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Interactions in Visualizations to Support Knowledge Activation

Kari Sandouka

INTERACTIONS IN VISUALIZATIONS
TO SUPPORT KNOWLEDGE ACTIVATION

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By
Kari Sandouka

Dissertation Committee:

Dr. Cherie Noteboom
Dr. Jun Liu
Dr. Surendra Sarnikar

DISSERTATION APPROVAL FORM

This dissertation is approved as a credible and independent investigation by a candidate for the Doctor of Philosophy degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this dissertation does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department or university.

Student Name: Kari Sandouka

Dissertation Title: Interactions in Visualizations to Support Knowledge Activation

Dissertation Chair/Co-Chair: Cherie Noteboom Date: May 4, 2020
Name: Cherie Noteboom

Dissertation Chair/Co-Chair: Date:
Name:

Committee member: Jun Liu Date: May 4, 2020
Name: Jun Liu

Committee member: Surendra Sarnikar Date: May 5, 2020
Name: Surendra Sarnikar

Committee member: Date:
Name:

Committee member: Date:
Name:

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ABSTRACT

Humans have several exceptional abilities, one of which is the perceptual tasks of their visual sense. Humans have the unique ability to perceive data and identify patterns, trends, and outliers. This research investigates the design of interactive visualizations to identify the benefits of interacting with information. The research question leading the investigation is *how does interacting with visualizations support analytical reasoning of emergent information to activate knowledge?* The study uses the theory of distributed cognition and human-information interaction to apply the design science research framework. The motivation behind the research is to identify guidelines for interactive visualizations to enhance a user's ability to make decisions in dynamic situations and apply knowledge gleaned from the visualization. An experiment is used to analyze the use of an interactive dashboard in a dynamic decision-making situation. The results of this experiment specifically look at the combination of interactions as they support the distribution of cognition over three spaces of a human-visualization cognitive system. The results provide insight into the benefits that interactions have for enhancing analytical reasoning, expanding the use of visualizations beyond communicating or disseminating information. Providing a broad range of interactions that work with multiple views of information increases the opportunities that users have to complete tasks. This research contributes to the information visualization discipline by expanding the focus from representing data to representing and interacting with information. Secondly, my results provide an example of a qualitative assessment based on the value of visualization, in comparison to traditional usability assessment.

DECLARATION

I hereby certify that this dissertation constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

I declare that the dissertation describes original work that has not previously been presented for the award of any other degree of any institution.

Signed,

Kari Sandouka

Kari Sandouka

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CHAPTER 1

INTRODUCTION

Background of the Problem

Data is the force behind how we learn, make decisions, and apply knowledge. Leveraging data is allows organizations to gain and maintain a competitive edge because it provides insights into products, services, business processes, and management control activities. The demand for automated processes to deal with data creates a dependence on computational tools and techniques which extend, partner, supplement, and support human cognition (Bumblauskas, Nold, Bumblauskas, & Igou, 2017; Davenport, Barth, & Bean, 2012). The velocity and volume of data create an inherent problem relating to comprehension and understanding. To deal with the velocity and volume of data, we need a mediating layer of abstraction, such as visualization (Berinato, 2016).

Visualizations provide a powerful means for making sense of data. Information visualizations refer to "the process of creating a mental understanding and notion of a concept by conveying information to the mind through perception channels (Meyer, Thomas, Diehl, Fisher, & Keim, 2010)." Information visualizations support human cognition by providing solutions to decrease information overload, support sensemaking, and assist with decision-making. The rate at which data is generated, collected, and stored creates hidden but valuable insights. Visualizations are a way to reveal hidden insights by combining the strengths of computers with those of humans (Hornbæk & Oulasvirta, 2017; Parsons & Sedig, 2014a). As visualizations help to reduce information overload, their structure creates a secondary problem. The single issue is no longer not having the right data at the right time. Instead, it transitions to having the ability to identify methods that can turn data into knowledge (Kohlhammer, May, & Hoffmann, 2009).

Information visualizations include interactive controls that empower users to explore data. It is unclear how the use of interactions results in better decision-making processes that activate knowledge. Despite extensive research into visualization design, there are lingering questions about the compatibility between how interactions are designed and how humans think and reason (Davenport, 2012; Kodagoda, Attfield, Wong, Rooney, & Choudhury, 2013; Matthew O. Ward, Grinstein, & Keim, 2015). Literature about information visualization has largely ignored interaction design. The prevailing assumption for interactions is that providing the mechanisms is sufficient, but this does not ensure that visualizations are useful or valued (Park, Bellamy, & Basole, 2016; Parsons, Sedig, Didandeh, & Khosravi, 2015).

Statement of the problem

Enabling users to explore information requires appropriate interactions for specifying how information is displayed and what information to display (J. Heer & Shneiderman, 2012). Interaction is fundamental to visualizations, but research hardly explains the benefits of how and why interactions work (Aigner, 2011). Ware (2012) describes interactive visualizations as a cognitive tool, much like a pencil or calculator. Extant research provides evidence for how static displays support cognitive activities, but the same evidence does not exist for interactive or dynamic visualizations (Endert, Chang, North, & Zhou, 2015; Parsons & Sedig, 2014a). As more information systems leverage the use of visualizations, there is a greater need for understanding the effectiveness of interactive controls (Munzner, 2014; Saket, Srinivasa, Ragan, & Endert, 2018).

The user is often separated from design activities for information visualization, resulting in a product that leads to the misinterpretation of data and error-prone decision making (Few, 2006). An ineffective visualization may cause pointless exploration, inaccurate or false knowledge, lost time, or lack of utilization due to frustration and confusion (Yalçin, Elmqvist, & Bederson, 2016). The lack of information or the abundance of information does not lead to ineffective visualization designs. The failure to anticipate people’s needs forms the basis of most information problems and poor decision making (Albers, 2012). Designers often strive for creating an impressive visual impact rather than generating accurate knowledge and decisions (Green, Wakkary, & Arias-Hernandez, 2011; Oghbaie, Pennock, & Rouse, 2016).

No single visual representation or interaction technique will be optimal for all tasks, leaving designers confounded with multiple design options. To create an impressive visual impact, designers often opt for a data-centric or task-centric approach to designing visualizations. On the other hand, human-centric techniques allow for the identification of the information needs required by sensemaking and decision-making processes. Focusing on the information needs will guide designers in implementing the appropriate interaction methods to support the right amount of information (Park et al., 2016). There is a lack of academic literature that supports the human-centric approach to visualization design, where the focus changes from what data is available to assist human reasoning (Kodagoda et al., 2013).

Objectives of the project

The purpose of this study is to explore how interactive visualizations support knowledge activation through analytical reasoning in dynamic decision-making situations. I endeavor to contribute to a better understanding of how the design of interactive visualizations supports human reasoning efforts. I offer theoretical and practical research guided by four objectives:

1) Visualization interfaces lack intuitive controls for interaction. The first objective is to identify affordances that are intuitive and easy to learn for users interacting with information.
2) The process of designing and developing visualization is a complicated endeavor created by ambiguously defined terms and taxonomies that are scattered across multiple disciplines. The second objective is to identify and consolidate terms and taxonomies for information visualization into a cohesive format.
3) Information Visualizations are often treated solely as communication tools. The opportunities for analysis activities are primarily ignored in academic literature. The third object is to demonstrate the benefits of visualizations for analysis activities, going beyond disseminating information.
4) There is little to no discussion of how knowledge is activated from using the interactive components within visualizations. The fourth object is to provide evidence that visualizations generate new or enhance existing knowledge leading to activation efforts.

This research aims to reduce the previously discussed gaps by developing an understanding of the interaction mechanisms through which visualizations improves knowledge activation. I draw upon the theory of distributed cognition and Human-Information Interaction (HII) to develop an empirical study. I strive to make the following contributions to information visualization research. First, I endeavor to define a connection between design theory and design practice for interactive visualizations, as defined by the first two objectives. Second, I expand on previous research of macro-level interactivity to investigate a holistic view of a visualization interface and how all elements support cognitive activities, as defined by the last two objectives.

CHAPTER 2

LITERATURE REVIEW

Theoretical Foundations

Knowledge Creation and Activation

Business intelligence is a process used by organizations to obtain, analyze, and distribute information and knowledge. It enables decision making by presenting information through perceptual interfaces, such as dashboards or scorecards (Sabherwal & Becerra-Fernandez, 2011). Business intelligence systems facilitate the decision-making process through four contributions: (1) disseminating information (real-time and historical), (2) generating the opportunity for new knowledge creation, (3) supporting conscious and anticipative decisions, and (4) providing information for future planning (Sabherwal & Becerra-Fernandez, 2011). Business intelligence facilitates these benefits through the use of visualizations. The variety of visualizations used by business intelligence systems require users to interpret and draw conclusions in a myriad of ways (Wakeling, Clough, Wyper, & Balmain, 2015). Unfortunately, human behavior is complex. There is no guarantee that the user viewing the information will recognize that there is a need to act, will be in the position to act, and will know how to act (Kirk, 2016).

The Analytical Capability Model encapsulates a holistic view of the process that uses data to produce outcomes (Davenport, Harris, De Long, & Jacobson, 2001). There are three layers in the model: context, transformation, and outcome. The context layer forms the basis of the model and consists of factors including strategy, skills and experience, organizational culture, technology, and data. These factors are not static; they are dependent on the interchange between each other. Turning data into results is a synergistic effort, not based on any single factor (Davenport et al., 2001). The transformation layer builds off contextual factors and guides analysis and decision making. Transformations of data develop insight, which is the process of converting data into knowledge. The last layer of the model represents outcomes, which are financial, procedural, or behavioral. Behavioral outcomes indicate acceptance or adoption of results. Procedural or process changes are implemented after behavioral changes. The combination of behavioral and procedural outcomes result in financial or economic changes in the organization (Davenport et al., 2001).

The starting point of the analytical capability model is data. Information Systems research often distinguishes between data, information, and knowledge. These three elements are often viewed as a hierarchy, with data as the foundation and knowledge at the top. Other views of the data-knowledge relationship include feedback loops where all the elements reinforce each other. In most cases, knowledge is derived from information, and information is derived from data. These models acknowledge that knowledge consists of experience, values, and insight (Wang et al., 2009). Information becomes knowledge through activities such as making comparisons, thinking of consequences, making connections, and sharing opinions through conversation (Levy, Pliskin, & Ravid, 2010). A valuable resource within today's organization is the knowledge residing individually and collectively among employees. Knowledge management systems are a type of information system that captures and share organizational knowledge. Effective knowledge management is considered key to achieving competitive advantage through behavioral and financial changes (Becerra-Fernandez & Sabherwal, 2001).

Knowledge management consists of four processes to handle knowledge: discover, capture, share, and apply (Becerra-Fernandez & Sabherwal, 2015). The four processes describe activities that occur within knowledge management, are further defined by seven sub-processes. The sub-processes directly relate to the interplay of tacit and explicit knowledge, as described by Nonaka (1994). Tacit knowledge is private, internal, and subjective. Tacit knowledge refers to personal experience, which is hard to translate to different forms of communication (Chilton & Bloodgood, 2008; Nonaka, 1994). Explicit knowledge is public, objective, and easy to share. Explicit knowledge is easily converted to numbers or symbols that are well understood (Chilton & Bloodgood, 2008; Nonaka, 1994).

The four modalities of the knowledge generation model are sub-processes to the knowledge management processes of discovery and capture. Discovery is the development of new knowledge from data and information. The production of knowledge occurs in one of two ways a) the data and information provide brand new insights or b) the data and information provide a new perspective that builds off prior knowledge. Capture is the retrieval of knowledge from people, artifacts, or organizations (Becerra-Fernandez & Sabherwal, 2015). The combination and externalization modalities convert tacit to new explicit knowledge, and the socialization and internalization modalities convert explicitly to new tacit knowledge (Nonaka, 1994). The sharing process communicates knowledge, whether tacit or explicit. The application process is when knowledge is used to make decisions and perform tasks (Becerra-Fernandez & Sabherwal, 2015). Application of knowledge may only occur when knowledge is available, which is dependent upon the discovery, capture, and sharing processes.

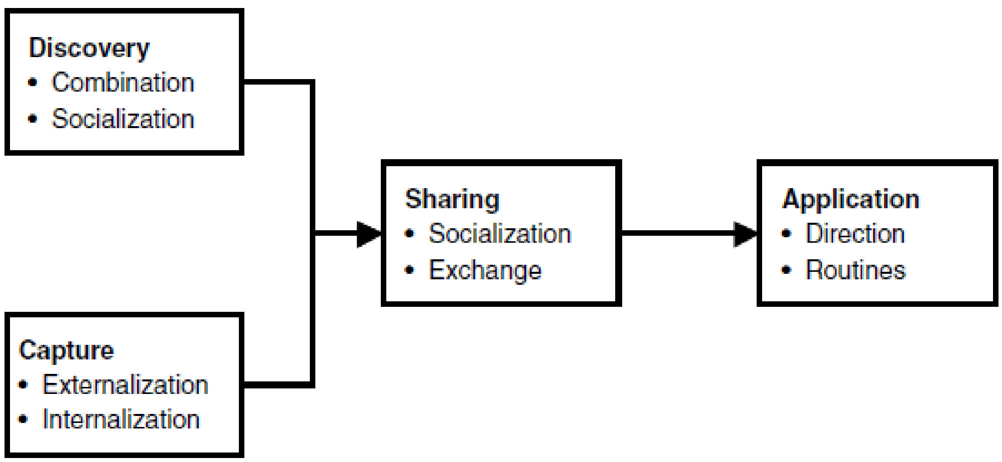


Figure 1. Knowledge Management Processes from (Becerra-Fernandez & Sabherwal, 2015)

The ultimate goal of knowledge creation is application, otherwise known as knowledge activation (Nonaka & von Krogh, 2009; Noteboom & Qureshi, 2014). Knowledge activation is a set of interacting identities that relate to the type of knowledge an individual holds. The three identities of knowledge activation are accountable, discretionary, or autonomous. At any given time, knowledge carries only one identity (Qureshi & Keen, 2005). Autonomous knowledge relates to experiences that are not easily shared with others, similar to tacit knowledge. Discretionary knowledge represents a choice. Individuals decide what knowledge to share and what to keep private. Accountable knowledge carries the weight of a requirement to share (Qureshi & Keen, 2005). Collaboration with others is a critical element of the knowledge activation process. The demand for knowledge provides a trigger for the user to decide which knowledge identity is needed to collaborate with others (Noteboom & Qureshi, 2014). While not explicitly stated, tenets of Nonaka's theory of knowledge creation are evident in the knowledge activation framework. There are similarities in which modalities come to play with the interactions of tacit and explicit knowledge. Application occurs when users enact an accountable identity, whether through discovery or capture knowledge management processes. Extant research states that effective knowledge management occurs when opportunities are provided for creating, retaining, and transferring knowledge. Opportunities develop from the results of experience, learning from collaboration, or observation (Argote, McEvily, & Reagans, 2003).

Information Visualization

Humans use visualizations when they want to learn something (Baker, Jones, & Burkman, 2009). Visualizations leverage the humans' visual system because of its capability to process images and recognize patterns, trends, and outliers (Card, Mackinlay, & Shneiderman, 1999; Jeffrey Heer, Bostock, & Ogievetsky, 2010; Speier, 2006). Visualizations act as a pipeline to transform raw data into images that can be interpreted. In other words, visualizations give data a tangible form. Having something 'real' allows humans to generate insights, make decisions, and formulate actions that may otherwise be impossible or difficult to do (Few, 2006; Van Wijk, 2005).

Diagrams, graphs, and pictures are typical types of representations used within visualizations (Zhang, 2000). When humans perceive visualizations, they decode various shapes, sizes, and colors to form an understanding of the data (Kirk, 2016). Leveraging the human's visual system shifts the cognitive load by coupling soft system attributes with hard system attributes (Bendoly, 2016; Speier, 2006). Soft system attributes relate to the human and include perceptive skills, cognitive reasoning, and domain knowledge. Hard system attributes relate to the computer and include data storage, data processing, and computing power. The coupling of soft and hard systems gives people access to knowledge and skills that may be unavailable solely with internal mental representations. Shifting cognitive load is a primary reason behind the use of visualizations. Card et al. (1999) provided initial research describing the value that visualization brings to cognitive processing. Tory and Moller (2004) refine the points to provide specific examples of support structures between visualization and cognition (see Table 1).

Table 1. How Visualizations Support Cognition from (Tory & Moller, 2004)

Method	**Description**
Increased Resources	
Parallel processing	parallel processing by the visual system can increase the bandwidth of information extracted from data
Offload work to the perceptual system	with appropriate visualizations, some tasks can be done using simple perceptual operations
External memory	visualizations are external data representations that reduce demands on memory
Increased storage and accessibility	visualizations can store large amounts of information in an easily accessible form
Reduced Search	
Grouping	visualizations can group related information for easy search and access
High-density data	visualizations can represent a large quantity of data in a small space
Structure	imposing structure on data and tasks can reduce task complexity
Enhanced Recognition	
Recognition instead of recall	recognizing information presented visually can be easier than recalling information
Abstraction and aggregation	selective omission and aggregation of data can allow higher-level patterns to be recognized
Perceptual monitoring	using pre-attentive visual characteristics allows monitoring of a large number of potential events
Malleable medium	visualizations can allow interactive exploration through manipulation of parameter values
Organization	manipulating the structural organization of data can allow different patterns to be recognized

External representations are not simple inputs or stimuli for the mind; instead, they are used alongside may cognitive tasks to influence behavior (Zhang, 2000). Visualizations operate as a catalyst for interpretations forming the basis of knowledge activation, where users are allowed to extract, explore, and create information (Al-Kassab, Ouertani, Schiuma, & Neely, 2014). Interpretation is subjective and affected by numerous factors, including prior knowledge, the capacity to utilize knowledge, cultural background, and the design of the representation (Al-Kassab et al., 2014; Kirk, 2016; Shah, Mayer, & Hegarty, 1999). It is challenging to provide specific visualizations that are suitable for all cognitive processes, highlighting the importance for designers to use human-centric techniques. Human-centric design techniques identify and understand the context in which visualizations will be used, allowing designers to produce designs that support human reasoning and cognition (Ya'acob, Ali, & Nayan, 2016).

Human-Information Interaction

Human-Information Interaction (HII) investigates the interaction between people and information. It is concerned with how and why people use, find, consume, work with, and interact with information to solve problems, make decisions, learn, plan, make sense of, discover, and carry out tasks (Fidel, 2012; Sedig, Parsons, Liang, & Morey, 2016). HII consists of a computer-based interaction but concentrates on the relationship between humans and information, not the relationship between humans and technology (Albers, 2012). Humans learn naturally, acquiring information and knowledge through experience and interaction with their environment. Learning by doing generates knowledge as a result of people forming or identifying relationships among informational elements (Albers, 2012). Through the process of learning by doing, humans use tools to mediate the elements of their environment to accomplish goal-oriented tasks (Green et al., 2011).

Humans interact with information to support their intensive thinking processes, such as problem-solving, decision-making, or performing other complex cognitive activities (Parsons & Sedig, 2014a). Cognition is the information processing system inside the brain. The theory of distributed cognition defines situations where cognition occurs inside and outside the brain. (Liu, Nersessian, & Stasko, 2008; Parsons & Sedig, 2014c). When users work with information, cognitive processes flow to where it is cheaper to perform them. Even though some people can do cognitive activities in their heads, there is always a point where the individual becomes overwhelmed (Kirsh, 2010).

Cognition is an emergent property that builds over time when an individual interacts with their environment. Cognition develops through perception and action (Liu et al., 2008). Cognitive overload develops as a response to new and evolving information that emerges as one interacts with their environment (Ya'acob et al., 2016). Visualizations are provided as a resource to decrease cognitive overload by providing an outlet for distributing cognition. Together, visualizations and humans form a joint cognitive system, where mental and computation processes are coordinated through interaction (Parsons & Sedig, 2014c; Reda, Johnson, Papka, & Leigh, 2016). Visualizations harness computational power to process and transform information. Humans use the visualization to change or adjust the representations of information.

The human-visualization cognitive system is conceptualized as five spaces: information, computing, representation, interaction, and mental. The information space is the environment, source, domain, or area from which information originates (Ya'acob et al., 2016). As users work with the visualization, the information space provides the data that users engage with, creating a discourse the human and the information (Liang, Parsons, Wu, & Sedig, 2010; Parsons & Sedig, 2014c). The computing space encodes and stores internal representations of items in the information space. The computing space also manipulates or performs operations on informational elements. The representations space encodes and displays visual representations of information. The interaction space allows users to view the information stored in the information space. Information is displayed through the visual representations created in the representation space. The mental space is where the human reflects on what they perceive and where internal mental events and operations take place (Liang et al., 2010; Parsons & Sedig, 2014a, 2014c).

Visualization designs should consider the cognitive processing of individuals, based on how the mental space mediates reality within the user's head. For typical users, the overall presentation of information becomes the basis for active mental models, influencing how the user will interpret the information (Albers, 2012). Cognitive activities occur within the mental space, including but not limited to apprehension, induction, deduction, retrieval, judgment, and comprehension. For visualizations to facilitate interactions within the environment, their design needs to be a place where the mental space will continually develop. This is a daunting task as each individual will interpret and comprehend visualizations differently due to different mental models (Ya'acob et al., 2016).

The representation space acts as a mental interface connecting the human mind to the information space. It is not possible to provide a single representation space that sufficiently meets all the information needs of users (Sedig, Parsons, & Babanski, 2012). The interaction space adds a layer to the representation space, expanding the possible services to users. Interaction is an epistemic action; it is the human's reflective and creative ability to use external actions to offload cognition (Albers, 2012). With interactive visualizations, cognition is distributed across the five spaces. Some processing takes place in the mental space, some is offloaded to the representation and computational space, and some take place in the interaction space (Hegarty, 2011; Parsons & Sedig, 2014a; Speier, 2006).

Users and visualizations create a dynamic system built from coordination and causal influence. The user and the visualization are continuously affecting and simultaneously being affected by each other (Kirsh, 1997; Sedig, Parsons, Dittmer, & Haworth, 2014). The Simple Visualization Model demonstrates the flexible context in which visualizations operate. The goal of visualization is insight, which is generated as humans participate in a feedback loop between interpreting the information and interacting with the visualization (Van Wijk, 2005). The feedback loop represents the relationship that is created and facilitated by interactions (Pike, Stasko, Chang, & O'Connell, 2009; Sedig et al., 2014; Van Wijk, 2005).

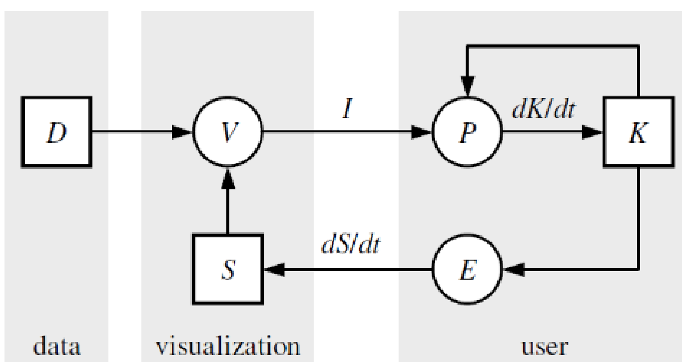


Figure 2. Simple Visualization Model from(Van Wijk, 2005)

The model shows how a user explores (E) information by perceiving (P) an image (I) and generating knowledge (K). The user can choose to explore the data further by changing the specification (S). As changes are applied, the visualization is updated, developing the relationship between the user and the information. Exploring data allows the user to see patterns, trends or information they did not previously know. New insights define new questions, hypotheses, or models. The feedback loop continues as long as the user initiates change (Van Wijk, 2005).

Knowledge includes what the user already knows and what they learn from exploring data. Knowledge activation represents the use of information in making decisions and performing tasks. The model shows how interaction is engrained in the context of using information visualization. It is a critical element enabling users to act upon what they know and what they see as knowledge is generated. Decision making is rarely a logical process. It involves users obtaining an understanding of the situation and doing something with that situation. Decision-making ability depends on the conversion between tacit and explicit knowledge through the knowledge management processes (Albers, 2012).

Interactions

Interactions are powerful tools that enable visual exploration and insight generation. Traditionally, interactions are defined as features that individuals use to manipulate visualizations, triggering the feedback loop (Endert et al., 2015; Pike et al., 2009). Interactions are not merely a use/no property of visualizations; instead, there are different degrees of interactions. The extent of participation in which a user can modify the visual representation defines the interactive feature of visualizations (Aigner, 2011). In turn, interaction becomes the process by which the human and visualization develop a give-and-take relationship centered on creating knowledge (Green et al., 2011; Parsons & Sedig, 2014c).

Interactions explicitly place humans in the loop where visualizations leverage the perceptual system reducing the cognitive load required for data analysis (Endert et al., 2015). There are several taxonomies defining interactions within visualizations (see Tables 2 and 3). Table 4 is a taxonomy that classifies interaction taxonomies from three different perspectives: high-level goals and user-intent centric, low-level activities and user-behavior centric, and system-level and software operation-centric.

Table 2. Common Interaction Mechanisms

(B. Shneiderman, 1996)	(D. Keim et al., 2008)	(Yi, Kang, & Stasko, 2007)	(Few, 2009)	(J. Heer & Shneiderman, 2012)	(Börner, 2015)	(Figueiras, 2015)
Overview		Overview	Overview	Overview	Overview	Overview
Zoom	Zoom		Zoom		Zoom	Zoom
Filter	Filter	Filter	Filter		Filter	Filter
Details on Demand		Details on Demand		Details on Demand		
History				History		
Extract				Extract		
	Relate	Relate		Relate	Relate	Relate
	Reconfigure	Reconfigure	Reconfigure			Reconfigure
	Projection				Projection	
	Distortion				Distortion	
		Elaborate / Abstract				
		Select	Select	Select		Select

Table 3. Interactive Patterns from (Sedig & Parsons, 2013)

Pattern	**Description**
Reconfigure	show a different arrangement
Encode	show a different representation
Filter	show data that meet specific criteria
Abstract / Elaborate	Show data with more or less detail
Connect	Show related data items
Explore	Show different data
Select	Select data item(s) as interesting

Table 4. Taxonomy of Tasks and Interactions in Information Visualization from (Ren, Cui, Du, & Dai, 2013)

Perspective	Publication(s)	Taxonomy
High-level goals, user-intent centric	(Card et al., 1999)	Forage for data, search for schema, instantiate, problem solve, author, decide, act
	(Liu & Stasko, 2010)	Mental model construction and simulation, external anchoring, information foraging, and cognitive offloading
	(North et al., 2011)	Perceive, capture, encode, recover, and reuse
	(Pike et al., 2009)	Explore, capture, encode, recover and reuse
Low-level activities, user-behavior centric	(Ben Shneiderman, 1996)	Overview, zoom, filter, details on demand, relate, history and extract
	(D. A. Keim, 2002)	Interactive projection, interactive filtering, interactive zooming, interactive distortion, and interactive linking and brushing
	(Amar, Eagan, & Stasko, 2005)	Retrieve value, filter, compute derived value, find extremum, sort, determine range, characterize distribution, find anomalies, cluster and correlate
	Wilkinson (2005) – The Grammar of Graphics	Filtering, navigating, manipulating, brushing and linking, animating, rotating and transforming
	(Few, 2009)	Comparing, sorting, adding variables, filtering, highlighting, aggregating, re-expressing, re-visualizing, zooming and panning, re-scaling, details on demand, annotating, and bookmarking
	(Yi et al., 2007)	Select, explore, reconfigure, encode, abstract or elaborate, filter, and connect
System-level, software operation centric	(Chuah & Roth, 1996)	Graphical operations, set operations and data operations
	(Matthew O Ward & Yang, 2004)	Interaction operators, interaction operands and spaces, and interaction parameters
	(J. Heer & Agrawala, 2006)	Package of software design patterns for Information Visualization in the form of class diagrams

Interactivity strengthens the human-visualization cognitive system (Sedig et al., 2014). Human-Information Interaction attempts to take the entire cycle of information interpretation and decision making and place it within the users' current situation. Once the user can find and interpret the information, they need to use it (Albers, 2012). To fully understand cognitive processing and how knowledge is activated, one must consider the entire interface and not the individual components (representation space and interaction space). Holistically understanding the human-visualization cognitive system is achieved through the lens of external interactivity. External interactivity is "the quality of interaction among mental, interaction, and representation spaces (Sedig et al., 2012)." Macro-interactivity factors are a subset of external interactivity, where the concentration is on different combinations of interactions to perform high-level cognitive tasks and activities. There are four macro-interactivity issues, which to date have only been defined and not thoroughly discussed (Sedig et al., 2012):

a) How different interactions complement one another in the context of performing particular tasks?
b) How interactions correspond to the users' conceptual models of how such interactions should function?
c) What is the degree that the potential benefits of interactions outweigh the cost and effort associated with learning how to use them?
d) What is the degree of control over the many parameters of a visualization that should be provided to users?

The concept of interaction is abstract, complex, and emergent. “Interaction is an abstraction because there is no single direct operationalization. It is complex in the fact that there are many contributing factors, which are themselves dynamic and complex. Interaction is emergent a the result comes from multiple components and cannot be reduced to the properties of those components (Parsons & Sedig, 2014a).” Seven concepts of interaction defined within Human-Computer Interface (HCI) literature help to further explain interaction.

