Investigating The Use of Visual Aids in Organizational Decision-Making: A Cognitive Perspective

by

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Abstract

Integrating cognitive science theories and practical applications, this thesis examines the role of visual aids in organizational decision-making, using sweet potato packing operations as a motivating case study. The research identifies significant gaps in current tools, which often fail to support all stages of decision-making, and proposes guidelines to design visual decision-support tools, that are grounded in cognitive science theories. These guidelines combine causal diagrams and interactive dashboards to assist the decision-making process and minimizes cognitive load by customizing information presentation based on user preferences and background, supporting their ability to process complex data. Additionally, Toulmin's model of argumentation is incorporated to improve the clarity and accountability of decision documentation. The study emphasizes the importance of aligning visualization tools with cognitive principles and user needs, aiming to enhance decision-making efficiency and effectiveness. The findings have broader implications for the design of decision-support tools in various industries, contributing to the development of more effective and user-centric visualization tools adaptable to dynamic decision-making environments.

Keywords: Decision-making, visualization, causal reasoning, sensemaking, cognition, causal diagrams

Dedication

I dedicate this to my parents, whose guidance and unconditional love have fueled my quest to satisfy my curiosities and forge my own path, and to my wife, for her unwavering support through all the expected and unexpected challenges and achievements.

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List of Acronyms

ANOVA	Analysis of Variance
CDD	Causal Decision Diagram
CDM	Causal-Explanation Based Decision-Making
CLD	Causal Loop Diagram
DI	Decision Intelligence
DSS	Decision Support System
GA	“Grower A” (Interview Participant #1)
ID	Influence Diagram
IT	Information Technology
LLM	Large Language Model
MI	“Mr. iPad” (Interview Participant #2)
ML	Machine Learning
RPD	Recognition-Primed Decision [Model]
RQ	Research Question
SD	System Dynamics
SDD	Sequential Decision Diagram
SFU	Simon Fraser University
SIAT	School of Interactive Arts and Technology
USDA	United States Department of Agriculture
WMC	Working Memory Capacity

Chapter 1.

Introduction

1.1. Context and Importance

1.1.1. Decisions

"Should I Stay or Should I Go?" asks the extremely popular song by The Clash. It presents the frustration and indecision that often accompany obscure decisions, where the cost-to-benefit or action-to-outcome factors are not clear. Our daily lives are made up of decisions – those we make ourselves and those made by others that affect us either directly or indirectly. Similarly, the functioning of organizations is determined by series of decisions, ranging from routine tasks and workflows to significant long-term strategies like acquisitions or mergers. These choices collectively shape both personal and organizational trajectories (Mariano & Baker, 2024; Steptoe-Warren et al., 2011).

Decisions are primarily guided by reasoning, which includes synthesizing multiple sensory stimuli along with pertinent information accessible to the decision-maker. Typically, this sensory data is visually presented, particularly in contexts that require scientific reasoning (Gooding, 2006, pp. 689). This visual representation may take the relatively simpler form of a list of color-coded checkmarks, or complex visualizations that require arduous training. Thus, visual stimuli play a fundamental role in the cognitive process by providing a clear and direct medium for conveying complex data, facilitating the generation of insights.

1.1.2. Visual Analytics

Visual analytics is aimed to support the analytical reasoning process through interactive visualizations (Thomas, 2005). However, decision-making often extends beyond purely analytical approaches, incorporating expertise (Phillips et al., 2016). The flow of information from the visualization to the decision-maker is prone to deviations due to biases, as it involves sense-making – a highly personalized process – influenced by numerous factors, such as the decision-maker's expertise (Lee et al., 2016; Salas et al., 2010; Zytek et al., 2022), motivation (Hagmayer & Sloman, 2009, pp. 34), stress levels (Giovanniello et al., 2023; Heereman & Walla, 2011), and the degree of uncertainty or ambiguity (Arend, 2022; Nowak & Bartram, 2023). Decision-makers must interpret the visualization, align it with their mental models, and through causal reasoning, conduct conscious or sub-conscious mental simulations to explore various actions that could lead to the desired outcome. This complexity presents significant challenges in decision support through visualizations that align with the mental decision processes of decision-makers.

1.2. Research Gap

Research on the impact of visual analytics tools and design of visualization tools for decision support have predominantly concentrated on the data analytics and presentation facets of decision-making, often overlooking the theory behind the perception of such visualizations (Park et al., 2022), as well as the crucial temporal (Hagmayer & Waldmann, 2002) and procedural dimensions. Furthermore, despite technological advances that enable increasingly complex software to aid in decision-making, many decision-makers in organizations still report using spreadsheets (Bartram et al., 2022; Dimara et al., 2022; Tory et al., 2021) and even perform better with tabular data compared to visualizations (Dimara et al., 2017a). This lack of utilization presents a gap in both research and practice, concerning the comprehensive support of causal reasoning and sensemaking through visualizations (Oral et al., 2024), rather than merely providing directive outputs.

1.3. Thesis Guide

This thesis aims to bridge this gap through an extensive scoping literature review to present and discuss cognitive science concepts that inherently impact decision making, followed by a systematic literature review looking into the visualization tools developed for decision making that have been published in the past fifteen years. The systematic literature review will evaluate their features and propose guidelines for building visual tools that could aid visualization designers in creating more intuitive tools for decision-makers that consider the end-user's sense-making as part of the design.

1.3.1. Research Questions

This thesis aims to answer the following research questions (RQ1-RQ3) through critical literature reviews, that ultimately aim to answer the final, overarching research question (RQ4).

