcements remains available for precise positional feedback but is kept serial and non-competing.

G3: Correspond tactile-to-computational functional semantics. Interface elements should have names and behaviors that describe what they do [29, 134]. The visual cross-filtering metaphor involves dragging handles along a spatial dimension; cross-perception preserves this by mapping a physical rail sliding to setting a filter boundary, reducing translation between user action and analytical action.

G4: Provide linked interaction across multiple data dimensions. Cross-filtering requires that a filter on one dimension immediately propagates to constrain coordinated views of others that share the same underlying dataset [1, 12]. The filter state set by tactile input must immediately determine the output displayed in linked views; without this, the technique only accomplishes single-view selection.

G5: Support fast, dynamic, and reversible interaction. The analytical value of cross-filtering depends on rapid hypothesis iteration [36, 80]. Filter adjustments must be continuous and incremental, system response must be low-latency, and any state must be immediately reversible. These motivate motorized faders with 1024 units of precision and a pre-computed data cube backend [54].

G6: Facilitate user-driven exploration. Cross-filtering is a direct manipulation paradigm in which the user, not an algorithm, controls the analytical flow [1, 118]. The user's physical manipulation of the filter handles is the direct and sole determinant of what the tactile output displays, with no intermediary statistical, language model, or non-deterministic interpretation.

7.5 Prototype: The Cross-Feelter

We instantiate cross-perception in a hardware prototype we call the *cross-feelter*: a device with two motorized linear faders that provide persistent, absolute tactile input state for brush handles, paired with a refreshable braille display for coordinated tactile output. All hardware schematics, firmware, and interface code are open-sourced at [REDACTED]; 3D-printable STL files

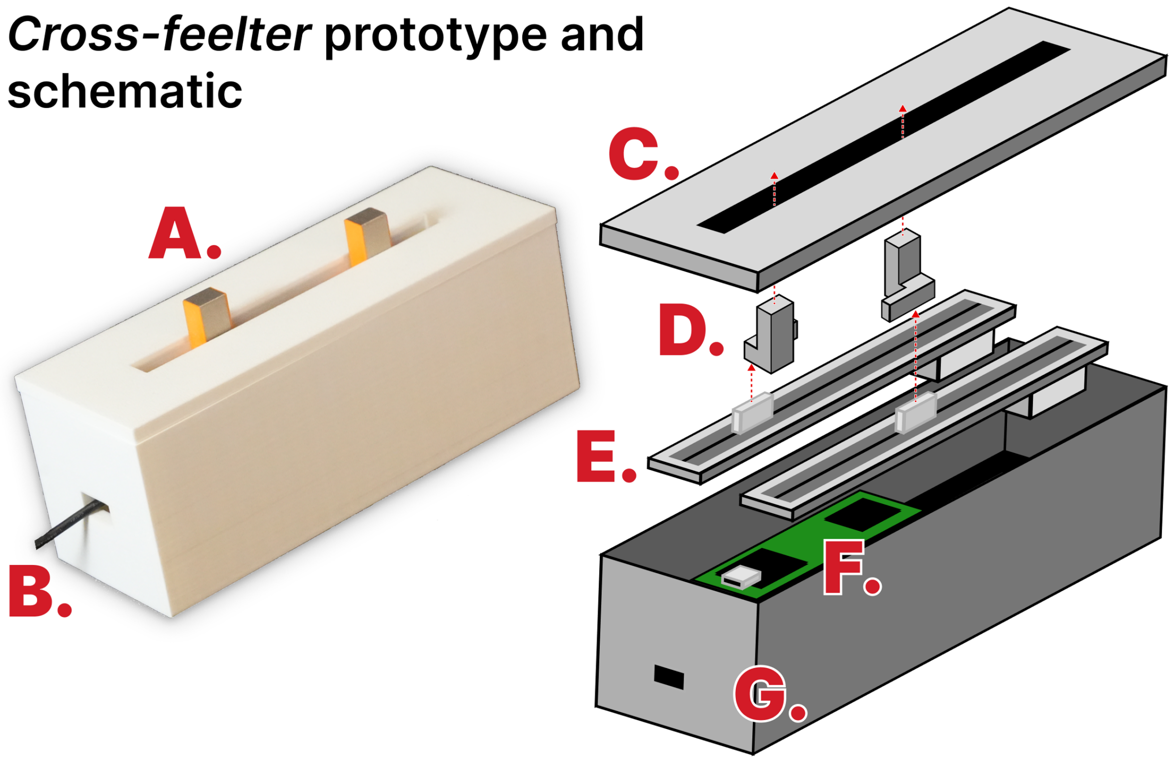

Figure 7.2: A. Our prototype *cross-feelter*. B. USB output (to computer). C. 3D printed rail cover. D. 3D printed knobs that consolidate rails into one. E. 2 motorized linear potentiometers. F. Arduino board. G. 3D printed casing.

for the housing components are available in our supplemental materials and on Thingiverse at [REDACTED]. The total cost of hardware components is $30–50 USD, which we designed intentionally to enable replication by the DIY-AT and maker communities [65, 120].

7.5.1 Interaction Flow

We begin with an idealized walkthrough of what a blind analyst actually does when using the cross-feelter to perform a cross-filtering task. This is the ground truth from which the hardware design choices derive; we describe the hardware in Section 7.5.2 with reference to the steps below.

Consider an analyst exploring a dataset of local rent prices and transit access across city neighborhoods. Three linked histograms are rendered in sequence on the refreshable braille display. The analyst wants to ask: *do neighborhoods with the highest rents also have better transit access?* At startup, the left knob sits at 0% and the right at 100%, representing an unfiltered view of the full distribution.

Step 1: Feel and filter. The analyst feels the starting state of the tactile data representations on the refreshable braille display, navigating between each chart and hearing supplemental screen reader descriptions alongside the touchable shapes formed from the pins. The analyst moves their hand or hands to the feelter device and slides the left knob rightward, narrowing the filter from below. As they move, an ARIA-live announcement reports the current percentage and knob name via the screen reader, providing precise serial feedback for positioning (G2). The analyst moves the right knob slightly leftward, hearing another announcement. The two knobs now define a range, say 75% to 90% of the rent distribution.