Table 5. Key Concepts of Interaction from (Hornbæk & Oulasvirta, 2017)

Concept	**View of Interaction**	**Key Phenomena and Construct(s)**
Dialogue	*the cyclic process of communication acts and their interpretations*	*mappings between the user interface and intentions; feedback from a user interface*
Transmission	sending messages over a noisy channel	message (bits) and the receiver; noisy channels
Tool Use	*a human that uses the tool to manipulate and act in the world*	*mediation by tools; directness of acting in the world; activity as a unit of analysis*
Optimal Behavior	*adapting behavior to goals, tasks, user interface, and capabilities*	*rationality; constraints; preference; utility; strategies*
Embodiment	action and being in situations of a material and social world	intentionality; context; coupling
Experience	an ongoing stream of expectations, feelings, memories	non-utilitarian quality; expectations; emotions
Control	interactive minimization of error against some reference	feedforward; feedback; reference; system dynamics

Research Question and Propositions

To maximize the quality and capability of decision-making in a continually changing world, mapping the appropriate mix of human and technology-centered resources to the characteristics of the decision-making context is necessary (Zack, 2007). The motivation for this research is to identify the benefits of interacting with visualizations to activate knowledge. While interactive mechanisms are available, little is known about how these mechanisms directly support analysis tasks nor what benefits the tools provide (Aigner, 2011). I apply the conceptualization of information visualization as a layered system, where cognitive activities are distributed among five spaces (information, computing, representation, interaction, and mental). By focusing on external interactivity, I investigate the influence of combinations of interactions across three of the spaces: mental, representation, and interaction. I assume that users approach a visualization as a tool to assist them with a task or set of tasks. As time passes, the user's interactions develop into a dialogue with the information. Using the visualization and understanding feedback from interactions results in behavior where cognitive activities are supported, and knowledge is activated. The motivation for my research builds from the Analytical Capability Framework using human-information interaction and distributed cognition as a theoretical framework. The assumption also follows extant research explaining how analysis activities work with visualizations to "engage in convergent and divergent thinking as information is explored (Thomas & Cook, 2005)."

A prime challenge for interactive visualizations in dynamic decision making is answering one question: *how does interacting with visualizations support analytical reasoning of emergent information to activate knowledge?* Decision making occurs as a result of comparing what is perceived and what is known. Current practices do not consider how people's questions depend on how they make decisions and interact with an information system (Albers, 2012). Computers will influence how people interact with the information; therefore, I intend to investigate the design of information visualizations further. I will use external interactivity and HII for guidance to identify design attributes and other factors for handling emerging information and supporting knowledge activation efforts.

Interaction as Tool Use

Visualizations are a primary means through which users access, work with, and interpret information. They are electronic tools that visually represent data and information through an interface that can be adjusted to match the expectations of a user (Parsons & Sedig, 2014b). Interaction typically refers to a set of controls provided for the user to manipulate the interface. The experience of manipulating the visualization creates a relationship between the user and the information (Hornbæk & Oulasvirta, 2017; Pike et al., 2009; Sedig et al., 2014). Together the visual representation and the interactive controls are a tool that can be used to mediate environmental elements when completing tasks.

There are two levels of interaction within visualizations, low-level and high-level. Low-level interactions occur between the user and the interface, as the user manipulates the visualization. Reactions to the manipulation(s) reveal patterns, trends, relationships, or other hidden features (Pike et al., 2009). Low-level interactions are mapped to low-level analysis tasks. The taxonomy for low-level analysis tasks capture's activities that occur when using information visualizations to understand data identifies ten tasks (Amar et al., 2005):

- Retrieve Value: identify the value(s) of an attribute for the given data point(s).
- Filter: find values satisfying a specific condition.
- Compute Derived: compute an aggregate value for a set of data points.
- Find Extremum: find data points having an extreme value for an attribute.
- Order (Sort): rank the data points according to a specific ordinal metric.
- Determine Range: find the span of values within a given set of data points and an attribute of interest.
- Characterize Distribution: characterize the distribution of a selected attribute's value over the set.
- Find Anomalies: identify anomalies within a given set of data points concerning relationships or expectations.
- Cluster: count the number of groups of similar data attribute values.
- Correlate: identify and determine useful relationships between the values of attributes.

High-level interactions occur between the user and the information space, where the user has purposeful intent to manipulate the information. High-level interactions are mapped to use-intents that identify the reason behind interacting with a visualization (Pike et al., 2009). The taxonomy for interactions organized around user intent identifies seven general categories (Yi et al., 2007):

- Select: mark something as interesting
- Explore: show me something else
- Reconfigure: show me a different arrangement
- Encode: show me a different representation
- Abstract / Elaborate: show me more or less detail
- Filter: show me something conditionally
- Connect: show me related items

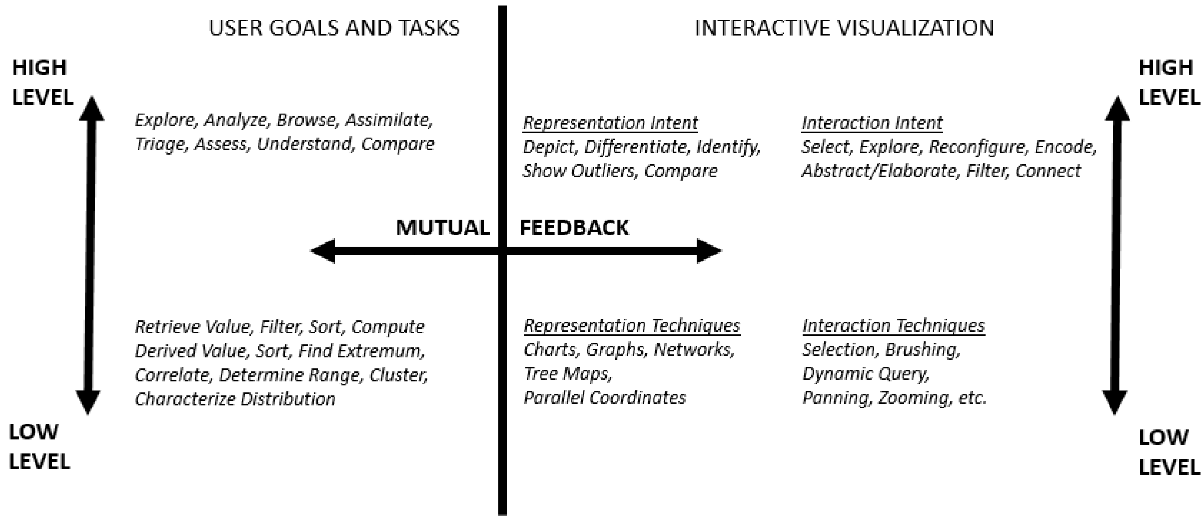


Figure 3. High-Level and Low-Level Interactions from (Pike et al., 2009)

I operationalize *interaction as a tool* by the design of the representation space featuring multiple views and feedforward cues. These constructs work together to provide cues for how the user should interact with the information. The strong and weak points of the representation space will affect the ease in which people can manipulate information. From a macro-level interactivity viewpoint, ease determines the effort that a user will need to learn how to use the interactions. The cost-benefit analysis that occurs for how to use interaction and its effect on the visualization will influence comprehension and understanding of the information (Albers, 2012; Sedig et al., 2014).

The representation space and human perceptual system are limited. It is not possible to visually represent the entire information space into one chart. Nor could a human's perceptual system to be able to absorb or perceive all the data and effectively integrate understanding with judgment. Visual analytical activities are not linear processes, and it is not possible to provide a single image that sufficiently meets the needs or goals of the user (Sedig et al., 2012). Providing multiple views of the dataset is an approach to handle visual complexity. The multiple-view technique uses two or more distinct representations to support the investigation of a single conceptual entity (Wang Baldonado, Woodruff, & Kuchinsky, 2000). Multiple views allow the user to see data from different perspectives, facilitate comparisons, and enable multi-dimensional explorations (Munzner, 2014).

Visualizations provide cues to assist decisions of where and how to navigate or explore information (J. Heer & Shneiderman, 2012). Even when interaction controls visible, it can be difficult for users to know and remember the intended targets and effects of the action (Sedig et al., 2016). Feedforward cues help users to perform actions by telling them what will happen. They communicate the interface's function, where the appearance and action of controls are different from the visual representation (Djajadiningrat, Overbeeke, & Wensveen, 2002; Vermeulen, Luyten, Hoven, & Coninx, 2013). These ideas are expressed through the following propositions:

Proposition 1 (Support for Tool Use): Multiple views enhance the user's ability to analyze data displayed in an information visualization system.

Proposition 2 (Support for Tool Use): Feedforward cues communicate the result(s) of specific actions allowing the user to be more deliberate with how they interact with information. Deliberate actions enhance the user's ability to analyze data displayed in an information visualization system.

Applying the concept of interaction as tool use defines design attributes for the representation space. I propose that the technique of multiple views and characteristics of feedforward cues enhance analytical reasoning and allow users to be in a better position to make decisions that apply knowledge gleaned from interacting with information in the visualization.

Interaction as Dialogue

Performing complex cognitive activities involves active and goal-directed information processes. This type of information processing is the use of working with some given information to derive new information (Parsons & Sedig, 2014a). Interaction as dialogue is the "cyclic process of communication acts and interpretations (Hornbæk & Oulasvirta, 2017)." Continual interactions between the user and the visualization generate a dialogue. As shown in the simple visualization model, users can change the specification of the visualization changing the image displayed, allowing for interpretation of the results (Liang et al., 2010). Dialogue, or the back and forth flow of information, distributes cognition across the representation and interaction spaces (Parsons & Sedig, 2014c).

Useful insight emerges from the experience of manipulating information. Opportunities for insight generation and accumulation coincide with the number of ways that users can ‘hold’ their data (Pike et al., 2009). Analytical dialogue is the relationship between interactive techniques, user goals, and tasks. It involves choices about which interactive control to use for manipulating the interface to help achieve the user’s goals. Norman’s Interaction Model describes the structure of action as users decide which controls to use and how to interpret the results. The model is composed of seven stages: (1) form the goal, (2) plan how to take action, (3) specify the sequence to take action, (4) perform the action, (5) perceive the results, (6) interpret the results, and (7) compare the outcome with the original goal (Norman, 2013).

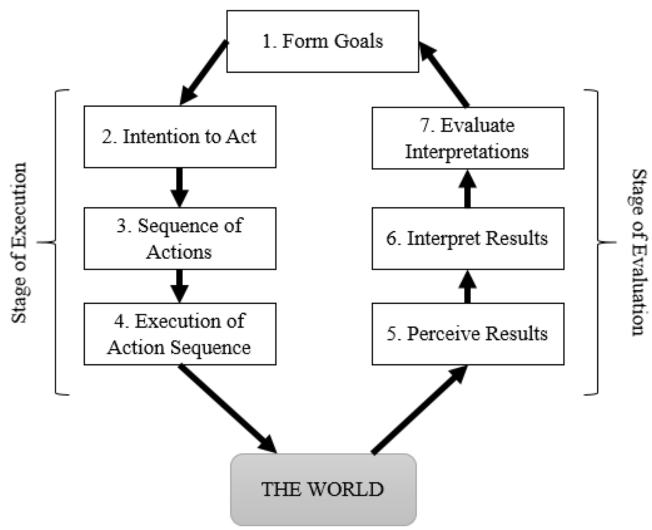


Figure 4. Interaction Model from (Norman, 2013)

There are two parts to every action: a) doing is the execution of the action, and b) evaluating is the interpretation and examination of the results (Norman, 2013). The formation of a goal is context-dependent and identifies what information is needed. Information needs trigger seeking and exploring behavior, which in turn influences the creation of the goal (Fidel, 2012). Once a goal forms, the user can decide how to act and proceed through the other phases of the interaction model.

Theoretically, the interaction model is sound; practically, a gap develops between when a user forms their goal and when the user takes action (Parsons & Sedig, 2014b). End-users often have difficulty interacting with visualizations because of the ‘Gulf of Execution.’. This gulf indicates a difference between what the user intends to do and what the user is allowed to do (Endert et al., 2015; Roth, 2013; Spence, 2007; Thomas & Cook, 2005). A second gap develops when users move from taking action to interpreting the results. The gulf on the other side of the model is called the ‘Gulf of Evaluation.’ This gulf indicates that the user has difficulty evaluating the results of their action(s). Step 7 of the model is evaluation, which compares outcomes to expectations that were identified when the goal was formed (Norman, 2013; Spence, 2007). People perceive information and develop or redevelop their mental models with active and recursive interactions with information. The presentation of the information provides access to and drives those interactions, which will consequently impact how users respond to or act upon information (Albers, 2012).

I operationalize *interaction as dialogue* by the design of the interaction space featuring coordinated interactions and a broad task focus. These constructs work together to support the user in taking action(s) and interpreting the results. Coordinated interactions help to connect low-level interactions with high-level interactions. They support the user in identifying data patterns and trends, while also supporting the interpretation or discovering the meaning of the information. From a macro-level interactivity viewpoint, coordinated interactions provide complementary actions that allow users to complete a task (Sedig et al., 2014).

An interaction technique may be useful on its own, but implementing both too few or too many can affect the quality of the dialogue (Baigelenov & Parsons, 2018). Individual interactions may independently support one particular action, or they can work together and assist the user in performing more complicated tasks and activities. There are two types of coordinating interactions. The first type is embedded in the multiple view design. The result of the interaction is applied to all views, not just one. The second is complementary, where interactions work together, allowing the user to switch from one interaction to another and engage in different forms of exploration (Sedig et al., 2014).

The visualization, including the set of interactions it uses, may serve well for one task and be poorly suited for another, even when working with the same data set (Munzner, 2014).

Fitness is the suitability of interactions to support a task that involves a given visual representation. When putting tasks at the center of the design effort, the representation and interaction space must form a cohesive unit that supports the user. Either the visualization is designed to optimally support one task or each tas tat a user ay perform, or the visualization is designed to support a wide range of tasks (Sedig et al., 2014).

The design of an interface affects the support of tasks and reducing the barriers to performing high-level cognitive activities. The interface design consists of both the representation space and interaction space and how they work together. Many designs fail because they assume that technology will address the problem. The human-centric design approach places humans at the center of the design effort. Achieving good human-information interaction cannot be based on a technological solution, rather it will be based on knowing how people respond to and are influenced by information and technology (Albers, 2012; Yalçin et al., 2016). Visualizations that are flexible enough to support multiple interactions and can support users with multiple tasks have an ideal human-information interaction design (Albers, 2012). These ideas are expressed in the following propositions:

> *Proposition 3 (Support for Dialogue): Coordinated interactions add a layer of depth to the representation space engaging the user and deepening the level of analysis and analytical reasoning. The depth of analysis enhances the user's ability to apply knowledge.*

> *Proposition 4 (Support for Dialogue): Multiple interaction mechanisms enhance the user's ability to dialogue with the information and achieve a higher number of tasks. The ability to complete more tasks creates more opportunities for the user to apply knowledge.*

Applying the concept of interaction as dialogue defines how users interact with information to achieve tasks. I propose that the design of the interaction space mus become a cohesive unit with the representation space to provide useful visualizations. Providing multiple interactions that support a broad range of tasks allows users to engage in analytical reasoning to enhance the opportunities for knowledge activation.

Interaction as Optimal Behavior

Interaction represents a problem space where cognition is enabled by the visualization but is distributed between the user and information system (Pike et al., 2009). There are four levels of granularity that describe cognitive activities: events, interactions, tasks, and activities. Events are physical actions and are the starting point for any development of cognitive activity. Interactions build from events and consist of actions performed along with the subsequent reactions. Tasks are goal-directed behaviors that provide the purpose behind interacting with information. Activities are the highest level, the ending point of developing cognitive activities. They are composed of sub-activities, which are composed of tasks and subtasks (Sedig et al., 2014; Sedig et al., 2016).

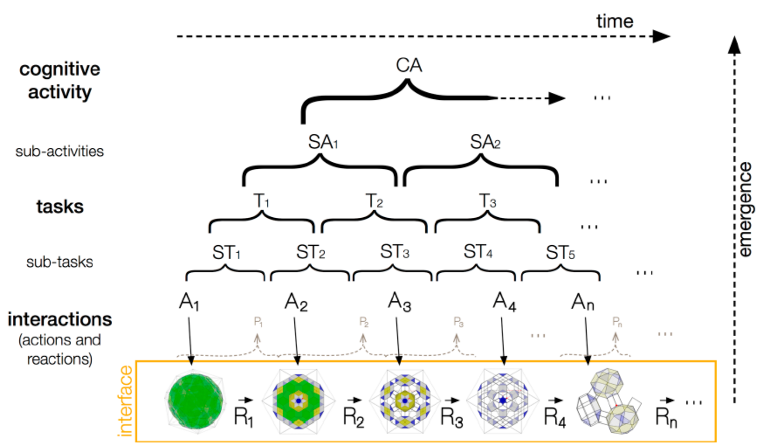


Figure 5. Levels of Cognitive Activities from (Parsons & Sedig, 2014c)

To achieve a goal, the user takes the path from events to activities. They do not follow a linear path but instead use high-level strategies to alter the information environment. Users transform the information they can access to support cognitive processing and ultimately achieve their goal (Parsons & Sedig, 2014a). Complex cognitive activities are hierarchical, embedded, and emergent. They do not occur spontaneously but develop over time, as the user interacts with information to complete sub-tasks and tasks. Cognitive activities become known and more prominent over time, as a result of applying each level to the goal (Sedig & Parsons, 2013).

I operationalize *interaction as optimal behavior* as the value of visualization. The ultimate purpose of using visualizations for analysis activities is to help humans perform cognitive work more efficiently (Ware, 2012). Visual exploration can be flexible without guidance, or it can be structured and guided by intuition or goals (Reda et al., 2016). The value of visualization supports high-level interactions as cognitive activities are developed, and users apply knowledge. Through the macro-interactivity lens, interaction as optimal behavior means that users understand how interactions function and the implementation of the visualization matches the user's mental model (Sedig et al., 2014).

Humans think in terms of their analysis tasks, which closely align with interactions. When interactive visualizations are effective, the user stays in the cognitive zone. When interactive visualization is ineffective, users develop inaccurate or false knowledge, lost time, and become frustrated (Green et al., 2011; Yalçin et al., 2016). Value goes beyond the ability to answer simple questions. It relates to the visualization's ability to convey a real understanding of data. Value is holistic, broad, and context-dependent (Stasko, 2014).

Proposition 5 (Support for Behavior): For any given set of data displayed in information visualization, the value of interacting with the information develops over time to positively influence analytical reasoning and knowledge activation.

Theoretical Summary

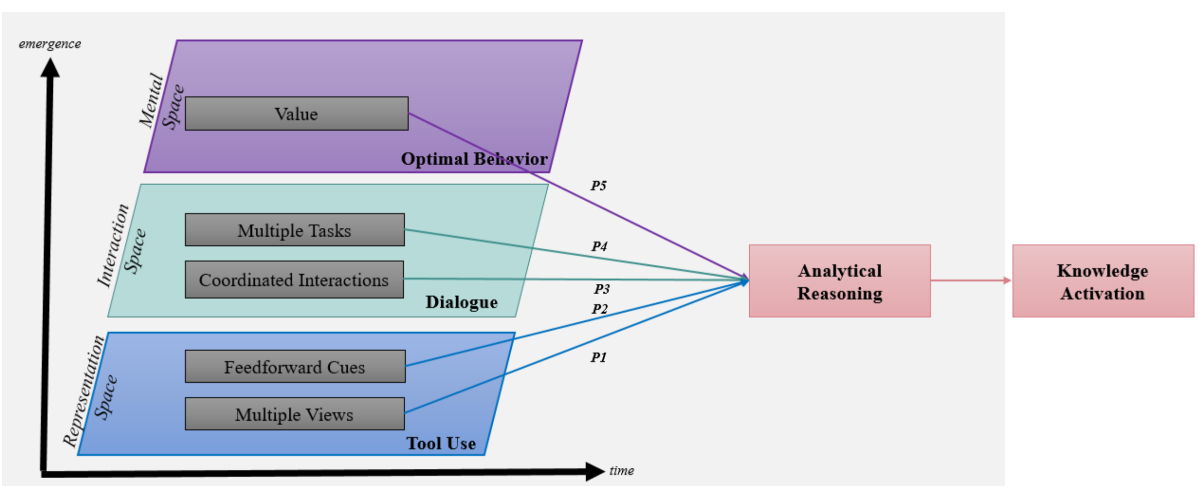


Figure 6. Research Model: Interactions to Support Knowledge Activation

To summarize, users need to be connected to their data and to analytical operations that provide insight (Pike et al., 2009). People's information needs will vary both between and within situations. Understanding factors that drive changes within a situation forms the basis for designing effective visualizations. This human-centric approach focuses on the influence of information need and information flow on decision-making processes (Albers, 2012). The design of interaction influences goal formation, task formation, and, ultimately, the performance of cognitive activities (Sedig et al., 2016).

My research proposes that interaction design must consider three concepts: as tool us, as dialogue, and as optimal behavior. Operationalized definitions will have two components: an action and a reaction. The design of the representation and interaction spaces determines implementation details of actions and reactions, which have an overall influence on the perceptual capabilities of the user. The design will either strengthen or weaken the human-visualization joint cognitive system (Sedig et al., 2016). The HII framework provides a theoretical lens to guide the design and evaluation of visualizations to support cognitive activities. To fully realize their goal, users must engage in an ongoing dialogue with the information (Kirsh, 1997). Through interactions, goals are continually formed, revised, and even abandoned based on what the user sees and thinks (Sedig et al., 2016). By understanding the information needs of individuals in dynamic decision-making contexts, the design of visualizations can implement interactions to better support knowledge activation efforts.

CHAPTER 3

RESEARCH METHODOLOGY

This research undertakes the design science paradigm, as guided by the information systems framework proposed by Hevner et al. (2004). The framework emphasizes the need to achieve relevance and rigor within information systems research. Relevance comes from addressing business needs in the appropriate environment rigor from appropriately applying existing foundations and methodologies from the knowledge base (Hevner, March, Park, & Ram, 2004).

The following sections thoroughly discuss a high-level approach to designing visualizations guided by HII and external interactivity factors. Design efforts following the HII framework result in visualizations that guide users through an epistemic cycle (Ya'acob et al., 2016). Users are provided with or form a goal that describes their intentions to use the visualization as a tool. To accomplish the goal or achieve the objective(s) with some cognitive output, the user carries out a set of actions. A dialogue forms between the user and the information, causing the mental space to repeatedly process and align with new or emerging information (Sedig et al., 2012). This cycle continues until the user achieves a goal, develops a new purpose, or ends the exploration for another reason.

The unit of analysis for this research is the interactivity process between users and a visualization, encompassing both representation and interaction space design. Based on the need to understand the interactivity process, I observe the phenomenon through a dynamic decision-making situation. Apart from defining the level of support needed by users to explore a phenomenon, this investigation aims to identify and examine the benefits of interacting with visualizations. The qualitative method is the most relevant of all methods for analyzing the results of this research. Qualitative inquiry works towards achieving a rich understanding by using a holistic approach that considers interplay among factors that influence visualizations, their development, and their use (Carpendale, 2008).

Hevner et al. (2004) emphasize the organization, existing technologies, and people within their framework for design science research (DSR). The HII framework allows for the design of visualizations to support users in complex and dynamic situations, addressing the organization piece of the DSR framework. Complex and dynamic situations require users to have integrated information for problem-solving and decision-making, addressing the other two elements of the DSR framework. Approaching design with human-centric techniques identifies the tasks to be accomplished, but also how users approach these tasks. The visualization, in turn, is designed to provide and represent information as needed for the situation and not just for a task (Albers, 2004).

Problem Context

The problem domain for this research is the use of information within production-distribution systems, from here on referred to as supply chains. Supply chains are networks of companies working under customer-supplied agreements and focusing on manufacturing issues (Galasso, Mercé, & Grabot, 2009). One of the most common decision-making tasks within supply chains is called the stock management problem. The stock management problem defines the decision-making process where the manager of a supply chain seeks to maintain a specified quantity of their product (Sterman, 1989). Stock management becomes a problem due to the bullwhip effect. The bullwhip effect is a phenomenon where orders to suppliers tend to have more substantial variances than sales to buyers (Croson & Donohue, 2006; Hofmann & Rutschmann, 2018; Senge, 2006; Sterman, 1989).

The bullwhip effect introduces uncertainty within supply chain decision-making processes. It does not occur at one single position in the chain; instead, its effects propagate throughout the chain. Decisions by one position in the supply chain will affect the rest of the chain. For the stock management problem, managers that base their re-ordering decision on inaccurate forecasts or incomplete information will pass the same problems to their suppliers, which cultivates the same issues in the remaining positions of the chain (Hofmann & Rutschmann, 2018). The traditional supply chain paradigm is one where partners operate independently. They work towards self-interest by using local information for decision-making processes. Despite the silo approach, there is often attempts to align information and decisions for the greater good, all the while serving the self-interest (Galasso et al., 2009).

Empirical Setting

The Beer Game is a role-play simulation that mimics the mechanics of a decentralized inventory system. The game is traditionally played on a board, which portrays the production and distribution of beer. Cases of beer are represented by tokens, which are manipulated by players (Sterman, 1989). The decision task of each player is a clear example of the stock management problem. Players must keep their inventory at a level that they can fill incoming customer orders while avoiding the situation of having unfilled customer orders (Senge, 2006; Sterman, 1989).

The Beer Game consists of supply chain teams that work to produce and distribute a brand of beer. Each supply chain team consists of four positions: retailer, wholesaler, distributor, and brewery. The game is designed to follow the traditional paradigm, each player works towards self-interest, although they are part of a team. The overall goal for the game is to be the player and team to have the lowest total cost. Participants play with self-interest in mind while attempting to achieve system objectives (e.g., producing and distributing beer) (Senge, 2006). Players stay in the same position for the entire game. They are responsible for placing orders to his/her upstream supplier and filling orders placed by his/her downstream customer over a series of periods (Sterman, 1992). Each period in the Beer Game simulates one week in a production-simulation cycle. There are four tasks to be repeated within each period (Croson & Donohue, 2006; Sterman, 1992):

a) Receive Delivery: receive a shipment of beer cases from the upstream supplier.
b) Receive Customer Order: receive the customer order from the downstream position.
c) Fill Customer Order: use the inventory on hand to fill any new backorders along with any new orders. If an order cannot be filled, the number of cases is recorded as back-ordered.
d) Place Order: request a new shipment of beer cases to the upstream supplier.

The structure of the Beer Game is founded upon the systems perspective (Senge, 2006). The uncertainties and complexity of supply chain decision making refer to factors that influence the decision-maker, such as time and customer demand. These forces help to explain the relationship and effects that play a strong role in planning, improving efficiency, and generating accurate forecasts (Hofmann & Rutschmann, 2018). Sterman (1989) believes that dynamic settings render decision-making difficult, particularly when there is only one decision-maker. Difficult decision-making is also attributed to the reduced saliency of feedback. For dynamic decision making within supply chains, saliency refers to the strength of the tie between feedback and decisions. When decisions are made in a decentralized fashion across multiple parties, the interaction of decisions and outcomes further degrades the saliency of feedback (Croson & Donohue, 2006).

Supply chain decision making and HII are two systematic structures that follow the logic of cognitive scientist David Kirsh (1997) "complex activities do not follow predefined trajectories. Goals are formed over time within the ongoing dialogue between a user and the information (Kirsh, 1997)." The stock management problem introduces the goal of effectively managing on-hand inventory. On-hand inventory is directly tied to customer demand and goods received from the supplier. Supply chains operate on estimates of customer demand because it is difficult to have good, accurate knowledge of what the demand will be. When customer demand is not available before the decision-making, the manager of the supply chain must account for this uncertainty. To deal with the uncertainty, supply chain managers have degrees of freedom that guide reactions to the fluctuations in customer demand while trying to maintain a balanced stock. There are four general degrees of freedom for supply chains: (1) smooth the internal production and make inventory; (2) temporarily decrease internal capacity; (3) subcontract; and (4) allow backorders (Galasso et al., 2009). The Beer Game is a test to see which degree of freedom and the extent of that freedom a player uses when making decisions.

Beer Game – Experiment Parameters

To illustrate the specifics of the Beer Game, I follow the specification from Croson and Donahue (2006). Each game consists of a supply chain team (b), where B is the number of teams in an experiment. Each position (p) in the team receives orders placed by its downstream customer (p-1), and places orders for additional inventory to its upstream supplier (p+1). As each period passes, the position completes the four tasks required by the game (receive deliveries, receive orders, fill orders, and place orders).

Normal production-distribution cycles include lags to handle processing and shipping delays. Lags are introduced into the flow of the Beer Game to make the game as realistic as possible. The flow includes a two-period order delay and a two-period shipment delay for the first three positions, and a three-period manufacturing delay at the fourth (Sterman, 1992). The flow of the game is demonstrated in Figure 7. The order quantity filled and shipped by each position during a period is defined by the following equations (Croson & Donohue, 2006). The game rules state that positions must fill customer orders as they are received and as on-hand inventory allows. Players cannot arbitrarily choose the number of cases to ship downstream. The fill orders based on the current inventory (number of cases at the end of the previous period plus any new cases delivered), the number of cases on backorder, and the number of cases received with the new customer order. Breweries have a longer lag time to account for the manufacturing or brewing process of the product.

My analysis focuses on order variation between individual participants, specifically looking at how decisions are made when using interactive visualization. Participants are not restricted on the amount of beer they order from upstream suppliers. They are encouraged to think about how much they order to minimize their total cost. Total cost is calculated for each period using the amount of inventory on hand and the number of backorders. The cost penalties specified by the game instructions are: holding cost is $0.50 per case per period and stockout cost if $1.00 per case per period.

