“It felt like I was part of the data”: Comparing Mouse, Touch, and Physical Interaction with Visualizations

by

Caroline Ka-Lai Wong

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Applied Science
in
Management Sciences

Waterloo, Ontario, Canada, 2020

Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

This work (which I am the first author in) has been submitted to the Proceedings of the 2020 ACM International Conference on Interactive Surfaces and Spaces (ISS'20) and is currently under review for publication.

Aside from my supervisor, Dr. Mark Hancock, I list my co-authors who contributed intellectual input and guidance in this submitted work:

- Dr. Petra Isenberg
- Dr. Bongshin Lee
- Dr. Tobias Isenberg
- Dr. Nathalie Henry Riche
- Dr. Sheelagh Carpendale

In particular, the node-link graphs and cluster analyses (Figure 5.1) featured in chapter 5 were created by Dr. Petra Isenberg. The digital application used in both Study 1 (chapter 4) and Study 2 (chapter 5) was implemented by Dr. Mark Hancock.

Abstract

With my two exploratory studies I contribute a deeper understanding of the different experiences people have when manipulating data representations using mouse, touch, and physical interaction. To uncover experiences rather than performance measures I employed two different methodologies in the context of "data connectedness." My first study used Likert-based questionnaires to determine differences in how connected participants felt to the data they were interacting with. To gain a deeper understanding, my second study employed a word selection activity (using the Desirability Toolkit), which led to much richer data. I found that people associated words like "engaged," "direct," and "satisfying" with touch and physical interaction, but often used words like "awkward," "dull," and "distant" with the mouse. My findings help to tease apart the characteristics of experienced interaction modalities in relation to how people feel about their connection to the data. Furthermore, my work provides a deeper look into how to measure abstract concepts such as connectedness that are highly elusive but important to understanding why certain ways of interacting with data may be more attractive, more liked, or even more effective.

Acknowledgements

Firstly, I would like to thank my supervisor, Mark Hancock. There are many things I have achieved over the course of my Masters which would not have been possible without his support and guidance. He has always provided a friendly and motivating environment for his students to succeed and as a result, helped me become a better researcher.

I would like to thank Oliver Schneider and James Wallace for serving as my readers and for providing insightful feedback for this thesis and from our previous Writing Review Circle sessions. I would also like to thank my collaborators on the studies included in this thesis: Petra Isenberg, Bongshin Lee, Tobias Isenberg, Nathalie Henry Riche, and Sheelagh Carpendale. This work would not be possible without their support and expertise.

Thank you to the members of the Touchlab, the HCI+Health Lab, the HCI Games Group, the Haptic Computing Lab, and the overall Games Institute community. I am grateful to have worked among many bright and inspiring individuals. I am especially grateful for Stacey Scott, who introduced me to the world of Human-Computer Interaction. Without her encouragement, I would not have been able to meet the wonderful people mentioned above.

I would like to thank my family for their love and support. I am thankful for my father who has always encouraged me to strive for success and for my mother for always believing in me.

Thank you to my friends for keeping me grounded throughout this journey. Despite our busy schedules, I am thankful to have found a group of fun people to share some of my favourite memories with. Lastly, I would like to thank Marco for embracing this journey with me, providing emotional support along the way.

Dedication

To my dearest friends, Danielle, Karen, and Kristin.

May we continue to overcome life's challenges together.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

Recently, research has attempted to gain insight about large sets of data with the help of machine intelligence but there remains a need for human interpretation of data. To perform these complex analyses, domain-experts often rely on information visualizations (visual representations of abstract data often in the form of graphs, diagrams, maps, etc. (Spence, 2001)), but these tools are not often easily accessible by non-experts (Börner et al., 2016; Domik, 2000). However, there is an increasing amount of personal data, such as that collected through exercise and time management apps, and public data provided by media outlets (e. g., worldwide recovery rates of an infectious disease), which non-experts often wish to investigate. One way that information visualizations have been made more available has been thought to be through interacting with multi-touch interfaces like tablets or mobile devices (Lee et al., 2012).

As technologies continue to advance, there exists a multitude of dimensions that can be assessed in order to improve our understanding of how people interact with them. More commonly, researchers tend to focus on how each interaction is executed in terms of performance measures such as speed and accuracy. In many cases, poor performance can lead to limited use of certain technologies. Consider a basic selection task where the goal is to select targets as they appear on a screen. Past literature has suggested that using touch interaction is faster but less accurate than using a mouse (Sears and Shneiderman, 1991). Studying performance measures like these can lead to design improvements such as simply increasing the target sizes or implementing higher resolution for touchscreens. The importance of performance measures is particularly true for interaction modalities, or the different ways or modes in which a person can perform an interaction (Beaudouin-Lafon, 2004). Furthermore, performance measures, such as speed and accuracy coupled with personal preference, workload, or fatigue have been used to understand interaction with information visualizations (Besançon et al., 2017; Isenberg et al., 2013; Lam et al., 2012; Nancel et al., 2011). Other aspects such as the presentation and design of visualizations and its effect on memorability (Bateman et al., 2010), empathy (Boy et al., 2017), and engagement (Haroz et al., 2015) have also been looked at in past work. However, the ways of interacting coupled with how it may contribute to other *affective* experiences, have not been formally looked at in terms of how people feel connected to data.

My work provides an initial glimpse into how an abstract concept such as *connectedness* can be measured when manipulating visualizations using mouse, touch, and physical interaction, which could inform how people design and interpret information visualizations in the future.

This chapter begins with the motivation for this research (section 1.1), followed by the scope of this work (section 1.2). I then present the research questions that guided this work (section 1.3) and the methods used (section 1.4). Finally, I present the primary contributions (section 1.5) and an outline summarizing the thesis chapters (section 1.6).

1.1 Motivation

Information Visualizations (InfoVis) are essential in helping people understand and explore data. Interaction techniques in particular have become essential in data exploration, as seen in the use of a mouse and keyboard to support fundamental operations such as selecting, filtering, and providing details on-demand (Yi et al., 2007). With the advancement of display and input technologies, visualization research projects have sought to build on direct pen and/or touch (Baur et al., 2012; Jo et al., 2017; Sadana and Stasko, 2014), mid-air gestural (Benko and Wilson, 2010; Nancel et al., 2011), and proxemic interaction (Badam et al., 2016; Jakobsen et al., 2013). More recently, efforts such as constructive visualization and data physicalization (Huron et al., 2014a,b; Jansen et al., 2013, 2015) have begun to empower people to explore data through physical data representations or through the use of physical visualization tokens.

With this wide variety of ways of interacting with data, researchers (Bruckner et al., 2019) often identify that touch input is perceived as being more direct. For example, when comparing mouse and touch in a game setting, Watson et al. (2013) found that people felt more competence, control, relatedness, and immersion. They also reported feeling happier and more engaged while playing the game. Observations have also alluded to people feeling a "physical connection" when directly touching a stroke-based non-photorealistic rendering on a large multi-touch display (Grubert et al., 2008). However, even though people seem to favour touch interactions over mouse interactions on multiple dimensions, the reasons for which remain elusive.

Most traditional measures used in the visualization research community to understand interaction with data are performance measures while affective experiences are not explored in depth. While performance is important, data exploration does not always need to be fast or precise if the person exploring the data wants to fully understand the information with which they are presented. Kennedy and Hill (2018) show that simply viewing everyday visualizations can elicit an emotional reaction. Some recent work has identified the importance of affective response and assessed how data visualizations can provide support for feelings of engagement (Amini et al., 2018) and empathy (Boy et al., 2017). Other work has also compared levels of engagement across input modalities like mouse and touchscreen (Besançon et al., 2017; Watson et al., 2013). However, it remains unclear how these ways of interacting influence people's affective experience of a "connection" to the data.

1.1.1 What is Connectedness?

Connectedness is not easy to define. In psychology, social connectedness is usually perceived as belonging or closeness in relationships with others and is often associated with well-being (Lee and Robbins, 1995). What does it mean to feel connected to data? Anyone that analyzes or visualizes a dataset could be said to have some form of connection with the data. Even if an individual has a strong interest in understanding a certain dataset, understanding one's data through a visualization often takes a willingness to spend time working with the visualization. Having positive associations with one's interactions with the visualization may increase a person's willingness to put in more time.

In this thesis, I present two studies that compare traditional mouse interaction to touch and physical interactions, with a focus on "connectedness". In the first study, I used Likert-based questions to elicit feelings of connectedness and self-determined motivation (Ryan et al., 2006), but it became clear early on that our construct of "connectedness" did not match participants' understanding of the term. From this study, I identified that participants understand connectedness in at least three different ways:

i) *emotional connectedness* – personal interest or gain from interacting with the data

ii) *physical connectedness* – direct or indirect physical movements with the data

iii) *cognitive connectedness* – engagement or learning from interacting with the data

Throughout my thesis, I touch on all three, but am specifically interested in exploring the effect that interaction techniques have on people's feelings of physical and cognitive connection to the data. In chapter 2, I discuss previous work on directness of interaction techniques (physical connection) and feelings of engagement through interacting with visualizations (cognitive connection).

In my second study, I leveraged a methodology from the Desirability Toolkit (Benedek and Miner, 2002) to elicit a qualitative understanding of the experience of using these three input modalities to create and manipulate data. These findings provide us with a rich understanding of the nuanced experiences of participants and, at a high level, suggest that people choose more positive words (e. g., "engaged," "direct," and "satisfying") to describe touch and physical input, but more negative words (e. g., "awkward," "dull," and "distant") to characterize mouse input. Furthermore, our findings help tease apart the characteristics of interaction modality associated with helping people feel connected to data. I also show that these factors, like familiarity, are not the same for, or even described the same way by, everyone.

1.2 Scope

In this thesis, I focus on three main research areas (see Figure 1.1): human-computer interaction (HCI), information visualization (InfoVis), and psychology. Within the area of HCI, my research targets multitouch input and interaction. My research also involves the InfoVis domain which looks directly at physicalization and emotional aspects of visualization such as empathy and engagement. My work also touches on the field of psychology, particularly on self-determination theory.

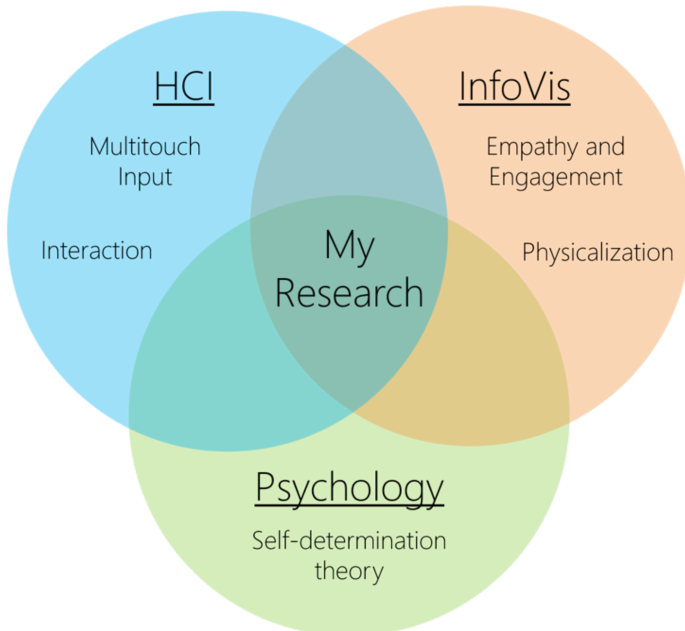


Figure 1.1: My research consists of three major research areas: HCI (multitouch input and interaction), InfoVis (empathy & engagement and physicalization), and Psychology (self-determination theory).

1.3 Research Questions

My thesis looks towards investigating the following research questions:

Question 1: How can the concept of connectedness to data be measured when exploring information visualizations? There is currently no validated scale for measuring the concept of connectedness to data. Scales exist for measuring similar concepts (see chapter 3) but these constructs are not entirely synonymous with connectedness themselves. Can existing validated scales that measure abstract concepts such as engagement (Amini et al., 2018) and "social connectedness" (Lee and Robbins, 1995) also be used to measure connectedness to data?

Question 2: Can the way people interact with data influence how people describe feelings of connectedness to the data? As described in section 1.1, observations of participants in previous studies have mentioned a "physical connection" or emotional reaction to data which suggests that there may be different types of connectedness. However, these affective experiences of connectedness have not yet been formally studied in the

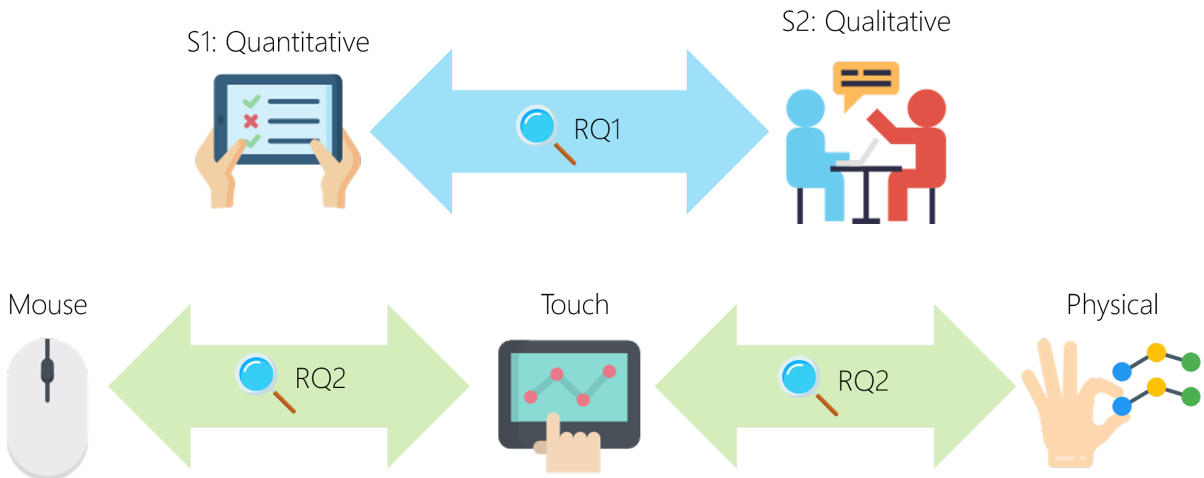


Figure 1.2: Diagram depicting my approach to answering my research questions. To answer Research Question 1 (RQ1), Study 1 looked to use quantitative measures whereas Study 2 used qualitative measures. To answer Research Question 2 (RQ2), I compared three ways of interacting (mouse, touch, and physical) with data in both studies.

context of interaction modality. If people do describe connectedness differently from each other, what aspects from certain interactions prompt such interpretations?

