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Visualizing the Beer Game: The Value of Interactions During Dynamic Decision Making

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ABSTRACT

Humans have several exceptional abilities, one of which is the perceptual tasks of the visual sense. Humans have unique abilities to perceive data and identify patterns, trends, and outliers. This research investigates the design of interactive visualizations to recognize the value and benefits of dynamic decision-making situations. Results from the Beer Distribution Game are analyzed to determine the value of visualizations (V = T + I + E + C). More precisely, the results show how users obtain insight when using a visualization tool and how those insights inform decisions. This paper discusses the value and benefits of interactive visualization for dynamic decision-making situations.

Keywords

Dashboard, Interactive Visualization, Knowledge Activation, Dynamic Decision Making.

INTRODUCTION

Designing effective visualization is a challenge due to the complexities of human behavior. Visualization provides a powerful means for making sense of data. Data is the force behind how we learn, make decisions, and apply knowledge. Leveraging data allows an organization to gain and maintain a competitive edge because it provides insights into products, services, business processes, and management control activities. Information visualizations refer to the "process of creating a mental understanding and notion of a concept by conveying information to the mind through perceptual channels [1]." There is no guarantee that the user viewing the information will recognize the need to act, will be in the position to act, or will know how to act [2]. No single visualization will be optimal for all tasks, leaving designers confounded with multiple design options. Designers opt for data-centric or task-centric design approaches to create an impressive visual impact.

On the other hand, human-centric techniques allow for identifying information needs that support sensemaking and decision-making. Focusing on the information needs guides implementing the appropriate interaction methods and visual representations to support human reasoning [3]. As users become more comfortable with their tasks and the visualization tool, they develop behavior that centers on analytic activities. The acceptance of the visualization tool creates and supports behavior to generate knowledge from dialoguing with the information. The interactive dialogue creates value, and value leads to knowledge activation. The purpose of this study is to explore how visualizations support analytical reasoning in dynamic decision-making situations

RELATED WORK

Humans use visualization when they want to learn something [4]. Visualizations leverage the human visual system because of its capability to process images and recognize patterns, trends, and outliers [5, 6]. Visualizations act as a pipeline to transform raw data into images that can be interpreted. Having something 'real' allows humans to generate insights, make decisions, and formulate actions that may otherwise be impossible or difficult to do [7, 8]. When humans perceive visualizations, they decode various shapes, sizes, and colors to form an understanding of the data [2]. Leveraging the human's visual system shifts the cognitive load by coupling soft system attributes with hard system attributes [6, 9]. 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.

External representations are not simple inputs or stimuli for the mind; instead, they are used alongside cognitive tasks to influence behavior [10]. Visualizations operate as a catalyst for interpretations forming the basis of knowledge activation. They support users during tasks that involve extracting, exploring, and creating information [11]. Interpretation is subjective and affected by numerous factors, including prior knowledge, the capacity to utilize knowledge, cultural background, and the design of the representation [2, 11, 12]. 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 [13]. Users and visualizations create a dynamic system built from coordination and causal influence. The user and the visualization continuously affect and simultaneously affect each other [14, 15]. The Simple Visualization Model demonstrates the flexible context in which visualizations operate. The goal of visualization is insight, generated as humans participate in a feedback loop between interpreting the information and interacting with the visualization [8]. The feedback loop represents the relationship that is created and facilitated by interactions [8, 15, 16].

The model shows how a user explores information by perceiving an image and generating knowledge. The user can choose to explore the data further by changing the specification that creates the image. As changes are applied, the visualization is updated, developing the relationship between the user and the information. Exploring data allows the user to see things they were not previously aware of. New insights define new questions, hypotheses, or models. The feedback loop continues as long as the user initiates change [8]. 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 [17].

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 [18, 19]. HII consists of computer-based interaction but concentrates on the relationship between humans and information, not the relationship between humans and technology [17]. 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 [17]. Through the process of learning by doing, humans use tools to mediate the aspects of their environment to accomplish goal-oriented tasks [20].

Humans interact with information to support their intensive thinking processes, such as problem-solving, decision-making, or performing other complex cognitive activities [21]. Cognition is the information processing system inside the brain. The theory of distributed cognition defines situations where cognition occurs inside and outside the brain. [22, 23]. 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 [24].

Cognition is an emergent property that builds over time when an individual interacts with their environment. Cognition develops through perception and action [22]. Cognitive overload develops as a response to new and evolving information that emerges as one interacts with their environment [13]. 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 [23, 25]. Visualizations harness computational power to process and transform information. Humans use the visualization to change or adjust the representations of information.