The scoping literature reviews aims to answer the following research questions:

- RQ1: What types of visualizations or visual tools are typically used for decision-making?
- RQ2: What are the cognitive processes a decision-maker goes through, or are relevant, when viewing a visualization and using it to make a decision?

The systematic literature review aims to answer the following research question:

- RQ3: What types of visualizations have been developed and published in academic journals in the past 15 years, and if so, how do such visualizations address the process of decision-making, beyond analytics and data?

The two literature reviews will be synthesized to develop guidelines that will aim to answer the following question:

- RQ4: What are the opportunities for designing visualizations based on cognitive theories and frameworks?

1.3.2. Objectives

The goal of this thesis is to synthesize current research findings into guidelines that direct future research and practice on how visualizations can support the decision-making process. This thesis shifts focus from the analytics aspect of Visual Analytics to explore how humans interpret visualizations within the context of decision-making. It highlights how visual data influences decision-making processes. For visualization designers, the thesis introduces a new design process intended to produce visualizations that are clear for decision-makers to understand, thereby reducing cognitive load. Additionally, for subject matter experts across various fields, the thesis details available methods and explains how these can enhance their decision-making flows.

1.3.3. Research Worldview

This thesis adopts a pragmatic research worldview, recognizing the importance of both practical outcomes and the underlying theoretical framework that guides decision-making processes. The pragmatic approach is chosen because it allows for the integration of various methods and perspectives to address the research questions comprehensively. This worldview is particularly suited to the multidisciplinary nature of the thesis, which bridges cognitive science, data visualization, and organizational decision-making.

1.3.4. Methodologies

Literature Reviews

The research begins with two comprehensive literature reviews to scope the cognitive science theories, typically used visualization tools for decision-making, and a systematic literature review to list and analyze recently published visualization tools designed to support decision-making. These reviews provide a foundational understanding of the current state of knowledge and identify gaps that this thesis aims to address. The literature reviews offer insights into the theoretical and practical aspects of visualization tools and their role in enhancing decision-making processes.

Development of Guidelines for Visualization Design

Based on the insights gained from the literature reviews, guidelines for visualization design are introduced, including a dual-screen visualization tool, suggesting the use of two separate screens displaying two separate visualizations regarding the decision. These guidelines integrate both qualitative and quantitative elements to support effective decision-making. It attempts to allow the decision-makers to visualize the entire decision process, manipulate variables, and simulate different scenarios, providing immediate feedback on potential outcomes. The guidelines are designed to be user-centric, as it aims to focus on user-needs and improve usability.

1.3.5. Thesis Process Diagram

The Thesis Process Diagram (Figure 1.1) outlines the structure and flow of research questions (RQs) derived from identified motivations, leading to the development of guidelines for designing visual decision-support tools. The motivations stem from three key areas: Oral et al. (2024) highlighting the lack of tools for the Design and Choice stages of decision-making beyond the intelligence phase, Bartram et al. (2022), Tory et al. (2021) discussing the complexity and limitations of current visualization tools, and the agriculture technology case concerning sweet potato packing operation, emphasizing the need for tools that integrate predictive analytics and decision-making. These motivations inform the research questions: RQ1 (Chapter 3) examines the types of visualizations or visual tools typically used for decision-making; RQ2 (Chapter 4) explores the cognitive processes users undergo when using visualizations for decision-making; RQ3 (Chapter 5) investigates how visualizations in academic publications have addressed cognitive concepts in agricultural decision-making over the past 15 years; and RQ4 (Chapter 6) identifies design opportunities for visualization tools by integrating sensemaking and cognitive science theories. The guidelines are then divided into three primary components: Dual-Screen Visualization (comprising Causal Diagrams for causal reasoning and Data Visualization Dashboards for iterative information and knowledge search), Scenario Exploration Support (generation and evaluation of alternatives to reduce cognitive load), and Toulmin's Model of Argumentation (providing structure for decision justification, reporting, documentation, and reuse). Additional considerations within the guidelines include real-time variable input, automated financial simulation, temporal aspects of decision-making, and user-specific customizability.