1.4 Approach

To answer these research questions, I ran two mixed-methods studies with different methodologies (see Figure 1.2). To investigate how the concept of connectedness to data could be measured while exploring information visualizations, the first study I ran focused on collecting quantitative data through validated Likert-scale questionnaires. Through consistent analysis of collected data as the study progressed, I found that using validated scales was not appropriate for capturing the concept of connectedness, as participants' interpretations of connectedness conflicted with the language they would naturally use to describe their experience when working with data. From there, I reviewed participants' interview responses regarding their interpretation of connectedness to inform a better method in measuring this concept. In my second study, I shifted the main focus from validated scales to a more qualitative methodology by incorporating the Desirability Toolkit—a usability measurement tool that looks at word-selection to describe experiences. By comparing both methodologies for measuring an elusive concept such as connectedness to data, I was able to directly observe the differences in feedback from participants, specifically what aspects of their experiences made them feel connected (or disconnected) to the data they were exploring.

To determine if the ways in which people interact with data influence how they describe feelings of connectedness to data, I compared the following input modalities for both of my studies: mouse, touch, and physical interaction. Each modality was used to explore and manipulate data from a scatterplot visualization. As part of the second study, modalities were able to be compared and contrasted side-by-side using the Desirability Toolkit where participants chose words that were relevant to their experiences with each.

1.5 Contributions

My work provides three primary contributions:

1. A demonstration that a qualitative, experience-focused methodology such as the use of the Desirability Toolkit can be leveraged to understand more nuanced affective experiences, such as "connectedness," in a lab study.
2. Findings from a pair of studies comparing mouse, touch, and physical input suggesting that the modality used to interact with data may influence how people describe feelings of connectedness to the data.
3. An initial look into how the use of vocabulary from the Desirability Toolkit helps people explain the abstract concept of connectedness to data when it comes to different ways of interaction.

1.6 Outline

This thesis is organized as follows: In chapter 2, I review past literature on input devices used to access interactive visualizations, the benefits of touch in visualization and other contexts, and feelings of empathy and engagement observed in the visualization realm. In chapter 3, I illustrate the main measurement approaches I utilized in both studies, including reasoning for why an initial approach was chosen and why the direction changed. In chapter 4, I describe the details of Study 1, including condition setup, order of tasks, procedure, data collection, and findings. In chapter 5, I reflect on findings from Study 1 which informed modifications for Study 2. Here, I describe an analysis of our qualitative data and findings. In chapter 6, I draw insights from the findings of both studies including the methodological journey of measuring complex concepts and the influence of interaction on connectedness. Lastly, in chapter 7, I reiterate the contributions of my work along with its limitations and opportunities for future work.

Chapter 2

Related Work

In this chapter, I discuss literature related to current work in the human-computer interaction (HCI) community which largely falls into three subfields:

Input Devices for Interactive Visualizations (section 2.1). As the variety of input devices extends beyond traditional mouse and keyboard to other devices such as touchscreens, pens, and tangible input, research into how they are incorporated with visualizations also broadens. Since my work focuses on the comparison of select input methods, this section will provide insights on previously compared aspects of interaction.

Benefits of Touch (section 2.2). A great deal of past work on input modalities includes touch input. Here, I discuss current known benefits of touch input and how they affect peoples' interaction experience. Additionally, I discuss the measurement of these experiences which informed my study design.

Empathy and Engagement in Visualizations (section 2.3). Emotions such as empathy and engagement have been observed as part of a person's experience when viewing or interacting with visualizations. I discuss how the design and presentation of visualizations elicited these feelings. In my work, I focus on investigating the abstract concept of feeling connected to data, whether this feeling *can* be observed through interaction and *how* it can be measured

2.1 Input Devices for Interactive Visualizations

Interactive Visualizations are usually accompanied by an input device like a mouse or a touchscreen. People can also interact with visualizations using non-digital methods such as physical tiles or tokens. Here, I discuss traditional mouse interaction and alternate input methods for exploring visualizations.

2.1.1 Traditional Mouse Interaction

Many InfoVis systems utilize mouse and keyboard for interaction and are accompanied by WIMP (Windows, Icons, Menus, and a Pointer) GUIs (graphical user interfaces) (Lee et al., 2012). Since the introduction of WIMP systems, the mouse has been praised for its ease in learnability and usability with Smith et al. (1982) describing it as a "Fitts' Law" device for navigating early desktop user interfaces.

Past literature has found that mouse is favourable in some instances. For example, when Meyer et al. (1994) compared user performance between relative input (e. g., mouse) to absolute input (e. g., touch), they found that mouse had superior performance in terms of speed, levels of fatigue, and subjective preference, given a small display to work with. Mouse also tends to be faster for when the size of a target in a selection task is smaller than 0.64 cm in width (Sears and Shneiderman, 1991).

Point-and-click WIMP interfaces also have quite a few drawbacks specifically in the realm of InfoVis. For example, Van Dam (1997) states that, "expert users are often frustrated by too many layers of 'point and click' and screen clutter due to too many widgets..." Van Dam also warns that mapping multi-dimensional data tasks to 2D widgets may sacrifice a natural experience. Despite these disadvantages, mouse input continues to be popular in InfoVis research. More recently, InfoVis has been appearing in contexts beyond a monitor (e. g., public displays) so WIMP interfaces may not be appropriate (Lee et al., 2012; Wigdor and Wixon, 2011). In my work, I compare mouse interaction with touch and physical interaction in terms of feeling connected to data. When exploring this unknown concept, it is important to consider the mouse's well-known strengths and flaws and whether it plays a role in one's affective experience.

2.1.2 Exploring Alternate Input Methods

With the increased commercial availability of touch input in the 2000s, researchers began to explore alternative, post-WIMP forms of input and the role of "natural" interaction (Van Dam, 1997; Nielsen, 1993; Beaudouin-Lafon, 2000, 2004; Watson et al., 2013), including for visualization applications (Lee et al., 2012). Alternatives to mouse input methods are frequently referred to as natural user interfaces (NUIs) (Wigdor and Wixon, 2011). According to Wigdor and Wixon (2011)'s book on touch and gesture for enabling NUIs, an NUI is “not a natural *user interface*, but rather an interface that makes your user act and feel like a natural”.

Since then, several studies explored how differences in input modalities affect how people interact with visualizations (Lee et al., 2012). For example, North et al. (2009) compared touch input on surfaces to interaction with physical tokens and mouse control to understand its usefulness for data exploration. They found that touch input shares some similarities with physical interaction, but that there are important differences, such as problems with group selections. Walny et al. (2012) specifically looked at a combination of pen and touch input on digital whiteboards, using a Wizard of Oz study to explore people's responses to the novel input possibilities. They found that their participants clearly assigned different tasks to the different input devices and that participants embraced mode- and button-less interfaces.

Later, Le Goc et al. (2016) investigated the differences between touch and tangible input by comparing how people work with flat physical chips, as opposed to tangible physical pucks. They found that the latter led to faster yet less precise input, and that their physical character was not often used. Next, Wun et al. (2016) compared the use of tangible tiles with mouse-based interaction to author bar charts. They found that the input method affected action sequences and the time spent on the visualization pipeline, suggesting that participants spent more time in the mouse condition in exploring the visualization tool than when using physical tokens. On the other hand, tokens seemed to encourage more time exploring visual mappings.

All these studies and discussions informed our own work and, in particular, our study design. Specifically, we used more graspable tokens than Le Goc et al. (2016) to provide more opportunity to use physical aspects of the tokens. 3D touch and tangible input was investigated by Besançon et al. (2017) which is less closely related to our work on 2D manipulations. Nonetheless, an interesting observation of their work was that participants achieved the same levels of input precision with all three input modalities, but still believed to be more precise with touch and mouse input than with tangible control. While a great deal of work has contributed to how interaction is incorporated with visualizations, how do the interactive devices themselves contribute to the feeling of connectedness to the data people are exploring?

2.2 Benefits of Touch

In this section, I discuss directness as a way of characterizing people's experiences when interacting with (i. e., manipulating) interfaces. In particular, I highlight studies on touch input that cite 'directness' as a general benefit when exploring data.

2.2.1 Directness

In response to the advancement of post-WIMP interfaces, researchers began investigating interaction systems and why people show fondness towards them. For example, to describe people's experiences with direct manipulation interfaces, Shneiderman (1993) proposed the following characteristics:

- continuous representation of the objects and actions of interest,
- physical actions (movement and selection by mouse, joystick, touch screen, etc.), or labelled button presses instead of complex syntax,
- rapid, incremental, reversible actions whose impact on the objects of interest is immediately visible, and
- layered or spiral approach to learning that permits usage with minimal knowledge.

Further, Shneiderman (1993) also states that there are two aspects of directness. One aspect is the distance between people's intentions and system capabilities. The idea here is that the shorter the distance, the stronger the directness. A shorter distance means that a person's actionable goals are easily achieved and are straightforward as made evident through the system's outputs. Shneiderman states that the other aspect of directness is engagement, that is, that people feel as though they are directly acting on objects and have a sense of control over the objects.

Building on Shneiderman's 1993 characterization of directness, Jacob et al. (2008) proposed the notion of "reality-based interaction", which encompasses four themes evident in emerging interaction styles for the real world:

- *Naïve Physics*: people have common sense knowledge about the physical world.
- *Body Awareness & Skills*: people have an awareness of their own physical bodies and possess skills for controlling and coordinating their bodies.

- *Environment Awareness & Skills*: people have a sense of their surroundings and possess skills for negotiating, manipulating, and navigating within their environment.
- *Social Awareness & Skills*: people are generally aware of others in their environment and have skills for interacting with them.

In their design considerations for InfoVis interaction, Lee et al. (2012) discuss embodiment as a sub-dimension within the dimension of "The Interspace between a Person and the Technology," specifically, they define embodiment as "the degree to which a person feels that the technology is an extension (or part) of them". When considering embodiment in terms of displaying data, multiple human capabilities must be accounted for which include motor memory, peripheral vision, optical flow, focal attention, and spatial memory (Ball and North, 2007; Dourish, 2004). When data is displayed on large displays, physical navigation acts as a form of embodied interaction (Ball and North, 2007).

Most past work on studying differences in input modalities has focused on touch input—also one of the input modalities I am interested in. As such, my work relates to which methodologies were used and their findings about touch input.

Previous work used validated scales (questionnaires that have been tested for validity and reliability) to show that direct touch, when compared to mouse as an input method, can improve people's experience in a variety of measures such as enjoyment, engagement, volition, and competence (Watson et al., 2013). In addition, informal observation suggests that people can feel a "physical connection" when directly touching a screen in the context of working with stroke-based non-photorealistic rendering (Grubert et al., 2008). The use of touch has also been shown to help novices in collaborative analyses, encouraging turn-taking in data exploration rather than electing a single person to be 'in charge' (Isenberg et al., 2009). These findings have led, for example, to the development of movable alternator pucks to extend the range of touch gestures on medical visualization tables (Lundström et al., 2011). Our work relates to this previous work by exploring ways to more systematically measure such benefits in comparison to mouse and physical interactions.

One general benefit of touch that is often cited is that it is 'direct.' More generally, input devices that are used to interactively explore data representations have often been described as being direct (e. g., touch) or indirect (e. g., mouse) in the past. To better allow researchers and practitioners to describe and understand this directness or indirectness of the interaction with visualizations, Bruckner et al. (2019) proposed a model that differentiates between several types of spatial directness, depending on the involved spaces (i. e., data, visualization, output, user, manipulation, and interaction spaces). Depending on the chosen visual mapping, output device, input device, and interaction design one can then discuss the needed mappings between these spaces to explain a system's directness or indirectness. For touch, this means that if we use visual mappings that live in a 2D plane, which is shown on a 2D display and also used to capture the touch input, then virtually no mental mapping is necessary between the visualization space and the input space. As a consequence, people who use such a touch-based exploration tool do not have to learn these mappings, and with well-designed interaction techniques can focus directly on their data exploration.

Our work indirectly tests this assumption by comparing a mouse-based (indirect) mapping in which output and manipulation space are different with a touch-based mapping in which they coincide. We also investigate physical interaction as our data elements are assembled on a flat surface, and participants interact with them on that surface. This modality should thus, like touch-based interaction, require no mental mapping efforts but there is also richer somesthetic feedback that may have an influence. In fact, we specifically focus on the question of connectedness to the data, which might be related to the question of mental mapping.

2.3 Empathy and Engagement in Visualizations

Designs of visualizations have been observed to elicit emotional reactions such as empathy and engagement regardless of intention. In this section, I discuss that there may not be one standard way of measuring these elusive emotional reactions when it comes to exploring data.

2.3.1 Attributes that Contribute to Emotional Reactions

Emotions play an integral role in how people engage with data. Contributing to the idea of a "sociology of data," Kennedy and Hill (2018) empirically investigated visualizations that people encounter in their everyday lives using a diary study and focus groups. They found that simply viewing visualizations elicited emotional reactions on spectrums of preference and learnability. This highlights that, while the data itself matters, it is equally important how the numbers make you feel. In Bateman et al. (2010)'s comparison of embellished and plain charts, they found that the more pictorial, embellished charts promoted increased engagement and long-term memory recall and suggest that emotions may have been a factor. Borkin et al. (2013) also systematically looked at how certain attributes from a set of over 2000 visualizations contribute to memorability.

Haroz et al. (2015) captured "initial user engagement," demonstrating that people were more enticed to look at isotypes rather than text or standard charts. More recently, designing visualizations to elicit feelings such as empathy have become a topic of interest in the community. Boy et al. (2017) hypothesized that anthropographic designs would elicit more empathy. Yet, despite a series of seven studies, they failed to capture any signal. However, when designing micro-robots as dynamic composite physicalizations, Le Goc et al. (2019) found that the use of robots as data representations promoted feelings of empathy as they were perceived as alive from their movements. While the presentation and design choices of visualizations have been shown to contribute to empathy and engagement, my work focuses on how choice of *interaction* may contribute to the feeling of connectedness to the data.

2.3.2 Measuring Abstract Concepts

The concept of "connectedness" to data that I explore in this thesis has not been previously studied. However, my work relates to past research that studies similarly elusive concepts, such as empathy and engagement. In their study of visualizations presented in video forms, Amini et al. (2018) developed and validated a scale measuring factors that contributed towards engagement (i. e., affective involvement, enjoyment, aesthetics, focused attention, and cognitive involvement) and showed that these videos increase viewer engagement. However, my work shows that validated scales may not always be the most fitting first step in measuring abstract concepts, connectedness in particular. The idea that visualizations can be designed in a way to elicit these feelings have implications for how people understand and relate to data. But design may not be the only factor to consider. Instead of the design, my work explores whether interaction modality may play a role in how connected people feel to the data.

2.4 Chapter Summary

In this chapter, I discussed past work within the field of HCI. In particular, I look at input devices for accessing interactive visualizations which involve traditional mouse interaction and alternative methods such as touch and tangible input. I also review past work exploring the benefits of touch input in regards to characterizations of directness. Lastly, I discuss the role of empathy, engagement, and emotional reactions in general when it comes to visualizations and how we could measure such abstract concepts.