Table 6. Beer Game Specification

	Notation	Additional Explanation
Total Number of Teams	B	
Supply Chain Team	b	
Position in Supply Chain	p	Retailer = 1; Wholesaler = 2, Distributor = 3; Brewery = 4
Time Period	t	
Total Time	T	
Inventory	$I_t^{p,b}$	≥ 0 – On-hand Inventory < 0 – Backorders
Shipment Quantity	$S_t^{p,b}$	
Order Quantity	$O_t^{p,b}$	
Retailer Customer Demand	D_t	
Total Customer Orders	$R_t^{p,b}$	for retailers: $D_t + -I_t^{p,b}$ for other positions: $O_t^{p,b} + -I_t^{p,b}$
Holding Cost	h^p	accumulates for on-hand inventory ($.50 per case)
Stockout Cost	s^p	accumulates for backorders ($1.00 per case)
Position Cost	$C^{p,b}(T)$	
Supply Chain Cost	$C^b(T)$	the sum of all position cost

Equation 1. Order Processing and Shipment Delays

$S_t^{p,b} = \text{MIN}\{D_t, \text{MAX}\{I_{t-1}^{p,b} + S_{t-2}^{p+1,b}, 0\}\}$ for p=1

$S_t^{p,b} = \text{MIN}\{O_{t-2}^{p-1,b}, \text{MAX}\{I_{t-1}^{p,b} + S_{t-2}^{p+1,b}, 0\}\}$ for p = 2, 3

$S_t^{p,b} = \text{MIN}\{O_{t-2}^{p-1,b}, \text{MAX}\{I_{t-1}^{p,b} + I_{t-3}^{p,b}, 0\}\}$ for p = 4

$I_t^{p,b} = I_{t-1}^{p,b} + S_{t-2}^{p+1,b} - D_t$ for p = 1

$I_t^{p,b} = I_{t-1}^{p,b} + S_{t-2}^{p+1,b} - O_{t-2}^{p-1,b}$ for p = 2, 3

$I_t^{p,b} = I_{t-1}^{p,b} + O_{t-3}^{p,b} - O_{t-2}^{p,b}$ for p = 4

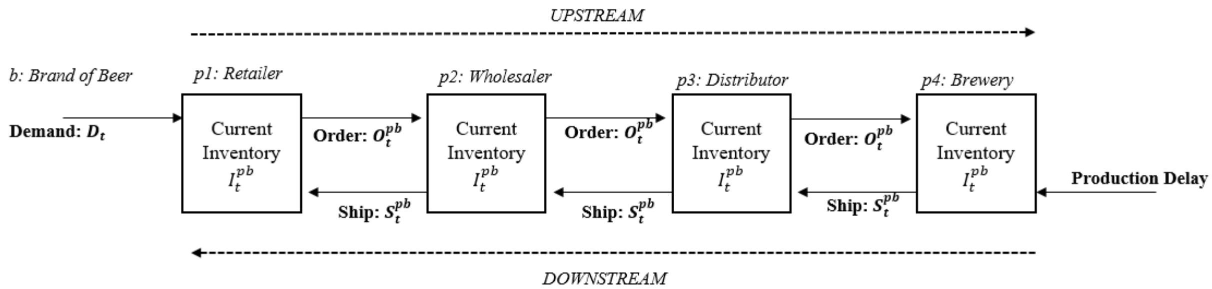


Figure 7. Beer Game Process Flow

Equation 2. Beer Game Costs

Position Cost $$C^p(T) = \sum_{t=1}^{T} h^p \operatorname{MAX}\{I_t^{p,b}, 0\} - s^p \min\{-I_t^{p,b}, 0\}$$

Chain Cost $$C^B(T) = \sum_{p=1}^{4} \sum_{t=1}^{T} h^p \operatorname{MAX}\{I_t^{p,b}, 0\} - s^p \min\{-I_t^{p,b}, 0\}$$

Application of the HII Framework

The Beer Game process flow is used to identify the progression through the HII layers as a user works with a visualization. The four conceptual layers of HII include high-level cognitive activities, tasks, interactions, and events. The game process explicitly identifies four tasks: (1) Receive Deliveries, (2) Receive Customer Order, (3) Fill Customer Order, and (4) Place Order. I define a fifth task that occurs throughout the game: Monitor Profit. The goal of the game is for each player to minimize cost for their position, meaning they need to pay attention to their cost as they manage their inventory. Managing inventory relates to filling customer orders and making the decision of how much beer to order from their supplier. Equation 3 provides the specification for each task in the Beer Game. Figure 8 provides a mapping of the Beer Game tasks to the upper levels of the HII Framework. A discussion of each layer follows in subsequent sections of this chapter.

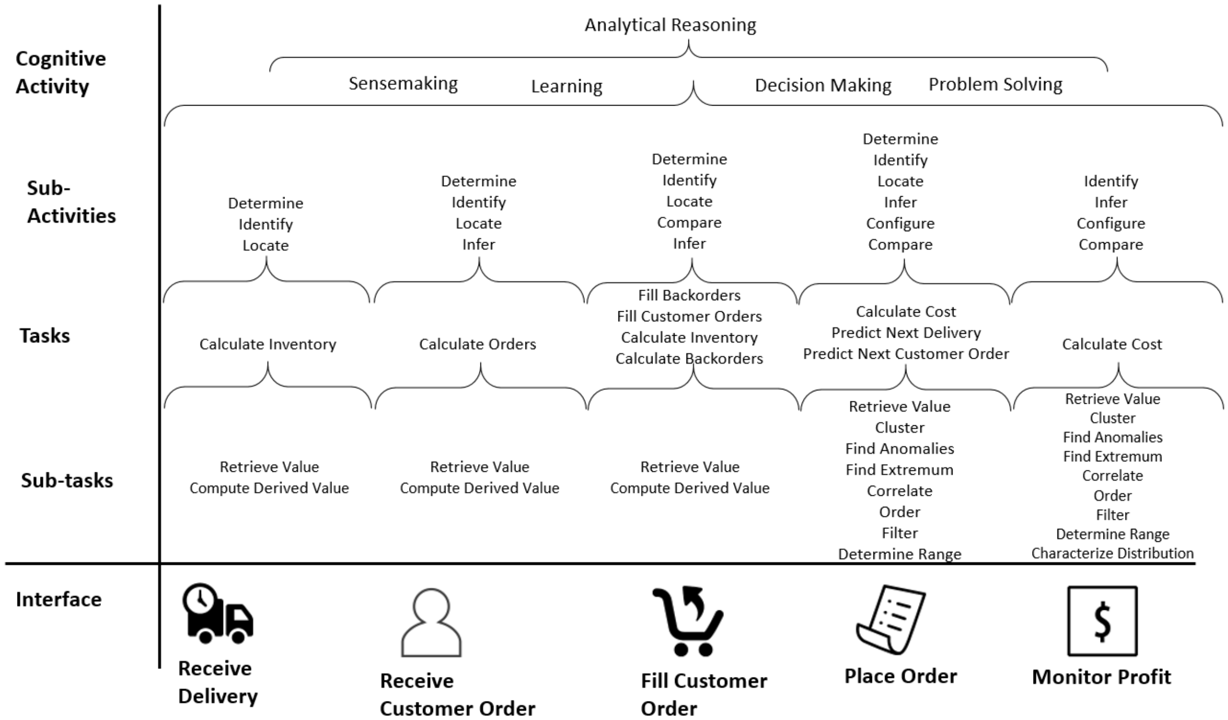


Figure 8. Beer Game Tasks within HII Framework (Upper Levels)

Equation 3. Beer Game Tasks

Step 1: Calculate Inventory	$I_t^{p,b} = I_{t-1}^{p,b} + S_t^{p+1,b}$	for p = 1, 2, 3
	$I_t^{p,b} = I_{t-1}^{p,b} + O_{t-3}^{p,b}$	for p = 4
Step 2: Calculate Orders	$R_t^{p,b} = D_t - \mathrm{MIN}\{(-I_t^{p,b}), 0\}$	for p = 1
	$R_t^{p,b} = O_{t-2}^{p-1,b} - \mathrm{MIN}\{(-I_t^{p,b}), 0\}$	for p = 2, 3, 4
Step 3: Fill Orders	$I_t^{p,b} = I_t^{p,b} - R_t^{p,b}$	if ≥ 0
	$-I_t^{p,b} = I_t^{p,b} - R_t^{p,b}$	if < 0
Step 4: Decide how much to Order	$O_t^{p,b} = ?$	
Step 5: Calculate Cost	$C^p(T)$	

Cognitive Activities. Knowledge activation is the conversion of knowledge into action (Qureshi & Keen, 2005). Identifying what and how users activate knowledge is the motivating purpose of this research. Knowledge activation represents the highest level of the HII framework, as I operationalize it as the final result of performing cognitive activities. Interactive visualizations support users in exploring and navigating the problem space, mental processing, and interacting with dynamic data (Cybulski, Keller, & Saundage, 2014). Data are a product of observation, and information is the transformation of data into a more effective and usable form. To understand the meaning of related information, individuals need to translate it into knowledge (Dadzie, Lanfranchi, & Petrelli, 2009). Interactive visualizations allow the user to select relevant data, analyze it from different perspectives, generate new ideas, and gain insights (Cybulski et al., 2014). Stepping from information to knowledge is performed by reasoning, which results in learning, problem-solving, decision-making, and sensemaking (Albers, 2012). High-level cognitive activities are emergent holistic processes, which help the user reach the point of activating knowledge (Dadzie et al., 2009; Qureshi & Keen, 2005).

Sub-activities are the second-highest layer in the HII framework. Tasks and subtasks combine to develop and achieve cognitive activities. The sub-activities of information visualizations relate to the taxonomies of tasks defined by Valiatia et al. (2006). Their taxonomy identifies seven activities that a user may accomplish when using a visualization. The seven activities are (Valiati, Pimenta, & Freitas, 2006):

- Identify: any action of finding, discovering, or estimating.
- Determine: any action of calculating, defining, or precisely identifying values.
- Visualize: graphically representing all (or desired) dimensions of data.
- Compare: analyze dimensions, data items, values, clusters, properties, and other visual characteristics.
- Infer: identifying, determining, or comparing information and inferring knowledge from the information.
- Configure: changing or configuring visual representations.
- Locate: any action of searching and finding the information already visualized, identified, or determined.

Tasks. There are steps within each game task that players must complete before moving on to the next step. The arrival of a shipment from the upstream supplier indicates the first game step. To complete this step, participants calculate their on-hand inventory using the number of cases remaining from the previous period and the number of cases delivered. The arrival of the customer's order indicates the second game step. The player needs to calculate the total number of requests to fill using the number of orders for the period and the number of cases back-ordered. To complete the third step, players must determine how many customer orders to fill. Players must determine what they can supply based on the number of cases in inventory and the number of customer orders they have. The fourth game task is to decide how much beer to order. Players can use any number of strategies to determine this number, such as predicting the next customer order, predicting the next shipment, or making a guesstimate. The last game step can be done at any time and consists of the player determining their performance by calculating cost.

Subtasks are defined by the low-level analysis tasks: retrieve a value, calculate a derived value, cluster, find anomalies, find extreme values, correlate, order, filter, determine the range, and characterize distribution (Amar et al., 2005). The sub-tasks explain how participants use visualizations to achieve visual cognitive activities, essentially activating knowledge. The first task is to calculate the on-hand inventory. Participants can use the visualization to retrieve the value of inventory from the previous period. The retrieved value is used to calculate the number of cases on hand as it is added to the number of cases received. Visualizations allow the user to determine the inventory on-hand with locating and identifying sub-activities. Participants can make sense of the situation by knowing what their on-hand inventory while anticipating future customer orders.

The second task is to calculate total orders and requires the number of cases back-ordered. Participants can retrieve this value from the visualization and then use the value to calculate total customer orders. The visualization allows the user to identify the number of cases back-ordered, and track the distribution of customer orders over time. Visualizations allow the user to make inferences about their current situation by identifying the number of cases on backorder and comparing the customer orders per period. The third task requires players to fill customer orders. Participants must know how many cases of beer they have on hand and compare that to what their total orders are. Visualizations allow the user to achieve the sub-activities of identifying, locating, and determining the information they need to fill customer orders.

The fourth task requires players to make a decision indicating knowledge activation. They need to be able to retrieve values of current inventory and backorders. Players are able to identify anomalies or extreme values, or cluster values to determine the impact of customer demand and shipments received with the visualization. These subtasks lead to the sub-activities of identifying, locating, and determining information that can be used to compare values and make correlations. The knowledge gathered from the visualization allows the participant to infer what could happen if they order a certain amount of cases. Configuring the visualization allows the participant to view the information from different perspectives, aiding the decision-making process.

The fifth task is subtle but essential. Players need to keep an eye on their bottom line, as their strategy for managing inventory affects their performance. Configuring the visualization allows participants to view the data from different perspectives and identify clusters, anomalies, or extreme values. Visualizations may also direct the user to characterize the distribution of inventory, customer demand, or shipment history. The subtasks lead to sub-activities such as identify and infer.

The previous discussion allows users to move from subtasks to cognitive activities using visualizations. Visualizations provide support for dynamic-decision making situations through the use of low-level analysis tasks and visual cognitive activities (see Figure 8 for explicit mapping). The lower levels of the HII framework include events and interactions. The design of the artifact provides a more thorough discussion of how visualizations also support events and interactions to allow the user to reach high-level cognitive activities.

Dashboard Artifact

The artifact developed by this research is an online interactive dashboard to supplement the board-based Beer Game. To the author’s knowledge, a visualization supplement does not exist. There are several options to play: (1) traditional version where the game is similar to a board game and players move tokens; (2) a table version where people use paper slips instead of objects; (3) an adapted table version where the bookkeeping is kept on a spreadsheet; and (4) a software version. The artifact is the differentiating factor of my research. The interactive dashboard creates a hybrid between the board and the adapted table version of the game. Players participate by playing the board game (i.e., moving tokens) and then use the interactive dashboard for bookkeeping and performance monitoring.

The human-visualization cognitive system is made up of five spaces. External interactivity focuses on three of the spaces: mental, representation, and interaction (Sedig et al., 2014). Design decisions for the artifact are based on the representation and interaction spaces. The representation space is concerned with choosing appropriate visual representations to support cognitive activities (Liang et al., 2010; Parsons & Sedig, 2014a, 2014b, 2014c). The representation space is defined by the following subsections: site layout, user interface, and graphical representations of data. The interaction space is concerned with how users are allowed to manipulate visual representations (Liang et al., 2010; Parsons & Sedig, 2014a, 2014b, 2014c). The interaction space is specified by the number and type of interaction mechanisms implemented in the design.

The dashboard uses the MAD framework. MAD is a three-tiered top-down analysis framework that offers an interactive structure to deliver information on demand. The first tier, *Monitoring*, provides a graphical summary of key performance indicators (KPIs). The second tier, *Analysis*, enables users to explore KPIs from multiple perspectives or dimensions using interactions. The third tier, *Demand*, offers the raw details that may be obscured in the other tiers (Eckerson, 2011).

The dashboard was created using Google Charts Application Programming Interface (API), JavaScript, and HTML. Google Charts is a free service that provides several charts enabled with interaction mechanisms. The Google Chart Dashboard allows programmers to manage multiple interactive charts using the same underlying data set (Google, 2019). The Google Dashboard allows me to implement a multiple view design technique with multiple interaction controls.

The Beer Game has five key performance indicators (KPIs): customer orders, order quantity, effective inventory (on-hand inventory at the end of the period minus backorders), backorders, and position cost. The dashboard displays data for all five KPIs through different perspectives using the MAD framework. The overall design of the provides information that allows the user to achieve their goal(s), where data is consolidated and arranged for at-a-glance monitoring (Few, 2006).

User Interface

The user interface consists of three major sections: (1) navigation and interaction controls, (2) the main canvas, and (3) summary information. The top navigational bar is consistently placed throughout the entire dashboard system. It provides navigational links to the different reporting tiers of the dashboard. The footer of the page contains a link to the data submission form and provides summary information. It is also consistently placed throughout the entire dashboard system. The main canvas for the page provides the interaction control bar and visualization designed for the selected report.

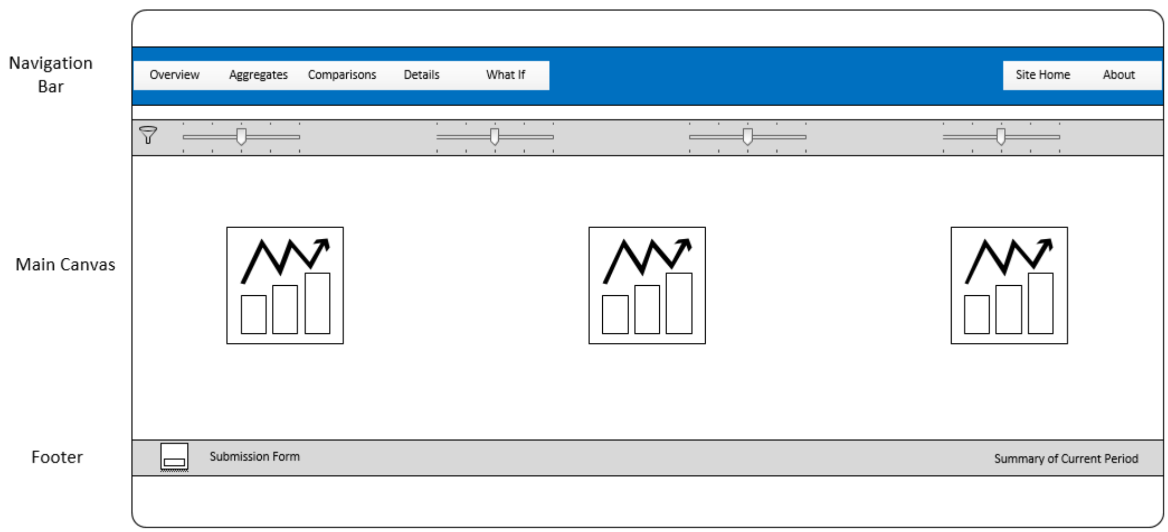


Figure 9. Dashboard Layout

Visualization Layout

The layout of the main canvas applies the multiple coordinated design technique using the Google Chart Dashboard. Users rarely accomplish their goals with a single representation (Munzner, 2014; Parsons & Sedig, 2014b). The multiple coordinated views technique is an exploratory technique allowing the user the ease of viewing data from various perspectives. Coordination among the view means that all representations simultaneously react to the manipulation triggered by interactions (Wang Baldonado et al., 2000). Providing more than one representation of the data creates multiple views. These views may be all of one chart type or different chart types. Through the use of multiple coordinated views, users can easily compare data from two or more representations (Munzner, 2014).

The monitoring layer provides an overview of the Beer Game data. This view consists of a line chart, a combination area-line chart, and a table chart. The data for the charts is near real-time and is updated on-demand by the players. The analysis layer consists of two pages: aggregate and comparison. The first, aggregate, provides descriptive statistics for the KPIs through the use of a line chart, a difference chart, and a table chart. The second, comparisons, offers four scatter plots with different combinations of KPIs. The details page provides the raw data as submitted by the user in a table chart. Interactions provided for each visualization are discussed in a subsequent section.

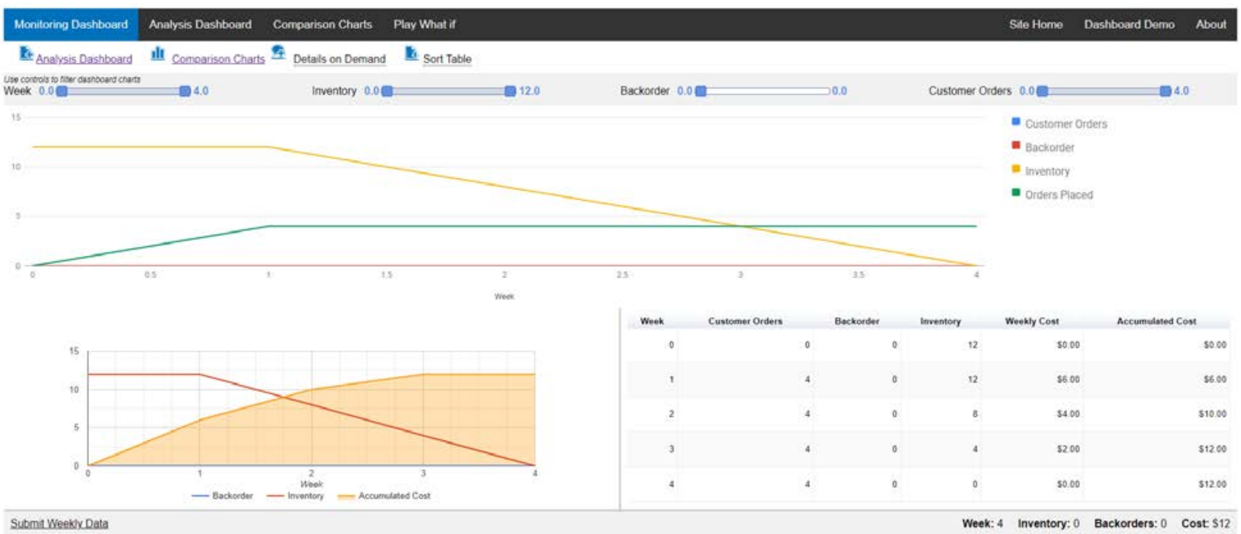


Figure 10. Monitoring Tier - Overview of KPIs

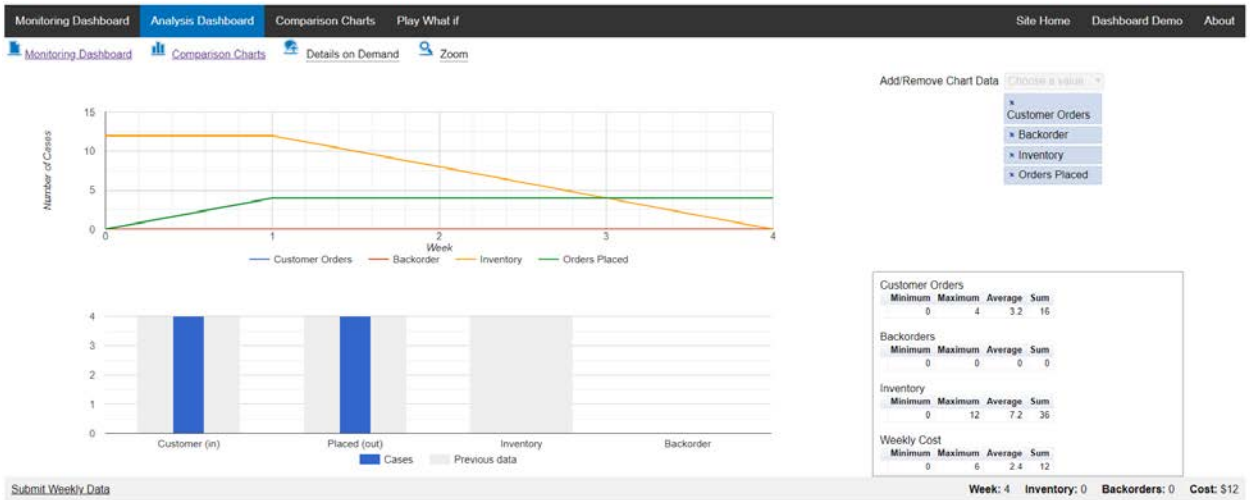


Figure 11. Analysis Tier - KPI Aggregates

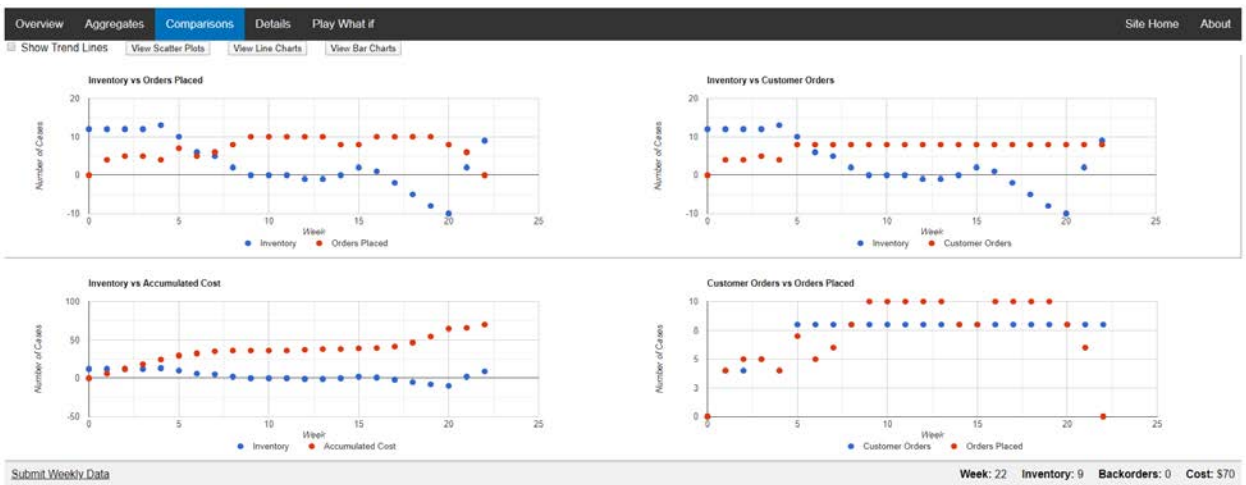
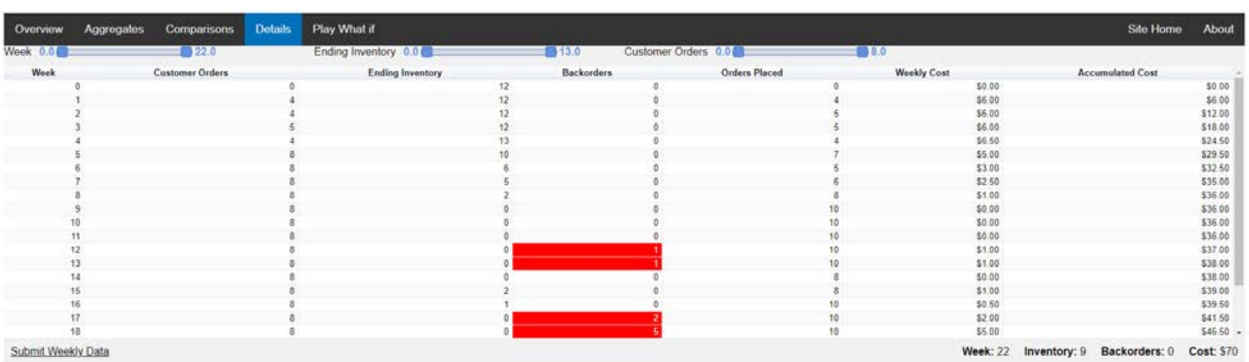


Figure 12. Analysis Tier - KPI Comparisons



Week	Customer Orders	Ending Inventory	Backorders	Orders Placed	Weekly Cost	Accumulated Cost
0	0	12	0	0	$0.00	$0.00
1	4	12	0	4	$6.00	$6.00
2	4	12	0	5	$6.00	$12.00
3	5	12	0	5	$6.00	$18.00
4	4	13	0	4	$6.50	$24.50
5	8	10	0	7	$5.00	$29.50
6	8	6	0	5	$3.00	$32.50
7	8	5	0	6	$2.50	$35.00
8	8	2	0	8	$1.00	$36.00
9	8	0	0	10	$0.00	$36.00
10	8	0	0	10	$0.00	$36.00
11	8	0	0	10	$0.00	$36.00
12	8	0	1	10	$1.00	$37.00
13	8	0	1	10	$1.00	$38.00
14	8	0	0	8	$0.00	$38.00
15	8	2	0	8	$1.00	$39.00
16	8	1	0	10	$0.50	$39.50
17	8	0	2	10	$2.00	$41.50
18	8	0	5	10	$5.00	$46.50

Figure 13. Details Tier - Raw Data

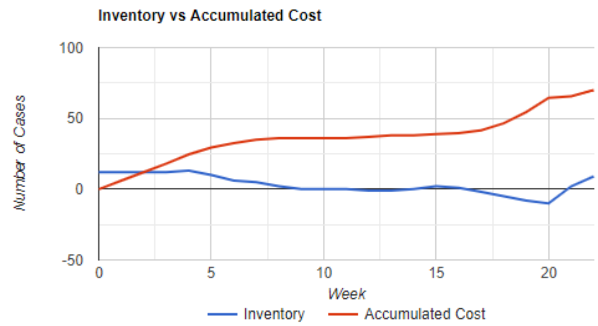
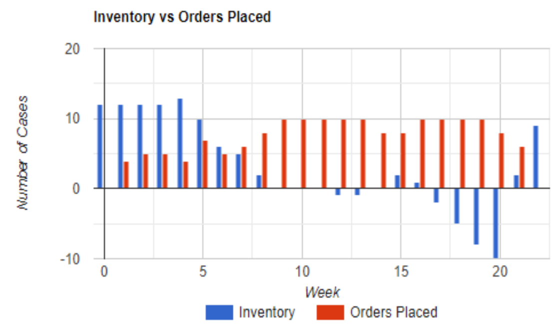
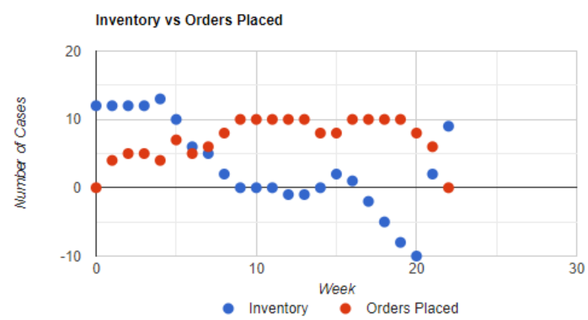
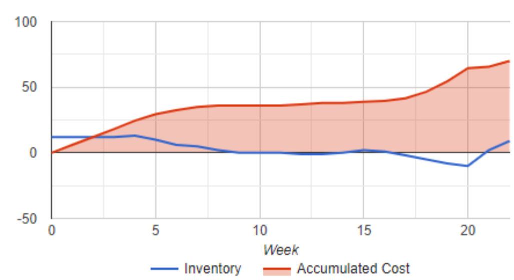
Visual Representations

The layout highlights the structural aspect of the dashboard system; however, the choice of graphical representations determines which data variables are displayed to the user. The Beer Game specification identifies key performance indicators, previously detailed in Equations 1 and 2. Extant research provides evidence that the majority of users can easily read bar charts, line charts, and data tables (Börner, 2015; Cleveland & McGill, 1984; Saket, Endert, & Demiralp, 2015; Wakeling et al., 2015). As with interactions, there are numerous guidelines for how to format charts to match the mental models of users. A review of guidelines specific to the design of dashboards is provided in the appendix. Saket et al. (2015) provide guidance specifically for the design of quantitative graphs, which were applied to the visual representations used in the artifact. Their guidelines tie the use of a specific chart type to the low-level analysis tasks (Saket et al., 2015). The guidelines stated below are specific to static visualizations and only guides the selection of chart to implement to support all levels of graphical literacy.