Step 2: Perceive the consequence. During filtering, the analytical environment updates linked histograms immediately on each knob movement. The analyst navigates the braille display to the transit histogram without touching the knobs. Because the knobs are motorized and maintain position, the filter state is preserved and readable by touch at any time (G1). They feel the updated distribution and compare it to the shape they perceived in the unfiltered state.

Step 3: Iterate. The analyst slides the left knob further right, narrowing to the top 10% of rents. The display updates. They feel the new shape. The pattern sharpens or changes, and they iterate again, building toward a hypothesis in the same cycle that sighted analysts perform visually. Each knob adjustment is a computational query: a gesture that constructs a question and immediately exposes its answer.

7.5.2 Hardware Design

The cross-feelter uses two motorized linear potentiometers (commonly called motorized faders in sound design hardware) mounted side by side in a 3D-printed housing (see Figure 7.2). Each fader provides a physical knob on a bounded rail.

Motorized, absolute-position faders (G1, G5). We chose rail-based faders over alternatives (touchpad, rotary encoder, joystick) for two reasons grounded in the G1 requirement. First, the fader is *absolute*: the knob's physical position on the rail directly corresponds to the filter boundary value, with no drift or accumulation. Second, the fader is *motorized*: the system can programmatically set knob position as well as read it. This bidirectionality is essential for cross-filtering: the system must be able to reset filter state on condition changes, counterbalance, and initialization, not only receive input. Prior work on brush-based accessible interfaces [116] used a touchpad, which provides no queryable positional state when the hand is lifted; prior work using non-motorized sliders [148] cannot be programmatically positioned. The motorized fader solves both problems.

Each rail terminates in a tactile boundary, a strong edge inset 4mm from the housing wall per tactile design guidelines [43], so the analyst can feel both the knob position *and* its position relative to each end of the scale (G1). The API reads and writes fader position every 5ms, providing up to 1024 units of precision, which maps well to histogram bin resolutions in practical cross-filtering datasets (G6).

Merged-rail housing (G3). We designed two housing configurations: one exposing the rails independently, and one using angled knobs to place both rails along a single track (Figure 7.2, part D). The merged-rail design, used for all data tasks in the study, ensures the left knob remains to the left of the right knob at all times (they cannot cross over). This preserves the functional semantics of a spatial filter range: left boundary is always left, right boundary is always right, matching the computational filter and the visual histogram (G3). The independent-rail configuration was used for the video interaction training task (Section 7.6.4), where the two rails served different functions (volume and position).

Our dual-fader design is similar in form to motorized fader-based systems proposed for axis interaction in AR/VR data environments [21, 119]; however, those systems presuppose sighted users operating in 3D visual contexts. Our design differs in three ways: (a) the housing constrains the two faders to a single interaction dimension to support filter semantics; (b) the motorized positioning enables two-way synchronization with the data interface; and (c) the entire system is designed for eyes-free operation as the primary use mode.

ARIA-live auditory feedback (G2). When a knob is moved, the interface emits an ARIA-live announcement to the screen reader reporting the new filter percentage. ARIA-live is set to `polite` mode, meaning announcements queue behind any active screen reader speech rather than interrupting it. This provides precise, serial auditory feedback for filter positioning without competing with other auditory streams in the environment (G2). Tactile feedback (the knob's physical position) and auditory feedback (the ARIA announcement) thus serve complementary roles: tactile provides continuous, queryable approximate state; auditory provides precise on-demand readout triggered by movement.

7.5.3 Analytical Environment

The cross-feelter operates within a web-based analytical environment purpose-built for this study (Figure 7.3). The environment presents three linked histograms derived from different variables in a shared dataset. Each histogram is rendered both visually (for debugging and sighted collaborators) and as a 60×40 pin array sent to the Dot Pad refreshable braille display.

Cross-filtering backend (G4, G5). We use Mosaic [54] to manage the cross-filtering logic. Mosaic pre-aggregates filter results across binned input values, enabling fast, low-latency responses to filter changes even over larger datasets (G5). It also provides a straightforward API for specifying a brush-filter interaction layer over a histogram dimension, including programmatic control of filter state and undo actions (G5). When the user moves a fader knob, the new filter boundaries are sent to Mosaic, which immediately updates the linked histograms, which are then re-rendered on the braille display. The render cycle from fader movement to updated tactile output is 500–1200ms on the Dot Pad hardware, fast enough to support iterative exploration, though slower than visual cross-filtering systems and a recognized limitation (Section 7.10).

Braille display output (G2). The Dot Pad provides a 60×40 binary pin array (pins raise or lower on command). We render each histogram as a bitmap at this resolution, trading fidelity for speed relative to a high-resolution braille embosser (which takes 3–4 minutes per page). At any time, the braille display shows one chart; the analyst navigates between charts using the screen reader. The visual representation of the target pin array is visible to sighted observers and collaborators in the environment (Figure 7.3, part A), illustrating the resolution gap that future advances in refreshable display technology could close.

Screen reader compatibility. The analytical environment is a standard web interface, accessible via any JAWS, NVDA, or VoiceOver-compatible screen reader. Cross-filter input controls are exposed as labeled range inputs so they can be operated by screen reader alone (providing the baseline condition for our study, Section 7.6). The ARIA-live region for fader announcements is separate from these controls and does not interfere with standard screen reader navigation of the interface.

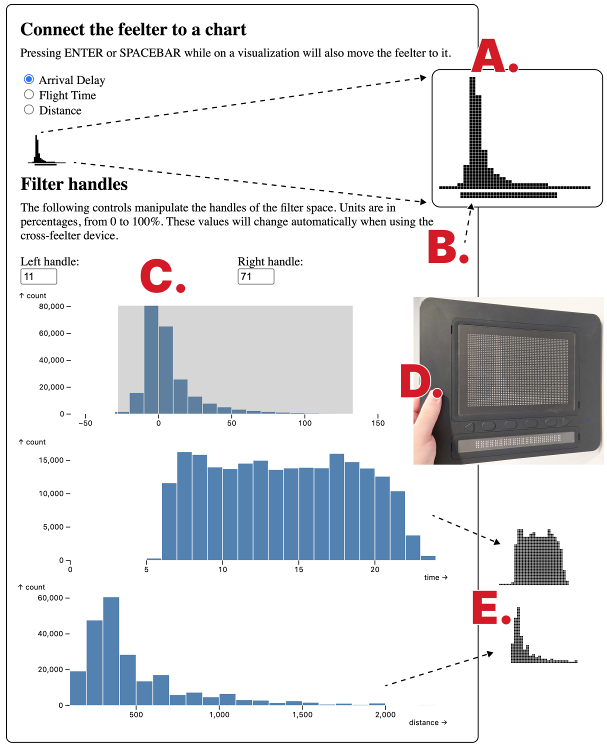

Figure 7.3: Our analytical environment. A. a 1 to 1 translation between visual and tactile that represents a 60x40 pixel-to-pin array. B. A tactile version of the filter location (if on the chart being focused). C. Cross-filtering controls, including text inputs for screen-reader only manipulation. D. Refreshable tactile display output. E. Example renderings of the other 2 charts.