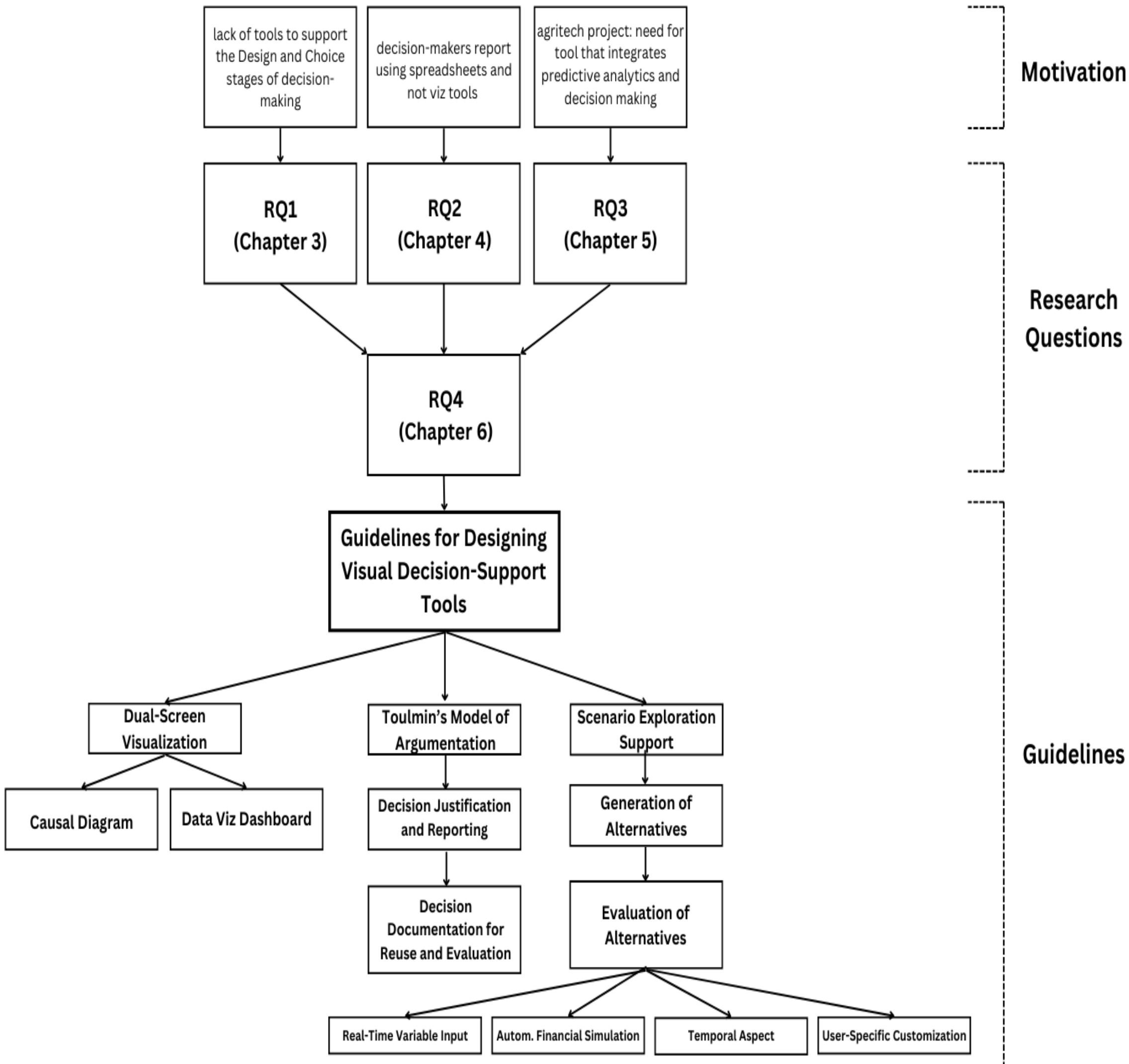


Figure 1.1 Diagram depicting the processes carried out in this thesis

Chapter 2.

Related Work

This section provides an overview of decision-making, various process models that have attempted to capture the decision-making process over the years, and several theories behind the mental models and processes of decision-makers. It also introduces the sweet potato packing operation decision from the agriculture technology study that our lab (Integrated Science Lab) is conducting, under a grant funded by the United States Department of Agriculture (USDA).

2.1. Decision Making

Decision making typically involves generating and evaluating multiple available options based on specific criteria and desired outcomes. Relatively simple decisions do not require extensive cognitive effort and can be addressed via prescriptive decision strategies (Klein, 1993). However, real-life decisions are often ill-defined, with numerous possible actions, outcomes, and intermediating factors, all with intricate associative or causal relationships. Pre-defined, prescriptive decision strategies are not effective in addressing these “ill-defined” (Klein, 1993, pp. 147), or “wicked” (Rittel & Webber, 1973; Wang & Ruhe, 2008, pp. 81) problems. These complex problems and/or decisions may be guided or assisted through robust, multimodal, yet easy-to-use tools, which must be built to support specific cognitive tasks carried out for various types of decisions.

2.1.1. Taxonomy of Decisions

Wang and Ruhe (2008) explored the process in the context of ‘wicked’ planning problems and developed a taxonomy of criteria for decision making, (Table 2.1).

Table 2.1 Taxonomy of strategies and criteria for decision-making

Category	Strategy	Criterion
Intuitive		
	Arbitrary	Based on the most easy or familiar choice
	Preference	Based on propensity, hobby, tendency, expectation
	Common senses	Based on axioms and judgments
Empirical		
	Trial and error	Based on exhaustive trial
	Experiment	Based on experiment results
	Experience	Based on existing knowledge
	Consultant	Based on professional consultation
	Estimation	Based on rough evaluation
Heuristic		
	Principles	Based on scientific theories
	Ethics	Based on philosophical judgment and belief
	Representative	Based on common rules of thumb
	Availability	Based on limited information and local maximum
	Anchoring	Based on presumption or bias and their justification
Rational		
Static		
	Minimum cost	Based on minimizing energy, time, money
	Maximum benefit	Based on maximizing gain of usability, functionality, reliability
	Maximum utility	Based on cost-benefit ratio (certainty, risks, uncertainty)
Dynamic		
	Interactive events	Based on automata
	Games	Based on conflict (zero sum, non-zero sum)
	Decision grids	Based on a series of choices in a decision grid

Note. Adapted from "The Cognitive Process of Decision Making" by Y. Wang, and G. Ruhe, 2008*, Novel Approaches in Cognitive Informatics and Natural Intelligence*, pp. 76

The authors point out that due to their unpredictable nature, intuitive and empirical decisions fall under "human intuitive cognitive psychology" and thus resist explanation through rational models (Wang & Ruhe, 2008, pp. 75). Consequently, their study focuses on rational decisions and their subcategories, which are distinguished through the use of static or dynamic strategies (Wang & Ruhe, 2008, pp. 77). Static decisions, which are predominant in organizational settings, are further divided based on the levels of uncertainty involved and the decision-maker's values and attitudes. According to Wang and Ruhe, pessimistic or conservative decision-makers often employ Bayesian Theory to minimize potential losses, whereas more optimistic decision-makers might use Game Theory to maximize potential gains (Wang & Ruhe, 2008, pp. 78), which highlights the impact of individual differences (Stanovich & West, 1998).