- Use bar charts for finding clusters
- Use line charts for finding correlations
- Use scatter plots for finding anomalies
- Avoid line charts for tasks that require readers to identify the value of specific data points
- Avoid tables and pie charts for correlation tasks.

Table 7 provides a description and example of each chart type used within the Beer Game Dashboard. All chart types are objects contained in the Google Chart API (Google, 2019).

Table 7. Dashboard Chart Types

Chart	Example
Line Chart displays quantitative data as a series of points connected by lines	
Bar / Column Chart display quantitative data using a series of vertical (column) or horizontal (bar) rectangles	
Scatter Plot display quantitative data, each represented by a graphical symbol	
Area Chart displays quantitative data as a series of points connected by lines and emphasizes the area between the axis and the line with color	

Difference Char
highlights the difference between two charts with comparable data

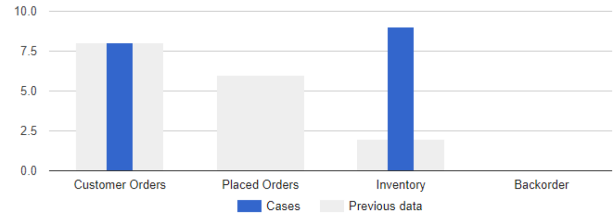


Table Chart
data table that can be sorted and paged

Week	Customer Orders	Ending Inventory	Backorders	Weekly Cost	Accumulated Co
0	0	12	0	$0.00	$0.0
1	4	12	0	$6.00	$6.0
2	4	12	0	$6.00	$12.0
3	5	12	0	$6.00	$18.0
4	4	13	0	$6.50	$24.5
5	8	10	0	$5.00	$29.5
6	8	6	0	$3.00	$32.5
7	8	5	0	$2.50	$35.0
8	8	2	0	$1.00	$36.0

Interactions

Interactions enable the user to explore data. They are actions intended to uncover new information (Ware, 2012). The seven interaction classes defined by Yi et al. (2007) are used to design the interaction space. Extant research identifies these classes as the most common ways to interact with visualizations (Börner, 2015; Figueiras, 2015; Munzner, 2014; Matthew O. Ward et al., 2015). The classes represent high-level interactions that relate to the user's intent for using a visualization.

Filtering operands allow the user to remove information they do not want to see, whether it is uninteresting items or specifying a range or condition. Filtering information aids cognition by hiding or revealing items that enable to user to quickly focus on what matters to them (Figueiras, 2015).

Figure 14. Filter with Dual-Valued Sliders

Selection operands allow the user to highlight or select data points of interest. Having the ability to mark or track items or sets of items is particularly useful when the data is dynamic (Figueiras, 2015). Yi et al. (2007) point out that "rather than acting as a standalone technique, select interaction is often coupled with other interactions to enrich user exploration and discovery."

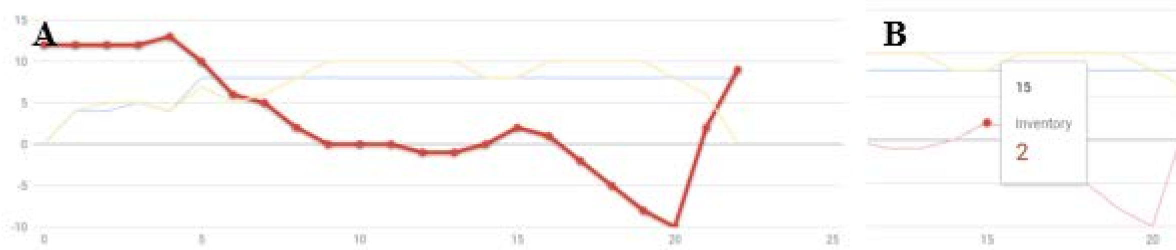


Figure 15. Selection Operands. A) Data series selection with mouse-over highlighting and distortion. B) Data Point selection with click-encoding and pop-up box.

Abstracting and Elaborating controls allow the user to modify the level of detail for the data displayed (Figueiras, 2015; Yi et al., 2007). This interaction technique supports two cognitive tasks. Viewing a smaller detailed view allows the user to organize the data and identify meaningful patterns by removing potentially noisy data. Secondly, a larger, more general view of data may hide contextual information that is necessary for decision-making tasks (Figueiras, 2015). The Beer Game dashboard includes two techniques for abstracting or elaborating the data: adding and removing variables and zooming. Adding and removing variables is an interacting technique that allows the user to control what is shown on the chart. The default view provides all KPIs as data series. The chart requires at least one selection of data, but the user has full control over what is added and what is removed. Zooming allows the user to select a subsection of the overview to display. The selected subsection is smaller and more detailed than the default chart. Zooming does not fundamentally alter the original visual representation (Figueiras, 2015).

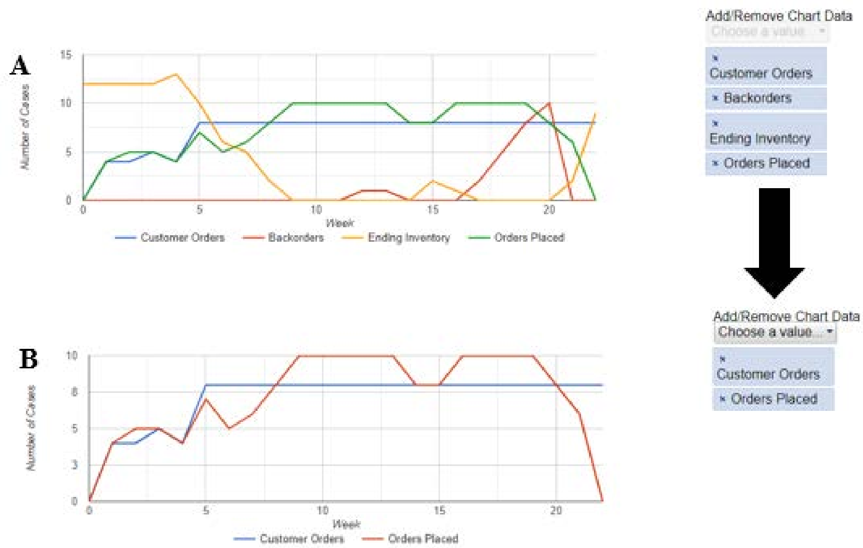


Figure 16. Abstract/Elaborate with Add-Remove. A) Default chart with four KPIs. B) Updated chart with user-selected variables.

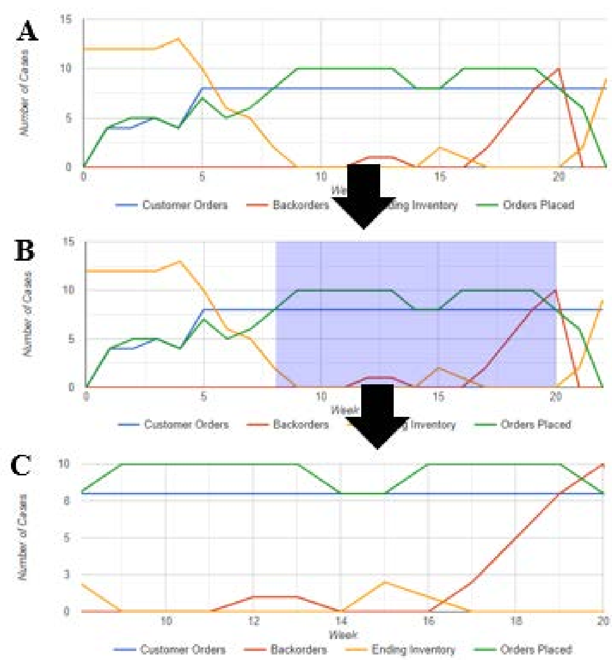


Figure 17. Abstract/Elaborate with Zoom. A) Default Chart. B) The zoom feature of Google Charts. C) Updated chart showing the selected subset of data.

Reconfigure and encoding controls allow the user to change how information is displayed. Altering the visual representation of the graph provides different perspectives of the data, which facilitates the discovery of new insights (Yi et al., 2007). The Beer Game dashboard provides three techniques for reconfiguring and encoding information: sorting, changing how the chart is displayed, and navigating between MAD tiers. Sorting is an interaction technique specific to the table chart. Sorting allows the user to change the order of the values displayed, either by ascending value or descending value (Google, 2019). Data in tables are sorted by the columns of data, as selected by the user.

A

Week	Customer Orders	Ending Inventory	Backorders	Orders Placed	Weekly Cost	Accumulated Cost
0	0	12	0	0	$0.00	$0.00
1	4	12	0	4	$6.00	$6.00
2	4	12	0	5	$6.00	$12.00
3	5	12	0	5	$6.00	$18.00
4	4	13	0	4	$6.50	$24.50
5	8	10	0	7	$5.00	$29.50

B

Week	Customer Orders	Ending Inventory	Backorders	Orders Placed	Weekly Cost	Accumulated Cost
0	0	12	0	0	$0.00	$0.00
1	4	12	0	4	$6.00	$6.00
2	4	12	0	5	$6.00	$12.00
3	5	12	0	5	$6.00	$18.00
4	4	13	0	4	$6.50	$24.50
5	8	10	0	7	$5.00	$29.50

C

Week	Customer Orders	Ending Inventory	Backorders	Orders Placed	Weekly Cost	Accumulated Cost
22	8	9	0	0	$4.50	$70.00
21	8	2	0	6	$1.00	$65.50
20	8	0	10	8	$10.00	$64.50
19	8	0	8	10	$8.00	$54.50
18	8	0	5	10	$5.00	$46.50

Figure 18. Reconfigure/Encode with Sort. A) Original table chart. b) Table chart sorted by column Backorders in ascending order. c) Table chart sorted by column Accumulated Cost in descending order.

Encoding controls enable the user to change what type of chart is displayed or by adding color or symbols to the chart. Encoding creates visual stimuli that attract the user's attention, whether by color, size, or shape. The changes may include completely changing the type of chart this is displayed or by changing the configuration of how data is displayed. Figure 15-A shows data series selection, highlighting what the user is interested in and distorting the other information in the chart.

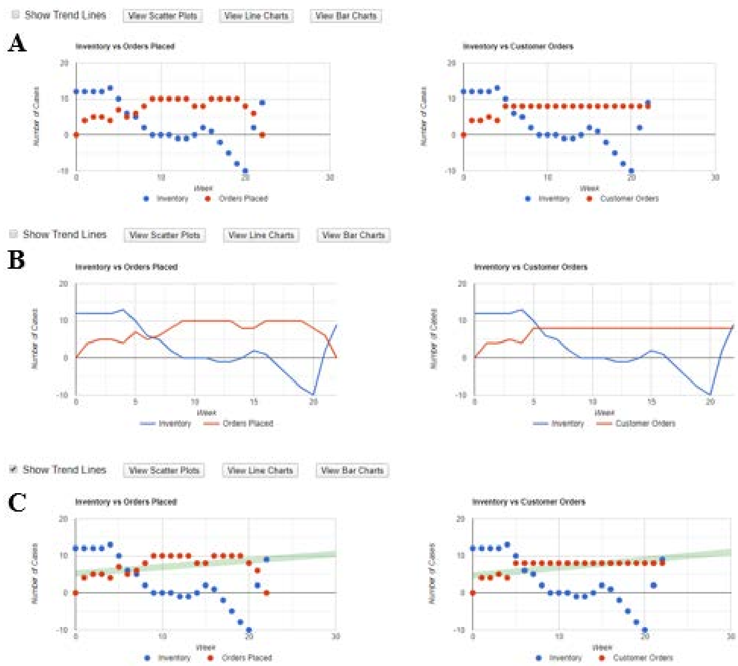


Figure 19. Reconfigure/Encode. A) Default View. B) Updated charts by changing chart type. c) Updated charts by displaying trend lines.

Navigation or exploration options are provided to allowing the user to view different views of the MAD framework. The default view for the Beer Game dashboard is the monitoring level, which is an overview of the data. The analysis tiers and detail tiers can be viewed by navigating to the dashboard report.

Figure 20. Reconfigure/Encode with Navigation

Connecting and relating controls enable users to view the relationship between data items. This type of interaction is important to tasks such as comparisons, where users need to see what kind of relationship or if a relationship exists between two or more data elements (Craft & Cairns, 2005). The Beer Game dashboard implements this interaction technique through two types of implementations: coordinated views and connected data points. The multiple coordinated view design technique simultaneously applies the results of an interaction with all graphs on the page. Selecting data points on a graphical chart or in the table chart will highlight the data points on the other charts on the page.

Figure 21. Connect/Relate with multiple coordinated views.

Week	Customer Orders	Ending Inventory	Backorders	Weekly Cost	Accumulated Co
0	0	12	0	$0.00	$0.0
1	4	12	0	$6.00	$6.0
2	4	12	0	$6.00	$12.0
3	5	12	0	$6.00	$18.0
4	4	13	0	$6.50	$24.5
5	8	10	0	$5.00	$29.5
6	8	6	0	$3.00	$32.5
7	8	5	0	$2.50	$35.0
8	8	2	0	$1.00	$36.0
9	8	0	0	$0.00	$36.0
10	8	0	0	$0.00	$36.0
11	8	0	0	$0.00	$36.0

Figure 22. Connect/Relate with data point selection.

"*Overview* first, zoom and filter, then details on demand (B. Shneiderman, 1996)" is the visual information seeking mantra. The mantra defines how to develop a visualization that is most effective for the user to analyze data. The default view of the Beer Game Dashboard is the monitoring tier (see Figure 10). It provides the user with a general context of the data set, with the ability to apply interactions for more detailed exploration.

Hybrid interaction techniques combine two or more of the interaction classes (Matthew O. Ward et al., 2015). Details on Demand is a hybrid technique that allows the user to view information through the combination of selection and abstraction/elaboration. Details on demand consist of obtaining additional information through a pop-up box or tooltip. The additional information is displayed when an item is selected and does not require the user to change the visual representation (Craft & Cairns, 2005; Yi et al., 2007).

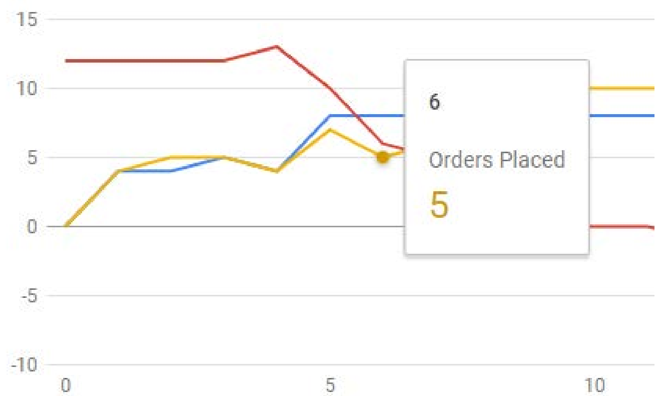


Figure 23. Hybrid with Details on Demand

Events

Interactions build from events, which are the physical actions taken by the user. Physical actions include hovering, clicking, and clicking, and dragging. Hovering indicates that the user has moved the mouse pointer over a specific element on the page, causing a reaction in the visualization (Park et al., 2016). The action of hovering is mostly associated with selection operands. Clicking indicates that the user has moved the mouse pointer over a specific element and clicked the mouse button at least once. The action of clicking is associated with selection operands, sorting interactions, and reconfiguring interactions. Clicking and dragging means the user has moved the mouse pointer over a particular feature, clicked and held the mouse button down while dragging the pointer to the left or right. Clicking and dragging are most often associated with filtering and zooming interactions.

Table 8. Mapping of Events to Interactions and Reactions

Event	Object of Interest	Interaction	Reaction
Hover	Data Point (Chart)	Selection	Encode
		Abstract-Elaborate	Details on Demand
	Data Series (Chart)	Selection	Highlight
			Encode
	Data Row (Table)	Selection	Highlight
Click	Data Point (Chart)	Selection	Encode
		Abstract-Elaborate	Details on Demand
		Connect	Encode
	Data Series (Chart)	Selection	Encode
	Data Row (Table)	Selection	Encode
	Column Header (Table)	Sort	Encode
	Selection List	Abstract / Elaborate	Encode
	Button	Reconfigure	Encode
	Checkbox	Reconfigure	Encode
Click and Drag	Sliders (Chart and Table)	Filter	Filter
		Connection	
	Chart Area	Abstract-Elaborate	Zoom

Feedforward Cues

Feedforward cues instruct the user how to interact with the visualization and what reactions to expect. The system is designed for general use, not specific to novice or subject matter experts. It was assumed that users had a basic knowledge of how to interact with visualizations. For instance, they know and understand the meaning behind the keywords ‘filter’ and ‘popup.’

It is unknown if users know when they can interact with the visualization, or if they are inclined to try (Boy, Eveillard, Detienne, & Fekete, 2016). Feedforward cues help to bridge the gulf of execution that forms when a user knows what action to take but do not know how to execute that action (Norman, 2013). Affordances play an essential part in the user experience. The design of affordance is critical to a user understanding the visualization interface (Kirsh, 2005). Users may gain perceived affordances when they think they know what actions can be performed. ‘Good design’ becomes a matter of displaying cues and constraints, which influences what the user sees as possibilities for action (Kirsh, 2005). Feedforward cues are the operationalization of perceived affordances. They explicitly state what the result of an action will be (Vermeulen et al., 2013).

Figure 24. Feedforward Cues as Labels and Icons

Figure 25. Feedforward Cues as Button Text

Application of the HII Framework Part 2

Previous sections of this chapter describe how low-level analysis tasks allow users to complete the Beer Game tasks. The game tasks are supported by visualizations that enable the user to perform high-level cognitive tasks. The design of the artifact provides conceptual ideas behind connecting the lower levels of the HII framework (events and interactions) to higher levels of the HII framework (subtasks, tasks, sub-activities, and activities). Figure 26 provides the full conceptual view of how visualizations support cognitive activities within a dynamic decision-making environment.

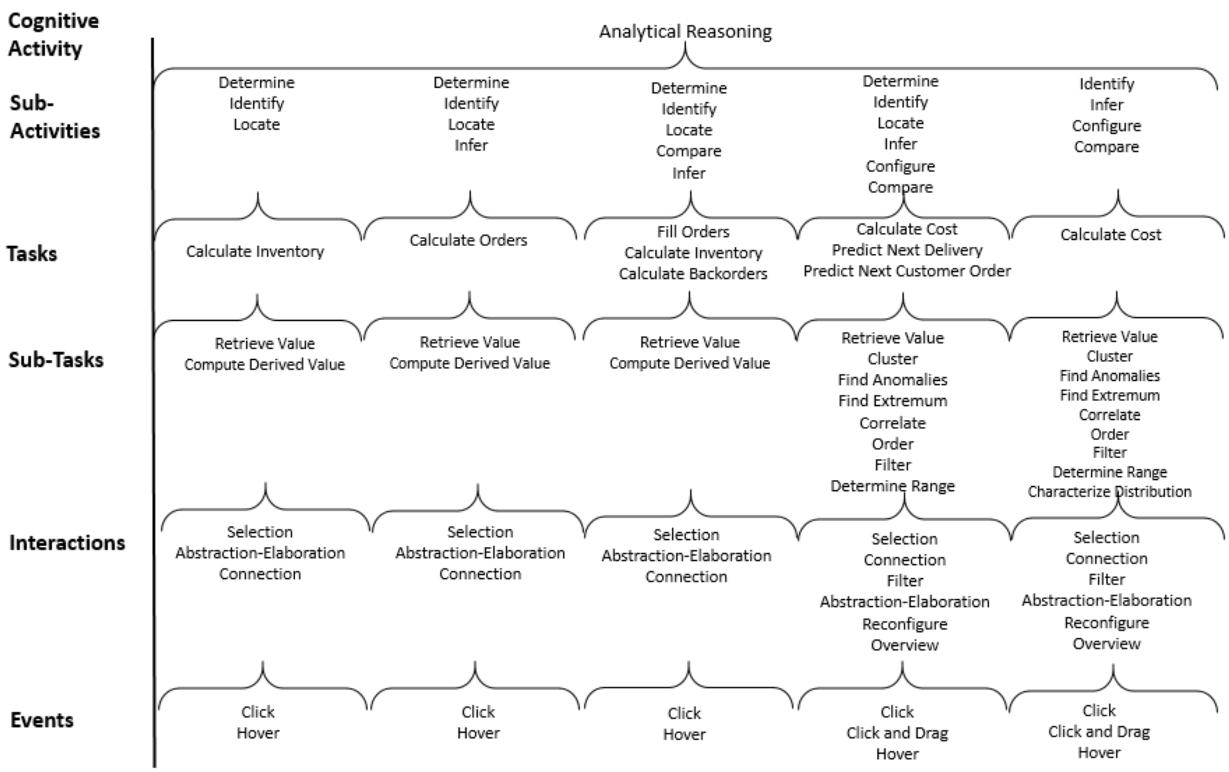


Figure 26. Mapping of Beer Game tasks to all Levels of the HII Framework

Evaluation

The utility of a visualization decreases when users try to go beyond what the designer envisioned (Albers, 2004). The artifact for this research was designed with human-centric techniques, which is a deviation from the traditional data-centric design methods for visualization systems. Visualizations that are designed to facilitate thinking by organizing information will have greater utility than those that are designed to provide answers (Albers, 2004). Human-centric design techniques consider how the user will think and reason for each task that they need to complete. The HII framework guides the designer to identify tasks that must be completed through dynamic decision-making situations. The design of the dashboard artifact was developed by identifying the tasks to complete and how elements of the HII framework work as a cohesive unit to achieve those tasks (see Figure 26).

Approaching visualization design with human-centric techniques allows for designers to identify how users perform cognitive activities when using visualizations. Evaluation of the artifact provides results that determine how external interactivity factors influence knowledge activation. Interacting with visualization is an epistemic cycle. Users take action to externalize their thought process and alter visual representations to support their mental operations and distribute the cognitive load (Ya'acob et al., 2016). Human-centric design approaches go beyond the data-centric design approach to focus on information needs and information relationships.

Beer Game Measures

The Beer Game is a common tool to demonstrate the systems-thinking perspective (Senge, 2006). Sterman (1989) initially developed the game to analyze managerial decision-making strategies. Through this study, he identifies three indicators of behaviors that result from playing the Beer Game: oscillation, amplification, and phase lag. The behavioral indicators define the decision strategies for players participating in the Beer Game. A comparison of these metrics provides insights into how people manage the decision-making process with uncertain information in dynamic situations.

Oscillation represents the fluctuations that dominate orders and inventory. The variations indicate that players often overreact to the levels of inventory when they receive customer orders. Each position receives orders from the downstream customer and fills the requests using their on-hand inventory. As inventory levels decline at the retailer position, their orders for more beer increase, causing a reduction in inventories at the other positions in the supply chain. In the same manner, the reverse is also true, as inventory levels increase, orders tend to decrease. Oscillation is measured by the time it takes a position to recover the initial inventory (12 cases), the period of the game with the smallest number of cases in inventory (can be negative), and the period of the game with the largest number of cases in inventory (Sterman, 1989).

Amplification shows the rippling effect caused by the variance of orders from customer to retailer to brewery (Sterman, 1989). There are four measures for amplification: average order quantity per period, the period with the largest order quantity, the largest order quantity, and the variance of orders. The values of order quantity are compared against the maximum and minimum information for inventory. Phase lag shows the periods with the game when each position orders the highest quantity of beer. The lag generally shows that positions later in the supply chain have a later date for peak orders, in comparison to those at the front of the chain (Sterman, 1989).

Table 9. Beer Game Behavioral Indicators from (Sterman, 1989)

	Customer	Retailer	Wholesaler	Distributor	Brewery
Oscillation (weeks)					
Time to Recover initial inventory		24	23	22	16
Date of Minimum Inventory		20	22	20	22
Date of Maximum Inventory		28	27	30	26
Amplification					
Peak Order Rate (cases/week)	8	15	19	27	32
Variance of Order Rate (cases/week)	1.6	13	23	45	72
Peak Inventory (cases)		20	41	49	50
Minimum Inventory (cases)		-25	-26	-45	-23
Range (cases)		45	88	94	73
Phase Lag					
Date of Peak Order Rate (week)	5	16	16	21	20

Visualization Measures

The effectiveness of visualizations is a subjective measure because of the inherent variety of contextual and perceptual factors. There are four guiding principles for evaluating information systems (Winckler, Palanque, & Freitas, 2004):

1) Identify the goals for a user and verify if the user can reach them within the visualization.
2) Identify the mechanisms of the interaction made available to the user and how they are useful to accomplishing tasks.
3) Identify the individual visual representations that have been used within the visualization to show data.
4) Relate goals, interaction mechanisms, and visual representations.

The performance measures from the Beer Game will provide insight into how players understand the purpose of the game. The goal of the game is to minimize costs by identifying a strategy to handle the stock management problem (Sterman, 1989). Previous sections of this chapter provide a thorough discussion of the visual representations and interaction mechanisms available within the Beer Game dashboard. Players of the Beer Game will be asked to complete a post-game questionnaire that includes debriefing questions, and task-technology fit questions (Goodhue, 1998; Sterman, 1992).

The purpose of visualizations is to generate insight, allowing humans to complete tasks more efficiently (Yi et al., 2007). When information visualizations become engrained in the behavior of humans, it signifies the value of the visualization. The value of a visualization encompasses a broad perspective, where the information system is used for analysis rather than simple answers. Value is determined by four elements: time (T), insight (I), essence (E), and confidence (C). The value of visualization provides an overall measure using time, insight, essence, and confidence. A qualitative formula to determine value is $V = T + I + E + C$ (Stasko, 2014). Evaluating the value of the visualizations extends beyond usability measures. Instead, evaluation is based on understanding what the visualization provides and if it allows the user to think deeper (Stasko, 2014).

Table 10. Value of Visualization Specification

	Notation	
Time	DT_T^{pb}	
	$\frac{\sum_{t=2}^{T}\left(DT_t^{pb} - DT_{t-1}^{pb}\right)}{T}$	
Insight	BEI_T^{pb}	
	$\frac{VAR\left(O_T^{pb}\right)}{VAR\left(D_T\right)}$	for p = 1
	$\frac{VAR\left(O_T^{pb}\right)}{VAR\left(O_T^{p-1,b}\right)}$	for p = 2, 3, 4
Essence	NSI_T^{pb}	
	$\frac{VAR\left(O_T^{pb}\right)}{VAR\left(S_T^{p+1,b}\right)}$	for p = 1, 2, 3
	$\frac{VAR\left(O_T^{pb}\right)}{VAR\left(O_{t-3}^{pb}\right)}$	for p = 4
Confidence	CON_T^{pb}	
Satisfaction	$\frac{\sum_{c=1}^{7} sat^c}{7}$	for task fitness
	$\frac{\sum_{m=1}^{8} sat^m}{8}$	for interactions
Importance	$\frac{\sum_{c=1}^{7} imp^c}{7}$	for task fitness
	$\frac{\sum_{m=1}^{8} imp^m}{8}$	for interactions
Value of Visualization	V = $DT + BEI + NSI + CON$	

Time (DT) represents the time needed to answer a variety of questions about the data. Visualizations should allow a person to minimize the total time needed for tasks when viewing visual representations and interacting with the information (Stasko, 2014). Time is measured by the minutes that pass between data submissions. The Beer Game dashboard provides near-real-time data because it updates whenever the user enters the game information for a period. Each period's submissions are tracked using a date/time stamp indicating when the user has finalized their decision.

Insight (BEI) represents the ability of a visualization to stimulate or discover insights about the data (Cybulski et al., 2014; Stasko, 2014). The bullwhip effect is a common phenomenon within supply chains and is used to measure the player's response to customer demand. Insight is measured by the Bullwhip Effect Index (BEI), or the variance of orders placed divided by the variance in customer orders received. A BEI greater than one indicates a level of panic, and less than one indicates a level of calm (Analytics, 2019).

Essence (NSI) represents the ability of the visualization to convey an overall sense of the data that goes beyond the superficial display of information. Users are able to identify patterns trends and other insightful information while performing cognitive activities. As users work with the visualization, they apply environmental aspects of the situation, impacting their interpretation of the information (Stasko, 2014). Essence is measure by the No-Strategy Index (NSI), representing the 'no-strategy' strategy. This decision strategy is one solution to the stock management problem. It ignores the fluctuations in customer demand and instead focuses on the shipments received from the upstream supplier. With this approach, the player thinks holistically about the situation and takes into consideration other factors within the supply chain (i.e., processing and shipment delays). They consider the impact of their decision on the entire chain and not just respond to customer demand (Senge, 2006). NSI is the variance of orders placed divided by the variance in shipments received. An NSI value greater than one indicates a holistic view of the supply chain, and less than one shows a local view of the supply chain.

Confidence (CON) is the ability to generate confidence, knowledge, and trust in the data (Stasko, 2014). Goodhue's Task Technology Fit questionnaire provides the basis for measuring confidence (Goodhue, 1998). Seven confidence measures represent six groups of task fitness. Each measure includes a rating for both satisfaction and importance; users rate how satisfied they are with the given aspect of task-technology fit, along with how important that element was to completing their goal.

- Right Data: the system maintains the needed basic fields or elements of data.
- Right Level: the system maintains data at the right level or levels of detail.