7.6 Data Exploration Study

We conducted a within-subjects study comparing cross-feelter-based cross-filtering (CF condition) against screen-reader-based cross-filtering (SR condition) across structured and open-ended data exploration tasks. Sessions were 90 minutes, conducted in person, and approved by our IRB.

7.6.1 Study Design

Overview. Our study employed a 2×2 Latin square design, fully counterbalanced across two factors: (1) condition order (CF-first vs. SR-first) and (2) dataset order (flight data vs. neighborhood data), producing four participant groups (Table 7.1).

Within each condition, participants performed two tasks on the same dataset: a 3-minute structured data-relationship task followed by a 10-minute open-ended data exploration. Counterbalancing both orders controlled for dataset familiarity, learning effects, and dataset-specific task difficulty.

Conditions. In the **CF condition**, participants used the cross-feelter (merged-rail housing;

Table 7.1: 2×2 Latin square study design. CF = cross-feelter condition; SR = screen reader condition.

Group	Condition order	Dataset order
A (n=4)	CF → SR	Flight → Neighborhood
B (n=4)	SR → CF	Flight → Neighborhood
C (n=4)	CF → SR	Neighborhood → Flight
D (n=3)	SR → CF	Neighborhood → Flight

Section 7.5.2) to manipulate cross-filter bounds, with the Dot Pad displaying linked histograms. In the **SR condition**, participants used their screen reader to operate labeled text input fields exposing the same filter controls, with the same Dot Pad display. The analytical environment was identical across conditions; only the input method differed.

Session procedure. Each session followed this order regardless of group:

1. Tech setup, baseline interview, introduction to tactile histograms and cross-filtering, baseline anxiety Likert question *(20 min)*
2. Device familiarization: video interaction task and brief semi-structured interview *(15 min)*
3. First data condition: structured task, open-ended exploration, Likert-scale interview *(20 min)*
4. Second data condition: structured task, open-ended exploration, Likert-scale interview *(20 min)*
5. Closing semi-structured interview *(15 min)*

7.6.2 Participants

We conducted our study with 15 blind participants: 8 without prior professional data expertise and 7 with it (data analysts, scientists, or engineers currently or recently employed in data-related roles). 7 participants identified as male, 8 as female.

Participants without data expertise, plus 2 with it, were recruited locally through community outreach. The remaining 5 participants with data expertise were recruited through professional networks and coordinated at mutual academic conferences, due to difficulty recruiting blind data scientists locally. All participants were screened for eligibility (blind, screen reader proficient, 18 or older, US citizen or permanent resident), informed of risks and voluntary participation, and compensated with a $50 gift card.

7.6.3 Datasets

Study tasks used two datasets selected through a community data-preference workshop. Pilot sessions revealed that participants were not engaged by our initial generic dataset, so we held a workshop at a local braille and talking book library (n=21 community members). Participants voted on datasets from topics including local politics, housing, and community life. The two highest-voted were: (1) rent prices across city neighborhoods, and (2) fish fry locations across city neighborhoods (a dataset reflecting a regional Catholic Lent food tradition observed broadly across denominations). Both are publicly available. A generic flight dataset was included as the second counterbalanced dataset.

Each dataset was configured with three histogram variables from a shared source, with cross-filter tasks designed to target a 75%–100% filter range producing a clear, unambiguous relationship between variables.

7.6.4 Device Familiarization: Video Interaction Task

Rationale. Before data tasks, participants completed a device familiarization activity using the cross-feelter to control a video feed rather than a data chart.

The goal was to build fluency with the motorized fader mechanism (absolute-position input, motorized output, the relationship between physical knob position and system state) without pre-exposing participants to the cross-filtering metaphor, data tasks, or the study datasets. A practice task using data histograms would have constituted condition-specific training, introducing learning effects that could confound the within-subjects comparison. Video scrubbing and volume control are familiar and intuitive interaction goals for all of our users, which served as a way for all of them to understand how to operate the device.

Task. Participants were asked to find the name of the person in the video recording, announced early in the clip. This simple information-retrieval goal required genuine device use while keeping cognitive demand low before the main study.

7.6.5 Introduction to Tactile Histograms and Cross-Filtering

At session start, after consent and the baseline interview, we provided a scripted introduction to tactile histograms and cross-filtering. We explained histogram structure, introduced the concept of linked histograms sharing a source dataset, and demonstrated cross-filtering with three histograms from a fruit example dataset, using two sheets of paper held over one histogram to physically simulate a spatial filter.

We framed filtering explicitly as an analytical activity: "filtering is a way to ask questions more than to find answers, to look for possible relationships that might exist in the data." Two follow-up questions gauged comprehension and interest before proceeding.

7.6.6 Data Tasks

7.6.6.1 Structured data-relationship task

Participants cross-filtered the dataset and answered a three-option multiple-choice question within three minutes. The question and options were available via screen reader in the interface; the facilitator restated them only if asked and did not otherwise intervene.

For the flight dataset: *"What is the relationship between filtering for longer flight distances and the arrival time of flights?"* (Correct: longer flights tend to arrive earlier compared to all flights.)

For the neighborhood dataset: *"What is the relationship between filtering for a higher number of fish fry locations and the rent price of a neighborhood?"* (Correct: neighborhoods with more fish fry locations tend to have higher rent prices.)