EMPIRICAL STUDY

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 [26]. One of the most common decision-making tasks within supply chains is called the stock management problem. This problem defines the process where the manager of a supply chain seeks to maintain a specified quantity of their product [27]. Stock management becomes a problem due to the phenomenon known as the bullwhip effect. The bullwhip effect is where orders to suppliers tend to have more substantial variance than sales to buyers [27-30]. The Beer Game tests players' analytical decision-making ability by placing them in a situation with changing and uncertain information. Players have sufficient and relevant local information but limited global information [31]. The uncertainties and complexity of supply chain decision-making refer to the factors that influence the decision-maker, such as time and customer demand. Analyzing the elements of the decision-making process help to explain the relationship and effects that play a substantial role in planning, improving efficiency, and generating accurate forecasts [29].

The Beer Game is a role-play simulation that mimics the mechanics of a decentralized inventory system. The game is traditionally played in person using a board that portrays the production and distribution of beer [27]. The Beer Game places participants in the center of the supply chain to test their response to the stock management problem. The game consists of supply chain teams that work to produce and distribute a brand of beer. Each chain has four positions: retailer, wholesaler, distributor, and brewery. Each player has the same goal: maximize their performance while attempting to achieve the system objective. Performance is based on the position cost, which is directly related to how a participant handles their inventory. The system's objective is to produce and distribute the brand of beer to the customer [30]. Participants are responsible for placing orders to his/her upstream supplier and filling orders placed by his/her downstream customer [31].

The artifact developed by this research is an online interactive dashboard. The interactive dashboard is a hybrid between the board and the adapted table version of the game. Players participate by playing the board game, where tokens represent beer cases. Tokens are moved between positions to simulate the receiving of beer from the supplier and the shipment of beer to the customer. The interactive dashboard is the data collection system, as well as the performance monitoring system. The dashboard charts are updated in near-real-time as users submit their data for each period. The Beer Game has five key performance indicators (KPI): customer orders, order quantity, effective inventory (on-hand inventory at the end of the period minus backorders), backorders, and position cost. The dashboard provides views that display all five KPIs and allows users to interact with the data at multiple levels. The design of the dashboards is to provide information that enables the user to achieve their goal(s), where data is consolidated and arranged for at-a-glance monitoring [7].

The layout of the dashboard applies the multiple coordinated design technique using the Google Chart Dashboard. Users rarely accomplish their goals with a single representation [32, 33]. The multiple coordinated views technique is a technique that allows the user to view data from various perspectives. Coordination among the view means that all representations simultaneously react to the manipulation triggered by interactions [34]. 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 [32].

Value of Visualization

The value of visualization supports high-level interactions as cognitive activities develop and users apply knowledge. Humans think in terms of their analysis tasks, which are closely aligned to interactions. When interactive visualizations are effective, the user stays in a cognitive zone. Value goes beyond the ability to answer simple questions; instead, it relates to the visualization's ability to convey a real understanding of the data [35]. Value is determined by four elements: time (T), insight (I), essence (E), and confidence (C). Time represents the time needed to answer a variety of questions about the data. Insight represents the ability of a visualization to stimulate or discover insights in the data. Essence is the ability to convey an overall sense of the data, going beyond the superficial display. Confidence is the ability to generate confidence, knowledge, and trust in the data [35]. A qualitative formula determines the overall value: $V = T + I + E + C$ [35]. Evaluating the value of visualization goes beyond usability measures and looks to understand how the visualization facilitates deeper thinking.

Beer Game

The Beer Game is played on three occasions: 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 was a total of thirty-six participants (see Table 1). Twenty people played the Beer Game using the visualization dashboard, with eight of these also playing the Beer Game using online non-visualization software. Sixteen people played the Beer Game using online non-visualization software, with eight being utterly new to the game. The in-person sessions lasted precisely two hours and were limited by time. The virtual session lasted approximately 15 minutes. The dynamics and rules for the Beer Game are the same, despite the playing format. 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 [31]. Participants are not informed of the number of periods in the game. The first in-person session completed 36 periods, the second 22 periods, and the virtual session completed 50 periods. All analyses for this research focuses on the data collected for 22 periods to keep it consistent among all participants.

Data was collected for each period of play and included (1) number of orders received from the downstream customer; (2) number of back-ordered cases at the end of the period; (3) number of cases received from the upstream supplier; and (4) number of cases in inventory at the end of the period. Cost is calculated for each period, as a running total for all periods played. Other elements calculated form this data include effective inventory (ending inventory less any backorders), the variance of customer orders, variance of orders placed, and variance of shipments received.