- Locatablity: the ease of determining what data is available and where.
- Accessibility: the ease of access to desired data.
- Meaning: the ease of determining what data elements mean.
- Ease of Readability: the ease of reading data provided by the system.
- Ease of Use: the ease of doing what is needed.

The evaluation of the artifact is two-fold. First, the evaluation considers the performance outcomes of the Beer Game. The way a person responds to the stock management problem is evidence through the analysis of Beer Game data. Second, the evaluation considers the influence on the decision-making process and the overall impact of using visualization.

Methodology Summary

This chapter details the research methodology for my investigation into how *interacting with visualizations support analytical reasoning of emergent information to activate knowledge*. The design science research framework identifies three main areas for the relevance and rigor of the research (Hevner et al., 2004). First, the *environment* is the problem space that contains the phenomenon of interest. Second, the construction and evaluation of an *artifact*. Lastly, the *knowledge base* that provides applicable theories and methods. The problem space for this research is supply chain logistics, specifically looking at the bullwhip effect and stock management problem. The Beer Game dashboard is the artifact that was created as a result of the research. Lastly, the research pulls from the theory of distributed cognition, human-information interaction framework, and the deep and rich research leveraging the human’s visual and perceptual systems.

Table 11. Evidence of DSR Guidelines adapted from (Hevner et al., 2004)

Guidelines	**Explanation**
Problem Relevance	Stock Management problem, which includes the following characteristics of wicked problems (Hevner et al., 2004) : • complex interactions among components of the problem and solution • critical dependent upon human cognitive abilities • critical dependence upon human social abilities
Design Evaluation	Value of Visualization
Research Rigor	Theory of Distributed Cognition Human-Information Interaction ecological approach External Interactivity and Macro-Interactivity Tasks and Taxonomies of Information Visualization
Design as Search	Experiment with repeated tasks

CHAPTER 4

RESULTS AND DISCUSSION

I endeavor to identify the benefits of interactions within visualization to generate and apply knowledge, with a particular focus on emerging information in a dynamic-decision making context. The following sections describe the results of my research, along with a discussion of theoretical and practical contributions. The investigation into the design of interactive visualizations to identify the attributes support external interactivity factors was conducted into two parts. The first part entails a pilot study to gauge how users know when or how to interact with visualizations. The second part involves an experiment to evaluate how users interact with visualizations to activate knowledge.

Procedures and Data Collection

Pilot Study

The initial step of this investigation was the execution of a pilot study to determine what interaction mechanisms support analysis tasks. The objective of the questionnaire was to gain insight into how users bridge the gulf of execution, guided by the questions: w*hat interaction mechanisms do users apply when answering questions about the data in a visualization?*

A questionnaire was distributed through email to undergraduate and graduate students of two rural universities[1]. The students were randomly selected by the Institutional Research offices at both universities. Participants were asked to visit a webpage that contained three sets of visualizations and answer two questions for each. There were 129 respondents to the survey, 74 percent were male, and 89 percent were from the 18-24 age bracket. Of the participants, 16 percent used charts for daily or weekly activities; 50 percent use charts at

[1] Dordt University IRB Approval 2/27/19 | Dakota State University IRB Approval 3/15/2019 (Approval #18-19-14)

least once a month, and 33 percent hardly use charts in their daily activities. The data collected from the survey included demographic questions (age, undergraduate or graduate student, and use of charts in daily activities), the participant's answers to the six questions, and satisfaction rating for how an interaction mechanism helps to answer the questions.

Experiment

The second step of the investigation was the execution of the Beer Game to determine how interactive visualizations support knowledge activation during dynamic decision-making situations. The Beer Game tests players' analytical decision-making abilities with emergent and unknown information, as the overall experience is based on dealing with high uncertainty and lack of global information (Senge, 2006). The Beer Game was played on three occasions[2]: two in-person sessions utilizing the Beer Game dashboard, and one virtual session using online software. Participants were undergraduate students and faculty that volunteered to participate and were not provided incentives for their time or performance. There were a total of twenty participants for the in-person Beer Game, from here on referred to as the treatment group.

The two in-person sessions lasted two hours, where the time limit was strictly enforced. Participants arrived at the classroom at a predetermined time and were assigned a position. Participants were told not to communicate with anyone during the experiment, as this is a standard rule of the Beer Game (Sterman, 1992). Participants were oriented to the rules and objectives of the game. They were provided with basic instructions and a demonstration of how to use the Beer Game dashboard. The virtual session lasted approximately 15 minutes, as the opponents in the Beer Game were played by artificial intelligence. Participants of the virtual session were provided the same instructions of the Beer Game as the in-person session, and a brief overview of how to use the online software. There were a total of sixteen participants for the virtual session of the Beer Game, from here on referred to as the control group. Eight of the participants also participated in the treatment group. This group is from here on referred to as Control-A. The other eight participants of the

[2] Dordt University IRB Approval 4/22/2019 with amendment approved 12/4/2019

control group only played the online version of the Beer Game, and are referred to as Control-B.

The dynamics and rules are the same, despite how a player participated in the Beer Game. Each position begins with an initial inventory of 12 beer cases, outstanding orders of four cases for two periods, and an incoming shipment of four cases for two periods (Sterman, 1992). Participants are not informed of the number of periods the game will run. The first in-person session completed 36 periods, the second 22 periods, and the online software completed 50 periods. All analyses for this research will focus on data collected for 22 periods for both the treatment and the control groups. Participants were not informed about the distribution of retail demand. All participants were told that their goal was to have the lowest overall cost and that there were penalties relating to inventory. Each position would be penalized for holding onto inventory (holding fee of $0.50 per case per period) and for stockout costs (backorder fee of $1.00 per case per period) (Sterman, 1992).

The Beer Game data is collected for each period of play and includes the number of orders received from the downstream customer, the number of cases left in inventory at the end of the period, the number of back-ordered cases at the end of the period, the number of cases received from the upstream supplier, and the number of cases ordered to replenish inventory. Cost is calculated each week, as is a running total for all periods played. Other elements calculated from this data include effective inventory (ending inventory less any backorders), the variance of customer orders, variance of orders placed, and variance of shipments received.

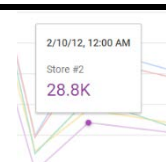
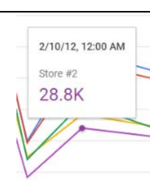
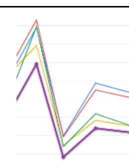
Results

Pilot Study

The pilot study survey was designed to simulate interactive visualizations displayed on a webpage. The survey questions about the visualizations focused on embedded interactions. Embedded interactions incorporate one or more interactive graphical encodings into visualizations (Saket, Srinivasan, Ragan, & Endert, 2018). The visualizations were designed for general users, not giving preference to expert or novice. The survey asked users to review three sets of visualizations and answer two questions for each set. Questions were developed using the low-level analysis tasks identified by Amar et al. (2005). The tasks were matched to embedded interactions available within each visualization set.

Table 12 provides a demonstration of how tasks, physical actions, and interactions converge to show what mechanisms support an activity. The selection operand offers the ability to select something as interesting (Yi et al., 2007). Selection occurs when the user clicks on an individual data point or data series, or by hovering over a single data point or data series. Selection operands are embedded interactions, responding to specific physical actions. Encoding elements of a visualization include, but are not limited to, length, position, size, and color (Saket, Kim, T., & Endert, 2017). Selection operands allow users to encode elements on a graph, as they see fit. For selection, encoding responses include changing the shape of the data point, changing the color of the data point or series, distorting the context of the chart, or displaying a pop-up box with additional data. Selection is used to complete tasks such as retrieving a value, finding an anomaly, or finding an extreme value.

Table 12. Selection Interaction Mapped to Tasks

Task(s)	**Event**	**Object of Interest**	**Embedded Interaction**	**Example**
Retrieve Value Find Extremum Find Anomaly	Click	Data Point	Encoding Details on Demand Focus + Context	
	Click	Data Series	Encoding Focus + Context	
	Hover	Data Point	Encoding Details on Demand	
	Hover	Data Series	Encoding Highlighting	

Data sets may be complex and may need different types of analysis or visualizations to make sense of them. Two of the three visualizations in the survey included more than one type of chart. This design decision speaks to the flexibility of information visualization tools and the differences in cognitive processing in users (Saket et al., 2015; Saket et al., 2017).

Embedded interactions do not provide affordances indicating their functional existence. Instructions were displayed in a yellow box below the chart(s) (see Figures 27-A and 28-B). It was assumed that once an individual had used or been informed of the embedded interactions, instructions were not needed for future use. Instructions for selections and details on demand were provided on the first visualization, and for zoom and sort on the second visualizations. As all of the embedded interactions were available in the third visualization, no instructions were posted.

The six survey questions were representative of a task or set of tasks. Questions were created using examples provided by Amar et al. (2005), as they related to the low-level analysis tasks (see Table 13). Each participant was asked questions relating to how interactions were used to complete low-level analysis tasks. The results from the survey were checked to verify if the participants were able to provide the correct answers as each question had one correct answer.

Table 13. Low-Level Analysis Task Questions

Low-Level Analysis Task(s)	**Question**
Find Extremum, Retrieve Value	What store had the highest sales over Thanksgiving (Black Friday) holiday?
Determine Range, Find Anomaly	What holiday season produced the fewest sales across the three years of data shown in the graph?
Order	What store number produced the most sales for regular weeks (non-event)?
Compute Derived Value	What is the difference between the non-event total sales for Store #35 and the total non-event sales for Store #36?
Cluster, Determine Range	What two departments have the largest Thanksgiving sales?
Characterize Distribution	How many departments had higher Thanksgiving sales in 2010, as compared to 2011?

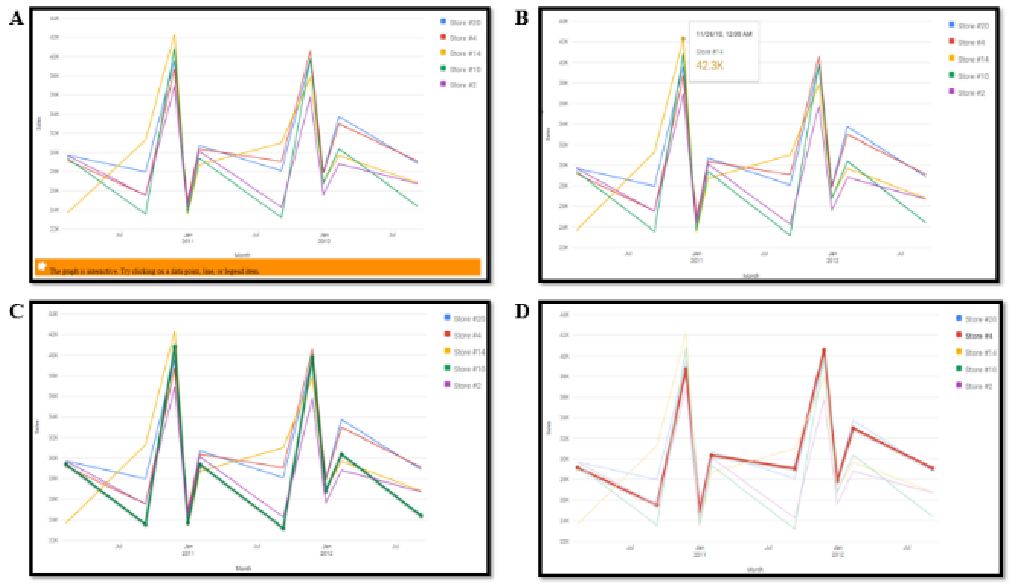


Figure 27. Pilot Study Visualization #1. A) Original Chart. B) Data point selection with Details on Demand; C) Data series selection with highlighting; and D) Data series selection with distortion.

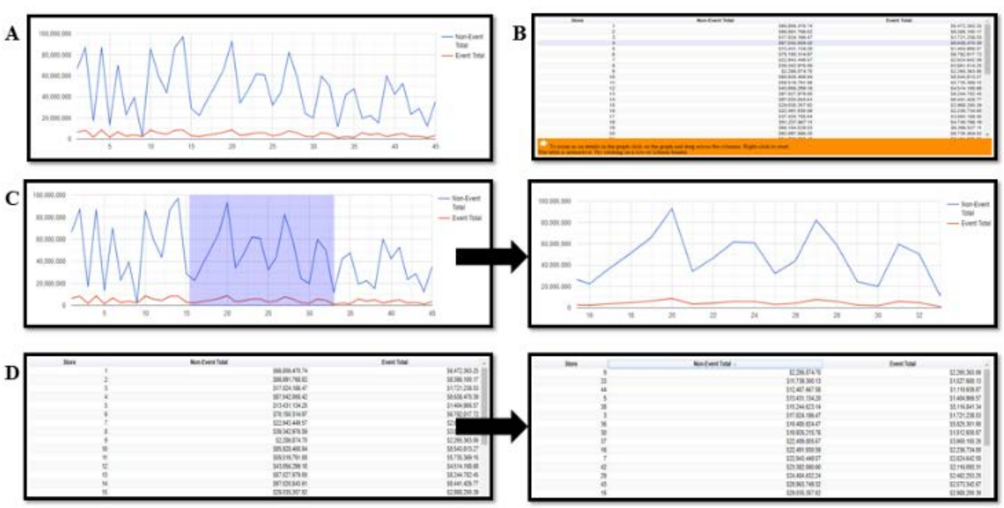


Figure 28. Pilot Study Visualization #2. A) Original line chart. B) Original Table Chart. C) Line chart with zoom; and D) Table chart with sort.

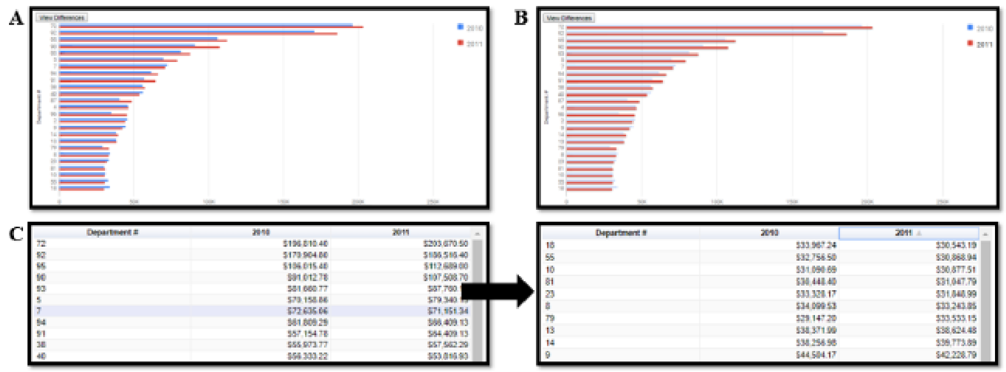


Figure 29. Pilot Study Visualization #3. A) Original bar chart; b) Data series selection with distortion; and c) Table chart with sort.

For the first visualization, participants were asked to a) find an extreme data point and retrieve its value; and b) determine the range of values and identify the anomaly. For the second visualization, participants were asked to a) retrieve a value after sorting the data; and b) compute a value based on the information provided. Lastly, participants were asked to a) identify the range of a cluster of data values and b) characterize the distribution of the values.

Participants were also asked to identify what interaction mechanism(s) were most helpful in completing the task. The selection and hover mechanisms were preferred for the first four questions. The users indicated that these mechanisms assisted them in completing tasks. The sort and hover interaction mechanisms were preferred for the last two questions. These mechanisms assisted in completing tasks relating to clustering the data points and characterizing the distribution of data. The use of selection and hover interaction mechanisms were favorable to helping participants answer the first and second questions correctly (see Figures A and B in Table 15). The results provide evidence that the selection interaction mechanisms are favorable towards aiding the low-level analysis tasks of finding extreme values, retrieving values, finding anomalies, and determining the range of data values.

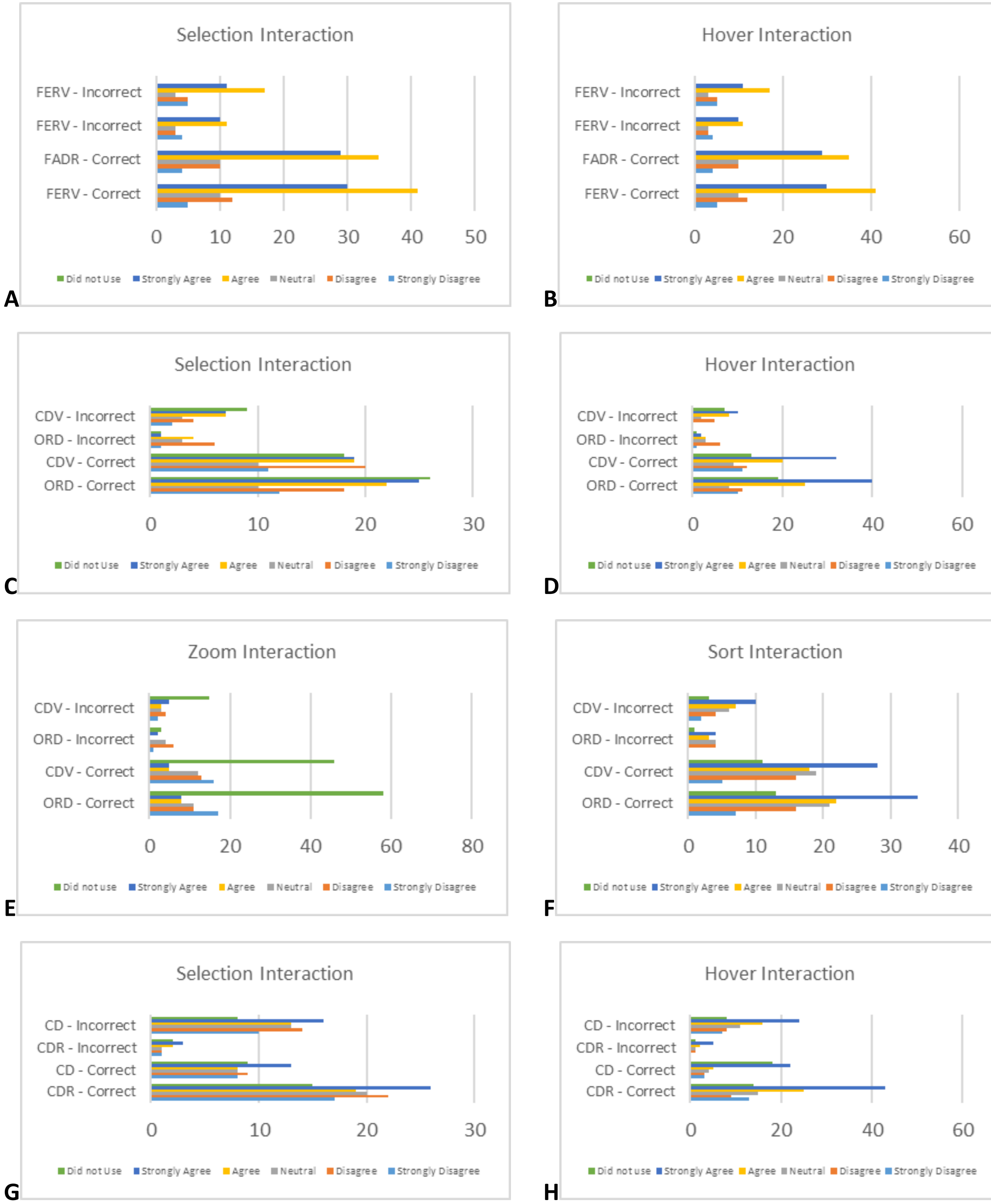
Table 14. Pilot Study –Question Results

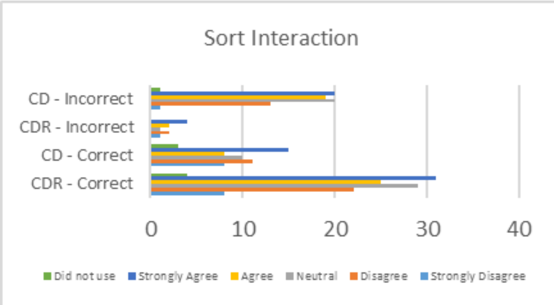
Visualization	Question	Task(s)	Correct	Incorrect
1	1	Find Extremum, Retrieve Value (FERV)	76%	24%
1	2	Determine Range, Find Anomaly (FADR)	68%	32%
2	3	Order (ORD)	88%	12%
2	4	Compute Derived Value (CDV)	75%	25%
3	5	Cluster, Determine Range (CDR)	92%	8%
3	6	Characterize Distribution (CD)	43%	57%

The second visualization consisted of two types of charts (line and table), with four embedded interactions. The participants with correct answers, favored the selection, hover, and sort interaction mechanisms (see Figures C, D, E, and F in Table 15). The second visualization did not provide instructions explicit to the use of selection and interaction. The lack of instructions for specific mechanisms may explain the higher number for 'did not use.' Survey participants stated that they did not know the zoom feature existed, despite posted instructions just below the chart. The third visualization also consisted of two types of charts (bar and table), with three embedded interactions. The three interaction mechanisms appear to support the tasks to identify clusters of data points, determine the range of data points, and characterize the distribution of data (see Figures G, H, and I in Table 15).

The zoom feature embedded in visualization two was not used to complete the analysis tasks. Responses to the question of why indicate that users did not know the functionality exists. Despite the instructions provided just below the chart, the affordance of embedded features is an important concept for overall effectiveness and utilization.

Table 15. Pilot Study - Use of Interaction Mechanisms





The results of the pilot study offer insights for how users interact with visualizations to complete tasks. Cognitive tools allow people to participate in more effective thinking processes (Ware, 2012). Before the efficiency of a tool can be measured, it is imperative to understand what aspects of the tool are being used. The results of this pilot study support extant research in that interactions are cognitive aids that help to reduce information overload (Blascheck et al., 2019; J. Heer & Shneiderman, 2012). It does not provide the full benefits of interactions, but the results were useful in guiding the development of the Beer Game dashboard. The pilot study results provide evidence that designers of visualization need to understand the coupling between interactions and visual representations.

Experiment – Behavioral Analysis

The Beer Game tests players' analytical decision-making ability by placing them in a situation with limited and uncertain information. The game is designed so that participants have good local information but severely limited global information. This limitation is in place to ensure that participants cannot coordinate decisions or jointly plan strategy (Sterman, 1989).

The traditional performance measure for the Beer Game is cost. As previously explained, cost accumulates each period as participants are penalized for holding onto inventory and not filling customer orders. The overall purpose of the game is to maximize profit by efficiently managing inventory (Senge, 2006; Sterman, 1992). Costs are calculated for each position and can be calculated for each supply chain team. The treatment group formed five complete supply chains. Table 16 provides the average costs for the 20 positions of the treatment group. The first row, Mean, provides the average cost for each position and the supply chain team. The other rows indicate the fluctuation of costs throughout the game. The minimum cost reflects the end of period 1, where the maximum cost reflects the end of period 22. The participants of the control group did not form complete supply chains. Final costs are not aggregated by supply chain, but reported by individual position (see Table 17).

Table 16. Beer Game Final Costs (Average of 5 Supply Chain Teams)

	Retailer	**Wholesaler**	**Distributor**	**Brewery**	**Chain**
Mean	$122.50	$119.20	$121.60	$223.70	$587.00
Minimum	$6.00	$6.00	$5.00	$4.00	$21.50
Quartile 1	$30.50	$30.50	$30.13	$30.25	$142.90
Quartile 3	$92.38	$84.38	$88.38	$136.38	$447.93
Maximum	$164.50	$188.00	$169.50	$455.00	$882.00
Range	$158.50	$182.00	$164.50	$450.50	$860.55

Table 17. Beer Game Final Costs (Control Group)

			Final Costs			
Retailer	$61.50	$95.50				
Wholesaler	$117.0	$474.00	$298.50	$176.00	$27.50	$926.50
Distributor	$174.50	$102.00	$237.0	$537.50		
Brewery	$567.00	$291.00				

Cost is directly tied to how players manage their inventory. An area-line combination chart provides a visual of the effect that inventory has on a position's overall cost (Figure 30). From the treatment group, the position with the overall lowest cost was a distributor with a balance of $65.00. The position with the overall highest cost was a brewery with a balance of $455.00. The distributor was able to fill most customer orders, showing a maximum of 5 backorders (displayed as -5 for effective inventory). The distributor's ordering strategy kept a sufficient amount of beer cases on hand to fill customer orders and avoid holding and stockout penalties. The brewery was not able to fill customer orders, showing a maximum of 64 backorders (displayed as -64 for effective inventory). This position fell quickly to customer demand, and while their ordering strategy has then backfilling orders, as of week 22, they have not been able to keep beer on-hand.

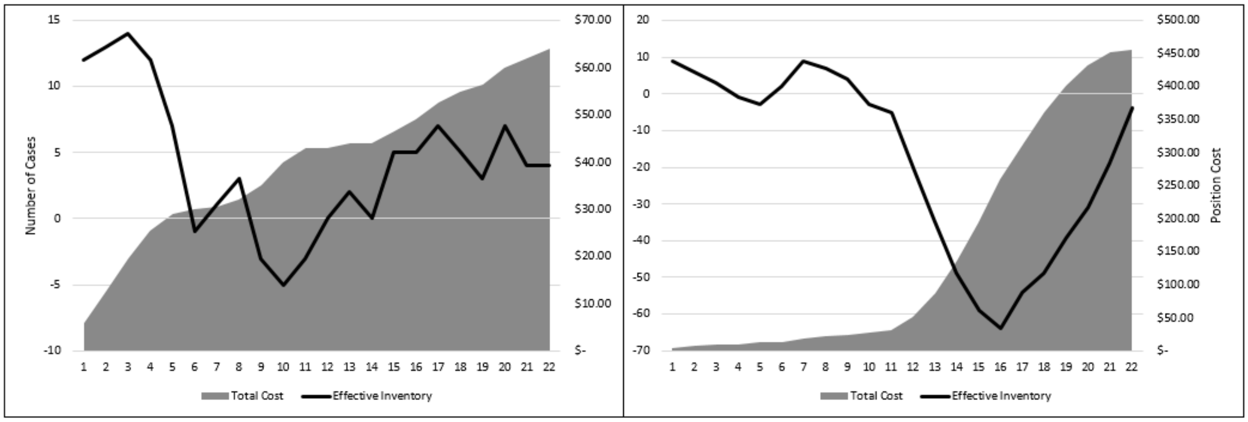


Figure 30. Lowest and Highest Position Cost for Treatment Group

Control Group A consists of the eight participants that played the Beer Game in both settings (in-person and virtual). The position with the overall lowest cost was a brewery with an ending balance of $62.50. The position with the highest cost was a manufacturer with an ending balance of $474.00. The effective inventory trend line for the brewery fluctuates period by period. This player encounters backorders in the first few weeks of the game, but quickly recovers and has the new problem of too much on-hand stock. After week 6, the brewery is able to fill all customer orders and maintain a decent on-hand stock of beer. The high cost for the wholesaler is due to inaccurate forecasting of customer demand. This player ordered a lot of beer, expecting high demand, and then could not sell or distribute their on-hand stock. Even though the penalty for unfilled customer orders is double that of holding onto inventory, this position provides evidence that any penalty adds up over time.

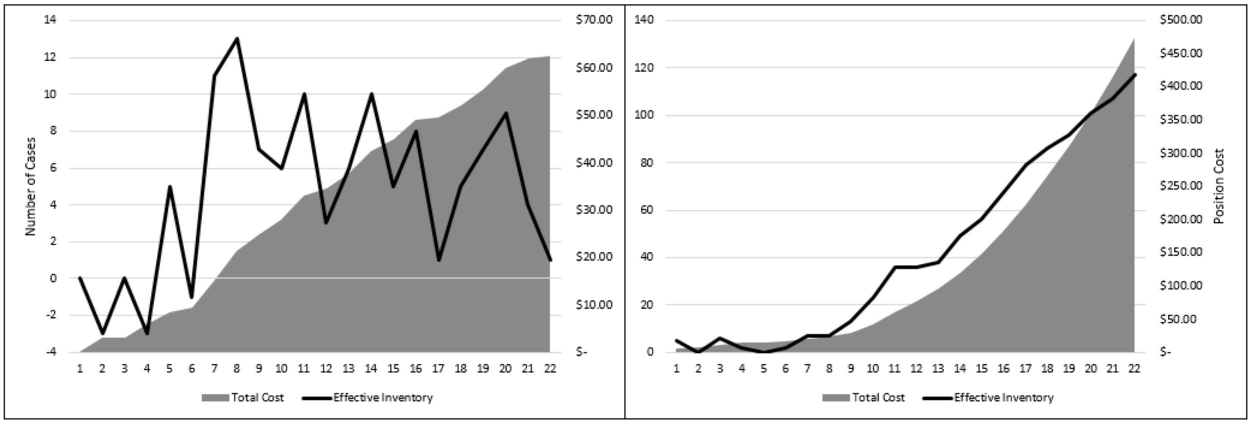


Figure 31. Lowest and Highest Position Cost for Control A Group

Control Group B consists of the eight participants that only played the online Beer Game. The position with the overall lowest cost was a retailer with an ending balance of \$61.50. The retailer avoided backorders until period 11. Their ordering strategy keeps them at just filling customer orders, and tend to recover from the periods they are unable to fill customer orders. The position with the overall highest cost was a wholesaler with an ending balance of \$474.00. The wholesaler is always able to fill customer orders, as they have zero backorders. This player overestimates customer demand and reaches 201 beer cases on hand around week 17.