We measured task completion rate (binary), time to completion (seconds), filter placement precision (distance of handles from target positions of 75% and 100%, scored in ±4% increments awarding 0.5/0.3/0.1 points per handle tier), and answer accuracy (binary).

7.6.6.2 Open-ended data exploration

Participants then performed a 10-minute open-ended exploration of the same dataset using a prompted, concurrent think-aloud method [2]. Before beginning, we framed the activity: "the purpose is not to *answer* questions but to *come up with* questions. This is how many data scientists explore unfamiliar datasets, by looking for possible relationships."

We measured: (1) *computational queries*: any filter manipulation followed by braille display inspection of one or more linked charts (filter changes without output inspection did not count); and (2) *spoken queries*: any data-related question voiced aloud, regardless of formality or answerability via cross-filtering.

7.6.7 Measures and Analysis

Quantitative analysis. Objective measures (completion rate, time, precision, accuracy, query counts) and subjective measures (5-point Likert scales for stress, cognitive load, future-task anxiety, and enjoyment) were collected per condition. A pre-study baseline anxiety item provided a pre-condition reference.

Analysis was conducted in Python (code and de-identified data in supplemental materials). Objective continuous measures were compared using paired t-tests. Likert-scale differences were evaluated using Wilcoxon Signed-Rank tests given the ordinal nature of the data. We report means, standard deviations, test statistics, and p-values; group-level results (data experts vs. non-experts) are reported separately where they diverge.

Qualitative analysis. Qualitative data comprised session audio/video recordings, facilitator notes, and closing semi-structured interview transcripts. The interview covered three topics: overall experience and condition comparison, interface and environment feedback, and future application ideas.

Analysis proceeded in two stages. In the first stage, two members of the research team independently reviewed all recordings, notes, and transcripts, generating initial codes at the utterance level. Codes captured themes across four domains: device usability (physical interaction, feedback quality, learning curve); condition comparison (speed, cognitive load, perceived control); analytical engagement (question generation, hypothesis articulation, confidence with data); and future use speculation. The two coders then resolved all disagreements through discussion, reaching consensus before proceeding.

In the second stage, codes were organized using affinity diagramming [51], conducted collaboratively by members of the research team working from the reconciled code set. Resulting themes inform the qualitative findings in Section 7.7 as well as our future use cases in Section 7.9.

7.7 Results

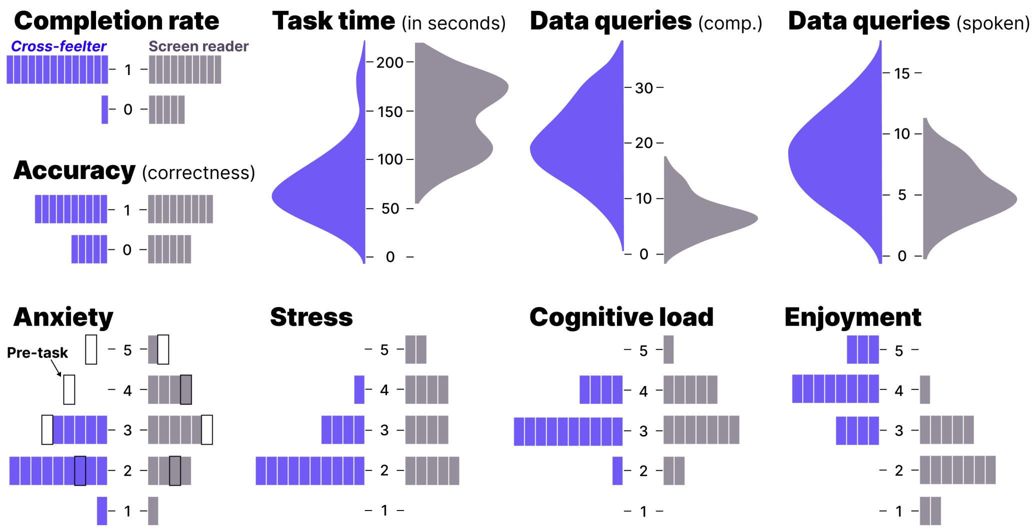

Figure 7.4: Results. Completion rate and accuracy are counts. Task time, data queries (computational), and data queries (spoken) are objective, observational measures. Anxiety, stress, cognitive load, and enjoyment are Likert-scale results from 1 ("very little") to 5 ("quite a lot").

Our analysis compared 15 blind participants performing cross-filtering tasks under two conditions: using the cross-feelter (**CF**) versus using a screen reader alone (**SR**). We report objective and subjective measures in turn. Full analysis code and de-identified data are available in our supplemental materials.

7.7.1 Objective Results

7.7.1.1 Substantially improved task completion rate and speed

For the structured data-relationship task, participants achieved a significantly higher completion rate with CF (mean = 0.93, SD = 0.26) compared to SR (mean = 0.60, SD = 0.51; paired t-test: $t = 2.646$, $p = 0.019$). Task completion time was significantly lower in the CF condition (mean = 75.53s, SD = 36.14) than in the SR condition (mean = 143.93s, SD = 34.65; $t = -6.876$, $p < 0.001$), a 90% improvement in speed.

7.7.1.2 Comparable accuracy and precision

Accuracy (correct multiple-choice answer) was higher in the CF condition (mean = 0.67, SD = 0.49) than SR (mean = 0.53, SD = 0.52), but this difference was not statistically significant ($t = 1.468$, $p = 0.164$). Notably, when filtering for only completed tasks, SR users showed marginally higher accuracy (SR: mean = 0.78; CF: mean = 0.71), though again non-significant ($t = 0.555$, $p = 0.594$). We interpret this in Section 7.8.2.

Filter placement precision (scored by proximity to target handle positions of 75% and 100%) was marginally higher in CF (mean = 0.66, SD = 0.37) than SR (mean = 0.59, SD = 0.34), with no significant difference ($t = 0.617$, $p = 0.547$).

7.7.1.3 Substantially increased quantity of data queries

During the open-ended exploration task, CF elicited substantially more computational queries (mean = 20.13, SD = 6.45) than SR (mean = 7.00, SD = 3.18; $t = 9.567$, $p < 0.001$), a 188% increase. Spoken queries were also significantly higher in CF (mean = 8.20, SD = 3.14) than SR (mean = 5.33, SD = 1.99; $t = 3.765$, $p = 0.002$), a 54% increase.