In my studies, I incorporate and compare mouse, touch, and tangible input for interacting with a scatterplot visualization while keeping in mind their varying levels of directness (i. e., from indirect to most direct). Previous work has shown that there may not be one standard way of measuring elusive concepts such as empathy and engagement so in my studies of measuring connectedness to data, I first incorporate validated scales as my main measurement tool and then shift to a more qualitative approach. In the next chapter, I describe in detail the methodologies I used in my studies. I discuss in more detail how they've been used in past research and initial observations of how they worked in my studies.

Chapter 3

Choosing a Methodology

In this chapter, I describe the methodologies I utilized for both studies. I draw on previous studies which have used validated scales to measure abstract concepts in attempt to measure connectedness. I then reflect on concerns over construct validity and why the methodology needed to be changed. Lastly, I detail the use of a usability measurement tool called the Desirability Toolkit (Benedek and Miner, 2002) and how it should be administered.

3.1 Use of Validated Scales

My work began by exploring methods for measuring "connectedness" when creating and manipulating data with new input modalities. I first looked at the methodology used to compare input modalities by Watson et al. (2013) in a game setting. We focused on modifying existing validated scales, such as those for player experience in games (Ryan et al., 2006) and intrinsic motivation (McAuley et al., 1989) in the context of working with data. Since there is currently no validated scale for measuring connectedness to data, we also modified a social connectedness scale (Aron et al., 1992) and affective slider (Betella and Verschure, 2016). In this section, I discuss the scales administered (see Appendix C) to participants in the first study and how they were modified for measuring people's interactions and connectedness with data.

Player Experience of Needs Satisfaction. The Player Experience of Needs Satisfaction (PENS) measure was developed by Ryan et al. (2006). PENS looks at player experience through the lens of self-determination theory (SDT) (Ryan and Deci, 2000) which addresses how intrinsic and extrinsic motivation relates to growth and well-being. PENS consists of 21 items that specifically address the following subscales: competence, autonomy, relatedness, presence-immersion, and intuitive controls.

Intrinsic Motivation Inventory. The Intrinsic Motivation Inventory (IMI) was validated by McAuley et al. (1989). The IMI consists of 18 items that look to assess intrinsic motivation through the following subscales: interest-enjoyment, perceived competence, effort-importance, pressure-tension.

PENS and IMI looked to explore experience in Watson et al.'s (2013) work comparing mouse and touch in a game scenario. While I also include these measures in my first study, I looked into how connectedness, a rather unexplored abstract in the InfoVis domain, could be measured. These proposed measures of connectedness are described below.

Inclusion of Other in the Self. The Inclusion of Other in the Self (IOS) scale was developed by Aron et al. (1992). IOS aims to measure the abstract concept of closeness, in particular, interpersonal interconnectedness. The scale consists of a single item which is composed of 7 Venn diagrams with increasing levels of overlap with "Self" in one circle and "Other" in the other. The respondent is then asked to "circle the picture below which best describes their relationship [with 'Other']."

Affective Slider for Human Emotion. The Affective Slider was developed by Betella and Verschure (2016) as a modernized version of Bradley and Lang's (1994) Self-Assessment Manikin (SAM). This measure is a digital self-reporting tool which is composed of two sliders that measure arousal and pleasure. The respondent is specifically asked to "move the slider to rate their level of arousal/pleasure."

In practice, my initial explorations with these modified scales proved difficult, as will be revealed in section 4.6. Participant interpretation of connectedness conflicted with the language they would naturally use to describe their experience working with data. While I intended to recruit 18 participants, I halted the first study with the sample size sitting at 9 as it became clear that the study design violated construct validity. Ongoing reflections from the qualitative responses from the nine participants revealed that connectedness to data was interpreted in different ways. In particular, people's interpretations could be categorized as emotionally, physically, or cognitively connected. These categorizations helped to inform my second study where I changed the methodology using validated scales to leveraging the Desirability Toolkit (Benedek and Miner, 2002) to provide a better qualitative understanding of people's experience.

Table 3.1: List of 105 words for evaluating user interfaces originally drawn from Benedek and Miner (2002)'s Desirability Toolkit.

Accessible	Controllable	Familiar	Meaningful	Simple
Advanced	Convenient	Fast	Misleading	Simplistic
Ambiguous	Counter-intuitive	Faulty	Motivating	Slow
Annoying	Creative	Flexible	New	Sophisticated
Appealing	Credible	Fresh	Non-standard	Stable
Approachable	Cutting edge	Friendly	Obscure	Stimulating
Attractive	Dated	Frustrating	Old	Straightforward
Awkward	Desirable	Fun	Ordinary	Stressful
Boring	Difficult	Hard to use	Organized	System-oriented
Bright	Distracting	High quality	Overwhelming	Time-consuming
Business-like	Dull	Illogical	Patronizing	Time-saving
Busy	Easy to use	Impressive	Poor quality	Too technical
Clean	Effective	Inadequate	Powerful	Trustworthy
Clear	Efficient	Incomprehensible	Predictable	Unattractive
Cluttered	Effortless	Inconsistent	Professional	Unconventional
Compelling	Empowering	Ineffective	Relevant	Understandable
Complex	Energetic	Innovative	Reliable	Unpredictable
Comprehensive	Engaging	Insecure	Responsive	Unrefined
Confusing	Entertaining	Intimidating	Rigid	Usable
Consistent	Exciting	Intuitive	Satisfying	Useful
Contradictory	Expected	Irrelevant	Secure	Vague

3.2 The Desirability Toolkit

The Desirability Toolkit was developed by Benedek and Miner (2002) as a usability measurement tool that assesses participants' satisfaction with a product. After interacting with that product, people are asked to view a list of "product reaction words" (e. g., "Easy to use," "Frustrating," or "Consistent") and asked to select all words that are relevant to their experience, which they then reduce to their top five words to describe in more detail (see Table 3.1 for the full list of 105 original words). These five words provide the foundation for a semi-structured interview. In their series of pilot studies, Benedek and Miner (2002) list a number of limitations and benefits of using the Desirability Toolkit. Here are the limitations they list:

- The tool was created as a practitioner's tool meaning that Benedek and Miner "intentionally traded [rigor from consistency] for richer responses from participants."
- This tool results in qualitative rather than quantitative data. Word counts are not intended to look for statistical significance but to indicate trends that become the foundation for discussion about the product.
- The results from this tool cannot be generalized. In the context of usability evaluations, "[participants] are biased towards information that [researchers] can use to judge the quality of the user experience for the participants who are in [their] usability evaluations and to suggest design changes."

Here are some of the benefits Benedek and Miner noted:

- This tool allows for candid feedback. Participants were more comfortable sharing negative feedback when engaged in conversation.
- The toolkit allowed for quick administration and analysis of the data. Data collection could take "as little as 5-10 minutes" and "recording data right into a form [could] be presented to a product team."
- The product team internalizes the users' message. After observing the participant's interactions with the product, the team is able to gain clarity on what aspects elicit a positive or negative reaction.

As mentioned in section 3.1, Study 1's set of participants had trouble conceptualizing the idea of connectedness when it was presented to them in the form of questionnaires. As to be discussed in section 4.6, the quantitative method was unsuccessful whereas the qualitative findings provided some insight on different types of connectedness. I decided to shift the focus from the questionnaires to the Desirability Toolkit as a more qualitative method.

Using the Desirability Toolkit in Study 2, we asked 18 new participants to think about their experience, rather than the specific data being explored or the performance of the input modality itself, when responding to questions. We customized the original Desirability Toolkit by using a list of 30 words (see Table 5.1) which included 12 words from the original toolkit like "Familiar" and new words derived from those commonly used by participants in Study 1 to describe their experiences. We included words with both their positive or negative associations (e. g., "Unfamiliar") but also added some words that did not have perfect antonyms in our list (e. g., "Awkward" versus "Engaging"). Throughout Study 2, the concept of connectedness first appeared in the Desirability Toolkit (i. e., inclusion of "Connected" and "Disconnected" in our word list) to avoid leading participants. Like in the original methodology, we conducted semi-structured interviews with participants after they had interacted with all modalities.

3.3 Chapter Summary

In this chapter, I described the validated scales used in Study 1. I also introduce the use of the Desirability Toolkit for Study 2. I discuss the intention of using validated scales as past research has done and discuss the shift to a more qualitative methodology.

As mentioned in chapter 2, I started my explorations by incorporating validated scales as my main method for measuring connectedness as prior work has done to measure other abstract concepts. The scales I chose were intentionally meant to target ideas around intrinsic motivation (PENS/IMI), interpersonal interconnectedness (IOS), and arousal and pleasure (Affective Slider) that may contribute to feeling connected to data. As for my second study, I looked to integrate the qualitative responses from my first study into a set of vocabulary (see Table 5.1) that could potentially describe a connected (or disconnected) feeling to the data in the form of the Desirability Toolkit which I described in detail in this chapter.

In the following chapter, I describe my first study and findings from this process in more detail. I provide a deeper look at the qualitative responses from participants regarding their interpretations of what it means to feel connected to data and how this informed modifications for my second study.

Chapter 4

Study 1

In my first study, I was interested in: *i)* understanding how using different interaction modalities (mouse, touch, and physical) could affect people's experience when interacting with visualizations, *ii)* using validated scales as a method to measure participants' feelings of connectedness to data, and *iii)* whether the modality affected how connected one felt to the data. However, after running nine participants we found that our study design was not adequate for our research questions: we outline why in section 4.6 (Findings). To avoid other researchers from encountering similar issues when studying elusive concepts such as connectedness, I provide the details of our initial study design and approach in this chapter.

4.1 Participants

Nine people (7 identifying as women, 2 as men) aged 22 to 28 ($Mdn = 25$) participated in the first study. As mentioned in chapter 3, I had intended to recruit 18 participants. All participants were students completing master's degrees: 5 studying engineering and mathematics fields and 4 environment and political sciences. All self-reported that they preferred to use their right hand to control the mouse. None of them reported a colour deficiency. Six reported familiarity with scatterplots.

4.2 Conditions & Setup

Participants interacted with a scatterplot visualization in three conditions (Figure 4.1):

Figure 4.1: My two exploratory studies compared the experiences people have when manipulating data representations using three different interactions: a) mouse, b) touch, and c) physical.

i) *mouse*: a monitor and a wireless mouse

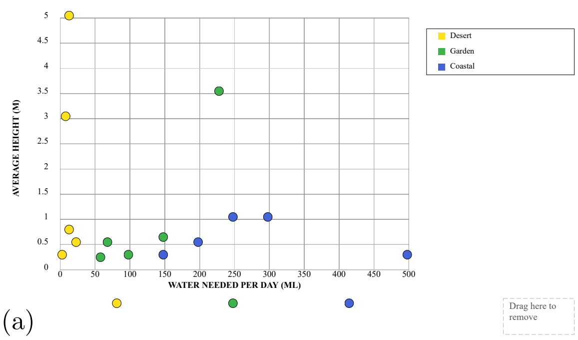
ii) *touch*: a monitor with touch enabled and no mouse

iii) *physical*: a physical non-digital representation

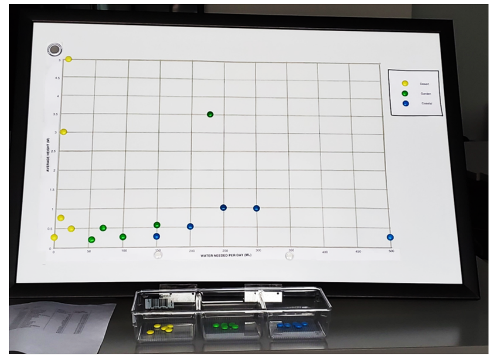
I used a Dell S2340T (1920 × 1080; 53 cm × 31 cm viewable area) monitor for both the mouse and touch conditions. Participants were shown the monitor's tilt capabilities (from 0° to 90°) and asked to adjust to their most comfortable viewing angle. We used a Logitech M325 wireless optical mouse for the mouse condition. For the physical condition, I used a 58 cm × 43 cm whiteboard as the grid space, 0.16 cm grey gridtape as gridlines, and 1.27 cm diameter painted magnetic pieces (resembling an M&M candy-like shape) as data points. The same table acted as the main working space, swapping the monitor for the whiteboard and vice versa as conditions changed. For each condition, I provided participants with printed datasets that were presented in table format. I captured video of each participant for the entirety of their session. I had one front-facing camera and one with a bird's-eye view of the workspace. Participants' digital interactions were captured using screen-recordings.

4.3 Datasets

I used three datasets with topics that participants would not likely be an expert in but should have general knowledge of: plants, tea, and cheese. For example, plant information was grouped into types of plants (desert, garden, and coastal). Information on the 15 plants included their "average height," "amount of water needed per day," "average number of leaves/stems," and a "green thumb rating" indicating how easy it would be to grow a particular plant in one's own home. Real plant names (or cheese or tea varieties) were



(a)



(b)

Figure 4.2: Visualizations: (a) digital representation (mouse and touch conditions) and (b) physical representation (physical condition).

included in the datasets. We introduced trends and outliers in the data to make the tasks more interesting. We ordered the data by group (e. g., the first five plants were always the desert type, followed by garden and coastal types) and coded by colour. Figure 4.2 shows the digital and physical versions of this visualization.

4.4 Tasks

In each condition, participants performed three tasks in the following order:

4.4.1 Task 1: Reconstruct the Visualization

This task got participants familiar with the data by having them identify missing data points. First, I presented the initial visualization to participants and asked them to take a moment to become familiar with it along with its corresponding dataset. The facilitator then concealed the visualization either by turning off the screen or asking the participant to look away from the physical board and randomly selected about half of the data points and removed them from the visualization. The participant was then asked to restore the visualization to its initial state while referring to the printed dataset sheet (i. e., not by memory). For the digital representation, participants could select and drag from an inventory of coloured data points. For the physical representation, I gave participants a tray of coloured magnetic pieces.

4.4.2 Task 2: Modify the Visualization (x-axis)

During this task, participants reconfigured the visualization after a new variable was introduced. First, the facilitator provided the participant with new information associated with the data they viewed during Task 1, noting that the information was the same with the exception of the x-values. For example, in the plant data, "average height" (y-values) would remain the same but "amount of water needed per day" (x-values) would be replaced with "average number of leaves/stems." The facilitator then updated the x-axis by either pressing a key for the digital representation or switching the paper print-out axis values on the physical representation. Since I wanted participants to experience a shift in the data, the facilitator instructed participants specifically not to add or remove points (i. e., clear the grid space) and to "move the points to their new locations." Participants were allowed to reference the dataset used for Task 1, in addition to the new dataset that contained the new variable.

4.4.3 Task 3: Modify the Visualization (y-axis)

Imitating Task 2, the facilitator provided participants with new data built on what they viewed in Task 2, noting that this time only y-values changed. Following the same example, "average number of leaves/stems" (x-values) remained the same, but "average height" (y-values) were replaced with "green thumb rating".