Platform	Group	Participants	Data Points
Dashboard	Treatment	20	440
	Treatment-A	8	176
	Treatment-B	12	352
No Dashboard	Control	16	352
	Treatment-A	8	176
	Treatment-B	8	176

Table 1. Experiment Groups

ANALYSIS

To determine the effectiveness of visualization to enhance analytical reasoning, we analyze the differences in ordering strategies for each player between the treatment and control groups. A series of t-tests were used to examine the participant's decision-making process and approach to the beer game. We analyze the differences between the participants for three variables: orders placed, bullwhip effect, and the 'no strategy' approach.

The first variable, orders placed, represents the ordering strategy of a player. Ordering strategy is the quantity ordered to the upstream supplier (i.e., Orders Placed). This value is the result of the one decision-making task of the game. The second variable, bullwhip effect, represents insight gained from working with the visualization. The bullwhip effect (BEI) measures how participants react to dynamic decision-making situations. BEI is the variance in orders placed divided by the variance in customer orders received. A BEI greater than one indicates the player's level of panic, whereas a BEI less than one indicates the player's level of calm [27, 28, 30]. The level of panic is an indicator of how participants deal with uncertain information to make decisions. The third variable, no strategy, represents the essence of the process. The 'no strategy' strategy (NSI) measures how players consider the overall, big picture of the game. The participants who employ this strategy order the exact amount of beer they receive from the upstream supplier. In other words, they do not react to customer demands [30]. NSI is the variance of orders placed divided by the variance in shipments received. An NSI value greater than one indicates a broader view of the situation, whereas an NSI value less than one indicates a local focus. It is an indicator of how the player views the game, whether their focus is locally on their inventory or do they consider other factors from being a part of the supply chain.

Three t-Tests are run on each variable to compare the differences between groups of participants (see table 2). The null hypotheses for all t-stat tests are the same: there is no difference between the visualization system and the non-visualization system. The results of the t-Tests are provided in Table 3. The t-Stat results for eight tests prove to be significant, with p-values falling below 0.05. The t-Critical value from these tests fall between the negative and positive t-Stat values, providing evidence that the means are different. The difference between the means is varied, with the most significant difference showing for groups that only played the game once. These results provide sufficient evidence to reject the null hypothesis. Participants using the visualization system performed better in the game, giving evidence of the value of visualization in dynamic decision-making situations.

	All Participants		Matched Pairs		Mismatched Pairs	
	Treatment	Control	Treatment-A	Control-A	Treatment-B	Control-B
Participants	20	16	8	8	12	8
	Orders Placed per Period					
Observations	440	352	176	176	264	176
Mean	7.20	8.42	7.94	7.10	6.93	9.47
Variance	2.70	48.94	22.72	17.06	22.04	79.53
Degrees of Freedom	549		175		240	
Difference in Means	1.26		0.85		2.53	

t-Stat	**-2.88**		1.70		**-3.46**	
t-Crit (2-tail)	1.96		1.97		1.97	
	Bullwhip Effect (BEI) per Period					
Observations	420	336	168	168	252	168
Mean	1.83	2.48	1.90	0.51	1.78	4.45
Variance	2.21	15.71	2.27	0.27	2.17	23.42
Degrees of Freedom	411		167		188	
Difference in Means	0.63		1.39		2.67	
t-Stat	**-2.87**		**11.33**		**-6.96**	
t-Crit (2-tail)	1.97		1.97		1.97	
	No Strategy (NSI) per Period					
Observations	420	336	168	168	252	168
Mean	1.66	0.85	1.41	0.59	1.84	1.11
Variance	8.60	1.69	3.55	0.29	11.93	2.96
Degrees of Freedom	604		167		391	
Difference in Means	0.81		0.85		0.73	
t-Stat	**5.10**		**5.23**		**2.83**	
t-Crit (2-tail)	1.96		1.97		1.97	

Table 2. t-Test Results

To determine the effectiveness of the visualization in supporting multiple tasks, we analyze the participant's perception of the supply chain. How a player views the supply chain indicates the situational factors that influence the decision-making task. We follow the example of previous research by applying a regression formula with the data collected from the Beer Game. Data from each player is evaluated to compare the orders placed in a period against the ending inventory, customer orders, shipments received, and backorders [28]. Ending inventory is the on-hand inventory from the previous period, where backorders represent any customer orders that could not be filled. Customer orders represent the quantity requested by customers, where shipment received is the number of cases delivered from the upstream supplier. All data points are captured for each period played in the game (T = 22) and are compared against the outgoing orders (orders placed).