7.7.2 Subjective Results

Subjective measures varied between participants with and without professional data expertise; we report group-level differences where they diverge meaningfully.

7.7.2.1 Reduced stress

Stress ratings were significantly lower in the CF condition (mean = 2.40, median = 2.0) than SR (mean = 3.20, median = 3.0; Wilcoxon $W = 4.000$, $p = 0.013$). The effect was driven primarily by participants without data expertise (CF: mean = 2.62, SR: mean = 3.75; $W = 2.500$, $p = 0.047$). Data experts reported similarly low stress across both conditions (CF: mean = 2.14, SR: mean = 2.57; $W = 0.000$, $p = 0.083$).

7.7.2.2 Comparable cognitive load

Cognitive load showed an observed difference in means (CF: mean = 3.13, SR: mean = 3.47) but was just outside statistical significance ($W = 4.000$, $p = 0.059$). We interpret both conditions as producing comparable cognitive load during task performance.

7.7.2.3 Lower future-task anxiety

Participants in the CF condition reported significantly lower anxiety about performing a future timed data task using the same tools (CF: mean = 2.27, SR: mean = 3.00; $W = 10.000$, $p = 0.017$). CF anxiety was also significantly lower than participants' baseline anxiety measured before any tasks ($W = 5.000$, $p = 0.003$), while SR anxiety was not ($W = 8.000$, $p = 0.132$), suggesting the cross-feelter reduced anticipatory anxiety relative to participants' pre-study state, while the screen reader did not.

7.7.2.4 Substantially improved enjoyment

Enjoyment was substantially higher in CF (mean = 3.93, median = 4.0) than SR (mean = 2.33, median = 2.0; $W = 0.000$, $p = 0.001$). This effect was strongest for participants without data expertise (CF: mean = 3.875, SR: mean = 2.000; $W = 0.000$, $p = 0.015$). One participant's unprompted remark captures the qualitative texture of this finding: *"Sighted people get to have this much fun when they work with data?"*

7.8 Discussion

Our findings suggest that cross-perception shows meaningful promise as an approach to accessible analytical data interaction. We discuss our results in relation to our four research questions, then develop the broader implications for the field.

7.8.1 Research Question Responses

R1 **(Exploratory): How might we envision and formalize a tactile interaction approach that enables coordinated, non-visual interaction across multiple spaces?** Cross-perception, as formalized in Section 7.4, provides one answer: an interaction technique grounded in principles from visual cross-filtering, spatial cognition, and blind information interaction, instantiated in a device with persistent-state motorized input and a linked tactile display.

The six design goals (G1–G6) constitute the formalization, and the design vignette demonstrates that the underlying cognitive mechanisms are ecologically grounded in expert blind reading practice. We intend this formalization to be extensible and generative; we demonstrate this extensibility in our future use cases in Section 7.9.

R2 **(Quantitative: Objective): In what measurable ways can we observe improvements to blind data interaction using our tactile interaction approach?** Cross-perception produced significant improvements in task completion rate (+55% absolute), task completion speed (90% faster), and quantity of data queries during open exploration (+188% computational, +54% spoken). Accuracy and precision were statistically comparable between conditions, though with a nuance discussed in Section 7.8.2 below.

R3 **(Quantitative: Subjective): What are the self-reported benefits, opportunities, and challenges that blind people experience with our tactile interaction approach?** Participants using the cross-feelter reported significantly lower stress, lower future-task anxiety, and substantially higher enjoyment than in the screen reader condition. These improvements were particularly pronounced for participants without data expertise, suggesting cross- perception may lower affective barriers to data work for blind users who are new to or learning data analysis.

R4 **(Qualitative): In what ways do blind data scientists imagine extending our approach?** Participants, especially those with professional data expertise, proposed substantive extensions including: a pre-rendered "interaction cube" for environments without a refreshable display; feelter-only navigation of data arrays and sequences; sonification paired with rail brushing; and multi-dimensional panning, zooming, and scatterplot brushing using multiple feelter units. These proposals are detailed in Section 7.9.

7.8.2 Accuracy and Precision Considerations

The comparable accuracy and precision results merit careful interpretation. Participants maintained similar correctness across conditions while performing substantially faster in CF. However, when filtering for completed tasks only, SR users showed marginally higher accuracy. One interpretation is that the additional time the serial screen reader interface imposed allowed for more deliberate verification before committing to an answer, while the cross-feelter's speed encouraged more rapid, and occasionally less careful, decision-making.

This is not necessarily a weakness of cross-perception. In genuine exploratory analysis, speed of iteration is often more valuable than precision on any individual query, since the point is to generate and test many hypotheses rather than verify a single one carefully. Some precision can be a little "fuzzy" if the gained effect has analytical benefit overall [67]. This difference in interaction patterns warrants further investigation and suggests the two approaches may support different analytical strategies rather than being simply faster and slower versions of the same strategy.

Future iterations should explore mechanisms that preserve the speed benefits of direct tactile manipulation while supporting careful verification when the task demands it (or example, a confirmation gesture or a "hold" mode that locks the filter and prompts output inspection before advancing).

7.8.3 The Case for Analytical Interaction as a Primary Research Site

The result most significant for the field is not the speed improvement but the query count. 20 computational queries in 10 minutes compared to 7 is not merely a faster version of the same activity. This increase in speed also reflects a qualitative shift in what participants were doing. In the CF condition, participants iterated hypotheses through direct manipulation; in the SR condition, they navigated toward output values that were structurally separate from their space of interaction. This maps directly to the distinction between analysis-oriented and access-oriented interaction: the screen reader, however capable at navigation, kept participants in a mode that structurally separated interaction and information; a descriptive mode. The cross-feelter enabled a *generative* mode where interaction and information are coupled.

The enjoyment gap is legible through the same lens. One participant's unsolicited remark, *"Sighted people get to have this much fun when they work with data?"* describes the experience of analytical agency. This is what visualization researchers have understood for decades to be the core value of interactive exploratory analysis: an experience of power over and with data interaction. This agency has not been consistently available to blind data practitioners, and the affective signature of its absence is measurable in our stress and anxiety results.