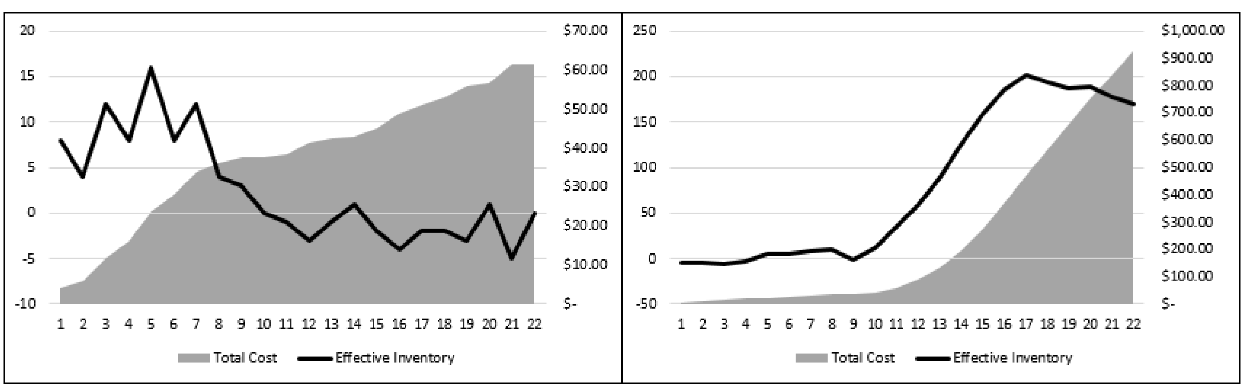


Figure 32. Lowest and Highest Position Cost for Control B Group

While cost is the primary measure of performance throughout the Beer Game, other data elements provide insights into the behavior of individual players. Behavioral indicators are oscillation, amplification, and phase lag. These indicators show how players react to dynamic situations, where supply and demand variables are unknown (Senge, 2006; Sterman, 1989). Effective inventory is the number of cases on-hand minus unfilled customer orders. Trend lines for effective inventory visually display how players manage their stock. When effective inventory is below zero, the position has outstanding customer orders to fill. When effective inventory is greater than zero, the position has beer cases on hand. Order quantity represents the amount of beer a player has requested from their upstream supplier. Trend lines for orders placed visually demonstrate a player's decision strategy throughout the game. Sharp peaks or deep valleys within the orders placed trend line can be compared to other data elements to see what factor(s) are influencing the player's decision.

Oscillation describes the ebbs and flows within effective inventory and orders placed for each position. As initially pointed out by Sterman (1989), when inventory levels decrease, players react by increasing the amount of beer they order from the supplier and vice versa. Analysis of effective inventory and orders placed provides evidence for or against oscillation.

For the treatment group, the average maximum number of cases in inventory is 20, with an overall range of -64 to 44. On average, the players held their minimum inventory in period 13 and maximum inventory in period 8. For the control group, the average maximum number of cases in inventory is 53, with an overall range of -24 to 201. On average, the players held their minimum inventory in period seven and maximum inventory in period 12. Figure 33 visually displays the effective inventory trend line for three supply chains from the treatment group. The range of overall inventory sets the scale for each graph (-64 to 44 number of cases). The waves of the trend line are indicators of oscillation throughout each position and throughout the supply chain.

For the treatment group, the average maximum orders placed are 16, with an overall range of 0 to 30. On average, players ordered their most beer in period 11, and the least amount of beer in period 9. For the control group, the average maximum orders placed are 21, with an overall range of 0 to 45. On average, players ordered their most beer in period five, and the least amount of beer in period 10. Figure 34 visually displays the trend line for orders placed of three supply chains from the treatment group. The range of overall orders placed sets the scale for each graph (0 to 30 cases). As with effective inventory, the waves of the trend line are indicators of oscillation.

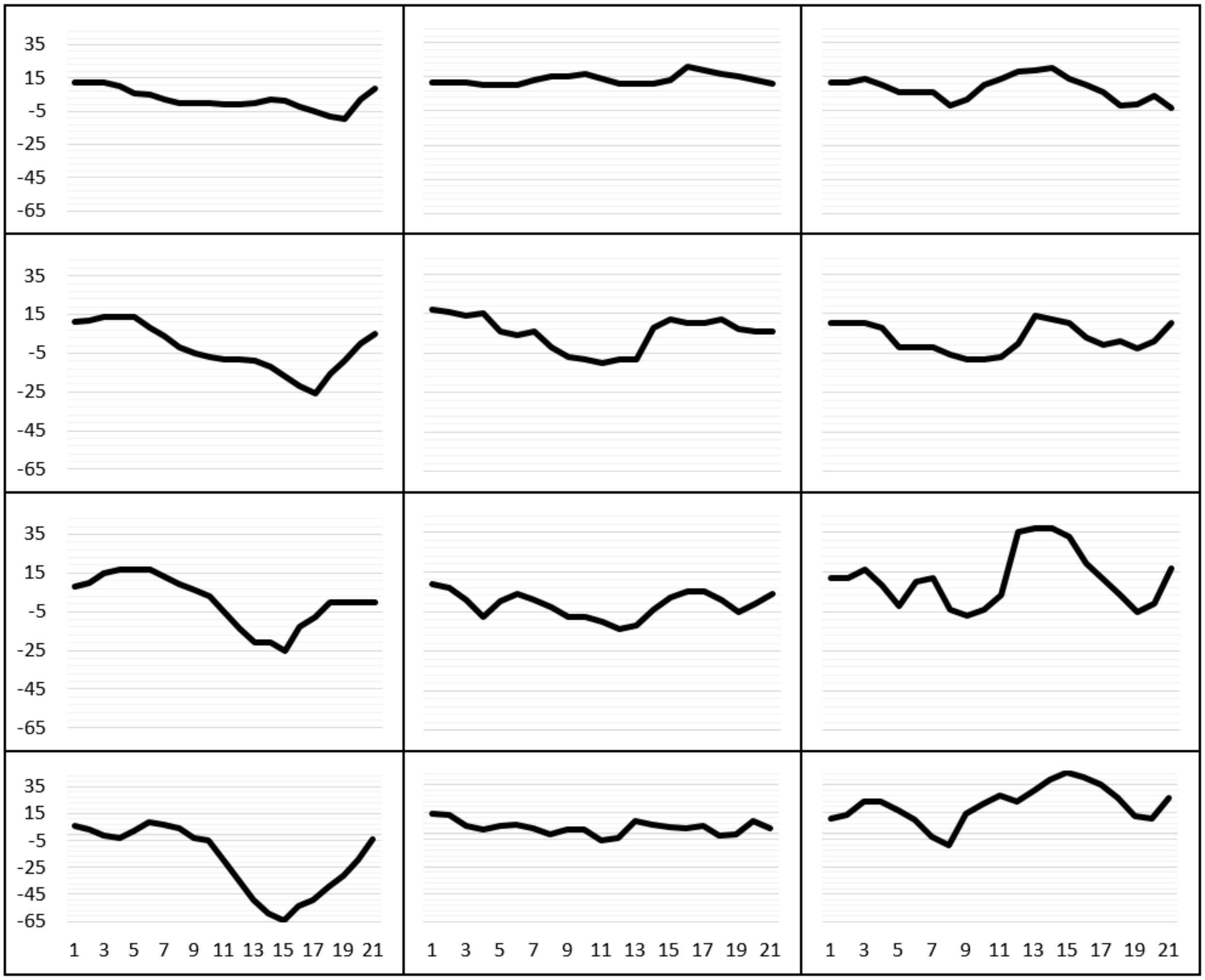


Figure 33. Experiment Results - Effective Inventory for Three Supply Chains. The horizontal axis represents time (t1 through t22). The vertical axis represents the number of cases. Each column is one supply chain; from top to bottom: retailer, wholesaler, distributor, and brewery.

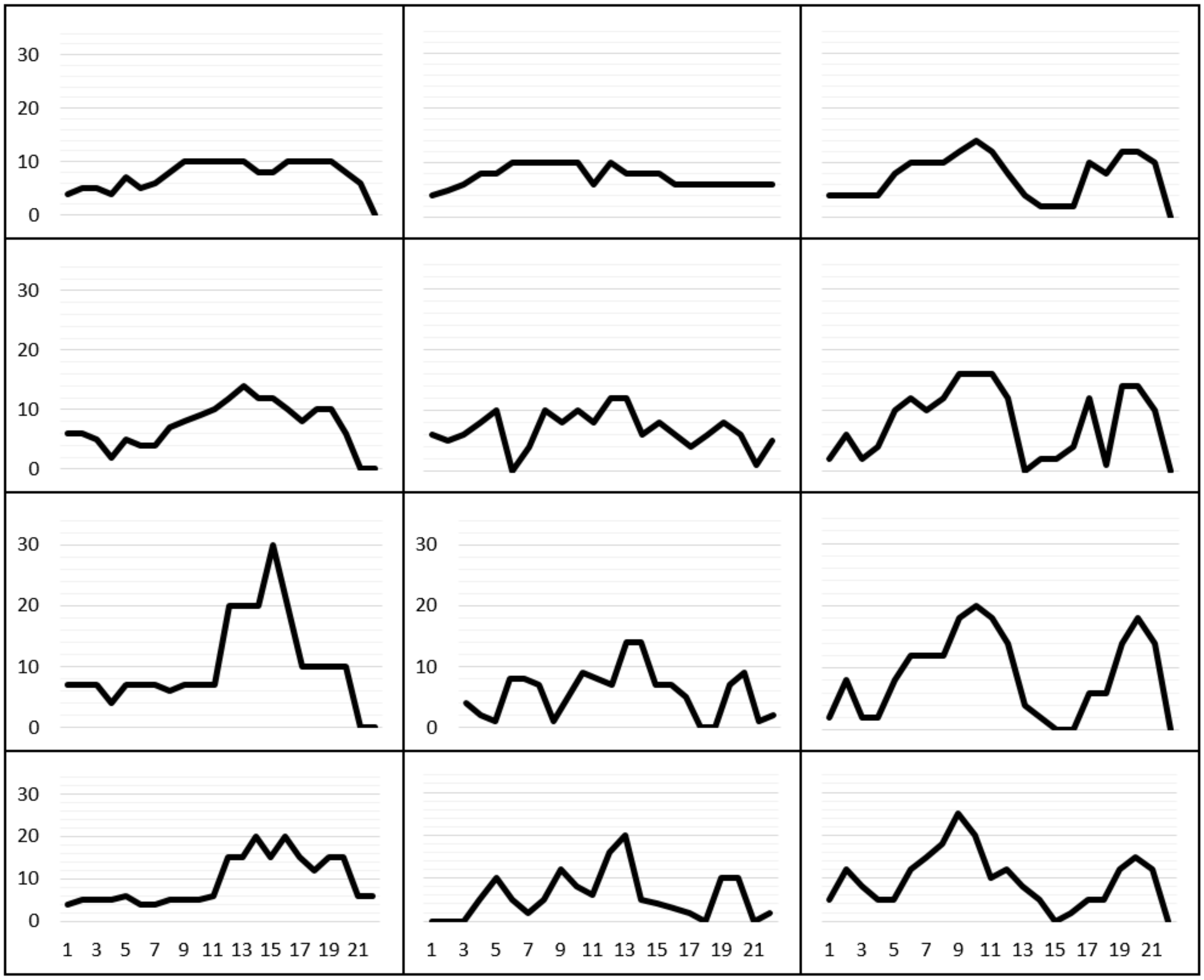


Figure 34. Experiment Results - Orders Placed to Upstream Supplier for Three Supply Chains. The horizontal axis represents time (t1 through t22). The vertical axis represents the number of cases. Each column is one supply chain; from top to bottom: retailer, wholesaler, distributor, and brewery.

A measure of decision strategy is to compare the pattern of ordering beer to the inventory levels. It is expected to see a rise in orders placed when inventory decreases and a decrease in orders placed when inventory increases (i.e., oscillation). Figure 35 shows the comparison of inventory to orders placed for randomly selected players of the treatment group. The top-left graph represents the retailer position. In period six, the inventory decreases as there is an increase in orders placed. In period 19, as the number of cases in inventory increases, the orders placed start to decline. The top-right graph represents the wholesaler position. The inventory of the wholesaler starts declining in period seven, but the wholesaler stays relatively consistent with the quantity of beer they order. The bottom-left graph represents the distributor position, and the bottom-right graph represents the brewery. The oscillation pattern is quite evident in these two positions. Whereas the wholesaler does not overreact to the declining inventory, the distributor and brewery have the opposite reaction.

Figure 35. Oscillation Example

Amplification is the increase of order variance as requests in the supply chain move from the customer to the brewery (Sterman, 1989). Evidence of amplification is shown through the changes in order quantity from customer to the retailer, retailer to wholesaler, wholesaler to the distributor, and distributor to the brewery. I analyze the ratio of average variances between positions for the treatment group.

Table 18. Ratios of Average Variance Between Positions

Pair	P+1 Order Variance	P Variance	Ratio of Variance
Retailer-Wholesaler	15.79	7.33	2.154
Wholesaler-Distributor	32.99	15.79	1.921
Distributor-Brewery	30.33	32.99	1.088

Previous research finds that the pair with the highest variance ration is wholesaler-distributor (Croson & Donohue, 2006; Sterman, 1989). I find the highest amplification to be between the retailer and the wholesaler. I attribute this change to the number of periods analyzed; my research is based on 22 periods, whereas others analyze data for 36 to 40 periods. My analysis is looking at what happens half-way through the game, as compared to the end. My analysis shows the variance of orders increases by positions as processing moves up the supply chain.

Overall the experiment shows an amplification factor of 450 percent. Customers start the game by ordering four cases of beer per period, and in period five, they increase their order to eight cases of beer per period (Sterman, 1992). By the time this change reaches the brewery, the peak order range is, on average 22 cases per week (a difference of 18 cases).

Equation 4. Amplification Factor

$$\frac{\Delta\, Brewery\ Orders}{\Delta\, Customer\ Orders} \qquad \frac{(22-4)}{(8-4)} = \frac{18}{4} = 4.5$$

The customer changes their order quantity once, but this change propagates throughout the chain. Figure 36 provides two examples of amplification. The distribution of customer orders is the same for all retailers. The vertical lines in the charts represent the peak order rate for the customer and the brewery or the start and end of the supply chain. In both examples, the brewery's peak order rate is much higher than the customer's peak order rate.

Phase Lag represents the date difference for when peak order rates occur for positions along the supply chain. The change in customer demand at the retailer propagates along the chain over time. The lag is identified when comparing the periods when each player orders the most beer from their upstream supplier. My results are consistent with extant research and show the lag in peak order rates from retailers to breweries (Croson & Donohue, 2006; Sterman, 1989). On average, the customer hits their peak order rate in period five, the retailer in period nine, and the brewery in period 13.

Figure 36. Amplification Example

This investigation focuses on order variation and how it varies between individual participants as they use the interactive visualization to make decisions. The behavior indicators show results on track with previous research (see Table 19). The environmental factors influencing decision making relate to limited information and the uncertainty surrounding supply and demand (Croson & Donohue, 2006; Sterman, 1989).

Table 19. Experiment Results - Beer Game Behavioral Indicators (Average of 5 Supply Chain Teams)

	Customer	Retailer	Wholesaler	Distributor	Brewery
Oscillation (weeks)					
Time to Recover initial inventory*		9	15	9	8
Date of Minimum Inventory		17	14	12	11
Date of Maximum Inventory		9	5	8	10
Amplification					
Peak Order Rate (cases/week)	8	14	19	22	32
Variance of Order Rate (cases/week)	2.4	7.33	15.79	30.33	32.99
Peak Inventory (cases)		18	14	19	27
Minimum Inventory (cases)		-4	-13	-11	-19
Range (cases)		22	28	30	46
Phase Lag					
Date of Peak Order Rate (week)	5	9	13	13	13

*Two retailers and two breweries did not recover inventory during the 22 time periods. Three wholesalers and three distributors did not recover initial inventory during the 22 time periods.

Experiment – Survey

At the end of the Beer Game, participants were asked to complete a debriefing survey. The survey had two parts: a) debriefing questions from the Beer Game instructions (Sterman, 1992); and b) task-fitness questions for the dashboard and interaction mechanisms (Goodhue, 1998). Participants rated size areas of task-fitness on a 10-point Likert scale for both satisfaction of use and importance to decision making.

Task fitness provides measures for how well an information system helps a user complete their goals. I used six constructs for task fitness, with a total of seven criteria. The top three measures of importance, as selected by Beer Game participants were, readability of the data, the system is easy to use, and data is provided at the appropriate level. The least important measure was maintaining the needed basic fields or elements of data. Participants were most satisfied with the accessibility of data and the ease of using the system.

Table 20. Experiment Survey - Task Fitness

Fitness Construct	**Question**	**Satisfaction**	**Importance**
Right Data	*maintaining the needed basic fields or elements of data*		
	Data provided by the system was what I needed to complete tasks	6.7	6.9
Right Level	*maintaining data at the right level or levels of detail*		
	Data provided by the system was at an appropriate level	7.4	8.0
Locatability	*ease of determining what data is available and where*		
	Easy to locate the data	7.0	7.9
Accessibility	*ease of access to desired data*		
	I can get data quickly and easily when needed	7.7	7.8
Meaning	*ease of determining what a data element means*		
	The meaning of data element is obvious or easy to figure out	6.3	7.7
Ease of use	*ease of doing what I want to do*		
	Data is displayed in a readable format	7.4	8.7
	System is convenient and easy to use	7.6	8.5

These results provide further evidence to support extant research; the use of multiple views is helpful for analytical reasoning. Design strategies to consider in the future is the actual implementation of the MAD framework. As interactivity is better understood, MAD can be implemented through the use of interactive controls as compared to individual pages that the user must navigate through.

The meaning of data elements is a measure marked with relatively high importance but had the lowest satisfaction score. The use of feedforward cues is necessary for the design to communicate what the results of actions will be. The implementation of those feedforward cues will be crucial to interpretation and perception. Designers must have a keen idea of the context in which the information system will be used and use appropriate label text and icons to convey functional affordance. Feedforward cues are necessary for the future development of visualizations. Embedded interactions, which do not have superficial functional affordances, must provide users references, so users know what the results of their actions will be. The pilot study results show that scaffolding does not work within visualizations. Providing instructions once with the expectation that users will remember what the interaction does and how to use it in subsequent graphs is a poor strategy for design. Having explicit feedforward cues with familiar icons, labels, or tool-tips is a more effective strategy for design. In addition to ranking the importance and satisfaction of the system, participants were given the option to leave additional comments:

- *I liked that it was a simple setup without too much extraneous data.*
- *The dashboard was helpful when needed.*
- *Having a variety of different visualizations was very useful.*
- *Preferred the line graphs to the scatter or bar charts.*
- *Trend lines were really helpful*

In addition to assessing the interface as a whole, participants were asked about the interaction mechanisms for the same criteria. Three participants stated that they did not use the interactive features, even though they used the visual representation to make decisions. The participants in the Beer Game selected three interactions to be of the highest importance to their decision-making processing: selection by clicking, details on demand, and sorting. Selection by clicking, filtering, and sorting received the highest satisfaction scores. Zooming received the lowest importance and satisfaction scores. The Add/Remove interactive features were second-lowest for importance and satisfaction. These results provide information on what actions the users take in order to make decisions when working with a visualization. In combination with the behavioral indicators, I can deduce what users achieve when interacting with visualizations (to be discussed in the next section).

Using more than one interactive mechanisms to analyze data can provide the same level of analysis as providing multiple pages to implement the MAD framework. The results from the Beer Game and the pilot study provide further information to what combination of interaction mechanisms people use through analysis and discovery. The combination of interactive mechanisms is dependent on the type of support offered to tasks (narrow vs. broad). When the interaction space is designed for a specific task (i.e., narrow), it is assumed that the performance for that one task is optimal, but maybe not for the overall user performance (Hegarty, 2011). The Beer Game dashboard was designed with a broad view of task support. Charts and pages were designed with the idea that a user may complete any one of the ten low-level analysis tasks with one visualization page and a choice of interaction mechanisms. The constraint to this design decision falls on what interactions are available for a specific chart. For instance, sorting is inherent to the table chart, and while it can be applied to a line graph, the end result is not always readable. As with the task-fitness, in combination with behavioral indicators, I can deduce what users achieve when interacting with visualizations and what may be the optimal approach (general vs. specialized task support).

The advantage of utilizing multiple interactive mechanisms is that users do not lose focus by having to navigate to a different page. Providing multiple options is a double-edged sword. On the positive side, the more options accommodate more individuals and their cognitive processes, as each individual has a different mental model and approach to how to use data. On the negative side, the cost of learning multiple pages and interactions may be cognitive overload in itself. Finding a balance between knowing what to implement will be greatly context-dependent, and even then, user-dependent. Knowing the end-user audience and what their needs are will be vital in developing the most effective design (i.e., different pages versus different layers of interaction). In addition to ranking the importance and satisfaction of the interactions, participants were given the option to leave additional comments:

- *Very useful and easy to understand*
- *The interactive part was my favorite, makes things more readable*
- *I didn’t use them much, but I think they would have been helpful*
- *Really good, probably more than we needed*
- *Time constraints limited the use of the dashboard*

Experiment – Use of Visualizations

Interaction as Tool Use

The first two research propositions test the concept of interaction as tool use. They operationalize interaction as the design of the representation space. Visualization is a tool used to "manipulate and act in the world (Hornbæk & Oulasvirta, 2017)." Key performance indicators for the Beer Game were displayed on all four tiers of the dashboard: monitoring, analysis using aggregate information, analysis using comparisons, and details. Through observation, the majority of the participants used the monitoring tier with the overview report. One participant used the details page throughout the entire game.

The overview report was created with the Google Chart dashboard control. It implements the multiple coordinated views, where multiple interaction mechanisms apply alterations to all charts listed on the report. The three views provided include a line chart, a table chart, and an area-line combination chart. The interactions available were four filters, selection, connected data points, and sorting. The details page provides one view, a table chart. Interactions for the details tier include four filters, selection, and sorting.

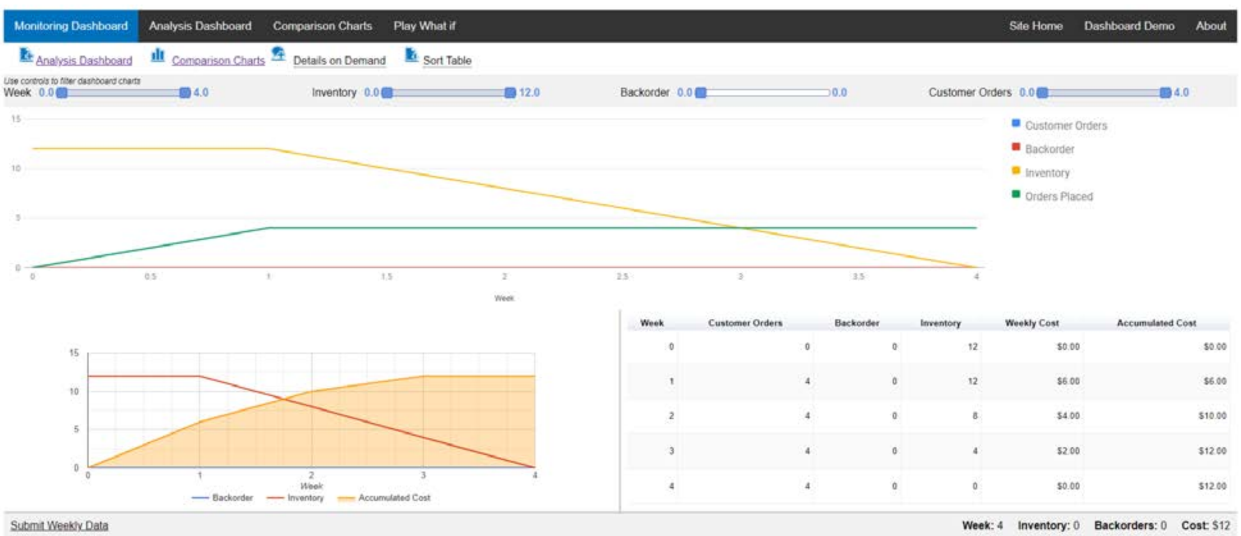


Figure 37. Monitoring Tier - Overview of KPIs

Proposition 1- Multiple Views: multiple views enhance the user's ability to analyze data displayed in an information visualization system.

To determine the effectiveness of visualization as they enhance analytical reasoning, I analyze the differences in ordering strategies for each player between the treatment and control group. The tests focus on examining the difference between participants using the different systems to play the Beer Game (visualization versus non-visualization). I analyze the orders placed data for three groups of participants (as described in Table 21)

Table 21. Analysis Groups

System Type	**Group Name / Description**	**Number of Participants**	**Number of Observed Data Points**
Visualization	Treatment	20	440
	Treatment –A players that match Control-A	8	176
	Treatment-B players that don't match Control-A	12	264
Non-Visualization	Control	16	352
	Control-A players that match Treatment-A	8	176
	Control-B	8	176

A series of t-tests were used to examine the quantity of beer ordered per period for the three groups in the experiment. Ordering strategy was selected as the comparison value because it is the output of the one decision-making task throughout the game. The data element, orders placed, is the value used to analyze decision strategies for each user. This element tracks the number of cases requested by the player to replenish their inventory. The null hypothesis is that there are no differences between the variances no differences between the means. Mainly, I am testing to see if a difference exists between using the visualization dashboard and a non-visualization system.

The results of the t-Test provide sufficient evidence to reject the null hypothesis (see Table 22). There is a difference between the means and the variance of ordering strategies when using a visualization system compared to not. The t-Critical value falls between the negative and positive t-Stat values ($-2.88 < 1.96 < +2.88$). The t-stat value is significant, as the resulting p-value is 0.0041, which is less than 0.05. The difference in observed means between the two groups is 1.25, providing further confidence in rejecting the null hypothesis.

Table 22. Orders Placed t-Test Results (Test Run #1)

		Analysis of Orders Placed per Period	
		Treatment	**Control**
	Participants	20	16
	Observations	440	352
	Mean	7.20	8.45
	Variance	22.70	48.94
t-Test	Degrees of Freedom	549	
	t-Stat	**-2.88**	
	t-Crit (2-tail)	1.96	

The Beer Game session using the visualization system occurred first, before the virtual trial. Eight participants played the game in both systems, which is the focus of the second set of tests (see Table 23). The results t-test provides evidence to reject the null hypothesis. There are differences between the means and the variances of ordering strategies between players when using the two systems. The t-critical value is higher than the negative value of the t-stat value, which supports the rejection of the null hypothesis. The difference in observed means between the two groups is 0.84, which is not as large as the difference between the overall treatment and control groups. The p-value for the matched pairs is 0.0907, which is not significant at the 95 percent level. The smaller difference and the insignificant p-value indicates that players learned something and changed their strategy before playing the Beer Game a second time.

Table 23. Orders Placed t-Test Results (Test Run #2)

Analysis of Orders Placed per Period (Matched Pairs)			
		Treatment-A	**Control-A**
	Participants	8	8
	Observations	176	176
	Mean	7.94	7.10
	Variance	22.72	17.06
t-Test	Degrees of Freedom	175	
	t-Stat	1.70	
	t-Crit (2-tail)	1.97	

The third test focuses on the results of players that only played the Beer Game once (see Table 24). The results of the third t-test provide further evidence to reject the null hypothesis. The p-value for this t-test is significant (0.0006), and the t-critical value falls between the negative and positive t-stat values (-.3463 < 1.970 < 3.463) The difference in observed means is 2.53. The results of the third test indicate that there is a difference between the two types of Beer Game (visualization vs. non-visualization), providing support for my first proposition.

Table 24. Orders Placed t-Test Results (Test Run #3)

		Analysis of Orders Placed (Unmatched Participants)	
		Treatment-B	**Control-B**
	Participants	12	8
	Observations	264	176
	Mean	6.93	9.47
	Variance	22.04	79.53
t-Test	Degrees of Freedom	240	
	t-Stat	**-3.46**	
	t-Crit (2-tail)	1.97	

Proposition 2- Feedforward Cues: feedforward cues communicate the results of specific actions allow the user to be more deliberate with how they interact with information. Deliberate actions enhance the user's ability to analyze data displayed in information visualization.

To determine the effectiveness of feedforward cues as they inform users of deliberate actions, I look at the relationship of satisfaction with elements on the dashboard and the ordering strategies of players. The artifact implements feedforward cues through tooltips, icons, and navigational labels. Four task-technology fitness measures relate to the implementation of feedforward cues: an appropriate level of data, easy to determine what data is available and where, can quickly and easily retrieve data elements, and the meaning of data elements are obvious or easy to figure out. Players from the treatment group rated their satisfaction through the Task-Technology Fitness evaluation survey. For each measure, they selected a number between 1 (not satisfied) and 10 (highly satisfied). The regression formula identifies the fitness measure that carries the most impact on how users analyze the data to decide how much beer to order for a given period.

The R^2 score for the resulting regression of orders placed compared to the satisfaction of the four fitness measures is 0.0363. The F-statistic is 4.893 and proves to be significant. The four coefficients for the four fitness measures are varied, and only one factor was identified as significant.

Table 25. Regression Results for Feedforward Cues

Fitness Measure	**Average Satisfaction (1-10 Scale)**	**Coefficient**	**p-Value**
Right Level	7.4	0.041	6.127
Locatability	7.0	-0.035	0.779
Accessibility	7.7	0.230	0.079
Meaning	6.3	0.206	**0.038**
Dependent Variable: Orders Placed per Period			

The results of the regression analysis do not provide sufficient support for proposition two. The R^2 value is low, and there are not enough significant factors to say that feedforward cues enhance analytical reasoning. It could be argued that the meaning of the feedforward cues within the dashboard are clear, but other elements of the game impacted the analysis abilities of players.

Interaction as Dialogue

The next two research propositions test the concept of interaction as dialogue. They operationalize interaction as the design of the interaction space. Visualization as dialogue is the “cyclic process of communication acts and their interpretation (Hornbæk & Oulasvirta, 2017).” Each page within the Beer Game dashboard contains a set of interactions. Overall, eight interaction mechanisms are provided: hover selection, click selection, details on demand, add/remove data points, zoom, sort, filter, and connect. Participants in the treatment group completed a post-game survey that included questions relating to the task-fitness of the interactions in the dashboard (Goodhue, 1998). Participants rated their satisfaction with the eight mechanisms on a 10-point Likert scale. Participants also rated how important the eight mechanisms are to their decision-making process.