4.5 Procedure & Data Collection

Participants completed a consent form, demographics questionnaire, and digital colour blindness test (Ishihara, 1987). Participants then interacted with scatterplot visualizations under the three conditions with three different datasets. I counterbalanced the order of conditions and datasets using a Latin square. The experimenter instructed participants to take as much time as needed, without needing to be perfect in the placements. After task completion, I asked participants if they noticed anything salient about the data (i. e., trends, outliers): as mentioned above, my motivation was to keep the task interesting. Participants concluded by completing questionnaires using validated scales. To analyze participants' experiences with each interaction modality, I collected questionnaire responses and conducted exit interviews.

4.5.1 Likert-based Questionnaires and Validated Scales

After each condition, I administered questionnaires to participants through Qualtrics, a survey data collection tool[1]. I first asked participants to rate their agreement with the following statement using a 7-point Likert scale: *"The way I moved the data made me feel more connected to it"*. With this question, I intended to get participants to think about the interaction modality (i. e., moving the data either with the mouse's cursor, their finger gliding across a screen, or by physically grasping the data points). The second question was a modified version of Aron's "Inclusion of Others in the Self" scale (Aron et al., 1992) to reflect "Inclusion of Data in the Self," where participants selected the most relevant Venn diagram (out of 7) with increasing degrees of overlap with "Self" in one circle and "Data" in the other. To measure autonomy, competence, and presence and immersion, we included the Player Experience of Needs Satisfaction (PENS) measure (Ryan et al., 2006). To measure intrinsic motivation, we included the Intrinsic Motivation Inventory (IMI) measure (McAuley et al., 1989). To measure levels of arousal and pleasure, we used the Affective Slider for human emotions (Betella and Verschure, 2016).

4.5.2 Exit Interviews

At the end of the study, I conducted semi-structured interviews where I asked participants about their overall thoughts and experiences with each display. I also asked participants how they perceived being asked questions regarding connectedness to data and what their definition of "connectedness" was.

4.6 Findings

Participants completed all three tasks in under 15 minutes on average (approximately 5 minutes per task). This was the case for all three conditions for a total of 45 minutes of modality exposure. As the study progressed, I found that participants had different perceptions of what being connected to the data meant to them which led to confusion in

[1] `http://www.qualtrics.com`

answering questionnaires and validated scales. I thus now present the qualitative findings from my first study in more detail and explain in the following section how they informed changes for Study 2.

When I asked participants how they interpreted connectedness to the data, I received many definitions. I grouped their definitions into three types: being *i)* emotionally, *ii)* physically, and *iii)* cognitively connected to the data.

I categorized personal interest in and what they gained from interacting with data as **emotional** connectedness:

> *"I interpreted [connectedness as]: did [the data] matter to me in some sense. For example, for plants, gardening is a hands-on thing [I did] as a kid. For cheese, I don't eat it except occasionally. For tea, it's half-way in between, drinking tea as a kid." (S1P09)*

When asked about what made their experiences interesting, participants referred to the topic of direct or indirect physical movements. I categorized these as **physical** connectedness:

> *"... [the touchscreen] allowed me to move [data with] my own hand instead of indirectly with a device and a mouse." (S1P03)*

Many participants also discussed engagement as an indicator to how much they learned or understood from the data. I categorized these comments as **cognitive** connectedness:

> *"I thought [connectedness meant] how engaged I felt, like if I felt bored. That's how I thought of the question." (S1P08)*
>
> *"[I interpreted connectedness as] how much I learned from the data, that's what I understood." (S1P02)*

These different interpretations of connectedness indicate a violation of construct validity in the questionnaires, making the quantitative results inconclusive. I, therefore, stopped collecting data after nine participants in Study 1 in order to rethink the study design and focus instead on qualitative measures.

4.7 Chapter Summary

In this chapter, I presented the first exploratory study. Here, I detail the condition and setup, datasets used, and tasks that participants performed. The main method of data collection was validated scales along with semi-structured interviews. I found that results from the validated scales were inconclusive due to conflicting perceptions of what participants thought being connected to the data meant.

One of the main takeaways from this study was found while I was assessing the qualitative findings as I was conducting the study. Interviews with participants revealed that there may be multiple types of connectedness to data. Emotional connectedness seemed to refer to participants' personal interest in the data, even if it meant preferring one generic topic over another. Participants' comments about physical connectedness pertained the most with the way they were interacting with the data, specifically referring to their perceived direct- or indirectness of their movements. Participants also described feeling cognitively connected to the data as they reflected on engagement and learnability from their experiences. As previously mentioned in chapter 2, prior work intentionally focused on the presentation and design of visualizations to evoke feelings of engagement whereas I presented my participants with a simple scatterplot (see Figure 4.2). If feelings of engagement and learnability of the data can still be achieved, ways of interacting could be a contributing factor. In the following chapter, I explore these varying interpretations which provided a foundation for the kind of vocabulary that could be used to describe connectedness to data.

Chapter 5

Study 2

In Study 2, I had the same focus as for Study 1, but steered towards a more qualitative approach to measure participants' feelings of connectedness to data. While I think that further work could generate a scale for the measure of connectedness I was seeking, the scales I chose didn't satisfy this criterium. Therefore, there was a clear need to establish a deeper qualitative understanding of connectedness, which I decided to pursue through the use of the Desirability Toolkit (Benedek and Miner, 2002), rather than a questionnaire-based approach.

5.1 Modifications to Study 1

The details of the conditions and the tasks remained the same as Study 1. Here, I summarize the changes I made to the setup, procedure, and data collection, as well as datasets based on the feedback and observations from Study 1. I piloted each of these iterations before I proceeded with participant recruitment.

5.1.1 Setup, Procedure, & Data Collection

I considered participants' feedback in regards to the physical condition: having a larger whiteboard to avoid overcrowding of data points and being able to adjust its tilt orientation. As such, I upgraded to an 89 cm $\times$ 58 cm whiteboard and added an adjustable easel with the same $0°$ to $90°$ tilt capabilities as the monitor.

I removed the questionnaires that were administered after each condition in Study 1, and replaced them with the Desirability Toolkit as the foundation for the exit interview. However, I did not remove the quantitative aspect completely. Following participant discussions about their word selection choices, I included a single 7-point Likert scale to rate their agreement on feeling connected to the data when using each modality. In contrast to Study 1 where I asked participants to complete questionnaires between conditions, I opted to ask for a score after they had reflected more deeply on all experiences using the Desirability Toolkit words.

5.1.2 Datasets

In Study 1, I chose different topics of data (i. e., plants, tea, and cheese) to counteract boredom and learning effects from seeing the same dataset in each condition. However, participants often inherently ranked the topics, leading them to feel biased towards certain datasets if they considered the content interesting to them rather than their interaction with them, which may have influenced how connected they felt. This was prevalent whenever participants talked about an emotional connection with the content of data. To decouple the feeling of connectedness to the content of the data rather than the interaction, I revised the datasets in each condition so that participants viewed three different datasets that provided information on the single topic: plants (15 different plant varieties for each dataset).

5.2 Participants

I recruited 18 new participants (9 identifying as women, 9 as men) for my second study. All participants were recruited from the same university as Study 1, with 14 completing undergraduate degrees and 5 completing master's degrees. Thirteen participants (including all master's participants) were in engineering, mathematics, and science programs, and the remaining five were in environment, health, and humanities programs. Their ages ranged from 17 to 30 ($Mdn = 21$). All participants stated that their familiarity with scatterplots ranged from "neutral" to "very familiar," and indicated weak to no red-green colour vision deficiencies. One participant was ambidextrous but all self-reported that they preferred to use the mouse with their right hand.

5.3 Data Analysis

For all words in my list I calculated frequencies of word selection for each modality (Table 5.1). I removed words that were not chosen at all. Next I generated participant-word tables for each condition with participants as variables (rows) and words as observations (columns). Each cell of the table contained a 1 if the participant chose the word and a 0 otherwise. On each table we calculated pairwise pearson correlations of all columns using Python's pandas DataFrame.corr function. The output of the computation was a word-word matrix holding correlation coefficients in each cell. On each correlation matrix I performed a hierarchical clustering using Ward's method and a squared Euclidean distance metric. I also generated a node-link graph of pairwise correlations between words, in which words were linked whenever there was a positive correlation (Figure 5.1). This methodology is borrowed from co-word analysis (Callon et al., 1986) and has been used in prior work in Visualization (Isenberg et al., 2017) and HCI (Liu et al., 2014).

Table 5.1: Frequencies of words selected in each condition. Words (except for 'Connected') are ordered by the frequency they were chosen by participants. The asterisk (∗) indicates that the word is in the original Desirability Toolkit word list.

Positive

Words	Mouse	Touch	Physical	Total
Connected	5	6	10	21
Familiar*	11	14	10	35
Direct	6	14	14	34
Straightforward*	9	12	10	31
Convenient*	10	12	6	28
Comfortable	8	9	10	27
Engaging*	3	8	11	22
Satisfying*	4	5	10	19
Stimulating*	4	9	5	18
Close	2	6	8	16
Fun*	3	6	7	16
Free	3	4	7	14
Immersive	0	5	7	12
Insightful	2	3	3	8
Meaningful*	1	2	0	3
Total	71	115	118	304

Negative

Words	Mouse	Touch	Physical	Total
Disconnected	4	0	1	5
Awkward*	9	3	3	15
Dull*	9	3	2	14
Limiting	6	2	6	14
Inconvenient	4	2	5	11
Uncomfortable	5	2	4	11
Boring*	5	2	2	9
Unsatisfying	2	2	4	8
Confusing*	2	3	3	8
Distant	6	0	1	7
Indirect	5	1	1	7
Unstimulating	4	0	2	6
Removed	4	1	0	5
Unfamiliar	1	1	2	4
Unimportant	2	1	1	4
	68	23	37	128

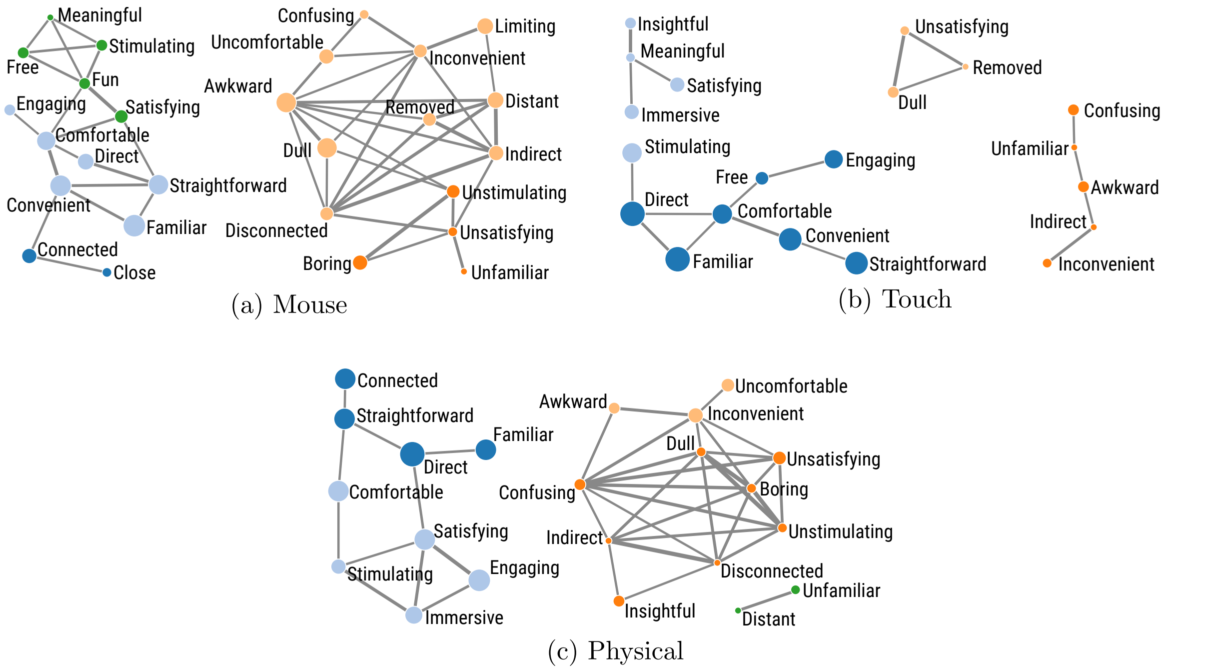


Figure 5.1: Node-link graphs of pairwise correlations between words mentioned by participants for the three conditions: all show more positive words on the left and more negative words on the right. The thicker the link, the stronger the correlation between the words: only connections with correlations larger than .5 are shown. Circle size corresponds to word frequency. Circle colour corresponds to cluster membership derived from a hierarchical clustering on the complete word correlation matrix for each condition.

To perform my qualitative analysis, I adopted elements from Braun and Clarke's 2012 approach to Thematic Analysis. In a traditional thematic analysis, codes are generated upon an initial familiarization with the data and themes are developed and refined. Due to the Desirability Toolkit's use of vocabulary to evoke conversation, the list of "codes" or words I used were predefined. These words were then classified as either positive or negative. In my findings, I discuss the most frequently-selected words in the context of participants' quotes and categorize their experiences into themes within each modality.

5.4 Findings

To present the qualitative findings, I address participants' experiences with the three conditions by analyzing their most frequently-selected positive and negative words, and their responses to questions explicitly asking about connectedness. I also discuss the quantitative results from the Likert-based question that asked if participants felt connected to the data while using each modality.

5.4.1 Mouse Interaction

Eight (out of 18) participants described an overall positive experience while using the mouse, often elaborating on its sense of familiarity and using it in everyday life. However, only 3 of these 8 expressed feeling the most connected to the data when using the mouse compared to the other two types of input. The 10 participants who described an overall negative experience generally explained that while using the mouse was not a bad experience, it didn't offer anything special and was associated with doing work. Figure 5.1a shows strongly-correlated terms mentioned by participants with a large number of negative terms in two orange-coloured clusters on the right and several correlated positive terms form three blue/green clusters on the left.

Conventional Familiarity

Table 5.1 shows the frequencies of words selected by participants in the study. For the mouse condition, the highest counts for positively-associated words were: "Familiar" (11), "Convenient" (10), and "Straightforward" (9). Figure 5.1a illustrates that these words correlated and clustered together. When asked to describe their choices in more detail, 10 participants expressed similar thoughts when using these three words, elaborating that they grew up using a mouse so that it was familiar and that they knew how it worked, making the experience straightforward and convenient for them.