The implication is that analytical interaction accessibility constitutes a distinct research problem, not an extension of the accessible rendering/description problem. The accessible visualization community has made substantial progress on helping blind users read and navigate data. What our results suggest is that reading data and analyzing data are sufficiently different activities that the techniques developed for one cannot simply be adapted for the other: they require different interaction architectures, different evaluation approaches, different design primitives, and sometimes even different hardware. We encourage researchers working at this intersection to treat analytical interaction as a primary site of inquiry: studying the existing practices of blind data analysts during open-ended exploration, identifying what analytical operations (filtering, outlier detection, hypothesis iteration, assumption testing) current tools support or foreclose, whether existing tools support direct interaction with data representations in these tasks, and designing interaction techniques grounded in these blind-centered findings, rather than in adaptations of what sighted-user interfaces already provide.

7.8.4 Toward Hardware and Physicalization in Accessible Data Interaction

Building on that previous point, a recurring practical constraint in accessible data interaction research is the emphasis on solutions that work within existing consumer device ecosystems: screen readers, keyboards, web browsers, and computationally synthesized audio. This is reasonable: it maximizes immediate reach and avoids asking blind users to acquire specialized equipment if the capabilities are already realized on existing computer and mobile hardware. But it also implicitly constrains the design space to what those platforms can support, and some of the interaction properties that matter most for analytical work (such as persistent physical state, absolute spatial position, simultaneous bilateral manipulation) are not well-approximated by software alone on current consumer hardware. Existing work (mentioned in Section 7.3) hasn't ignored this problem, but this existing work is a small minority. Priorities in research have predominantly focused on leveraging *existing* software, hardware, and computational models towards problems and barriers blind people face, rather than innovation towards *novel* hardware and physicalization systems.

The cross-feelter's component cost ($30–50 USD) and the availability of all schematics under an open license suggest that the hardware barrier is lower than it might appear. The more substantive barrier is that the visualization and accessibility communities have not yet developed strong shared practices around hardware prototyping and physical interaction design. Work from the tangible and physicalization communities is directly relevant here, including the insight that physical materials afford interaction properties that screens do not, among them permanence, resistance, and the kind of spatial memory that our design vignette illustrates. Bringing these ideas into contact with accessible data interaction research is, we believe, a productive direction.

The future use cases our participants proposed, discussed in detail in Section 7.9, illustrate the range of what becomes thinkable when the design space is extended beyond the screen: pre-rendered interaction outputs for environments without powered displays, motor-driven data array navigation, multi-axis spatial exploration using multiple feelter units, and sonification navigated through physical rail position. These proposals emerged from a structured speculative futuring exercise [27] with participants who are themselves blind data practitioners. They are worth treating as design starting points, not only as participant feedback.

The field has successfully applied careful empirical and design methods to the challenge of making non-visual data representations perceivable. Extending that rigor to the challenge of making data manipulable through the hands, with all the hardware and prototyping work that entails, is the direction we are advocating.

7.9 Future Use Cases

The following use cases were developed through the speculative futuring exercise [27] conducted as part of our closing interview, with contributions from participants and the research team. We

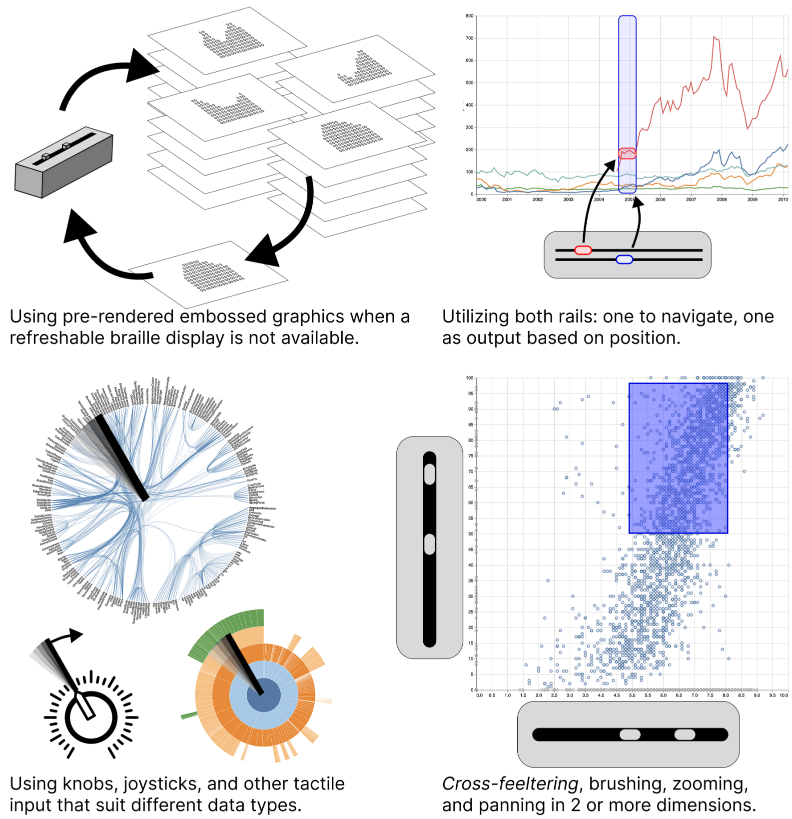

Figure 7.5: Speculative future use cases for our *cross-perception* approach, contributed by our participants.

present them as design starting points grounded in the cross-perception framework, each addressing a limitation of the current prototype or extending the approach to new contexts. Figure 7.5 illustrates all four cases.

7.9.1 Cross-Perception Without a Powered Display: The Pre-Rendered Interaction Cube

Refreshable braille displays remain expensive ($8k–$20k USD) and are not universally available. The current prototype depends on the Dot Pad to render cross-filter output in real time, which means the full cross-perception loop is unavailable to users without access to one.