While Wang and Ruhe's (2008) taxonomy of decisions effectively categorize strategies and criteria for algorithmic formulation, it also underscores a vital aspect of visualization design research. These decision strategies and processes are critical considerations when developing visualizations intended to support decision-making. Rational decisions in organizations often necessitate the integration of multiple perspectives and data from various sources. This data must be considered and analyzed in a structured flow that aligns with the decision process. Properly accounting for this flow is essential in the design of visualizations to effectively support decision-making efforts.

2.1.2. Adaptive Decision Strategies

Investigating how humans make decisions, Gary Klein proposed a dual-process model wherein humans engage in rapid decision-making highly dependent on past experiences (Klein, 1993, 1998). He introduced the Recognition-Primed Decision (RPD) Model to elucidate the human decision-making process under time constraints, suggesting that individuals assess situations and act swiftly, leveraging their previous experiences (Figure 2.1). According to Klein (1993), operational decisions are typically recognitional, shifting to analytical only when justifications are necessary or when data are abstract.

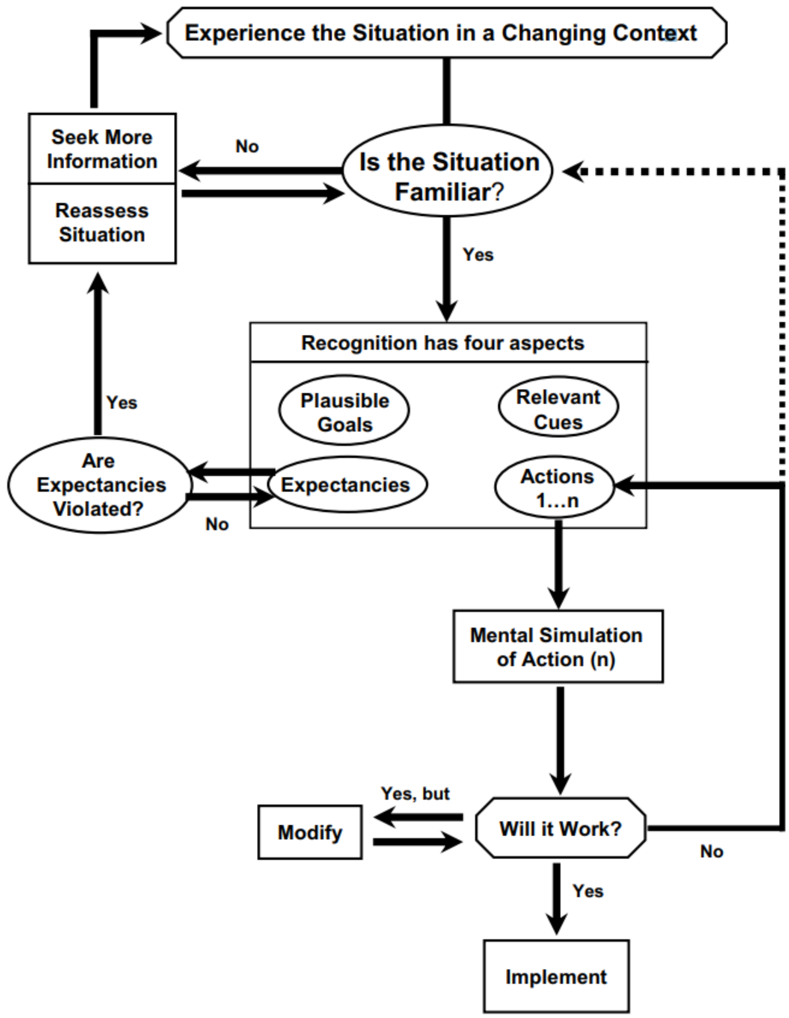


Figure 2.1 Recognition-Primed Decision (RPD) Model.

Source: "Naturalistic Decision Making" by G. Klein, 2008, *Human Factors: The Journal of the Human Factors and Ergonomics Society*, pp. 459

In the domain of recognitional decision-making, experience enhances the initial and immediate analysis — or recognition — of the decision environment, leading to more accurate problem representations. Experienced decision-makers are adept at quickly constructing one or more potential actions and mentally simulating them to identify at least a satisfactory solution (Klein, 1993), which some argue is intuition. Given the constraints of time pressure, decision-makers often commit to actions they believe will yield desirable outcomes without waiting for a thorough evaluation and analysis of alternatives, a phenomenon explained through the Bounded Rationality Theory. This indicates that the decision-making process varies depending on the problem's complexity and temporal scope. Notably, while experience generally has a positive impact, it introduces a subjective element that can lead to potential biases, a concept further explored by Amos Tversky and Daniel Kahneman (Kahneman & Tversky, 1996; Tversky & Kahneman, 1974).