> *"Honestly, ["Familiar"] was the first one that popped in [my] mind immediately just because I use a mouse every day, I've been using them since I was a kid. I know how to click and drag."* (S2P09)

Movement Difficulties and Distance from the Data

The highest counts for negatively-associated words were “Awkward” (9), “Dull” (9), “Distant” (6), and “Limiting” (6), with “Awkward” correlating strongly with “Distant” and “Dull”. When describing the mouse experience with “Awkward”, 5 participants complained about the nature of having to use fine-tuned movements when adjusting points.

> *“The mouse is awkward because you have to be precise with your movements. It’s an external [object], it’s [not as easy as] just using your finger.”* (S2P11)

When elaborating on their choice of “Dull”, 3 participants compared their experience to the other modalities.

> *“I’m expecting [more] from technology, more immersion, and more control. So seeing [the mouse is]... especially when I’m confronted with very much more tactile methods, it just seems [almost] passé or obsolete.”* (S2P04)

In the 3 instances where “Limiting” was described, participants were concerned with physical movement while holding the mouse, as though it was a barrier.

> *“I had to move my hand in such a way that the mouse picked up what I wanted . . . There’s just another extra step for the information flow to go through.”* (S2P04)

When discussing “Distant,” 3 participants referred to the mouse as creating distance from their hand to the screen.

> *“[My] hand’s [on the mouse] and the information’s [on the screen] . . . that just made it feel like I was . . . far away I guess. Imagine I’m writing on a whiteboard, it’s as if I was holding onto a stick attached to a pen writing.”* (S2P18)

Connectedness: Unnatural Movements vs. Well-known Usability

Half of the participants selected either “Connected” (5) or “Disconnected” (4) when reflecting on their mouse experience. I also explicitly asked all participants if they felt more connected to the data while using the mouse. Despite some participants not selecting the words themselves, all were able to elaborate on the idea of connectedness to the data and whether or not they felt it. When asked if they felt connected to the data while using the mouse, this participant expressed the following:

> *"No. [The mouse] felt more familiar ... but it's just one more thing that my information has to go through ... [The mouse is] one more foggy lens in front of my eyes... more like a kaleidoscope. It changes how I see things, I have to rewire my brain into thinking a certain way."* (S2P04)

This participant even characterized the mouse as a foreign object since they perceived that the mouse was interacting with the data rather than themselves.

> *"No. I guess the pointer's kinda like a third arm. It's like I'm not really... it's just moving the [points] around with the mouse. It's not like my hand's on the screen doing it or me picking it up, it's like using a different tool to do it and it's kinda alien-like."* (S2P06)

However, there were 3 participants who specifically expressed that they felt connected to the data while using the mouse due to their familiarity with the device.

> *"With the mouse specifically, it's that connection in the sense that it's working in a sense that I don't notice it. ... [it's not] making me consciously think, 'wow, this is frustrating."'* (S2P09)

In summary, some participants reported a positive experience with the mouse due to its familiarity and well-known usability. However, those who described a negative experience commented on the mouse's tendency to support unnatural movements. Those who mentioned growing up with mice favoured its familiarity while others disliked having their movements constrained.

5.4.2 Touch Interaction

Fourteen participants had overall positive experiences while using the touchscreen, often expressing a preference in using their own hands over using the mouse to manipulate points. From these participants, 7 said they felt more connected to the data while using the touchscreen than with the mouse but less connected than when using the physical board, and 2 said that using the touchscreen made them feel the most connected to the data out of all three modalities. Participants who described an overall negative experience with touchscreens explained that touchscreens were much more recent in their lives so they were not as familiar with them in comparison to the mouse; others disliked minor details about the interface.

Perceived Control Through Hand Movements

The positively-associated words with the highest counts were "Direct" (14), "Familiar" (14), "Convenient" (12), and "Straightforward" (12). These words, along with "Comfortable" (9) and "Stimulating" (9) were strongly correlated in their use and clustered together across participants (Figure 5.1b). Descriptions of "Familiar," "Convenient," and "Straightforward" were very similar to the mouse where participants expressed that they knew how touchscreens worked by just "dragging and dropping." However, this familiarity differed from the mouse where it emulated real-life physical movement.

> *"It was familiar in that it's very related to physical life where you touch something, it moves. You push something, it moves. You pick something up and move it somewhere else."* (S2P04)

Notably, "Direct" was one of the most selected words to describe the touch experience that was not used as frequently for the mouse experience. When elaborating on this word selection, participants often discussed a sense of directness when manipulating the data with their hands, comparing it to the physical condition.

> *"I think it's the same as using the physical board, there's no boundary, it's a one-way interaction between the data point and your hand, me and myself."* (S2P14)

When elaborating their selection of "Stimulating," this participant described their experience as immersive and how the interaction helped them remember insights about the data.

> *"Because I could immerse myself into this environment where I can move the screen and I can physically move the data points, it was stimulating because it immersed me in the data. I felt like I had control over where [the data] was going."* (S2P04)

Favouring the Mouse's Familiarity

The highest counts for negatively-associated words were "Awkward" (3), "Confusing" (3), and "Dull" (3). Only one participant (S2P16) explained her choice of "Confusing" in detail, recalling that she would "move the wrong [data points] and [would] have to fix it."

Participants who used "Dull" referred to more nuanced experiences such as finding the visualization tasks themselves dull (S2P11) or that the texture of the screen felt too 'plasticky' (S2P15). Participants who used "Awkward" explained that touchscreens, although familiar, were not as conventional due to late exposure to them. These were the same participants who felt connected to data while using the mouse due to familiarity.

> *"I haven't been using touchscreens as long [as mouse and keyboard]. If I had been using them that long, then it probably wouldn't have felt as awkward."* (S2P09)

Connectedness: Direct Manipulation vs. Advocating for Mouse

Some participants selected "Connected" (6) while none selected "Disconnected" when reflecting on their touch experience, which didn't necessarily mean none felt disconnected. When asked directly about feeling connected to the data, participants would compare touch to the other modalities. This participant spoke specifically about the way he moved the data:

> *"[Touch] was way more connecting to use [than the mouse]. The visualizations were all the same ... but in terms of actually moving the [data] ... I felt more connected to it as everything I moved was with my hand rather than with a mouse ... when I was done, [I had the] sense of 'okay, I did this' rather than [an] image on the screen."* (S2P05)

The same group favouring the mouse expressed a sense of disconnectedness to touch, as they referred to being more accustomed to the mouse and that this familiarity made them feel more connected.

> *"In terms of connectedness, no. I would say mouse slightly [feels] more connected. It probably has to do with my childhood because I grew up with [a mouse]."* (S2P12)

In summary, people reported touch to be familiar in a similar way to mouse except that participants praised its directness of manipulation and ability to support real-life movements. However, the same group that praised the mouse could not disregard its familiarity.

5.4.3 Physical Interaction

The physical condition had the most overall positive response with 15 participants describing an affinity towards the board's and magnet's tactile qualities. Eleven of these said they felt the most connected to the data when using the physical board than with the other modalities, and 2 said that they felt the same amount of connectedness while using the board and touchscreen. Participants who described an overall negative experience emphasized difficulty in placing points (e. g., long finger nails) or they saw the board as highly impractical in terms of portability.

Satisfying the Sense of Touch

The highest counts for positively-associated words were "Direct" (14), "Engaging" (11), "Connected" (10), "Comfortable" (10), "Familiar" (10), "Satisfying" (10), and "Straightforward" (10). As seen in Figure 5.1c, these words also tended to correlate and cluster together. "Straightforward" was used in a similar way as with the mouse and touch conditions where participants understood how to do the task using the medium.

> *"...you take the magnet, you plot where you think it belongs."* (S2P01)

"Direct" was also a frequently-selected word in the touch condition which participants associated with being able to use their own hands rather than an external device to move data. Here, "Direct" was used to convey the same thought of being able to use one's sense of touch, in addition to being able to actually grasp the data.

> *"I could reach out and touch the data and pick it up and move it somewhere else... it's more of a sense of like, there's nothing between [my] hand and the data."* (S2P09)

"Familiar" was also a frequently-selected word in both mouse and touch conditions, referring to familiarity with using mice as children or touchscreens in their everyday lives. For the physical condition, participants were unfamiliar with using magnets and physical boards to visualize data but equated familiarity with using their hands, some reminiscing about doing hands-on activities during childhood. This idea was also prevalent in participants' explanations for "Comfortable."

> *"It's something you do as a kid. You're used to touching things and moving them around. [It's] something I've always done so it [wasn't] new or different."* (S2P08)

"Engaging" and "Satisfying" were selected the most frequently to describe physical experiences over the other modalities. When elaborating on these word choices, participants referred to the physical board as satisfying their sense of touch by receiving tactile feedback from moving the data.

> *"I was actively engaged in this. [The] big thing is the touching . . . I feel like when there's more sense incorporated, I was more mentally present, per se . . . It was like when I had the touchy feeling, it was more tactile."* (S2P01)

Physical Limitations of Constructive Visualizations

The highest counts for negatively-associated words were "Limiting" (6) and "Inconvenient" (5). Recall that when "Limiting" was used to describe the mouse condition, participants mainly referred to having their movements constrained by using the mouse itself. For the physical condition, participants used "Limiting" and "Inconvenient" to describe a similar constraint on movement but in reference to the physical limitations of using real-life objects such as not being able to place two data points on top of each other securely or not being able to perform a continuous drag due to other data points obstructing their path. There were also concerns over the perceived legitimacy in using a physical board to present data.

> *"It's not going to be taken as seriously . . . You won't always have a big whiteboard and magnets to graph your data so it's physically inconvenient."* (S2P01)

Connectedness: Data Interpretation Through Kinesthetics

Despite the physical limitations of the board, "Connected" (10) was one of the most frequently-selected words while "Disconnected" (1) was not as frequent. Many sentiments toward connectedness related to descriptions of "Engaging" and "Satisfying" where participants felt that because they were 'physically moving the data themselves,' they felt connected to the data. The notion of being able to interpret and understand the data better also emerged.

> *"[I] was actually working with the data ... I could physically move around and to me that felt like I was connected with it. It was more meaningful ... I noticed more patterns. I felt like it was actually something I was doing rather than the menial drag, click, drag, click."* (S2P01)

In summary, participants were not familiar with using a board and magnets to work with data but used the term "familiar" to describe their ability to use their hands to move objects in their everyday lives. For many participants, including some who favoured mouse over touch, the physical modality helped them feel the most connected to the data, perceiving no barrier between their hand and the data.

Reflecting on the qualitative responses from Study 1 and Study 2, people provided richer responses when using the Desirability Toolkit. More specifically, the way people describe some of the interactions are worth highlighting (e. g., describing the mouse as a "kaleidoscope" or a "third-arm"). The toolkit also showed that although people found the physical condition limiting, it didn't affect how connected they felt.

5.5 A Quantitative Score of Connectedness

After the interview concluded, we asked participants to rate their agreement on a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree) with the statement: *I felt connected to the data when interacting with it using this device*, for each modality. Figure 5.2 depicts a significant difference between physical ($M = 5.78$, $SD = 1.80$) and mouse conditions ($M = 4.06$, $SD = 1.70$). Bootstrapped confidence interval difference between physical and mouse at 95% are between 0.50 and 2.72 (does not cross 0). Participants felt more connected to the data in the physical condition than the mouse condition. However, results did not capture significant differences for the touch condition. R scripts for this analysis can be found in Appendix E.

5.6 Chapter Summary

In this chapter, I presented my second exploratory study. The conditions and tasks remained largely the same as in Study 1 with some major modifications: using the same topic for datasets and shifting to a more qualitative approach by using the Desirability Toolkit as the main method of data collection. The findings from this study are presented

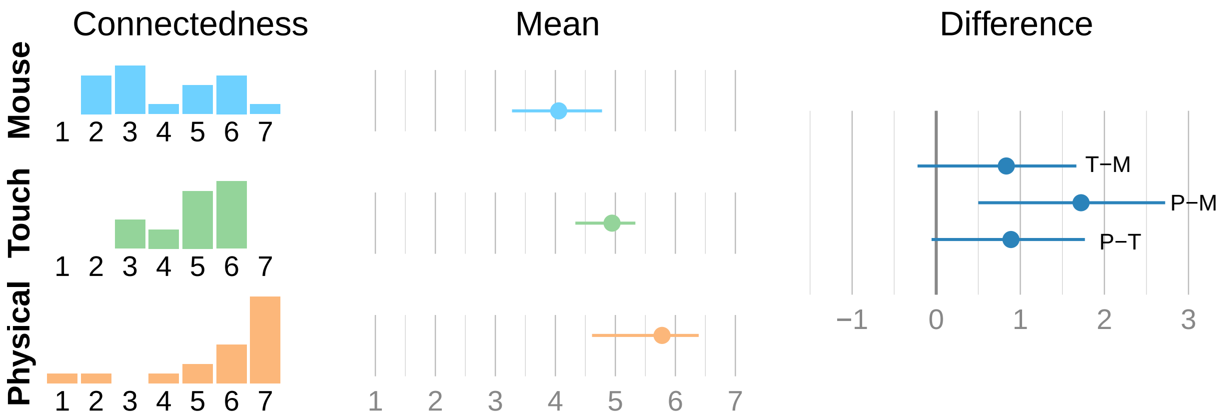


Figure 5.2: Frequencies of agreement scores from connectedness scale used in Study 2 along with bootstrapped confidence interval differences. Pairs with significant differences do not cross the 0 line.

as a combination of word frequencies, word correlations, and explanations provided by participants for their word choices.

Contrasting the previous study, participants did not have conflicting interpretations of connectedness as they were able to pick “Connected” from the word list and explain what aspects of their experience made them feel connected to the data. Alternatively, participants also had no issue explaining why an experience felt “Disconnected”. When describing connectedness while using the mouse, most participants felt a lack of connectedness, associating the interaction with unnatural movements. However, some participants described feeling connected to the data while using the mouse because of their familiarity for the device. When discussing the touch condition, participants talked about connectedness in relation to directness which I discussed as a general benefit in chapter 2. Those who described feeling disconnected to the data while using touch prioritized the mouse’s familiarity. Lastly, the physical condition promoted the highest counts of “Connected” out of all three conditions with many describing the idea of moving physical objects familiar and bing able to understand the data better. While using the Desirability Toolkit showed general likes or dislikes from each condition, the main takeaway from this study is that participants were able to describe feelings of connectedness (or disconnectedness) to data in different conditions.

In the next chapter, I reflect on the findings from both studies. I specifically report on how using the different methodologies in chapter 3 produced very different results when measuring connectedness to data. I also synthesize qualitative findings from each modality to make suggestions on how they affect how people talk about visualizations.

Chapter 6

Discussion

In this section, I discuss how the changes in methodology (see chapter 3 from Study 1 to 2 affected how people talked about connectedness from forming their own interpretations to using a vocabulary to help tease apart this abstract concept. From Study 1, I found that multiple types of connectedness existed (emotional, physical, cognitive). In Study 2, I leveraged Study 1's qualitative findings to create a vocabulary to help people describe connectedness to data which differed depending on interaction modality. Here, I expand on both of these findings by discussing use of different methodologies for studying the elusive concept of connectedness and provide suggestions for what kinds of interactions are better for relating to the data.