One solution is to pre-render the interaction outputs for a given dataset before a session begins. The cross-feelter's filter operates over a bounded, discretizable range; it is feasible to pre-compute a set of interaction results at binned filter positions and emboss them onto paper as an "interaction cube" of tactile states, analogous to the data cube that Mosaic pre-computes for fast cross-filtering over large datasets [54]. After each filter manipulation, the user turns to the corresponding page in a booklet of embossed tactile charts, reducing the interaction loop from 3–4 minutes (a full embosser render) to roughly 10 seconds. This approach trades the continuous, real-time update of the powered display for a discrete but physically permanent output, which has its own advantages for users who prefer to annotate or revisit prior states or even compare multiple outputs simultaneously, like in the dual-task comparison vignette in Section 7.4.1.

7.9.2 Sequential Data Navigation with Continuous Positional Feedback: Feelter-Only Chart Interaction

Serial navigation of data arrays using a screen reader is slow because the user must step through observations one at a time without any persistent sense of their position within the full range [30].

A single cross-feelter could replace this with continuous physical scrubbing. Most charts and datasets have finite, bounded observations in any given dimension; these bounds map naturally onto the full range of a fader rail. One rail would scrub through the ordered observations as the user moves the knob, with the screen reader announcing the current value. A second rail, motorized, would move its knob to a position encoding the corresponding value in a second data dimension, like a rising and falling bar in a bar chart.

More broadly, different input devices could be matched to different data topologies. A rotary dial would suit circular or periodic data (seasonal patterns, directional data); a joystick would suit data with an infinite or continuous range such as a parametric function or model output.

7.9.3 Sonification Navigation via Physical Rail Position

Navigating within a sonification (seeking to a specific region, comparing two positions, returning to a reference point) is currently difficult even on touch-enabled devices, because scrubbing through audio provides no queryable positional state when the hand is not actively in contact with the surface [17, 18, 19]. This is the same object-permanence problem that motivated the cross-feelter's design for cross-filtering.

A cross-feelter rail could serve as the navigation input for a sonification: physical position on the rail maps to a position within the audio timeline or data domain, and the motorized mechanism maintains that position when the hand is lifted. The user can navigate to a region of interest, remove their hand, let the sonification play, return to the rail, and feel exactly where they left off.

7.9.4 Multi-Dimensional Spatial Interaction: Rails as Input and Output

Two cross-feelter units, one arranged as an x-axis controller and one as a y-axis controller, could support spatial panning, zooming, and brushing over tactile maps or scatterplots, which are interactions that currently lack a satisfactory non-visual implementation because pinch-and-zoom gestures provide no queryable positional state for the zoom extent or pan position. Each feelter unit would maintain the current viewport bounds in its two rails, readable by touch at any time.

More substantially: the motorized rails could serve as *system output* for spatial queries. When a user asks "where is this object?" of a map or image, the system could drive the rails to the corresponding x and y positions and bounds. This would let the user feel the location directly rather than receiving a verbal coordinate and build a spatial mental model of a spatial layout.

7.10 Limitations

Our study's controlled task design (three-minute timed tasks with multiple-choice answers) prioritized speed and query quantity, which are the right measures for a proof of concept but do not capture the full texture of blind data analysts' real exploratory workflows. Activities common in open-ended analysis, such as wrangling messy data, identifying outliers, and questioning assumptions, were not represented. An ethnographic or longitudinal study would be better suited to those questions, and we encourage that work.

The Dot Pad's 500–1200ms render latency falls outside the max 500ms threshold at which Liu and Heer identify measurable degradation in exploratory analysis quality [80]. Our query count results are therefore a conservative lower bound on what cross-perception could support with faster display hardware.

Novelty effects may have inflated subjective measures. The enjoyment and anxiety improvements may attenuate with extended exposure, though the effect may persist in contexts such as some classroom, work, or onboarding settings, where engagement is itself valuable.

Finally, we compared against a screen reader baseline because screen readers are the dominant interaction tool for blind users working with data and all of our participants were proficient in screen reader use. More granular comparative work against other emerging tactile and voice-based input strategies would further characterize where cross-perception sits in the broader interaction space.

7.11 Conclusion

We introduced cross-perception, a tactile interaction technique that adapts cross-filtering for blind data analysts by preserving the simultaneity of input and output perception that makes the technique analytically valuable. We formalized it through six design goals grounded in principles from visual analytics, spatial cognition, and blind information interaction; instantiated it in the *cross-feelter*, a low-cost motorized fader device; and evaluated it against a screen reader baseline with 15 blind participants.

In our study, Cross-perception substantially improves task completion speed, data query generation, and subjective experience, with particularly strong effects for participants without prior data expertise. The result that matters most is not the speed improvement but the query count: participants using the cross-feelter generated nearly three times as many analytical queries during open exploration, reflecting both a quantitative improvement and a qualitative shift away from navigating data toward interrogating it.

We argue that analytical interaction accessibility—the capacity for blind users to filter, conjecture, and test hypotheses through direct manipulation—is an open research problem that deserves sustained attention as a primary site of inquiry, distinct from accessible rendering. The future use cases our participants proposed suggest that extending the design space to include hardware and physicalization opens directions that software-only approaches cannot reach.

Part VI

Conclusion

Chapter 9
Discussion & Future Work

9.1 What is a "tool?" A reflection on the social and material identity of tools

In the introduction of this dissertation, I use the example of a hammer: a hammer can destroy and it can construct. So is the *use* of a technology what constitutes it? Do we understand the hammer as the *thing we swing, to destroy and to build*? Should we?

This thesis engages domains of tools and tool-making for accessibility: evaluation, navigation, interaction, and personalization. But these categories for work do not fully characterize the upstream conditions that our software systems and data interfaces inherit.

In my work specifically on accessibility, a larger social reality becomes apparent that shapes the question, "what is a tool?" far more than how an individual might use one, or the domains of work that our tool-making inhabits. My research journey has navigated multiple social and political thresholds, from changes to law in the European Union, to the enactment of Title II as part of the update to the Americans with Disabilities Act. These laws have motivated a significant interest in accessibility research, solutions, guidelines, and technologies. In the midst of this, we have seen the rise of overlays and generative AI solutionism [52] and subsequent lawsuits and grass-roots resistance.

For my work, this is mostly good news. Legal change produces motivation, and even with predatory technology attempting to address real problems, pushback is widespread and active. But this paints a picture of the reality that my work inherits: many tools cannot even be used, or cease to be used, if there is not a social, political, and material set of conditions in place motivating those tools, providing resources for their construction, regulating their use, and examining the outcomes of what they accomplish. Tools and technologies are often a response to social, cultural, political, and legal realities that we first negotiate.