The distinction between rapid, often subjective decision-making and the deliberate evaluation of alternatives has led to frameworks that cover the full spectrum of human decision-making (Epstein, 1994; Hammond et al., 1987; Kahneman, 2003a, 2003b; Klein, 2008; Sloman, 1996), which have found widespread acceptance among the public. Hammond et al. (1987) introduced a continuum of intuition and analysis, positioning decisions based on the level of available information and time constraints. Sloman (1996) continued the discussion around two distinct systems for reasoning, associative and rule-based. These systems can work simultaneously and complementarily, although the rule-based system often dominates the other. Kahneman (2003a, 2003b) described System 1 and System 2 thinking, identifying two distinct cognitive processes that are activated by various factors, including the decision-maker's motivation and the temporal scope, as discussed by Klein (1993). System 1 involves rapid, almost automatic thinking and is developed and solidified over time, while System 2 is engaged in situations that require deliberate analytical and logical thinking, resulting in a significantly higher cognitive load and a slower process (Kahneman, 2003a, 2003b). System 1 closely mirrors Klein's naturalistic RPD Model (1993), emphasizing quick decisions based on intuition, a comparison Klein (2008, pp. 458) himself later affirmed.

The RPD Model includes the quick generation and evaluation of alternatives, though the analysis ends once a satisfactory solution is found—a concept originally termed "satisficing" (Simon, 1955). When confronted with ambiguity, complexity, or unclear cues, decision-makers may need to mentally simulate various scenarios and evaluate their outcomes (Klein, 2008), relying on their expertise or intuition (Hammond et al., 1987). This becomes problematic when a decision requires justification, as intuition is rarely communicated effectively in logical terms. Consequently, organizations are increasingly trying to incorporate data-driven insights within this stage of analysis, where hierarchical reporting is essential, as decisions often need to be justified to a superior and lacking a data-driven basis for a decision can be problematic. Using rational argumentation methods, such as those proposed by Toulmin (1958), to structure intuitive decisions could facilitate such justification processes, even if conducted internally without external reporting.

When to Optimize? When to Satisfice?

In their exploration of decision-making under different conditions of certainty and uncertainty, Artinger et al. (2022) discuss the critical distinction between two prominent approaches in decision theory: optimization and satisficing. This separation is deeply rooted in the inherent differences in decision environments as identified by Simon (1955). Satisficing refers to the selection of an option that meets a threshold of acceptability rather than achieving the optimal outcome, or optimizing. Under conditions of risk, where all relevant information is assumed to be known, optimization strategies—anchored in rational choice theory—are considered superior, reflecting a constructivist rationality that aims for the best outcome based on the data available (Artinger et al., 2022, pp. 626-627). In contrast, in environments characterized by uncertainty, where not all variables can be known or predicted, satisficing strategies are more relevant.

Artinger et al. (2022) emphasize the necessity of recognizing the limitations and appropriate contexts for applying different decision-making models. They caution against broadly categorizing all decision-making scenarios as cases of uncertainty, which can lead to overlooking the specific demands and characteristics of each situation. Instead, they advocate for a more tailored approach where decision-making strategies are seen as tools that are effective, depending on whether the scenario involves clear risks or uncertainties. This method promotes adaptability in decision-making, urging practitioners to carefully consider the information available and the nature of the problem at hand. By adopting this adaptable strategy, organizations can not only manage predictable elements, such as known risks and available information, but also remain agile enough to effectively respond to unforeseen challenges. These unexpected challenges, such as sudden market shifts or technological disruptions, require quick thinking and flexibility, highlighting the value of preparedness in both stable and volatile conditions.

Second Order Thinking

Second order thinking, an essential cognitive strategy for adept decision-making, becomes particularly relevant in the landscape of recognitional decision-making where rapid judgments and mental simulations are prevalent (Nowinska & Pedersen, 2024; Sunstein & Ullmann-Margalit, 1999). Second order thinking involves considering not just the immediate effects of a decision, but also the series of consequences that follow. This form of thinking requires a decision-maker to look beyond obvious outcomes and predict the cascading effects of their choices, which often involve complex interdependencies and extended temporal scopes.

Aligning with the cognitive demands of recognitional decision-making, experienced decision-makers leverage their deep knowledge and intuition to swiftly navigate through complex decisions (Phillips et al., 2016), a notion that extends to the navigation of visualizations for decision-making (Pirolli & Card, 2005). However, these decisions are sometimes made under significant time pressures and might not always allow for the extensive deliberation required to evaluate long-term consequences. Second order thinking addresses these gaps by prompting decision-makers to iteratively consider 'what then?' scenarios beyond the immediate horizon. This evaluation enhances the depth and foresight of their decision-making processes under various constraints.

Data-Driven Decision-Making

Businesses are increasingly utilizing data to drive more informed decision-making, a strategy that has proven effective. Research by Brynjolfsson and McElheran (2016) shows that this approach has increased productivity by 5-6% and has also led to a higher market value for companies (Brynjolfsson et al., 2011). This success has prompted further investigation into the cognitive mechanisms underlying these processes, drawing more researchers to explore how data influences rational and analytical business decisions.

Data is often perceived as objective, because it comprises numbers, statistics, and mathematical elements, creating a sense of solid grounding for rationality and analytical reasoning. In business settings, disputes are frequently resolved using findings from data analytics, reflecting the trusted nature of data-driven decision-making. However, despite the pervasive use of data and analytics, intuitive judgment, derived from experience and expertise, remains a valued component in decision-making across businesses of all sizes, even when the decision falls under the rational category of the taxonomy of Wang and Ruhe (2008).