6.1 The Complexity of Measuring Connectedness

The progression from Study 1 to Study 2 has shown that measuring connectedness is much more complex than originally thought. The nuance of the idea of "connectedness" wasn't captured in existing validated scales and requires further testing and a deeper qualitative grounding. In Study 1, I found that participants were confused by the questionnaires, often asking, "What do you mean by 'connected'?" This uncertainty prompted participants to produce their own definitions of connectedness, which alluded to the idea that there may be multiple types of connectedness (emotional, physical, and cognitive) to data than originally presumed.

I first reflect on the decision to restrict the topic of the datasets to one. As noted in section 4.3, I originally used three different topics to counteract boredom and learning effects that could arise from seeing the same data in Study 1. Responses from the interviews suggested that the content of the data may have played a role in whether they felt connected (i. e., emotionally) to the data. But I was interested in whether the modality affected how connected one could feel to the data, not the content of the data itself. From the findings from Study 1 and Study 2, I have established that if the main focus of measuring connectedness is to stem from the type of modality, the topic of the data must remain the same. As shown in section 4.6, even if participants do not show a strong preference towards a certain topic, they will find some way to rank their options even if it means reflecting on childhood experiences (S1P09). In Study 2, participants interacted with the same topic. As expected, the interviews revealed no reports of participants showing a preference towards any of the datasets.

The second change I made was reducing the use of validated scales and Likert-based questionnaires in favour of the Desirability Toolkit. From Study 1, I observed that participants had different interpretations of connectedness and were not able to accurately quantify their interaction experience through questionnaires, leading to inconclusive results. One participant made a comment about one of the items from the PENS Presence and Immersion scale in Study 1:

> *"[When] moving through the data I [feel as if] I am [actually in] the data'? Who will agree [with] this? [It's like] I [became] a tulip for a second? Ha ha!"* (S1P05)

Participants from Study 1 often steered towards the performance aspect of each modality, comparing precision and speed rather than feelings of connectedness to the data. While there are instances where speed and accuracy matter, forming connections with data may require slower, more thoughtful interactions and the choice of modality may help or hinder the feeling of connectedness.

When the Desirability Toolkit was introduced in Study 2, participants were able to reflect on various aspects aside from performance such as engagement, directness, and satisfaction. In contrast to S1P05, one participant described her word selection of "Immersion" in the following way:

> *"I was more immersed with the information. It was sort of real ... with [the board], I was touching, doing... like I was actively doing something so it felt like I was part of the data. Not a plant but like... yeah, sorry." (S2P01)*

The stark differences in responses show that connectedness is not easy to measure; yet, these studies show one way to better understand an elusive concept such as connectedness. I demonstrate a progression from participants not understanding what connectedness means to selecting it from a list of words and explaining it in the context of an experience. While I do not claim to have perfected a measurement technique for connectedness, nor do I devalue the use of validated scales, I offer a look into how using a qualitative method, such as the Desirability Toolkit, can tease apart this or similarly abstract concepts with respect to creating or manipulating data visualizations.

6.2 How People Relate to Visualizations

These findings suggest that people talk about visualizations differently depending on modality. In general, using the mouse was interpreted as autonomous or associated with work. While some felt that they were doing "mindless work" (S2P01), others found it comforting:

> *Maybe because in my lab I always work with the mouse, it's very comfortable for me. (S2P13)*

Using touch was often compared to playing a game or offering an interactive perspective when working with the data:

> *"I found [touch] the most fun. I think it's just a combination of using technology and also the physical use of my hands that made it the most enjoyable to me." (S2P06)*

With the physical board, participants discussed the feeling of doing something concrete compared to the digital platforms where they were just moving "a bunch of pixels on a screen." One participant expressed a sense of accomplishment (S2P12) as he and others compared moving the data in real-life to other concrete activities such as handwriting notes and feeling like it has been "worked on."

The topic of mistrust in the digital platforms also emerged. One participant claimed that her data points "just disappeared" off the screen between the time she switched her gaze from the screen to the dataset sheet. Review of her video and screen-recorded session revealed no such occurrences. There was also a fear that storage of digital data would be insecure:

> *"[Technologies are] resilient to a certain extent. The data can be accessed by different types of people. I know that the [physical] board is secure as long as it's in a room and no other person comes into it. I guess it also has to do with my personal mistrust of data . . . " (S2P12)*

Given their presence in everyday life, mouse and touch were unsurprisingly described as familiar, convenient, and straightforward. Both modalities could be used for work or entertainment purposes. In the context of this study, many associated using the mouse with work, simultaneously selecting "Disconnected" to describe their experience. Disconnection, although categorized as a negative word in this study, is not necessarily bad. In situations where people must work with sensitive topics, they may not want to form a connection with it. In these instances, the findings suggest using a mouse can make such data feel "far away."

Touch provided a direct and stimulating experience. Participants' comments about their touch experience reflected a sense of autonomy as they described feeling in control and like they, themselves, were interacting with the data (S2P04, S2P05). Touch also provided a sense of connection with the data in that participants found themselves immersed in it. The cases of personal data, such as self-tracking of personal habits and finances, are good examples of when it is more desirable and useful for people to feel connected to their data. Our findings suggest that using touch to interact with such data can help people remember it better and provide an interactive aspect to better understand patterns or trends.

People felt most connected to the data when using the physical board. Many described feeling satisfied that they were able to touch a concrete data representation. Although many enjoyed this tactile, hands-on experience, they recognized that it was not the most practical in terms of portability, running analyses, and other advantages that the digital forms could potentially have. Despite these limitations, people still felt a sense of assurance with the data because the data was "real" and they had the muscle memory of where they moved the data and how they moved it.

6.3 Chapter Summary

In this chapter, I summarized the findings from both studies and discuss them at a higher level. Reflecting on the progression from Study 1 to Study 2, measuring an elusive concept such as connectedness to data proved to be challenging when trying to quantitatively measure it in Study 1. When presented in a vocabulary list in Study 2, connectedness was actively chosen and explained with ease by participants. These findings show that while connectedness to data is complex, it is still able to be teased apart. Additionally, Study 2 found that participants talked about visualizations differently depending on the modality used. A deeper look into these findings suggest that people's experience may be comfortable, fun, or even untrustworthy depending on the device they use.

Chapter 7

Conclusion

7.1 Contributions

In this thesis I presented two studies that contribute to three main research areas: human-computer interaction (HCI), information visualization (InfoVis), and psychology. The primary contributions of this work are summarized below.

1. A demonstration that a qualitative, experience-focused methodology such as the use of the Desirability Toolkit can be leveraged to understand more nuanced affective experiences, such as "connectedness," in a lab study.

2. Findings from a pair of studies comparing mouse, touch, and physical input suggesting that the modality used to interact with data may influence how people describe feelings of connectedness to the data.

3. An initial look into how the use of vocabulary from the Desirability Toolkit helps people explain the abstract concept of connectedness to data when it comes to different ways of interaction.

7.2 Limitations

The digital and physical representations offered specific interactions with simple scatterplot visualizations. This setup allowed me to confirm that differences in experience with different inputs can clearly exist. In the pilots I also tested the use of bar charts as alternative representations but their token representation was not very *constructive*. As participants found that creating bar charts from scratch became quite tedious, I became concerned about the study duration. Participants also allowed for a smaller margin of error when placing tokens as there was a tendency to align bars perfectly which was not pertinent to our tasks. In some cases, people expected a "snap-to-grid" option in our digital representation which could have been seen as "Convenient", or conversely, "Limiting". This option was also not possible in our physical representation.

7.3 Future Work

While my studies focused on scatterplots, the types of tasks and interactions performed have been similarly applied to a multitude of other visualizations (Yi et al., 2007). It will be interesting to study if the type of data representations and their manipulation with similar tasks and interactions will lead to results different or similar to my findings. Additionally, my studies used generic data (i. e., plants) as to not bias participants into favouring the topics rather than the interaction. It would be interesting to see how levels of connectedness may change when people interact with data they are already invested in.

Unlike the mouse and physical interactions, the touch interaction does not have its own standard way of interacting with visualizations yet: drag-and-drop mimics mouse interaction with a single input, and thus may not be the ideal way for touch especially with a large monitor. For example, a bi-manual interaction might be better suited for adding data points to the scatterplot with touch interaction. For example, tapping on a target location with a finger of a dominant hand while pointing on a data item with a finger of a non-dominant hand was recently introduced in InChorus (Srinivasan et al., 2020). As my studies are concerned with affective reactions, having a novel and more engaging and natural way of manipulating data items with touch could reveal additional value that touch interaction brings to data visualization.

Similarly, I can imagine going beyond a single input modality for interacting with data. For example, it's possible to combine the digital representation (as an output display) with tangibles (as an input method), and see if and how this combination affects people's feeling of connectedness to the data. My study findings provide a glimpse as to what potential digital attributes could bring (e. g., perceived legitimacy) or take away (e. g., feelings of nostalgia or mistrust in digital platforms) to our physical representation. I hope that my work inspires many more interesting ideas to devise and test novel interactions.

Lastly, although the validated scales used in my studies did not translate the idea of connectedness to data well, I believe it would be of great value to develop and validate a scale for connectedness to data. From Study 1, the findings provide a starting point that there exists at least three types of connectedness to data (emotional, physical, cognitive). Study 2 also provides a glimpse into what kind of vocabulary could be implemented into questionnaire items and whether or not certain words should be used with caution as they may allude to multiple meanings.

7.4 Closing Remarks

In this thesis, I presented my findings from two studies conducted to measure how people feel connected to data when interacting with three different input modalities—mouse, touch, and physical; one using quantitative methods (Likert-based questionnaires and validated scales) and the other with a focus on qualitative methods (Desirability Toolkit). Contrary to previous work that has been able to measure other abstract concepts, such as engagement (Amini et al., 2018; Watson et al., 2013), I found that connectedness was different enough that it required us to retrace our steps. By providing a vocabulary to choose from, people were able to seamlessly talk about their interaction experiences with details that went beyond what the questionnaires were measuring. I show that people felt varying levels of connectedness to data when using the different interfaces.

From these insights, I have made suggestions on when certain input modalities would be appropriate for forming connections with data. I showed that while connectedness remains an elusive construct to measure quantitatively, tools such as the Desirability Toolkit can help provide a rich understanding of how the choice of interaction can influence experience and connectedness with a visualization.

References

Amini, F., Henry Riche, N., Lee, B., Leboe-McGowan, J., and Irani, P. (2018). Hooked on data videos: Assessing the effect of animation and pictographs on viewer engagement. In *Proc. AVI*, pages 21:1–21:9, New York. ACM.

Aron, A., Aron, E. N., and Smollan, D. (1992). Inclusion of other in the self scale and the structure of interpersonal closeness. *Journal of Personality and Social Psychology*, 63(4):596–612.

Badam, S. K., Amini, F., Elmqvist, N., and Irani, P. (2016). Supporting visual exploration for multiple users in large display environments. In *Proc. VAST*, pages 1–10, Los Alamitos. IEEE Computer Society.

Ball, R. and North, C. (2007). Realizing embodied interaction for visual analytics through large displays. *Computers & Graphics*, 31(3):380–400.

Bateman, S., Mandryk, R. L., Gutwin, C., Genest, A., McDine, D., and Brooks, C. (2010). Useful junk? The effects of visual embellishment on comprehension and memorability of charts. In *Proc. CHI*, pages 2573–2582, New York. ACM.

Baur, D., Lee, B., and Carpendale, S. (2012). Touchwave: Kinetic multi-touch manipulation for hierarchical stacked graphs. In *Proc. ITS*, pages 255–264, New York. ACM.

Beaudouin-Lafon, M. (2000). Instrumental interaction: an interaction model for designing post-wimp user interfaces. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*, pages 446–453.

Beaudouin-Lafon, M. (2004). Designing interaction, not interfaces. In *Proceedings of the working conference on Advanced visual interfaces*, pages 15–22.

Benedek, J. and Miner, T. (2002). Measuring desirability: New methods for evaluating desirability in a usability lab setting. In *Proc. Usability Professionals Association Conf.*, page 57, Bloomingdale, IL, USA. UPA.

Benko, H. and Wilson, A. D. (2010). Multi-point interactions with immersive omnidirectional visualizations in a dome. In *Proc. ITS*, pages 19–28, New York. ACM.

Besançon, L., Issartel, P., Ammi, M., and Isenberg, T. (2017). Mouse, tactile, and tangible input for 3D manipulation. In *Proc. CHI*, pages 4727–4740, New York. ACM.

Betella, A. and Verschure, P. F. (2016). The affective slider: A digital self-assessment scale for the measurement of human emotions. *PLOS ONE*, 11(2):e0148037:1–11.

Borkin, M. A., Vo, A. A., Bylinskii, Z., Isola, P., Sunkavalli, S., Oliva, A., and Pfister, H. (2013). What makes a visualization memorable? *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2306–2315.

Börner, K., Maltese, A., Balliet, R. N., and Heimlich, J. (2016). Investigating aspects of data visualization literacy using 20 information visualizations and 273 science museum visitors. *Information Visualization*, 15(3):198–213.

Boy, J., Pandey, A. V., Emerson, J., Satterthwaite, M., Nov, O., and Bertini, E. (2017). Showing people behind data: Does anthropomorphizing visualizations elicit more empathy for human rights data? In *Proc. CHI*, pages 5462–5474, New York. ACM.

Bradley, M. M. and Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. *Journal of behavior therapy and experimental psychiatry*, 25(1):49–59.

Braun, V. and Clarke, V. (2012). Thematic analysis. *APA Handbook of Research Methods in Psychology*, 2.

Bruckner, S., Isenberg, T., Ropinski, T., and Wiebel, A. (2019). A model of spatial directness in interactive visualization. *IEEE Transactions on Visualization and Computer Graphics*, 25(8):2514–2528.

Callon, M., Law, J., and Rip, A., editors (1986). *Mapping the Dynamics of Science and Technology*. Palgrave Macmillan, Hampshire, UK.

Domik, G. (2000). Do we need formal education in visualization? *IEEE Computer Graphics and Applications*, 20(4):16–19.

Dourish, P. (2004). *Where the action is: the foundations of embodied interaction*. MIT press.

Grubert, J., Carpendale, S., and Isenberg, T. (2008). Interactive stroke-based NPR using hand postures on large displays. In *Eurographics Short Papers*, pages 279–282, Goslar, Germany. Eurographics Association.

Haroz, S., Kosara, R., and Franconeri, S. L. (2015). Isotype visualization: Working memory, performance, and engagement with pictographs. In *Proc. CHI*, pages 1191–1200, New York. ACM.