Analyzing the coefficients identifies the more substantial factors influencing the decision-making task (see Table 3). Players are penalized for having too much on-hand inventory at the end of a period ($0.50 per case per week) and for having backorders ($1.00 per case per week). All players are aware of the penalties from the start of the game, and the cost per week was provided as a KPI on the dashboard. Backorders were an influential factor to the players as they decided how much beer to order. Ending inventory from the previous period and customer orders were also highly influential in the decision-making task. There are three factors that provide insight into the Beer Game decision-making strategy: bullwhip, the presence of an oversupply of stock in the chain, and a participant's value of the supply chain as a whole. If the bullwhip effect does not exist, then the value of orders placed is equivalent to customer orders received (α_R - 1). The coefficients for inventory, backorders, and shipments received imply the presence of an oversupply within the chain ($\alpha_I = \alpha_S = \alpha_N = -1$). The number of backorders determines a player's value of the supply chain. If backorders are greater than ending inventory, the player under-weights the supply chain and does not view the process holistically ($\alpha_N > \alpha_I$) [27].

	Ending Inventory	Customer Orders	Shipments Received	Backorders	Period	R-Sq	Sig. F
Treatment	-0.209	0.605	0.021	0.143	-0.048	0.799	**0.0044**
Control	-0.0149	-0.302	-0.199	-0.113	-0.115		
Control-A	-0.101	-0.116	-0.118	0.107	-0.051	0.665	**0.0297**
Control-B	-0.197	-0.488	-0.280	-0.333	-0.178	0.697	**0.0373**

Table 3. Regression Coefficients – Value of Supply Chain based on Orders Placed

	Participants	Bullwhip Effect	Oversupply of Stock	Under Weigh Supply Chain
Treatment	20	1	0	16
Control	16	0	0	10
Control-A	8	0	0	6
Control-B	8	0	0	4

Table 4. Decision-Making Strategy Factors – Participant Count

Table 4 provides the count of participants for each of the Beer Game decision factors. One player from the entire experiment did not have bullwhip. Their coefficient for customer orders was 1.00, meaning their order to the upstream supplier matched their incoming customer order. Overall, there was a large difference in the coefficients for customer orders and the expected value of 1.0. The average customer order coefficient for the treatment group was .605, for the control-A group -0.116, and the control-b group -0.488. All players experienced overstock throughout the supply chain. Two players had a coefficient for inventory around -.600 and were the closest to the expected value of -1. As with customer orders, the average inventory coefficients varied among the participant groups. The average for the treatment group was -0.209, for the Control-A group -0.101 and the Control-B group -0.197. The value placed on the supply chain indicates how players viewed the entire process by analyzing other factors such as shipping and processing delays. The weight of the supply chain is based on the relationship between backorders and inventory. The majority of participants under-weighed the supply chain, feeding into the fact that the game is designed to provide sufficient and relevant local information and minimal global information.

The t-tests provide insight into the difference between a visualization-based system and a non-visualization-based system. The comparison of the experiment groups allows us to identify how visualizations support analysis. Overall, the participants using the visualizations were more effective in their ordering strategies, as evident by the results of the t-stat tests. The regression formula identifies the value placed on the supply chain, which encompasses all the tasks that a player might account for throughout the simulation. The visualization group had a much larger R-squared value in comparison with the control subgroups. The decision strategies of the participants align with those identified in extant research [27, 28], as the focus tends to be on customer demand while under-weighing the overall value of the supply chain. The more profound analysis of the bullwhip effect and no-strategy approach indicates that the use of visualization enhances the analytical reasoning and decision-making capabilities of participants.

The investigation detailed in this paper provides evidence that interactive visualizations fill multiple roles throughout dynamic decision-making with emergent information. Visualizations provide value that increases performance opportunities as well as supports the user in accomplishing numerous tasks at once

CONCLUSION

Our investigation and results provide evidence that identifying user tasks and designing visualizations to support those tasks is an effective solution to supporting knowledge activation. The results provide early research into the value of visualizations outside of usability measures. Interactions built into the visualization 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 [36] and the idea of distributed cognition across spaces of a joint cognitive system [21]. The cognitive abilities of individuals are substantially different. 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. Our results provide evidence that giving users multiple perspectives of data through a coordinated multiple-view design is useful. The coordinated multiple-view design reaches a broader audience and more diverse cognitive abilities because it allows the user to take control over what data they see and how they see it [32].

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 [37]. 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. We identify two future research steps that are necessary for the information visualization domain. The first is more research towards understanding and identifying proper affordances for interactions. For instance, delving deeper into the cognitive, physical, sensory, and functional affordances for interaction design [38]. 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.

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