Data-driven decision-making is categorized into five levels by Buijsse et al. (2023), which reflect the extent of data and analytics utilized in the decision-making process. These levels range from minimal data use at Level 1 to comprehensive utilization at Level 5, where data is used to describe, forecast, and optimize decisions. Additionally, implementing data analytics in decision-making faces two key barriers (Buijsse et al., 2023). The first is an individual barrier, where the decision-maker is required to prioritize data as the primary input, setting aside personal interpretations and intuition. While this approach aims to enhance objectivity and rationality, it paradoxically involves the decision-maker's judgment in determining which data are relevant and accurate. It also obfuscates how intuition and expertise will be integrated into this process. Moreover, this necessity to make personal selections naturally introduces a level of subjectivity into the process, which leads to the second barrier. The second barrier, termed the Data Science Barrier by the authors, necessitates agreement among decision-makers on the data, principles, assumptions, and concepts used in the analytics process (Buijsse et al., 2023). It is during this stage that decision-makers justify their – often at least partly subjective – reasoning to other decision-makers or stakeholders and take part in what resembles a negotiation process to reach an agreement (Lotov et al., 2004, pp. 5).

Understanding data analytics and data science as the backend of data-driven decision-making only represents the “tip of the iceberg” (Berret & Munzner, 2023) as it sets the stage for the next crucial step: effectively communicating these analyses and findings to decision-makers. This is typically achieved through data visualization, which must be clear, accurate, and appropriately tailored to the needs of the decision-making process (Kosslyn, 1994). However, given the individual differences between decision-makers and the processes of decision-making, this is easier said than done.

2.2. Visualizations and Decision Making

Recognizing that visual stimuli significantly influence analytical reasoning (Kosslyn, 1994), researchers have posited that visualizing otherwise non-visual stimuli, or in some cases visually ineffective stimuli such as large tabular data, could help the decision-making process by facilitating reasoning (Canonico et al., 2022; Cardinaels, 2008; Park et al., 2022; Smedberg & Bandaru, 2023; Zhu & Chen, 2008). Subsequent studies have aimed to validate these hypotheses and explore the cognitive mechanisms involved, seeking to better understand how visual representations impact decision-making.

As articulated by pioneers like Shneiderman (1996), the essence of using visualization is to gain insight, not to merely produce pictures. This insight-driven approach is critical for discovery, decision-making, and explanation, enabling users to not just see data but to understand and interact with it meaningfully. This means providing tools that do more than display numbers; they must illuminate relationships and outcomes that affect operational decisions. The concept of external cognition explains how visualizations assist in bridging the gap between internal cognitive processes and external informational structures (Hutchins, 1996). By extending cognition beyond the mind to include interactions with visual representations, these tools help manage the complexity inherent in decision environments. For instance, through the use of visual knowledge tools, which can arrange or manipulate information to reveal patterns (Shneiderman, 1996), users can grasp complex operational dynamics at a glance. These tools act as cognitive amplifiers, enhancing the ability to monitor large data sets under time pressure, a critical capability when managing intricate systems, such as in supply chain logistics.

According to Oral et al. (2024), decision-makers often go through a three-stage process, consisting of Intelligence, Design and Choice, responsible for analyzing information, generating, and evaluating available action items, and selecting the best path based on certain criteria, respectively. While many visualization tools effectively support the Intelligence stage of decision-making by enhancing the identification and analysis of information, they often fall short in the Design and Choice stages where decision-makers conceptualize and select among alternatives (Oral et al., 2024). This gap underscores the need for tools that not only present data but also facilitate interaction and manipulation to support comprehensive decision-making processes. Enhancing the flexibility and visibility of these tools could significantly improve their effectiveness, particularly in these later stages. By designing interfaces that allow decision-makers to easily alter and experiment with displayed information, visualization tools can better support the comprehensive needs of decision-making from start to finish.

Scott McCloud's exploration of sequential visual storytelling adds another layer to understanding complex data through narrative techniques (McCloud, 1994). By structuring data presentation in a sequential format that mirrors natural thought progression, McCloud's approach makes intricate data sets more narrative and thus, easier to navigate. This method proves particularly beneficial in decision-making contexts where the sequence of events or processes must be clearly understood to make informed decisions. By guiding the user through a visual journey, these techniques not only clarify the data but also engage the user more deeply, making the decision process not only more efficient but also more insightful. A similar method could be employed to guide the user through a decision process, which is inherently directional and sequential.

2.2.1. Visual Analytics Process

The visual analytics process, as initiated by van Wijk (2005), involves creating visual representations from data to enable knowledge generation. This process starts with initial analytical methods that develop these visualizations, setting users on a cycle of deepening their data understanding through continuous visual interaction. This approach helps users refine their insights and confirm earlier findings through ongoing engagement with the visual data.

Keim et al. (2008) built on this notion by emphasizing the critical integration of human cognitive abilities with computational capabilities within the visualization framework (Figure 2.2). The authors advocate for designs that enhance the decision-making process by allowing both human and computational strengths to be utilized effectively (Keim et al., 2008). This is achieved by enabling users to tailor visualizations to their specific requirements while ensuring comprehensive visibility of data, facilitating a fluid progression from data analysis to knowledge generation. This interactive and iterative feedback loop is pivotal for effective decision-making, illustrating the dynamic interaction between user engagement and data visualization (Keim et al., 2008).