I recently spoke on this at a keynote in Australia, on how a hammer isn't *just* a tool and that the idea that "the only thing that matters is how a tool is used" limits how we really understand tools. Instead, I spoke about how a standard, household hammer requires iron and wood. That alone leads to a whole universe of different questions. Western Australia's conservation efforts were disrupted when a significant amount of natural iron was discovered in a wildlife preserve. So laws were passed and now iron is mined there. That iron is largely exported. And Australia then, whether with Australian iron or not, mostly imports their small tools. Iron is sent out, and through a complex network of trade (likely indirectly related to the iron), hammers are brought in. A "hammer," to even exist at all, relies on multiple levels of human governance, international relations, and complex infrastructures of trade.

And while my metaphor is largely motivated to encourage younger practitioners to consider the "iron mines" in the technologies they use, such as modern generative AI, it is also an area that is not adequately explored and addressed in terms of accessibility research.

Research on accessibility is dependent on funding, which is often dependent on political priorities and action. Depending on the current social and political state of the world at large, accessibility research itself may never gain the opportunities required in order to innovate and produce new tools at all. And as the US's 2025 federal cuts to research demonstrated, millions of dollars devoted to accessibility research can be lost to political agendas. It is for this reason that engagement with policy recommendation and guidance is essential. Personal political activity and involvement is also essential. Researchers who genuinely believe in accessibility as a human right or as a dignity that all people deserve should work with policymakers to ensure that there are material and structural resources in place for this work to continue. We cannot naively believe that technology, divorced from the realm of social and political forces, is capable of solving accessibility barriers [124]. Without enforcement and threat of litigation, very little accessibility work has been accomplished in the past by technology companies alone.

Not featured in these chapters (as they were merely stapled in research papers from previous publications) is the policy and outreach work involved in seeing that work like *Chartability* and *Data Navigator* are used in real contexts, including by organizations that govern and influence the lives of many people. Immediate incentives to produce novelty may not be enough to sustain the larger socio-cultural and political ecosystems that our work participates in and is downstream from. We must also get involved.

9.3 Who is responsible for repair?

Lastly, I want to revisit one of my opening points, where I argue that the *tool-makers* are first responsible for repair. This is true. However, the most pressing issue I have faced in recent years is mostly unmentioned across these research projects: tool-makers might be responsible, but this is because they are the only ones who have the *power* to make things accessible. Does this always need to be the case? Can we imagine an artifact's authority over the user's ability to access being designed towards self-subversion [44] or de-centralized agency [15, 73, 94], instead? What might that look like, concretely?

In *Softerware*, we begin to engage this larger problem in terms of an idealized state where a user can repair or re-design their own experiences. But to me, this self-repair is like laying down train tracks for yourself as you move a locomotive, but then lifting up your own tracks behind you as you go. You're the only one helping yourself. This is not ideal, for you or others.

What we need are broad, lasting, infrastructural changes. On the web, this problem becomes quite difficult to solve. A personal computer or device? Again, someone can auto-design their interfaces into a better state. But back when I started *Chartability*, the WebAim Million's report showed more than 95% of the top one million website home pages contain at least one critical accessibility error. And now, more than 6 years later, that proportion is unchanged [137].

Some had imagined that generative AI would solve the massive infrastructural repair problems we face. But unfortunately, the latest WebAim Million report shows that since 2020, ARIA usage has increased and correlates to more errors, while use of tabindex on a page has increased nearly 300% and also correlates to more errors on a page. If anything, during the age of generative AI, we have seen existing bad patterns worsen in prevalence and complexity.

I firmly believe that a tools-based approach is not enough on its own. Tool-making cannot be the *only* intervention on inaccessibility. Tools and tool-making, as our thesis argues, have a powerful role to play. But we simply can't tool our way out of failed infrastructure and inadequate policy when someone else *owns* the tools and tool-making. Visiting a website is like going into someone else's home: arranged according to their effort, tastes, and so on. If you can't access their home, you essentially need to request that they let you in personally. Website repair always falls to the owner and maintainer of a website, and they largely don't take any meaningful action.

Sidewalks outside of homes are a good parallel to this problem. Sidewalk accessibility is a massive infrastructural problem [106], and yet localities treat sidewalk maintenance in different ways: some, like where I presently live in the south hills of Pittsburgh, put the onus on the homeowner whose house and property the sidewalk touches. In other places, sidewalks are considered a public path, similar to a roadway, and are maintained through public tax and resource management. To no surprise, privately-maintained, public-access sidewalks are worse for people in pretty much every way than publicly-maintained ones [143]. This is because private homeowners don't care about sidewalk maintenance unless the city manages to fine them or they get sued.

And the web is a collection of private spaces that you visit privately. There is no truly shared, universally democratic, public space on the web. Centralization is partly to blame: sharing space while scaling leads to consolidation.

So my future work will continue to wrestle with the same tensions of scale, repair, and anti-consolidation of power, motivated by the same WebAim Million report. But now I look to questions of *democratic* and *radical* access to accessibility repair. The barriers I hope to tackle in the future are political and infrastructural. Perhaps tool-making will participate in this work, but it seems clear now from my work that the upstream technical problems and socio-political conditions that tools inherit, will likely not be addressed by tools alone.

What does "democratic" and "radical" infrastructure work look like? It will probably be an extension of *Softerware*, to some degree. I imagine future research that explores public-first spaces, ones where access is socially negotiated and repair belongs to all of us. Is this an autonomous space, like an autonomous zone [7] separate from the web? Above it, looking down into it, like shared annotation tools but capable of sharing the manipulation of websites [105]? A space with ambient co-repair, modeled after projects that bring people together [113] or that allow community "fixing" of misinformation [66]? Perhaps feminist thought on the ethics of care can help us [55, 85]? Or maybe it will be something else entirely; I'm not yet sure. But what made the web fantastic years ago is long gone; most of it has been hedged into corporate spaces that are controlled, maintained, and repaired by corporate power. And these entities are notoriously bad at repair. What I imagine in the future involves reclaiming a sense that the web is *ours*, belongs to *us*, and that ultimately *we* are responsible for making it accessible.

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