Table 26. Experiment Survey - Interaction Task Fitness

Mechanism	**Average Satisfaction**	**Average Importance**
Hover Selection	4.4	5.6
Click Selection	4.9	5.6
Details on Demand	4.2	6.0
Add/Remove Variables	3.4	5.4
Zoom	3.8	5.0
Sort	4.7	5.8
Filter	4.6	5.7
Connect	5.6	6.2

Task fitness provides measures for how well the interaction support users in completing tasks. Three participants stated that they did not use the interactive features, even though they used the visual representations to make decisions. The participants in the Beer Game selected three interactions to be of the highest importance to their decision-making processing: selection by clicking, details on demand, and sorting. Selection by clicking, filtering, and sorting received the highest satisfaction scores. Zooming received the lowest importance and satisfaction scores. The Add/Remove interactive features were second-lowest for importance and satisfaction. These results provide information on what actions the users take to make decisions when working with a visualization. In combination with the behavioral indicators, I can deduce what users achieve when interacting with visualizations.

Proposition 3 – Coordinated Interactions: coordinated interactions add a layer of depth to the representation space, engaging the user, and deepening the level of analysis and analytical reasoning. The depth of analysis enhances the user's ability to apply knowledge.

To analyze the differences between the various interactions provided by the dashboard, I look at the relationships between satisfaction with interactions and the ordering strategies of players. The artifact implements eight interaction mechanisms across multiple pages of the dashboard. The regression formula identifies the interaction mechanisms that carry the most impact on how users complete the decision-making task. The resulting R^2 score for the resulting regression of orders placed compared to the satisfaction of the eight interaction mechanisms is 3.6 percent. The F-statistic is 2.005 and proves to be significant.

Table 27. Regression Coefficients for Interaction Type

Interaction	**Average Satisfaction**	**Coefficient**	**p-Value**
Filter	4.6	-0.150	0.3150
Hover	4.4	0.727	0.0513
Click	4.9	0.162	0.6726
Sort	4.7	-0.072	0.6231
Add-Remove	3.4	-0.004	0.9776
Zoom	3.8	-0.413	0.1611
Connection	5.6	-0.060	0.5717
Details on Demand	4.2	-0.523	**0.0260**
Dependent Variable: Orders Placed per Period			

Coordinated interactions are a set of mechanisms that work coherently together to support analysis tasks. A regression formula was also used to compare combinations of interaction mechanisms and orders placed per period. The regression analysis was used to identify what combination had the most impact on a player's decision-making. The results R^2 score for the coordinated interactions is 0.032, with a significant F-statistic of 2.045. The coefficients for several combinations were 0.000, and none were significant.

To analyze the difference between each type of interaction, I conducted repeated measures of analysis of variance (ANOVA). The resulting F-statistic for differences between individual interactions was 20.79, which is larger than the F-critical value of 2.012.

Table 28. ANOVA Results for Interactions

Interaction	**Average**	**Variance**
Filter	5.70	9.23
Hover	5.45	7.97
Clicking	5.85	8.05
Sort	5.80	9.58
Add-Remove	4.80	10.28
Zoom	4.95	7.77
Connection	6.80	6.88
Details on Demand	5.25	6.90
Filter & Details on Demand	4.77	9.08
Connect & Details on Demand	5.48	7.59
Zoom & Details on Demand	3.42	2.67
Connect & Hover Selection	5.40	8.07
Sort & Hover Selection	5.32	9.90
Zoom & Click Selection	3.73	2.28
Zoom & Hover Selection	3.34	3.06
Add-Remove & Click Selection	5.35	10.54
Add-Remove & Hover Selection	4.97	10.49
Filter & Click Selection	5.08	8.57
Filter & Hover Selection	4.69	9.57

The results of the experiment do not fully support proposition three. The use of interactions does provide a layer of depth the representation space, increasing the ability to analyze data. However, the exact use of interactions is too varied to identify what specifically helps users perform cognitive activities.

Proposition 4 – Multiple Interactions: providing multiple interaction mechanisms enhances the user's ability to dialogue with information and achieve a higher number of tasks. The ability to complete more tasks creates more opportunities for the user to apply knowledge.

To determine the effectiveness of how interactions support multiple tasks, I test participants' perceptions of the supply chain. How a player views the supply chain indicates the situational factors that players are responding to or identifying what factor has the most substantial impact on the player's ordering strategy. I follow the line of research from Croson and Sterman by applying a regression formula using all data collected from the Beer Game. Chapter 3 identifies the five main tasks of the Beer Game: (1) calculating inventory when a shipment arrives, (2) calculating total customer orders to fill, (3) determining what orders can be filled and what is to be placed on backorder, (4) determining how many cases to order and (5) monitoring performance. The decision-making task of the Beer Game is placing an order, and the elements of the regression formula indicate the biggest influence on a user's decision is. Data from each player is evaluated to compare the orders placed in a period against the ending inventory from the previous period, orders received as a shipment from the upstream supplier, orders received from the customer, and any backorders (Croson & Donohue, 2006). The regression was completed for each player in the experiment (36 total) and then averaged per group.

Table 29. Regression Results - Value of the Supply Chain

Experiment Group	**R-Square**	**Adjusted R-Square**	**F**	**Significance F**
Treatment	0.799	0.729	19.49	**0.0044**
Control-A	0.665	0.560	9.93	**0.0297**
Control-B	0.697	0.599	12.60	**0.0373**
Dependent Variable: Orders Placed per period				

Analyzing the coefficients identifies the factors that play a more substantial influence on the decision making task (see Table 30). For the 20 participants in the treatment group, three coefficients identified as significant to the decision making ask. For the majority (12 out of the 20), backorders were highly significant, and thus highly influential to the decision for how many cases to order. The second most significant factor as ending inventory for the previous period, followed by customer orders. In comparison to the control group of the 16 participants, ending inventory was highly significant, followed by period.

Table 30. Regression Coefficients - Value of the Supply Chain

	Ending Inventory $I_{t-1}^{p,b}$	**Customer Orders** $\boldsymbol{R_t^{p,b}}$	**Shipments Received** S_t^{pb}	**Backorders** $N_t^{p,b}$	**Period** t
Treatment	-0.209	0.605	0.021	0.143	-0.048
Control	-.0149	-0.302	-0.199	-0.113	-0.115
Control-A	-0.101	-0.116	-0.118	0.107	-0.051
Control-B	-0.197	-0.488	-0.280	-0.333	-0.178
Dependent Variable: Orders Placed per period					

There are three factors that provide insight into a player's decision strategy while playing the Beer Game: bullwhip effect, presence of an oversupply of stock within the chain, and the player's value or weight given to the chain as a whole. If the bullwhip effect does not exist, then the value of orders placed is equivalent to customer orders received $\propto_R = 1$. The coefficients for inventory, backorders, and shipments received imply the presence of an oversupply within the chain $\propto_I = \propto_S = \propto_N = -1$. A player's value of the supply chain can be determined by looking at their backorders. If backorders are greater than ending inventory, the player under-weighs the supply chain and does not view the process holistically ($\propto_N > \propto_I$)(Sterman, 1992).

Table 31. Decision-Making Strategy Factors

	Participants	Bullwhip Effect $\propto_R = 1$	Oversupply of Stock $\propto_I = \propto_S = \propto_N = -1$	Under Weigh Supply Chain $\propto_N > \propto_I$
Visualization	20	1	0	16
Control	16	0	0	10
Control-A	8	0	0	6
Control-B	8	0	0	4

Table 31 shows the count of participants for each of the factors described above. One player from the entire experiment did not have bullwhip. Their coefficient for customer orders was 1.00, which means their order to the supplier was equivalent to what they received from the customer. Overall, there was a large difference in the coefficient for customer orders and 1.0. The average coefficient for customer orders varied among the different participants: Treatment group = 0.605, Control-A group = -0.116, and Control-B group = -0.488.

All players experience overstock throughout the supply chain. Two players had a coefficient for inventory around -.600, which are the closets values to what was expected (-1). As with customer orders, the average coefficients for inventory varied among the different participants: the average for the treatment group as -0.209, the average for control-A was -0.101, and the average for control-B was -0.197.

The value placed on the supply chain indicates how players viewed the entire process and took into account processing and shipment delays. The weight of the supply chain is based on the relationship between the coefficient for backorders and inventory. Eighty-percent of the treatment group's backorder coefficient is higher than their inventory coefficient, indicating they under-weighted the supply chain. This value compares to seventy-five percent of Control group A and fifty-percent of Control group B.

The regression formula identifies the value placed on the supply chain, which encompasses all of the tasks that the user must account for during the game. The visualization group had a much larger R^2 value (0.791) compared to the control groups (0.672 and 0.0678). These results provide support for my fourth proposition. The interactions embedded in the visualization system allow individual players to complete more tasks, which creates opportunities for applying knowledge. The table below provides a mapping between the factors used in the regression formula and the tasks, subtasks, and activities identified for each step in the Beer Game. For the treatment group, which used the visualization system, ending inventory, customer orders, and backorders were most significant to their decision-making process of deciding how much beer to order. For the control group, which used the non-visualization system, ending inventory and time were most significant to their decision-making process.

Table 32. Mapping Regression Coefficients to Beer Game Tasks

Game Task	Sub-Task(s)	Low-level Task(s)	Visual Cognitive Activities	High-Level Cognitive Activities	Data Element
Receive Delivery	Calculate Inventory	Retrieve Value Compute Derived Value	Identify Determine Locate	Sensemaking	S_t^{pb}
Receive Customer Order	Calculate Total Orders	Retrieve Value Compute Derived Value	Identify Determine Locate Infer	Sensemaking	D_t or $O_t^{p-1,b}$
Fill Customer Order / Backorders	Fill Backorders Fill New Customer Orders Calculate Inventory Calculate Backorders	Retrieve Value Compute Derived Value	Identify Determine Locate Compare Infer	Sensemaking Problem Solving	$R_t^{p,b}$ $\pm I_t^{p,b}$
Place Order	Predict Customer Order Predict Incoming Shipment	Retrieve Value Cluster Find Anomaly Find Extremum Correlate Order Filter Determine Range Characterize Distribution	Determine Identify Locate Infer Configure Correlate	Decision Making Learning	$\pm I_t^{p,b}$ S_{t+1}^{pb} $R_{t+1}^{p,b}$
Monitor Profit	Calculate Cost	Retrieve Value Cluster Find Anomaly Find Extremum Correlate Order Filter Determine Range Characterize Distribution	Identify Infer Configure Compare	Sensemaking Learning	h^p and s^p $C^p(T)$

Interaction as Behavior

The fifth proposition tests the concept of interaction as behavior. It operationalizes interaction as an influence on the mental space. Design aspects of the interaction and representation space should facilitate the continued guidance, growth, and development of the mental space (Ya'acob et al., 2016). Interaction as this level is "adapting behavior to goals, tasks, user interface, and capabilities (Hornbæk & Oulasvirta, 2017)." This investigation considers the continual back and forth flow of information and interaction across three spaces of the human-visualization cognitive system: representation, interaction, and mental. Extant research has provided evidence that cognitive activities emerge over time, indicating that the value of visualizations grows to where the user considers the visualization as more than just a tool or a dialogue with information. Instead, the visualization becomes part of their behavior because they find value in reducing cognitive load.

The value of visualization includes four concepts: decision time, insight, essence, and confidence. Measuring these indicators show how players use the visualization to implement and adjust their decision-making strategy throughout the game. Table 33 provides an overview of the value of visualization. The averages for each position of the treatment group are displayed for Time, Insight, and Essence.

Table 33. Experiment Results - Indicators for Value of Visualization (Average of 5 Teams)

	Retailer	Wholesaler	Distributor	Brewery
Time (minutes)				
Average Decision Time	2.8	2.9	2.9	2.7
Minimum Decision Time	1.0	1.6	1.2	1.0
Maximum Decision Time	6.2	7.6	6.4	6.0
Range	5.2	6.0	5.2	5.0
Insight				
Average BEI	2.94	2.34	2.08	1.39
Peak Customer Order (cases)	8	10	14	19
Minimum Customer Order	4	2	0	0
Range	4	8	14	19
Essence				
Average NSI	0.53	0.84	1.09	0.82
Peak Receive Rate	17	19	22	24
Minimum Receive Rate	2	1	0	0
Range	15	18	22	24

Decision Time (DT) represents the time needed to answer a variety of questions about the data (Stasko, 2014). Possible questions asked throughout the game include but are not limited to: how many cases are in inventory? How many cases are on backorder? How many total customer orders do I need to fill this period? How am I performing? The dashboard is updated near-real-time upon submission of data for each period. The date/time stamp of each data submission is used to track the decision time for players in the treatment group. The average decision time per position and the range of decision times per position is provided in Table 33. Overall, the average decision time decreases for each position in the supply chain. Figure 38 shows the average decision time for each supply chain in the treatment group. The chart compares the average decision time for three different periods of the game (average of the first four weeks, an average of the middle four weeks, and an average of the last four weeks). The decision time for each team decreases the longer they use the visualization to aid their decision-making task.

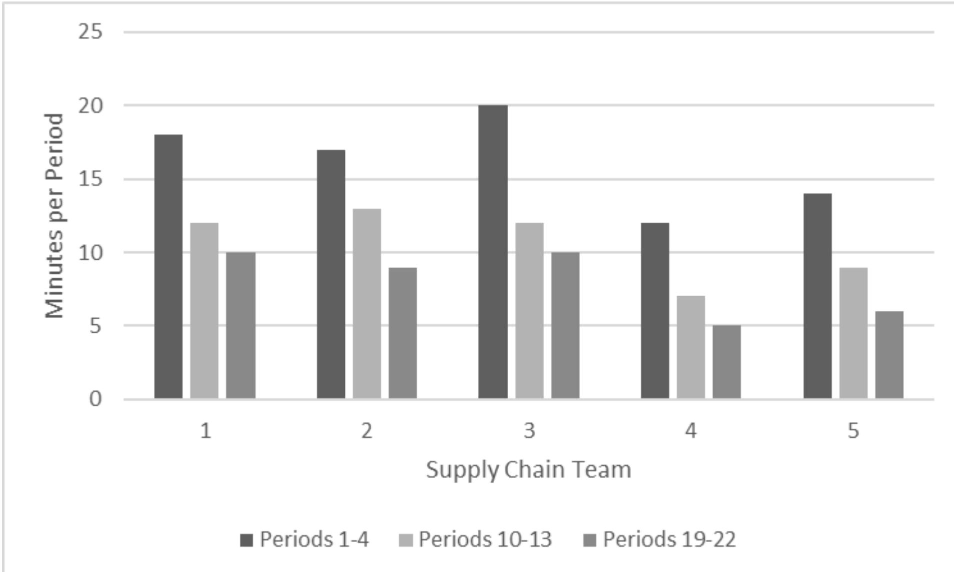


Figure 38. Average Decision Time for Treatment Group Supply Chains

Insight (BEI) is the visualization's ability to spur questions about the data or guide the users to explore the data (Stasko, 2014). The bullwhip effect index (BEI) measures insight as a way to see how participants react to dynamic decision making situations. Receiving customer orders is the second step for each period. For the treatment group, the maximum number of customer orders averages 13 cases per period, with an overall range of 0 to 30. On average, the largest customer orders were received in period 11, and the least ordered in period 9. For the control group, the average maximum customer orders were 21, with an overall range of 0 to 45. On average, the largest customer orders were received in week 5, with least ordered in period 10. Figure 39 provides the trend lines for customer orders of three supply chains from the treatment group. The range of customer orders sets the scale for each graph (0 to30).

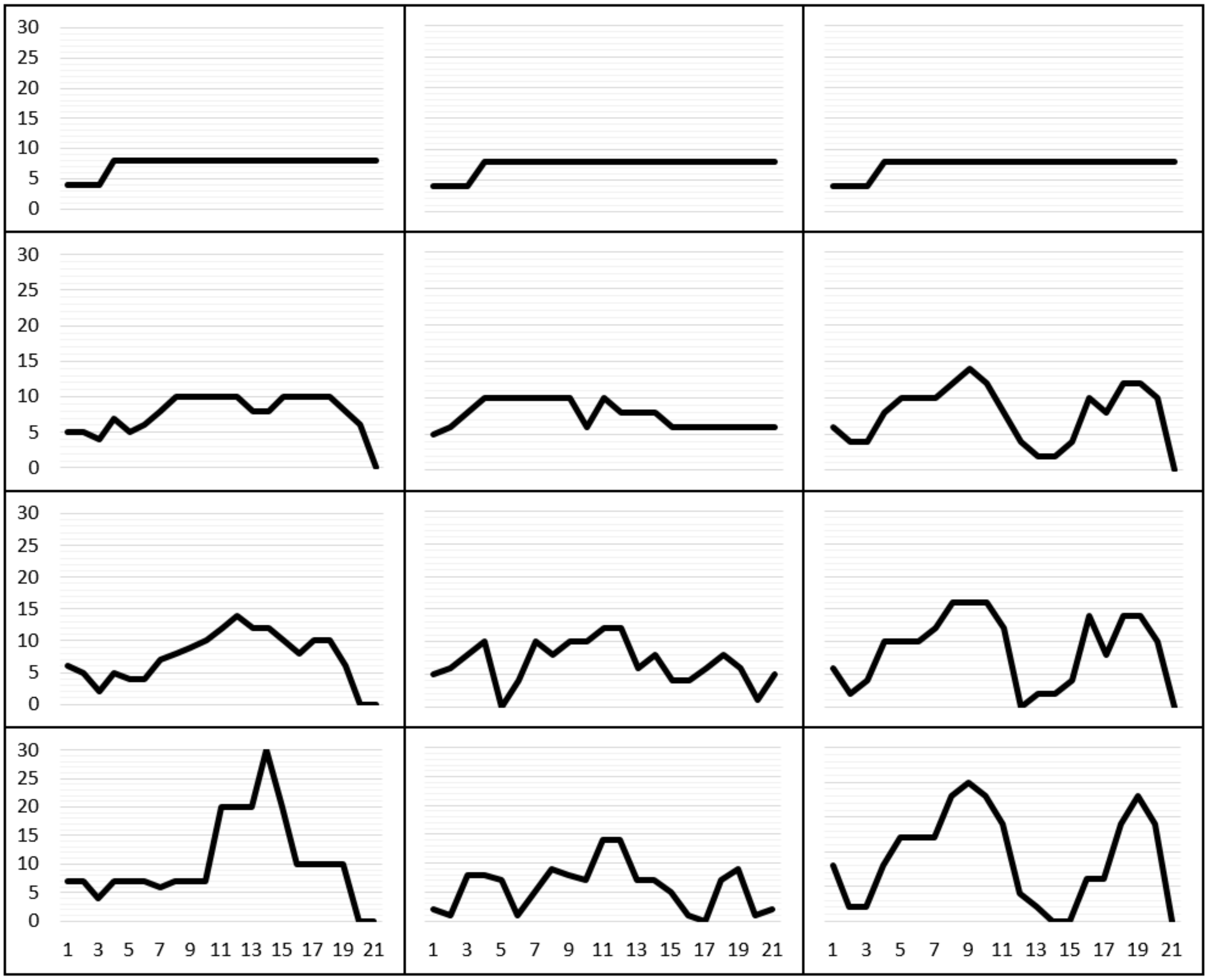


Figure 39. Experiment Results - Customer Orders for Three Supply Chains. The horizontal axis represents time (t1 through t22). The vertical axis represents the number of cases. Each column is one supply chain. From top to bottom: retailer, wholesaler, distributor, and brewery.

BEI is the variance in orders placed divided by the variance in customer orders. A BEI greater than 1 indicates the player's level of panic, whereas a BEI less than 1 indicates the player's level of calm. A high panic level is a standard reaction for the Beer Game (Croson & Donohue, 2006; Senge, 2006; Sterman, 1989). Overall, the treatment group averages a BEI of 2.19, whereas the Control group averages a BEI of 3.01. When comparing the BEI values for the subsets of each experiment group, the matched pairs adjusted their overall strategy between playing the in-person game and the virtual game. Their BEI decreases from 1.90 to 0.61. On the other hand, the BEI for the control group that only plays the virtual Beer Game has a much higher BEI (5.51) when compared to the BEI values for the players that only played in the in-person Beer Game (2.38).

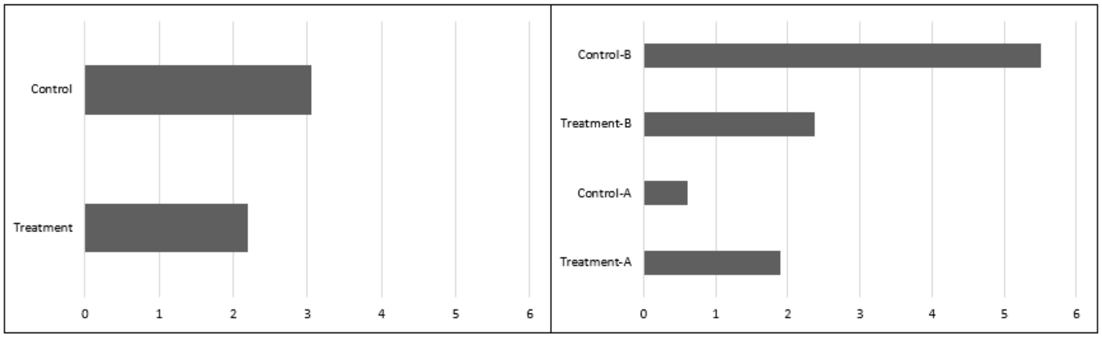


Figure 40. Experiment Results - BEI Comparisons. The left-hand side shows the overall average for the two experimental groups. The right-hand side shows the average for the subsets of each experiment group.

BEI is based on the variance of orders placed and the variance of customer orders. The player in the treatment group with the highest BEI is a retailer (6.93). The retailer's variance in orders placed is 16.50, with a high of 14 cases and a low of zero cases. The variance in customer orders is 2.38, with a high of eight cases and a low of four cases. The player in the treatment group with the lowest BEI is a brewery (0.50). The brewery's variance for orders placed is 30.43, with a high of 20 cases and a low of four cases. Their variance for customer orders is 57.98, with a high of 30 cases and a low of zero cases. Figure 41 provides the trend lines for customer orders and orders placed that graphically shows the variation between the two data elements.

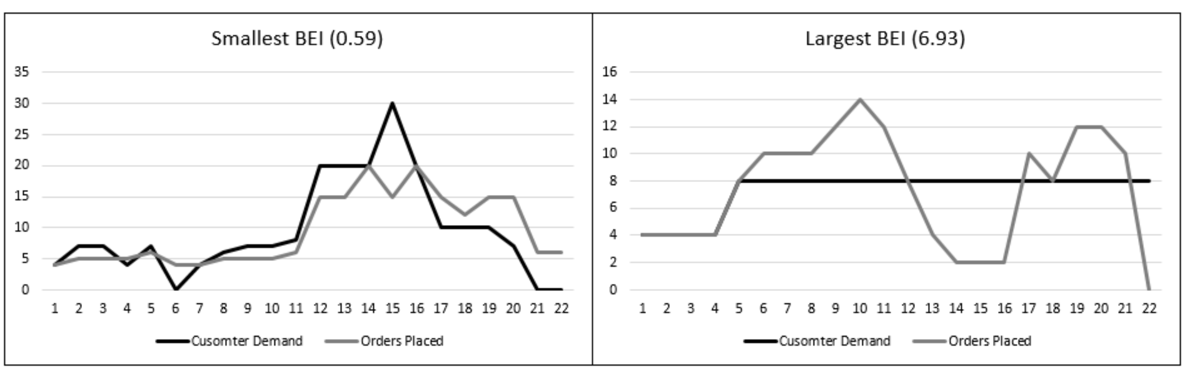


Figure 41. Insight Example

Essence (NSI) is the ability of the visualization to drive the user to think deeper than what the visualization shows. It is the ability to convey an overall sense or take away from interacting with the information (Stasko, 2014). The 'no-strategy' strategy index (NSI) measures essence to see how players consider the overall, big picture of the game. The 'no-strategy' strategy for the Beer Game directs players to order the exact amount of beer as they receive from the upstream supplier. In other words, they do not react to customer demands. Receiving shipments is the start of each period. For the treatment group, the maximum number of cases received in a period averages 20 (range of 0 to 40). On average, players received the most number of cases in period 16, and the least in period 8. For the control group, the maximum number of cases received in a period averages 21 (range of 0 to 45). On average, players receive the most number of cases in period 10, and the least in period 4. Figure 42 provides the trend lines for shipments received for three supply chains from the treatment group. The range of shipments received sets the scale for each graph (0 to 40).

NSI is the variance of orders placed divided by the variance in shipments received. An NSI greater than 1 indicates a player has a broader view of the situation and is considering more than just the data in front of them. An NSI less than 1 indicates the player is more centrally focused and taking the data in front of them at face value. Overall, the treatment group averages an NSI of 0.82, whereas the Control group averages an NSI of 0.84. When comparing NSI values for the subsets of each experiment group, the participants that played both Beer Games paid less attention to the entire chain because their NSI decreased from 0.90 to 0.71. In comparing participants that only played one Beer Game, the treatment group averaged an NSI of .77 and the control group .97.

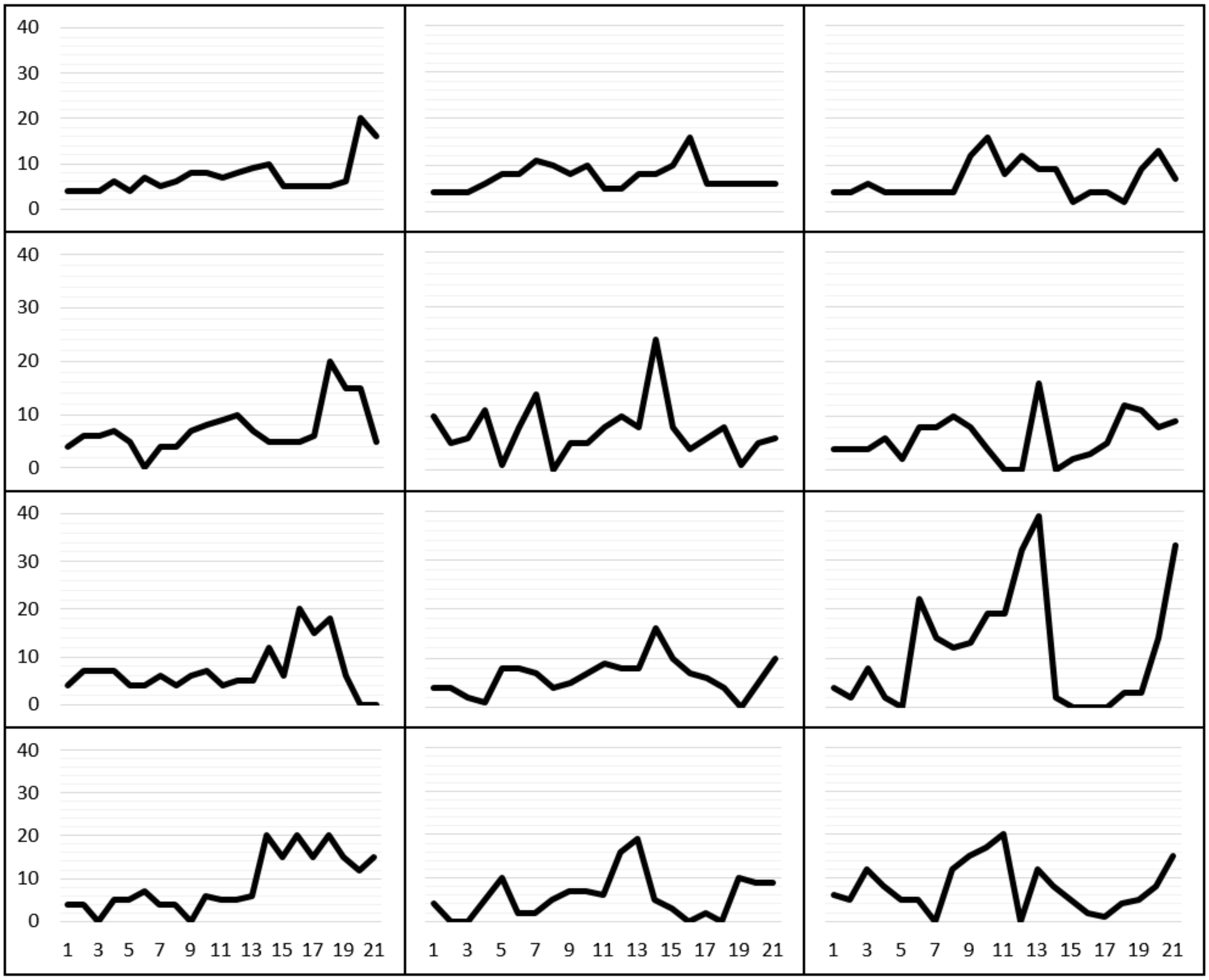


Figure 42. Experiment Results - Shipments Received. The horizontal axis represents time (t1 through t22). The vertical axis represents the number of cases. Each column is one supply chain. From top to bottom: retailer, wholesaler, distributor, and brewery.

The player in the treatment group with the highest NSI is a distributor (2.09). The distributor's variance in orders placed was 51.48, with a high of 30 cases and a low of zero cases. The variance in shipments received was 24.66, with a high of 20 cases and a low of zero cases. The player in the treatment group with the lowest NSI is a retailer (0.07). The retailer's variance for orders placed is 2.38, and variance for shipments received is 34.16. Figure 43 provides the trend lines for a shipment received, and orders placed that graphically shows the variation between the two data elements.