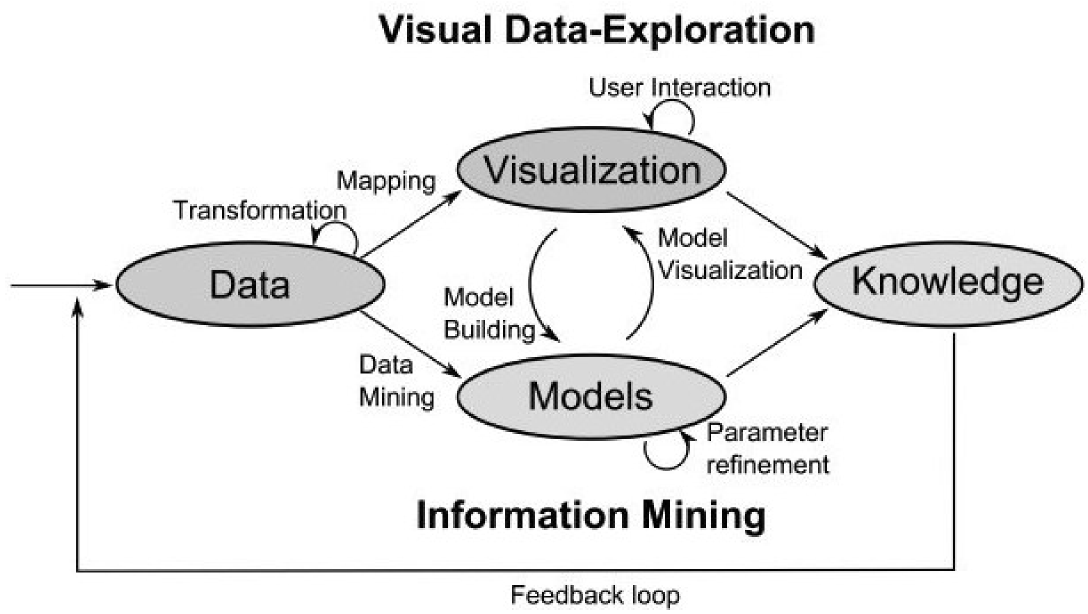


Figure 2.2 Visual Data Exploration and Information Mining Loop
Source: "Visual Analytics: Definition, Process, and Challenges" by D. Keim, G. Andrienko, J-D Fekete, C. Gorg, J. Kohlhammer, G. Melancon, 2008, *Information Visualization,* pp. 156

Expanding on Keim et al.'s framework, Sacha et al. (2014) offer a modified model that distinctly incorporates both computer algorithms and human cognitive. Their model outlines three critical loops: exploration, verification, and knowledge generation. The exploration loop refers to interaction with visualizations to extract new insights; the verification loop involves testing these insights to formulate data-driven hypotheses; and the knowledge generation loop focuses on solidifying these insights into actionable knowledge. Sacha and colleagues (2014) also suggest that enhancing user interaction with visual data can significantly increase the reliability of the conclusions drawn from such analytical processes.

Seeking to deepen the understanding of how visual tools influence decision-making, Canonico and colleagues (2022) explored the role of knowledge visualization in multi-objective decision-making contexts. Their findings are encapsulated in a model of the organization decision-making process, depicted in Figure 2.3. This model illustrates the use of visualization tools at two critical points: initially to generate knowledge, and subsequently to distribute this knowledge among the decision-making group. This helps establish common ground, which is essential for achieving the desired outcome of the decision-making process (Canonico et al., 2022, pp. 1088).

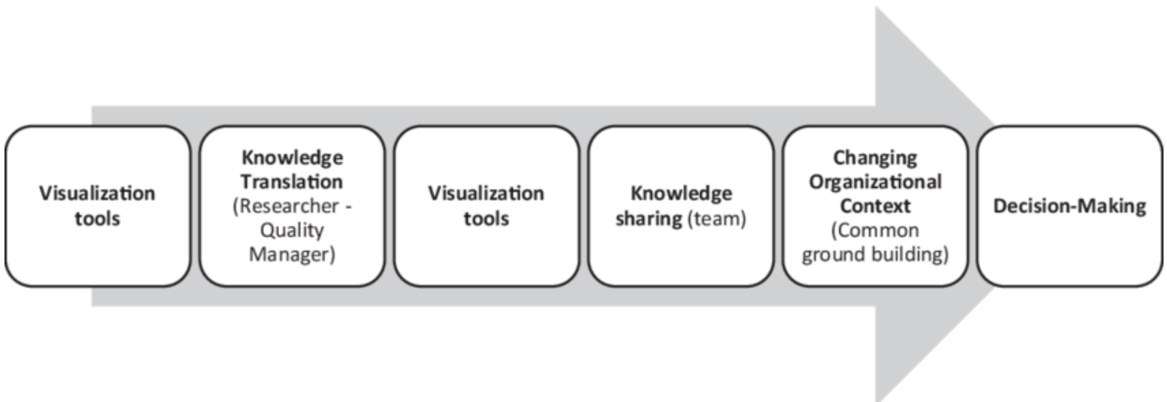


Figure 2.3 The knowledge visualization process
Source: "Visualizing knowledge for decision-making in Lean Production Development settings. Insights from the automotive industry" by P. Canonico, E. De Nito, V. Esposito, G. Fattoruso, M. Pezzillo Iacono, G Mangia, 2022, *Management Decision*, 60, pp. 1088

Although visual analytics has significantly enhanced decision-making processes, many users still rely on spreadsheets (Bartram et al., 2022; Tory et al., 2021). One major reason for this switch is the difficulty users face in making sense of data through visualizations (Bartram et al., 2022). When there is misalignment between the prepared visualization tool and the decision-makers' values, concerns, and criteria for decision quality (Yates et al., 2003), the tool is often ignored or underutilized. This disconnect can lead to ineffective decisions and wasted employee efforts. Additionally, users need to account for decisions and justify them to external stakeholders or senior management, which contributes to the continued use of spreadsheets (Bartram et al., 2022, pp. 7). Visualizations designed with consideration of users' sensemaking and cognitive processes may help address these issues, making it easier to integrate visual analytics into decision-making and reduce reliance on spreadsheets.