Huron, S., Carpendale, S., Thudt, A., Tang, A., and Mauerer, M. (2014a). Constructive visualization. In *Proc. DIS*, pages 433–442, New York. ACM.

Huron, S., Jansen, Y., and Carpendale, S. (2014b). Constructing visual representations: Investigating the use of tangible tokens. *IEEE Transactions on Visualization and Computer Graphics*, 20(12):2102–2111.

Isenberg, P., Isenberg, T., Sedlmair, M., Chen, J., and Möller, T. (2017). Visualization as seen through its research paper keywords. *IEEE Transactions on Visualization and Computer Graphics*, 23(1):771–780.

Isenberg, T., Hinrichs, U., and Carpendale, S. (2009). Studying direct-touch interaction for 2D flow visualization. In *Proc. CoVIS*, pages 17–20, Germany. Univ. of Munich.

Isenberg, T., Isenberg, P., Chen, J., Sedlmair, M., and Möller, T. (2013). A systematic review on the practice of evaluating visualization. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2818–2827.

Ishihara, S. (1987). *Test for colour-blindness*. Kanehara Tokyo, Japan.

Jacob, R. J., Girouard, A., Hirshfield, L. M., Horn, M. S., Shaer, O., Solovey, E. T., and Zigelbaum, J. (2008). Reality-based interaction: a framework for post-wimp interfaces. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 201–210.

Jakobsen, M. R., Sahlemariam Haile, Y., Knudsen, S., and Hornbæk, K. (2013). Information visualization and proxemics: Design opportunities and empirical findings. *IEEE Transactions on Visualization and Computer Graphics*, 19(12):2386–2395.

Jansen, Y., Dragicevic, P., and Fekete, J.-D. (2013). Evaluating the efficiency of physical visualizations. In *Proc. CHI*, pages 2593–2602, New York. ACM.

Jansen, Y., Dragicevic, P., Isenberg, P., Alexander, J., Karnik, A., Kildal, J., Subramanian, S., and Hornbæk, K. (2015). Opportunities and challenges for data physicalization. In *Proc. CHI*, pages 3227–3236, New York. ACM.

Jo, J., L'Yi, S., Lee, B., and Seo, J. (2017). TouchPivot: Blending WIMP & post-WIMP interfaces for data exploration on tablet devices. In *Proc. CHI*, pages 2660–2671, New York. ACM.

Kennedy, H. and Hill, R. L. (2018). The feeling of numbers: Emotions in everyday engagements with data and their visualisation. *Sociology*, 52(4):830–848.

Lam, H., Bertini, E., Isenberg, P., Plaisant, C., and Carpendale, S. (2012). Empirical studies in information visualization: Seven scenarios. *IEEE Transactions on Visualization and Computer Graphics*, 18(9):1520–1536.

Le Goc, M., Dragicevic, P., Huron, S., Boy, J., and Fekete, J.-D. (2016). A better grasp on pictures under glass: Comparing touch and tangible object manipulation using physical proxies. In *Proc. AVI*, pages 76–83, New York. ACM.

Le Goc, M., Perin, C., Follmer, S., Fekete, J.-D., and Dragicevic, P. (2019). Dynamic composite data physicalization using wheeled micro-robots. *IEEE Transactions on Visualization and Computer Graphics*, 25(1):737–747.

Lee, B., Isenberg, P., Henry Riche, N., and Carpendale, S. (2012). Beyond mouse and keyboard: Expanding design considerations for information visualization interactions. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2689–2698.

Lee, R. M. and Robbins, S. B. (1995). Measuring belongingness: The social connectedness and the social assurance scales. *Journal of counseling psychology*, 42(2):232.

Liu, Y., Goncalves, J., Ferreira, D., Xiao, B., Hosio, S., and Kostakos, V. (2014). CHI 1994–2013: Mapping two decades of intellectual progress through co-word analysis. In *Proc. CHI*, pages 3553–3562, New York. ACM.

Lundström, C., Rydell, T., Forsell, C., Persson, A., and Ynnerman, A. (2011). Multi-touch table system for medical visualization: Application to orthopedic surgery planning. *IEEE Transactions on Visualization and Computer Graphics*, 17(12):1775–1784.

McAuley, E., Duncan, T., and Tammen, V. V. (1989). Psychometric properties of the intrinsic motivation inventory in a competitive sport setting: A confirmatory factor analysis. *Research Quarterly for Exercise and Sport*, 60(1):48–58.

Meyer, S., Cohen, O., and Nilsen, E. (1994). Device comparisons for goal-directed drawing tasks. In *Conference companion on Human factors in computing systems*, pages 251–252.

Nancel, M., Wagner, J., Pietriga, E., Chapuis, O., and Mackay, W. (2011). Mid-air pan-and-zoom on wall-sized displays. In *Proc. CHI*, pages 177–186, New York. ACM.

Nielsen, J. (1993). Noncommand user interfaces. *Communications of the ACM*, 36(4):83–99.

North, C., Dwyer, T., Lee, B., Fisher, D., Isenberg, P., Inkpen, K., and Robertson, G. (2009). Understanding multi-touch manipulation for surface computing. In *Proc. Interact*, pages 236–249, Berlin, Heidelberg. Springer.

Ryan, R. M. and Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist*, 55(1):68.

Ryan, R. M., Rigby, C. S., and Przybylski, A. (2006). The motivational pull of video games: A self-determination theory approach. *Motivation and Emotion*, 30(4):344–360.

Sadana, R. and Stasko, J. (2014). Designing and implementing an interactive scatterplot visualization for a tablet computer. In *Proc. AVI*, pages 265–272, New York. ACM.

Sears, A. and Shneiderman, B. (1991). High precision touchscreens: design strategies and comparisons with a mouse. *International Journal of Man-Machine Studies*, 34(4):593–613.

Shneiderman, B. (1993). 1.1 direct manipulation: a step beyond programming languages. *Sparks of innovation in human-computer interaction*, 17:1993.

Smith, D. C., Irby, C., Kimball, R., and Harslem, E. (1982). The star user interface: An overview. In *Proceedings of the June 7-10, 1982, national computer conference*, pages 515–528.

Spence, R. (2001). *Information visualization*, volume 1. Springer.

Srinivasan, A., Lee, B., Henry Riche, N., Drucker, S. M., and Hinckley, K. (2020). Inchorus: Designing consistent multimodal interactions for data visualization on tablet devices. In *Proc. CHI*, New York. ACM.

Van Dam, A. (1997). Post-wimp user interfaces. *Communications of the ACM*, 40(2):63–67.

Walny, J., Lee, B., Johns, P., Henry Riche, N., and Carpendale, S. (2012). Understanding pen and touch interaction for data exploration on interactive whiteboards. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2779–2788.

Watson, D., Hancock, M., Mandryk, R. L., and Birk, M. (2013). Deconstructing the touch experience. In *Proc. ITS*, pages 199–208, New York. ACM.

Wigdor, D. and Wixon, D. (2011). *Brave NUI world: designing natural user interfaces for touch and gesture*. Elsevier.

Wun, T., Payne, J., Huron, S., and Carpendale, S. (2016). Comparing bar chart authoring with Microsoft Excel and tangible tiles. *Computer Graphics Forum*, 35(3):111–120.

Yi, J. S., Kang, Y. A., and Stasko, J. (2007). Toward a deeper understanding of the role of interaction in information visualization. *IEEE Transactions on Visualization and Computer Graphics*, 13(6):1224–1231.

APPENDICES

Appendix A

Digital Scatterplot Application

A.1 Source Code

The source code for the digital application is available at the following repository link: https://osf.io/xrmsp/?view_only=98cf479c41ed470c8e241ef8ed1bf35f.

Appendix B

Research Ethics Materials

B.1 Study 1 & Study 2

UNIVERSITY OF WATERLOO

Name of Researcher, Faculty, Department, Telephone & Email:

Dr. Mark Hancock, Associate Professor – Department of Management Sciences, University of Waterloo
519-888-4567, mark.hancock@uwaterloo.ca
Caroline Wong, MASc Candidate – Department of Management Sciences, University of Waterloo,
519-888-4567, ck4wong@uwaterloo.ca
Dr. Sheelagh Carpendale, Associate Professor, University of Calgary, sheelagh@cpsc.ucalgary.ca
Dr. Bongshin Lee, Senior Researcher – Microsoft Research, U.S., bongshin@microsoft.com
Dr. Nathalie Henry-Riche, Researcher – Microsoft Research, U.S., nathalie.henry@microsoft.com
Dr. Tobias Isenberg, Senior Research Scientist, Inria, France, tobias.isenberg@inria.fr
Dr. Petra Isenberg, Research Scientist, Inria, France, petra.isenberg@inria.fr

Title of Project:
Investigating Differences in User Experience When Exploring Data Visualizations with Touch and Mouse

Sponsor: NSERC
This work is done as part of Caroline Wong's masters thesis.

This consent form, a copy of which has been given to you, is only part of the process of informed consent. If you want more details about something mentioned here, or information not included here, you should feel free to ask. Please take the time to read this carefully and to understand any accompanying information.

Purpose of the Study:

We are interested in differences in user experience when using an interactive touch display and traditional computer and mouse. In particular we are looking at how certain psychological needs are satisfied and how immersive the experience is. We are also interested in how differences between touch and mouse directly effect a data visualization task.

What Will I Be Asked To Do?

You will first be asked to provide some demographic information. You will then be asked to complete two data visualization tasks where you explore two different datasets with a sample scatterplot application. After each task you will be asked to fill out questionnaires on your experience. At the end of the study there will be a short interview about the experience. The study will take approximately 1.5 hours (5 minute demographic questionnaire, 20 minutes for each scatterplot task, 7 minutes each post-task questionnaire, 7 minutes interview). The entire study will be video recorded (with permission), including the post-study interview.

Your participation is entirely voluntary. You may refuse to participate altogether, or may withdraw from the study at any time without penalty or loss of remuneration by stating your wish to withdraw to the researchers. There is no penalty for withdrawing.

What Type of Personal Information Will Be Collected?

Should you agree to participate, you will be asked to provide some basic demographic information, such as age or sex.

Are there Risks or Benefits if I Participate?

There are no known risks or benefits associated with your participation in this research.

Will I Receive Remuneration?

You will be provided with $15 for your participation. The amount received is taxable. It is your responsibility to report the amount received for tax purposes. You will still receive this incentive if you withdraw from the study at any time.

What Happens to the Information I Provide?

You are free to withdraw from this study at any point. If this occurs, we will immediately stop collecting data from you, ensuring that only data for which you have given consent is used. No identifying information (e.g., name) will be recorded with the questionnaires or any data collected.

We will also collect computer logs from the software you are using, and may take notes during the study. These will also be included in the analysis.

All data received from this study will be kept for at least 7 years on a password protected computer, or in a locked cabinet. Only the investigators indicated on this form will have access to the raw data. Surveys in this study will be administered using Qualtrics, however no identifying information will be kept there. When information is transmitted over the internet privacy cannot be guaranteed. There is always a risk your responses may be intercepted by a third party (e.g., government agencies, hackers). University of Waterloo researchers will not collect or use internet protocol (IP) addresses or other information which could link your participation to your computer or electronic device without first informing you. If you prefer not to participate using this online method, please inform of the researchers so you can participate using an alternative method such as a paper-based questionnaire. The alternate method may decrease anonymity but confidentiality will be maintained

There may be reasons to transfer the information we collect to researchers at a different institution. If this is the case, we will make sure that there is no identifying information (name, email, etc) in the information transferred. You will be identified by a number only. Data will be transferred using a secure network or a physical password protected harddrive.

In any reports created based on this study, you will be represented anonymously, using a pseudonym or participant number (e.g. Participant 4). No personal or confidential information will be published.

Questions/Concerns

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee (ORE #21825). If you have questions for the Committee contact the Chief Ethics Officer, Office of Research Ethics, at 1-519-888-4567 ext. 36005 or ore-ceo@uwaterloo.ca.

If you have any further questions or want clarification regarding this research and/or your participation, please contact:

Dr. Mark Hancock,
Department of Management Sciences
519.888.4567, mark.hancock@uwaterloo.ca

Caroline Wong
Department of Management Sciences
519.888.4567, ck4wong@uwaterloo.ca

Consent

A copy of this consent form has been given to you to keep for your records and reference. The investigator has kept a copy of the consent form. By signing this consent form, you are not waiving your legal rights or releasing the investigator(s) or involved institution(s) from their legal and professional responsibilities."

Please put a check mark on the corresponding line(s) that grants us your permission to:

With full knowledge of all foregoing, I agree, of my own free will, to participate in this study	*YES __*	*NO __*
I agree to let my answers collected in the questionnaires be directly quoted, anonymously, in the presentation of the research results.	*YES __*	*NO __*
I agree to allow researchers to video-record me during the session.	*YES __*	*NO __*
I agree to allow researchers to screen-record me during the session.	*YES __*	*NO __*
I agree to let my answers to the questionnaires and interview be reported in anonymous, aggregate form, in the presentation of the results.	*YES __*	*NO __*
I agree to let any of my quotes collected through video-recording the session to be used anonymously, in the presentation of the research results.	*YES __*	*NO __*

Participant Name: ________________________________ (Please print)

Participant Signature: ________________________________

Witness Name: ________________________________ (Please print)

Witness Signature: ________________________________ Date: _YYYY_ /_MM_/_DD_

UNIVERSITY OF
WATERLOO

Feedback Letter

Dear participant,

I would like to thank you for your participation in this study. As a reminder, the main purpose of this study is to look at the differences between user experience between using a touch screen and using a mouse when looking at data visualizations. Your participation will help us better understand how users' psychological needs, mood and motivation are affected. If you wish to be further informed about the results of the study, please contact ck4wong@uwaterloo.ca.

Sincerely,

Caroline Wong

Student Investigator

Department of Management Sciences

This study has been reviewed and received ethics clearance through a University of Waterloo Research Ethics Committee (ORE #21825). If you have questions for the Committee contact the Chief Ethics Officer, Office of Research Ethics, at 1-519-888-4567 ext. 36005 or ore-ceo@uwaterloo.ca.
For all other questions contact Caroline Wong at ck4wong@uwaterloo.ca or Dr. Mark Hancock at mark.hancock@uwaterloo.ca.

Department of Management Sciences
University of Waterloo

Participants Needed For Research in Human Computer Interaction

We are seeking participants to explore data visualizations using a touch screen and a traditional computer and mouse. Participants will also be using physical objects (e.g., blocks). We are looking at the differences in user experience in between each device.

Your participation will take place by exploring a scatterplot visualization games, one on each input device. In between each session you will be asked to answer questionnaires about the experience. The study will take approximately 1.5 hours. In appreciation of your time you will receive $15.