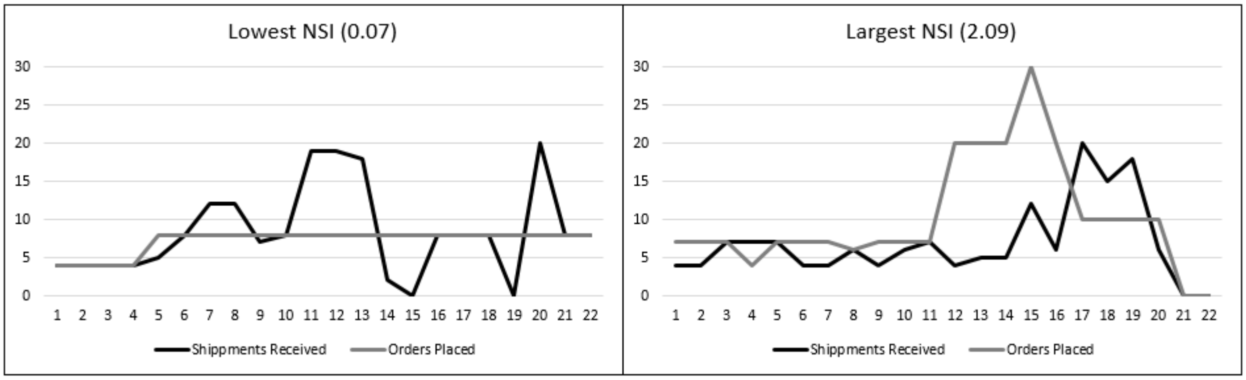


Figure 43. Essence Example

Confidence (CON) is a level of trust that users have with the data when using a visualization (Stasko, 2014). It is a measure indicating the effectiveness of visualization in helping users to learn. The more comfortable a user is with the visualization and interacting with the information, the more confidence the user has in their ability to turn data into knowledge. I measure confidence as a ratio between satisfaction and importance using the Task-Technology Fitness constructs for Dashboard elements and interaction mechanisms. External interactivity encompasses the entire interface of visualization, so the design attributes of representation space and interaction space are analyzed to determine users' confidence (Sedig et al., 2014).

The value of visualization is a qualitative measure testing the visualization's ability to guide users in decision-making tasks. The measure is based on time, insight, essence, and confidence. My investigation uses a combination of outcomes from the Beer Game and user input to determine the value of visualization for each player. Table 35 demonstrates the visualization value, calculated for each position in the Beer Game. The average final cost is shown as a comparison between the Beer Game performance outcome and the value of visualization. The two positions with the highest value of visualization also have the lowest cost.

Table 34. Experiment Survey - Confidence Measures

Fitness Measure	**Satisfaction (scale 1-10)**	**Importance (scale 1-10)**	**Confidence**
Right Data	6.7	6.8	7.3
Right Level	7.4	8.0	8.0
Locatability	7.0	7.9	6.2
Accessibility	7.7	7.8	8.0
Meaning	6.3	7.9	5.6
Easy to Read	7.4	8.7	6.8
Easy to Use	7.6	8.5	7.1
Hover Selection	4.4	5.6	3.9
Click Selection	4.9	5.9	4.2
Details on Demand	4.2	6.0	3.5
Add-Remove	3.7	5.4	2.5
Zoom	3.8	5.0	3.0
Sort	4.6	5.8	4.0
Filter	4.6	5.7	4.1
Connect	5.6	6.2	5.4

Table 35. Experiment Results - Value of Visualization

	Retailer	**Wholesaler**	**Distributor**	**Brewery**
Time (range)	5.2	6.0	5.2	5.0
Insight	-2.94	2.34	2.08	1.30
Essence	0.53	0.84	1.09	0.82
Confidence	8	12	12	11
Value	**11.6**	**17.7**	**17.1**	**16.8**
Final Cost	$122.60	$119.20	$121.80	$223.70

Participants of the treatment group completed a debriefing questionnaire about their experience playing the Beer Game. Humans learn by doing, and after using the visualization once or twice, they can apply the newly created knowledge to other visualizations and other situations. Three of the debriefing questions related directly to the use of visualization throughout the game. The comments made by participants provide insight into how users think and reason while using graphs, building their value of visualization for analysis activities.

Table 36. Experiment Survey - Debrief Question #1

Did you notice any patterns in your graphs? When did you notice the pattern(s)?
• Mostly followed the inventory graph looking for trends
• Consistent orders in and out (around period 5 or 6)
• Cost rose steadily; customer orders and orders placed are similar
• Overreacted due to backlog and orders did not maintain stability (after period 3)
• I was stable until I got whacked by a demand spike (period 12)
• Recognizing the pattern of orders (period 11)
• Did not look at the charts
• Line graphs were useful to stabilize orders and draw down inventory
• Steady excess inventory, then excess backorders, then rebound
• Fluctuations in inventory
• The more orders placed the lower inventory went and vice versa

Table 37. Experiment Survey - Debrief Question #2

Was there a point in the game where visualizing your data brought a great insight? If so, what was the insight?
• To get a sense of how to project for the future; should have looked at order trends instead of inventory
• Consistency of the customer orders
• Supply and demand; run the inventory down by ordering less
• Tried to rely on the average order number
• I should have had a set number of cases on hand at all times
• I could see the bullwhip effect coming, but did not know how to float it
• Consistent orders in helped me to have more consistent orders out

• A wide variation causes the ripple effect in the supply chain, so stability/consistency was more ideal
• Overview plot was helpful – liked seeing the trends
• It was hard not to react even with having data
• Looking at customer orders versus orders placed and realize that there were more orders being placed than orders being made

Table 38. Experiment Survey - Debrief Question #3

What helped with generating insight?
• Inventory trend line
• Time
• Aggregate data – average orders
• Inventory versus Custome Orders graph
• Details page
• Looking at that charts would have helped me
• Looking at the slope of the trend
• Seeing the large hump in inventory changed my strategy for ordering
• Real-time data submissions and updates to the charts

Proposition 5 – Value: for any given set of data displayed in information visualization, the value of interacting with information develops over time to positively influence analytical reasoning and knowledge activation.

To analyze the value of visualizations, I further examine insight and essence variables. Insight is measured by Bullwhip Effect Index (BEI), and essence is measured by the No-Strategy Index (NSI). The overall BEI and NSI values for a player provide evidence for how they play the game and the strategy they employ to make decisions. Figure 44 shows trend lines for BEI of selected positions from the treatment group. The top two graphs show players with an overall low BEI. The bottom two graphs show players with an overall high BEI. The trends for players with the high BEI identify a level of panic as the game progressed.

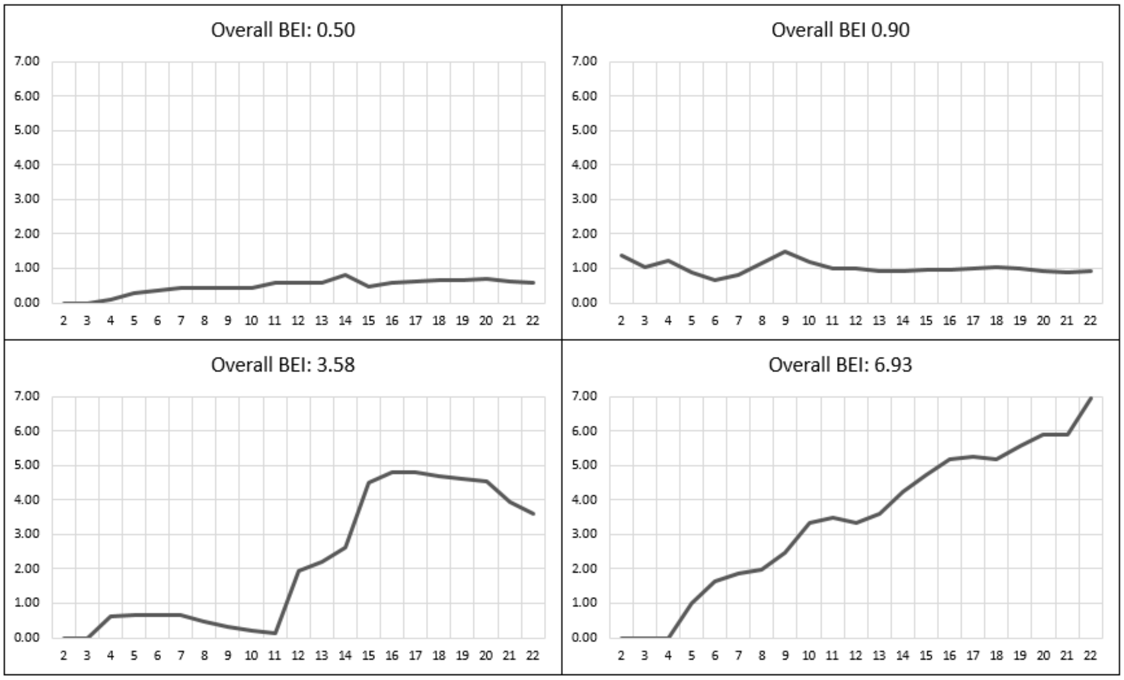


Figure 44. BEI Trends

In following the same pattern for testing hypotheses of previous propositions, a series of t-tests are used to examine the BEI for each participant. BEI is calculated for each period of the game by dividing the variance of orders placed by the variance of customer orders (Analytics, 2019). The first test run examines the differences between the treatment and control groups; the second test run examines the differences between matched pairs of the treatment and control groups, and the third test run examines the differences between players that only played the Beer Game once.

Table 39. BEI t-Test Results (Test Run #1)

		Treatment	**Control**
	Participants	20	16
	Observations	420	336
	Mean	1.83	2.48
	Variance	2.21	15.71
t-Test	Degrees of Freedom	411	
	Difference in Means	0.63	
	t-Stat	**-2.87**	
	t-Crit (2-tail)	1.97	

The null hypothesis is that there are no differences between the variances, and there are no differences between the means. Bullwhip effect identifies the level of panic or level of calmness a player exhibits while playing the game. The results of the t-Test provide sufficient evidence to reject the null hypothesis. There is a difference between the means and variance of Bullwhip effects for the experiment groups. The t-Critical value falls between the negative and positive t-stat value (-2.87 < 1.97 < +2.87), and the t-stat value is significant (0.0000). The difference in observed means for BEI is 0.63, providing further confidence in rejecting the null hypothesis.

The results of testing differences between the treatment and control groups provide sufficient evidence to reject the null hypothesis. To further define the differences, I analyze subsets of each group, first by comparing the matched pairs (see Table 40) and second by comparing the results from those that only played one game (see Table 41). In comparing results for matched pairs, the t-stat is significant and is greater than or less than the t-Critical value (-11.33 < 1.97 < +11.33). The same is true when comparing results for the other subset of the treatment and control groups (-6.96 < 1.97 < +6.96).

Table 40. BEI t-Test Results (Test Run #2)

		Treatment-B	**Control-B**
	Participants	8	8
	Observations	168	168
	Mean	1.90	0.51
	Variance	2.27	0.27
t-Test	Degrees of Freedom	167	
	Difference in Means	1.39	
	t-Stat	**11.33**	
	t-Crit (2-tail)	1.970	

Table 41. BEI t-Test Results (Test Run #3)

		Treatment-B	Control-B
	Participants	12	8
	Observations	252	168
	Mean	1.78	4.45
	Variance	2.17	23.42
t-Test	Degrees of Freedom	188	
	Difference in Means	2.67	
	t-Stat	**-6.96**	
	t-Crit (2-tail)	1.97	

Figure 45 provides the trend lines for NSI values of selected positions from the treatment group. No-strategy decision making indicates that their supply of beer (shipments received) instead of the demand (customer orders). Focusing on the supply of beer means the player is taking into account the delays built into the supply chain. NSI is calculated as the variance of orders placed divided by the variances of shipments received. An NSI value greater than one indicates that the player is thinking more holistically about the game and not reacting to customer demands. The top two graphs provide trends for players with an overall low NSI. At the start of the game, the players had a high NSI, indicating at first they took int account the amount of beer they received from their supplier. As the game continued, the players turned their attention to other factors, dropping their NSI. The bottom two graphs provide trends for players with an overall high NSI.

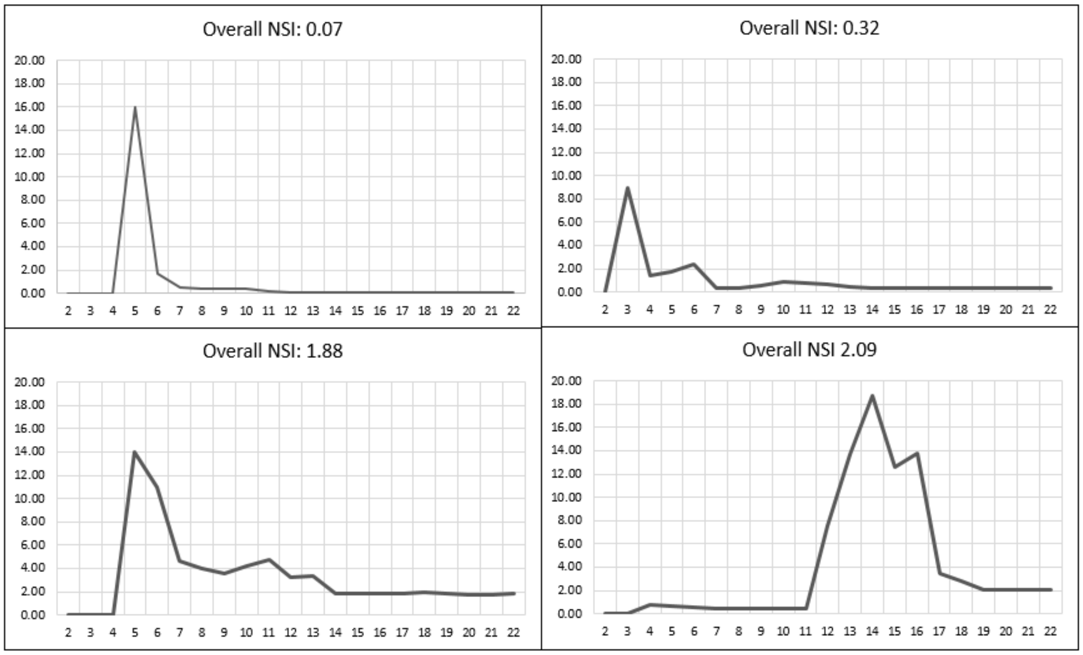


Figure 45. NSI Trends

A series t-Tests are used to examine the NSI values per period for groups in the experiment. NSI represents one strategy of the Beer Game that takes into account the entire supply chain. The results from the tests are provided in Tables 42, 43, and 44. The results from these tests are in accordance with the BEI analysis, where there is enough evidence to reject the null hypothesis. When comparing the variances and means, there are differences between treatment and control groups. The differences between the means are large enough to provide secondary support to reject the null hypothesis.

Table 42. NSI t-Test Results (Test Run #1)

		Treatment	Control
	Participants	20	16
	Observations	420	336
	Mean	1.66	0.85
	Variance	8.60	1.69
t-Test	Degrees of Freedom	604	
	Difference in Means	0.81	
	t-Stat	**5.10**	
	t-Crit (2-tail)	1.96	

Table 43. NSI t-Test Results (Test Run #2)

		Treatment	Control
	Participants	8	8
	Observations	168	168
	Mean	1.41	0.59
	Variance	3.55	0.29
t-Test	Degrees of Freedom	167	
	Difference in means	0.85	
	t-Stat	**5.23**	
	t-Crit (2-tail)	1.97	

Table 44. NSI and t-Test Results (Test Run #3)

		Treatment	Control
	Participants	12	8
	Observations	252	168
	Mean	1.84	1.11
	Variance	11.93	2.96
t-Test	Degrees of Freedom	391	
	Difference in Means	0.73	
	t-Stat	**2.83**	
	t-Crit (2-tail)	1.97	

The decision strategies of the participants align with those identified in extant research (Croson & Donohue, 2006; Sterman, 1989), as the focus tends to be on customer demand while under-weighing the overall value of the chain. The more in-depth look at BEI and NSI for participants indicates that the use of the visualization enhances the analytical reasoning and decision-making capabilities of the players. Overall, the mean of the NSI for the treatment group shows that users pay attention to factors of the game other than customer demand. The results from value analysis, BEI analysis, and NSI analysis provide support for the fifth proposition. Over time users become more confident in their abilities and working with visualization, creating value of the tool and dialogue, which in turn changes their behavior.

Summary of Results

To summarize, the investigation provides evidence that interactions fill multiple roles through the process of dynamic decision making with emergent information. The first two propositions identify the design of the representation space to define interactions as a tool. The representation space encodes and displays visual representations of information (Liang et al., 2010). Extant research provides evidence that the specific style of representation has an impact on the end-users perception and interpretation of the information (J. Heer & Shneiderman, 2012; Munzner, 2014; Sedig & Parsons, 2016; Speier, 2006). Multiple views and feedforward cues are techniques for designing interactive visualizations. My results provide evidence for the first research proposition: visualizations with multiple views enhance analytical reasoning and knowledge activation. My results do provide sufficient evidence to support the second research proposition fully: feedforward cues communicate the results of actions that allow for users to be more deliberate in interacting with information.

The interaction space contains controls to manipulate the interface, which gives the user access to the information space. The information space is visually displayed through the representation space. As users can freely manipulate data, they explore and discover relationships, which enhances their analytical reasoning and knowledge application abilities (Kodagoda et al., 2013). My results show that the transition from approaching the visualization as a tool and entering into a dialogue is not instantaneous. The dialog develops over time as users a) redefine their goal, b) understand the processes they must follow when completing a task, and c) understand how to use the interactive features of the system. As the dialogue forms, it is essential to understand that the user is not just an observer. They do not only read the information form the representation. The value of interactions comes from the user being an active participant (Ya’acob et al., 2016). They must follow through the steps of the interaction model, but knowing what their goal is, deciding what actions should happen, and then following through with those actions.

The mental space is where cognition occurs. It is the place where users actively perceive and interpret data from the visualization tool. Confidence in using the tool and dialoguing with the information develops over time. As confidence grows, the value of the visualization increases.

Implications for Visualization Design

I reflect on my work as it applies more generally to Information Systems in all domains, not just supply chain logistics. I used a human-centric approach for the design of my artifact, the Beer Game dashboard. The approach was first to identify tasks that needed to be accomplished and then investigate how a user may accomplish those tasks (Sedig et al., 2012). This differs from a more data-centric approach where the focus is on the data and how to represent it best. Using the results from the evaluation of my research, I suggest the following guidelines for designing interactive visualizations.

G1. Use multiple views for dynamic decision-making situations. My results provide evidence that giving the users multiple perspectives of data is more useful for analysis and activating knowledge. The multiple views should include multiple formats and not just many of the same chart. Users prefer line and table charts over bar and scatter plots.

G2. Use multiple interactions for dynamic decision-making situations. My results show that users positively respond to having many options for interacting with information. The multiple interactions allow the user to explore the information at varying levels.

G3. Provide selection operands to retrieve values, find anomalies, and find extreme values. My results show selection operands are useful to users when the task requires the to retrieve values, find anomalies, or find extreme values. If combined with details on demand, the act of retrieving a specific value is helpful despite the visual representation.

G4. Avoid the zoom interaction for charts needed for low-level analysis activities. My results show that users often ignore the zoom interaction for data charts that are used for low-level analysis activities. The zoom feature was marked as the least important by beer game participants and not used at all within the pilot study.

G5. Provide sorting features for table charts. The ordering feature for low-level analysis tasks was the second most used interaction, closely following selection operands.

G6. Training. The use of visualizations and fully understanding the benefits of interaction takes time. Actively providing instructions, whether through help guides or feedforward cues, will engage a wide variety of users.

CHAPTER 5

CONCLUSIONS

The research discussed throughout this paper investigates the use of interactive visualizations to activate knowledge. The design of the artifact used human-centric approaches that first identified tasks to complete and then examined how users approach those tasks. The theory of distributed cognition and the human-information interaction (HII) framework allows for an ecological approach to understanding how and why humans use, find, consume work with, and interact with information (Fidel, 2012). A deeper understanding is needed to realize the benefits that interactions have for problem-solving, decision-making, learning, planning, making sense of, discovering, and carrying out tasks.

I approach the use of visualizations through three concepts of interaction. First, the user approaches visualization as a tool, where they can manipulate the data, which represents something in their world. By using visualizations as a tool, the user enters into a dialogue with the information. Dialogue is a cyclic process, where interactions cause reactions in the visualization to be processed and interpreted. As the dialogue develops, the user changes their behavior and adapts to using the visualization to inform their decision-making processes. The HII framework guided this investigation with the concept that a human and visualization create a joint cognitive system. Narrowing down the focus to external interactivity allowed me to investigate interactions as they support cognitive activity across three spaces in the system (representation space, interaction space, and mental space). The quality of interaction across the three spaces is called external interactivity (Sedig et al., 2014). I specifically look at the combination of interactions to support cognitive activities by investigating four issues of macro-interactivity (Sedig et al., 2014).

I focus my attention on how individuals activate knowledge through a dynamic decision-making process that is dependent on emergent information. In essence, by using interactive visualizations, how do people enhance their analytical reasoning when dealing with factors that may be out of their control? My five research propositions are broadly framed around four macro-interactivity questions:

a) What interactions should be made available?
b) Do interactions correspond with the user's mental models of how interactions should work?
c) How do interactions complement one another?
d) Should constraints be placed on the execution order of interactions?

The results of my research do not provide definite answers to these questions; instead, they offer implications for practice and theory.

Implications for Practice

The cognitive abilities of individuals are substantially different. To design visualizations that are not specific to a domain or a subject matter expert, designers need to consider the design of the representation space and the design of the interaction space, and how the design affects the mental space. The human is a critical element in the design and can't be ignored for the sake of assumptions. Creating a visualization that is engaging to those who may not be experts or have well-defined analytical skills will create an environment that is more about facilitating the discovery process than just communicating a result.

Knowledgeable people not only have information but also have the ability to integrate and frame the information with the context of their experience, expertise, and judgment (Grover & Davenport, 2001). Information Visualization provides information that should be used to aid decision-making, not make the decision. Fully activating knowledge is a process of finding people or technology with relevant knowledge and using it effectively. Effective use of knowledge includes a willingness to provide, access, and share the knowledge as and when needed (Qureshi & Keen, 2005).

Results from my investigation show visualization tools can do more than just disseminate information. Visualizations provide opportunities to achieve a broad range of tasks and support analytical reasoning that leads to knowledge activation. The visualization tool itself will not decide for you but provides an outlet for cognition to be distributed, supporting users with high-level cognitive activities (i.e., sensemaking, learning, problem-solving, etc.). Visualizations designed with multiple views reach a broad range of users, as the multiple perspectives provide the opportunity for decreasing visual complexity and enabling exploration (Munzner, 2014).

Interactions within visualizations deepen the representation space by allowing the user to not only manipulate the data but start dialoguing with the data. Providing multiple interaction mechanisms broadens the scope of what a user can accomplish. Users with the ability to dialogue with the information in numerous ways increase the number of tasks they can complete by using the visualization tool.

Lastly, my results provide a warning to designers. Ideas that a designer may have for what is most effective may not carry over to what a user thinks. The utility of the visualization decreases when users try to go beyond what the designer envisioned (Albers, 2004). Human-centric approaches to visualization design focus on human reasoning needs, not just how to best represent data. There are cognitive differences that will affect the utility of visualization when the designer does not consider the human side of the visualization.

Implications for Theory

One of the gaps discovered in my literature review was the lack of academic literature to support a human-centric approach to visualization design (Kodagoda et al., 2013). My investigation and results provide evidence that identifying user tasks and designing visualizations to support those tasks, is an effective solution to supporting knowledge activation.

My results provide early research for how interactions connect low-level analysis tasks to high-level cognitive activities in a dynamic-decision making process. It also offers early research into the benefits and costs of interactions, from a user point of view. Over time, the value of visualizations grows by users who work with visualizations. Interactions allow the user to move from just using a tool to dialoguing with the information and eventually changing their behavior. Users understand that the information system is more than just a system, and the human-visual cognitive system grows stronger. My research provides support to the Analytical Capability Model (Davenport et al., 2001) and the idea of distributed cognition across spaces of a joint cognitive system (Parsons & Sedig, 2014a).

External interactivity focuses on three layers of the human-visualization cognitive system (mental, interaction, and representation) for distributed cognition. There are four issues identified at the macro-interactivity level. The results of my research provide evidence for designing visualization to address three of these issues. The first issue is *the degree to which the potential benefits outweigh the cost and effort associated with learning (Sedig et al., 2014)*. My results provide evidence that learning how to interact with visualization is not something to be taken for granted. Users are not only dealing with information overload but are also dealing with cognitive overload. Designing visualizations with a scaffold-learning approach is not adequate; users need instructions or cues for how to interact with information throughout an entire visualization tool. Over time, the learning curve drops, indicating that users become more confident and comfortable with interacting with and interpreting information.

The second issue is *the degree of control that users are given to change parameters of interactions (Sedig et al., 2014)*. The Beer Game dashboard did not restrict the execution order of interactions and provided multiple interactions for each MAD tier. The design approach was to support a broad range of tasks, in comparison to designing one or two visualizations for specific tasks. The participants in the experiment preferred the broad-range approach and having the feeling of control in terms of applying interactions. The free will choice supported a broad range of people and their different cognitive abilities.

The third and four issues are *how different interactions complement one another while performing a task* and *how interactions correspond to the users' conceptual models of how interactions should function (Sedig et al., 2014)*. The results of my research do not provide a clear solution to these issues. The feedforward cues offer direction for how to interact with users, but there is complexity in deciding what interactions to use for a given visualization. Secondly, my results do not provide a clear understanding of the order in which interactions were used to identify what mechanisms complement one another.

Limitations and Future Work

Visualization literacy is an emerging field that is not fully defined. The cognitive dependence used as a basis of visualization literacy encourages the problem to remain wicked. A limitation of this research was the overall holistic view of the process. The approach of using a dashboard looked at how an interactive system can support dynamic decision making with emergent information. To fully understand the benefits of interactions, the research needs to go to a deeper level. More information is needed to show what interaction mechanism is used for a particular low-level task in multiple contexts.

A second limitation is the context-dependence of my research. My focus was on supply chain logistics with limited global information. There are general tendencies that can be carried forward for future research, but questions relating to the amount of data and how interactions are used in big-data contexts remain. The third limitation of my research relates to learning curves. The Beer Game is meant to be played by individuals that have limited experience in supply chains. There is a learning curve for the supply chain process, which competes with the cognitive effort put towards learning a visualization system and fully benefiting from it.

Lastly, my research is limited by the qualitative assessment approach. Understanding how users think and reason provide a level of insight that cannot be tracked through mechanical measures. The survey measures are one measurement tool to gain an understanding of how users think. A limitation of this research is not having an automatic assessment method, like eye-tracking or click-tracking. An automated evaluation would provide a non-biased evaluation to measure how users interact with information.

I identify two future research steps that are necessary for the information visualization domain. The first is more research towards understanding and identify proper affordances for interactions. For instance, delving deeper into the cognitive, physical, sensor, and functional affordances for interaction design (Hartson, 2003). Providing designers with ideas for what these look like, what are the best icons or labels to use, and how each of the affordances works together for completing tasks within a given context would be practically and theoretically relevant. Secondly, looking at the complementary functions of interactions. Research that delves deeper into what interactions are used, in what order, and in what combination with other interactions at the level of low-level analysis tasks is needed for the growth of interactive visualization design research.

Human behavior is complex. A simple statement that best describes the challenge behind designing visualizations. There is no guarantee that the user viewing the information will recognize that there is a need to act, will be in the position to act, and will know how to act (Kirk, 2016). As users become more comfortable with their tasks and the tool, they develop behavior that centers on using the visualization for analytic activities. The acceptance of the visualization of the tools itself, and the knowledge generated from the dialogue creates value, and value leads to knowledge activation.

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APPENDICES

APPENDIX A: DESIGN PRINCIPLES

Author(s)	**Artifact**	**Design Principle(s)**
(Begoli & Horey, 2012)	Knowledge Discovery from Big Data	Support a variety of analysis methods
		One size does not fit all
		Make data accessible
(Eckerson, 2006)	Dashboard	Layered Architecture
		Maximum of Seven Key performance indicators
(Elmqvist et al., 2011)	Fluid Interactions	Use smooth animated transitions between states
		Provide immediate visual feedback on interaction events
		Minimize indirection in the interface
		Integrate user interface components into the visual representation
		Reward Interaction
		Ensure the interaction 'never ends'
		Reinforce a clear conceptual model
		Avoid explicit mode changes
(Few, 2006)	Dashboard	Single Screen, no Scrolling
(Goodhue, 1998)	Information Systems: Identifying Needed Data	Contain the right data, at the right level
		Easily locate the needed data
		Meaning of data elements should be clear
	Information Systems: Integrating and Interpreting Accessed Data	Data must be accurate enough to be interpreted correctly
		Data from different sources that are integrated should be compatible
		Presentation of the data must be easy to interpret
		Data must be current enough
(J. Heer & Shneiderman,	Interactive	Visualize data by choosing visual encodings

2012)	Dynamics for Visual Analytics	Filter out data to focus on relevant items Sort items to expose patterns Derive values or models from source data
		Select items to highlight, filter or manipulate Navigate to examine high-level patterns and low-level detail Coordinate views for linked, multidimensional exploration Organize multiple windows and workspaces
		Record analysis histories for revisitation, review and sharing Annotate patterns to document findings Share views and annotations to enable collaboration Guide users through analysis tasks or stories
(Maheshwari & Janssen, 2014)	Dashboard	Visual communication at a glance
		Multi-level design
		Data interpretation support
(Tufte, 2001)	Graphical Integrity	Show data variation, not design variation
		The number of variable dimensions depicted should not exceed the number of dimensions in the data
		Graphics must not quote data out of context
(Wu, Kao, & Shih, 2018)	Analytical System Design	Enable Induction and Deduction (bottom-up/top-down reasoning)
		Enable Knowledge Externalization
		Enable Data Provenance
		Enable Uncertainty-Aware Knowledge Generation