Contact Caroline Wong at ck4wong@uwaterloo.ca

This study has been reviewed by and received ethics clearance through a University of Waterloo Research Ethics Committee

Touch Data Study
ck4wong@uwaterloo.ca

Touch Data Study
ck4wong@uwaterloo.ca

Touch Data Study
ck4wong@uwaterloo.ca

Touch Data Study
ck4wong@uwaterloo.ca

Touch Data Study
ck4wong@uwaterloo.ca

Touch Data Study
ck4wong@uwaterloo.ca

Touch Data Study
ck4wong@uwaterloo.ca

Touch Data Study
ck4wong@uwaterloo.ca

Touch Data Study
ck4wong@uwaterloo.ca

Touch Data Study
ck4wong@uwaterloo.ca

Appendix C

Validated Scales

C.1 PENS

1. I feel competent with this data.
2. I feel very capable and effective when interacting with the data.
3. My ability to interact with the data is well matched with this dataset's challenges.
4. This data provides me with interesting options and choices.
5. This data lets you do interesting things.
6. I experienced a lot of freedom with this data.
7. Learning the way I interact with the data was easy.
8. The ways one interacts with the data is intuitive.
9. When I wanted to do something with the data, it was easy to remember the corresponding interaction.
10. When working with the data, I feel transported to another time and place.
11. When working with the data, it feels like my surroundings disappear.
12. When moving through the data I feel as if I am actually in the data.

13. I am not impacted emotionally by the data.
14. The data was emotionally engaging.
15. I experience feelings as deeply while working with the data as I have in real life.
16. When working with the data I feel as if I was part of a story.
17. When I accomplished something with the data I experienced genuine pride.

C.2 IMI

1. I enjoyed this task very much.
2. Doing this task was fun.
3. I would describe this task as very interesting.
4. While doing this task, I was thinking about how much I enjoyed it.
5. This task did not hold my attention.
6. I think I am pretty good at this task.
7. I am satisfied with my performance on this task.
8. After doing this task for a while, I felt pretty competent.
9. I am pretty skilled at this task.
10. I couldn't do this task very well.
11. I put a lot of effort into this task.
12. It was important to me to do well at this task.
13. I tried very hard while doing this task.
14. I didn't try very had at doing this task.
15. I felt tense while doing this task.
16. I felt pressured while doing this task.
17. I was anxious while doing this task.
18. I was very relaxed while doing this task.

C.3 Inclusion of Other in the Self

Inclusion of Other in the Self (IOS) Scale

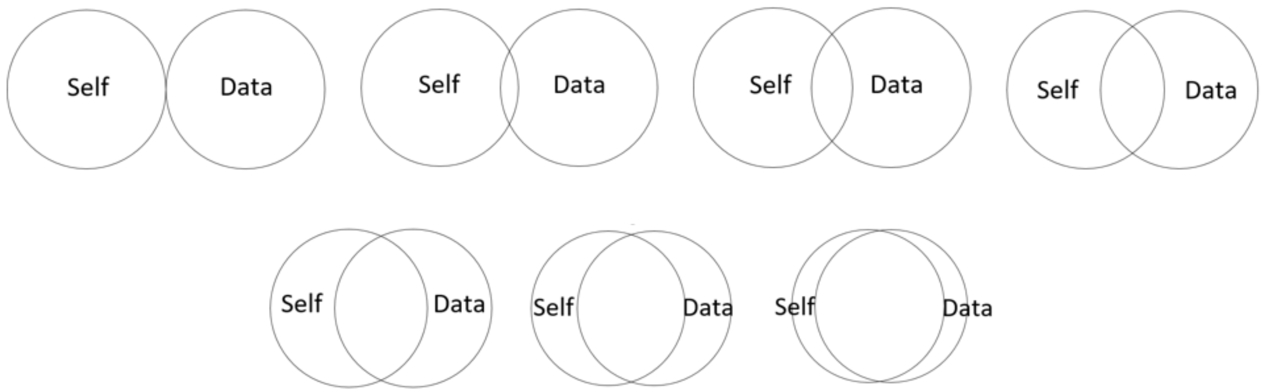
This survey accompanies a measure in the SPARQTools.org Measuring Mobility toolkit, which provides practitioners curated instruments for assessing mobility from poverty and tools for selecting the most appropriate measures for their programs.To get a copy of this document in your preferred format, go to "File" and then "Download as" in the toolbar menu.

Age: Child, Teen, Adult
Duration: < 3 minutes
Reading Level: 9th to 12th grade
Number of items: 1
Answer Format: Circle a diagram

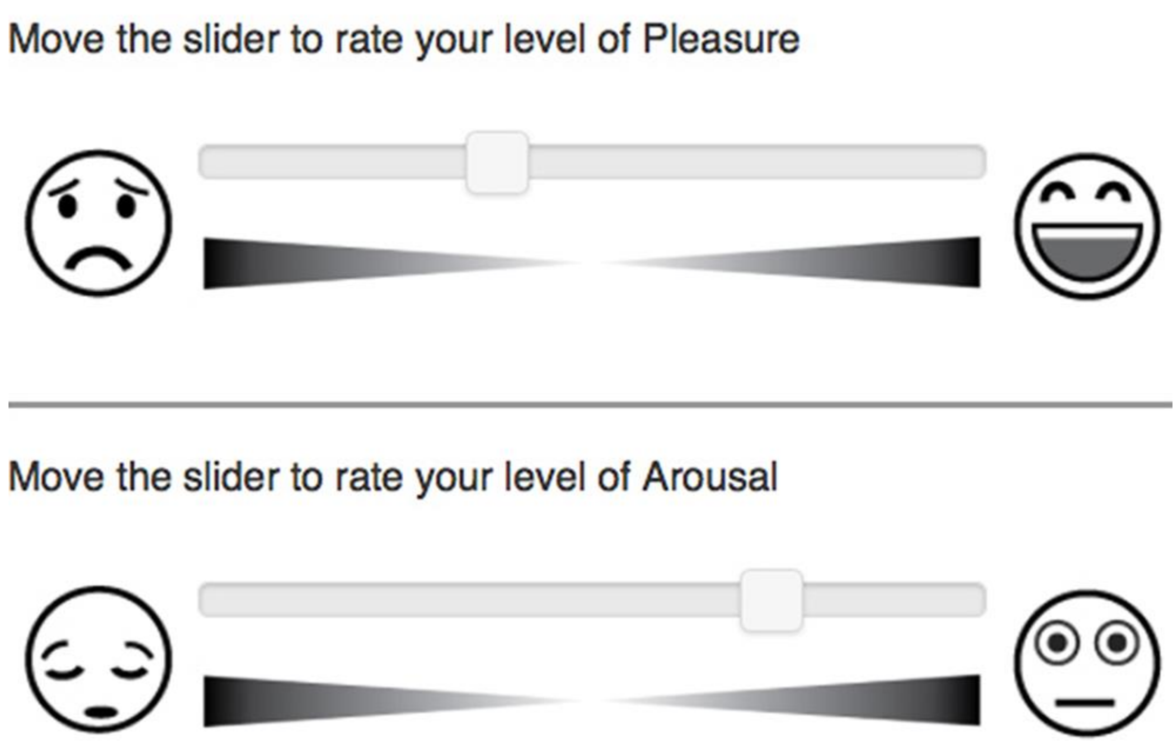
Scoring: Respondents choose a pair of circles from seven with different degrees of overlap. 1 = no overlap; 2 = little overlap; 3 = some overlap; 4 = equal overlap; 5 = strong overlap; 6 = very strong overlap; 7 = most overlap. The number chosen is the respondent's score.

Sources:
Aron, A., Aron, E. N., & Smollan, D. (1992). Inclusion of other in the self scale and the structure of interpersonal closeness. *Journal of Personality and Social Psychology, 63*(4), 596-612.

Instructions: Please circle the picture that best describes the extent to which you feel connected to the data you just interacted with.



C.4 Affective Slider



Appendix D

Desirability Toolkit

D.1 Word Choice Sheets

Participant #: YourCompanyName

Step 1: Read over the following list of words. Considering your experience with the data when you interacted with it using ________, tick those words that best describe your experience. You can choose as many words as you wish

- ☐ Awkward
- ☐ Boring
- ☐ Close
- ☐ Comfortable
- ☐ Confusing
- ☐ Connected
- ☐ Convenient
- ☐ Direct
- ☐ Disconnected
- ☐ Distant

- ☐ Dull
- ☐ Engaging
- ☐ Familiar
- ☐ Free
- ☐ Fun
- ☐ Immersive
- ☐ Inconvenient
- ☐ Indirect
- ☐ Insightful
- ☐ Limiting

- ☐ Meaningful
- ☐ Removed
- ☐ Satisfying
- ☐ Stimulating
- ☐ Straightforward
- ☐ Uncomfortable
- ☐ Unfamiliar
- ☐ Unimportant
- ☐ Unsatisfying
- ☐ Unstimulating

Step 2: Now look at the words you have ticked. Circle five of these words that you think are most descriptive of your experience.

Appendix E

R Scripts from Analysis

E.1 R Scripts

Scripts used to analyze connectedness likert data. Original source: https://aviz.fr/blinded from Pierre Dragicevic and Yvonne Jansen (2017).

Additional scripts and analyses is available at the following repository link: `https://osf.io/xrmsp/?view_only=98cf479c41ed470c8e241ef8ed1bf35f`.

```
################################################################################
# Scripts used to analyze connectedness likert data.
# Scripts used: "CI.helpers.R", "misc.helpers.R", "plotting functions.R"
#
# Source: https://aviz.fr/blinded
# 2017 Pierre Dragicevic, Yvonne Jansen
################################################################################

# Clean up memory
rm(list = ls())

library('dplyr')
library('plyr')

source("CI.helpers.R")
source("misc.helpers.R")
source("plotting functions.R")

# indicated whether we want ggplot to save the generated plots
save_plots <- TRUE
# print plots to screen
print_plots <- TRUE

results_file <- "likert_for_mark"
figure_path <- "plots/"

# Values reported by Tal and Wanksink to add to our plots as a comparison
bws_nochart <- 6.12
bws_chart <- 6.83
```

```
bws_p <- 0.04

data <- read.csv(paste("data/", results_file, ".csv", sep=""), sep = ",")

# Column is present in experiment 1, which replicates the question from BwS experiment 1
# if("effectiveness" %in% colnames(data)) {
#   conn_mouse <- data[data$condition=="no_graph",]$effectiveness
#   conn_touch <- data[data$condition=="graph",]$effectiveness
#   variable_name <- "Perceived effectiveness"
# }
conn_mouse <- data$mouse
conn_touch <- data$touch
conn_phys <- data$physical
variable_name <- "Connectedness"

##### CIs for connectedness on a 1--7 scale

mean_conn_mouse <- meanCI.bootstrap(conn_mouse)
mean_conn_touch <- meanCI.bootstrap(conn_touch)
mean_conn_phys <- meanCI.bootstrap(conn_phys)

mean_conn_diff_mt <- diffMeanCI.bootstrap(conn_touch, conn_mouse)
mean_conn_diff_mp <- diffMeanCI.bootstrap(conn_phys, conn_mouse)
mean_conn_diff_tp <- diffMeanCI.bootstrap(conn_phys, conn_touch)

print.title(variable_name)
cat("Mean connectedness mouse: ", format_ci(mean_conn_mouse), "\n")
cat("Mean connectedness touch:    ", format_ci(mean_conn_touch), "\n")
cat("Mean connectedness physical: ", format_ci(mean_conn_phys), "\n")
```

```
cat("Difference (mouse vs. touch):           ", format_ci(mean_conn_diff_mt), "\n")

cat("Difference (mouse vs. physical):        ", format_ci(mean_conn_diff_mp), "\n")

cat("Difference (touch vs. physical):        ", format_ci(mean_conn_diff_tp), "\n")


# NHST version for comparison (used in the original paper, but not part of this planned analysis)


ttest_mt <- t.test(conn_touch, conn_mouse)

ttest_mp <- t.test(conn_phys, conn_mouse)

ttest_tp <- t.test(conn_phys, conn_touch)

mean_conn_diff_normal_mt <- c(mean(conn_touch)-mean(conn_mouse), ttest_mt$conf.int[1],
ttest_mt$conf.int[2])

mean_conn_diff_normal_mp <- c(mean(conn_phys)-mean(conn_mouse), ttest_mp$conf.int[1],
ttest_mp$conf.int[2])

mean_conn_diff_normal_tp <- c(mean(conn_phys)-mean(conn_touch), ttest_tp$conf.int[1],
ttest_tp$conf.int[2])

cat("(m v. t, using a t-test)       ", format_ci(mean_conn_diff_normal_mt), "p =",
format_number(ttest_mt$p.value), "\n")

cat("(m v. p, using a t-test)       ", format_ci(mean_conn_diff_normal_mp), "p =",
format_number(ttest_mp$p.value), "\n")

cat("(p v. t, using a t-test)       ", format_ci(mean_conn_diff_normal_tp), "p =",
format_number(ttest_tp$p.value), "\n")


# Display distributions of efficacy judgments and confidence intervals for estimates


## compile CIs and BwS results into a dataframe for plotting

eff_df <- NULL

eff_df <- add.ci.to.df(mean_conn_mouse, "mouse", "mouse", eff_df)

# eff_df <- add.ci.to.df(c(bws_nochart, bws_nochart, bws_nochart), "no chart", "BwS", eff_df)

eff_df <- add.ci.to.df(mean_conn_touch, "touch", "touch", eff_df)

# eff_df <- add.ci.to.df(c(bws_chart, bws_chart, bws_chart), "chart", "BwS", eff_df)
```

```
eff_df <- add.ci.to.df(mean_conn_phys, "physical", "physical", eff_df)


eff_diff_df <- NULL

eff_diff_df <- add.ci.to.df(mean_conn_diff_mt, "mt", "diff1", eff_diff_df)

eff_diff_df <- add.ci.to.df(mean_conn_diff_mp, "mp", "diff2", eff_diff_df)

eff_diff_df <- add.ci.to.df(mean_conn_diff_tp, "tp", "diff3", eff_diff_df)

# eff_diff_df <- add.ci.to.df(ci_from_p(bws_chart - bws_nochart, bws_p), " ", "BwS", eff_diff_df)


# plotting for experiment 1

eff.hist.mouse <- histo(conn_mouse, 7, "mouse", 0, 1, fillvectorMouse)

eff.hist.touch <- histo(conn_touch, 7, "touch", 0, 1, fillvectorTouch)

eff.hist.phys <- histo(conn_phys, 7, "physical", 0, 1, fillvectorPhys)

eff.cis <- connectedness.ciplot(eff_df, eff_diff_df)


plot <- drawVertical(eff.hist.mouse, eff.hist.touch, eff.hist.phys, eff.cis, name.eff.exp1, "Difference")

if (save_plots) save_plot(paste(sep= "", figure_path, "perceived_connectiveness_plot.pdf"), plot,
base_aspect_ratio = 3, base_height = 2)

if (print_plots) print(plot)
```