2.3. Case of Decision Making in Sweet Potato Packing

Under a grant funded by the United States Department of Agriculture (USDA), our lab (Integrated Science Lab) at Simon Fraser University (SFU) School of Interactive Arts and Technology (SIAT) partnered with two other stakeholders in the United States to investigate how sweet potato packers make decisions and whether the Decision Intelligence (DI) methodology can facilitate and improve their decision-making process. As part of this project, a comprehensive interview session aimed at producing a diagram of the decision process of two sweet potato farmers, "Grower A" (GA) and "Mr. iPad" (MI), was conducted to better understand the optimization challenges in agricultural operations. This qualitative case study focuses on enhancing decision-making processes surrounding the matching of harvested produce to market demands.

The interview consists of interactive dialogue mainly between the two growers and a DI expert, who is asking questions in order to depict the growers' mental model of the decision as accurately and thoroughly as possible.

2.3.1. Problem Definition

GA and MI have access to multiple fields of sweet potatoes, each containing a variety of sizes of sweet potatoes, ranging from Small to Giant. The size distribution of each field is unknown, as the growers are forced to make educated guesses based on what they see. GA and MI's operations receive orders from customers, for specific sizes of sweet potatoes. For example, a supermarket chain places an order for a certain weight of Small and Medium sweet potatoes, given the shoppers preference for those sizes. On the other hand, a pet food production facility places an order for Giant sweet potatoes, given the lower price per weight. Once a field is harvested and processed, or in other words, washed and cleaned, the sweet potatoes must either be sent out to fulfill an order, or be sent to cold storage, which is costly. Thus, to eliminate this cost, sweet potato growers typically send out higher quality potatoes that are already in cold storage, to fulfill an order of a lower quality, incurring a loss in potential revenue. GA and MI must gauge the size distribution in each field and based on the orders they have received and potential future orders they estimate, make a decision on which field to harvest and process. Their goal is to maximize revenue generated through fulfilling as many orders as possible, while incurring as little cold storage costs as possible, at the end of the business day. This creates a critical decision point in managing costs and preventing revenue loss by avoiding the unnecessary use of cold storage for produce that could be sold directly. This matching problem, a 'maximum utility' decision as categorized by Wang and Ruhe (2008), requires precise alignment of production output (type and volume of processed potatoes) with market demand (incoming orders).

Current Decision-Making Process of GA and MI

Currently, Grower A (GA) and Mr. iPad (MI) employ a combination of intuitive and empirical decision-making strategies, largely relying on their experience and educated guesses. These strategies are primarily manual and mental, involving a considerable amount of trial and error. For instance, they make educated guesses about the size distribution of sweet potatoes in each field and decide which fields to harvest and process based on incoming orders and potential future demands. This manual approach, while rooted in their expertise and intuition, often lacks precision and can lead to inefficiencies, such as unnecessary cold storage costs or missed opportunities to fulfill higher-value orders.

The tools currently in use include spreadsheets for recording data and basic predictive analytics for forecasting orders. However, these tools are not fully integrated into their decision-making models. The visual tools employed are basic, often limited to tabular data representations that fail to capture the complex dynamics and causal relationships inherent in their operations. This reliance on spreadsheets and basic predictive tools highlights a significant gap in the decision-support systems available to GA and MI, which often results in a reliance on their intuition and experience rather than data-driven insights. As a result, the decision-making process can be slow, labor-intensive, and prone to errors.

2.3.2. Identified Themes

In the conversation, GA underscores their current and critical need to optimize the matching of already harvested and stored potatoes to incoming orders, aiming to maximize the value derived from each batch of produce. MI contributes with practical insights, again emphasizing the importance of accurate predictions about the potential output of each storage type to make informed decisions about processing and order fulfillment.

The growers discuss the necessity of predictive analytics that utilize historical data, trend analysis, and seasonal yield information to better forecast incoming orders and align them with available stock. Both growers state that a tool designed to help them make more informed decisions, ultimately aiming to minimize cold storage cost and maximize the revenue generated, would be a meaningful upgrade to their current method of decision making, which is largely manual and mental. The insights from GA and MI highlight the need for advanced decision-support tools that reduce reliance on intuition by providing actionable, data-driven insights, as well as structuring the decision in a logical format, thereby improving the economic efficiency of agricultural produce handling.

- **Importance of Predictive Analytics**: Both GA and MI emphasized the need for accurate predictive analytics to forecast incoming orders and align them with available stock and compare different scenarios.
- **Alignment with Growers' Mental Models**: The necessity for tools that align closely with the growers' mental models was highlighted, as the growers requested visual tools that support their decision processes, not rewire them.
- **Reduction of Reliance on Intuition**: Another key theme is the reduction of reliance on intuition through the provision of actionable, data-driven insights, and decision structure that facilitates causal reasoning.

The discussion and elicitation process is crucial for uncovering the mental structures of the decision-making process and identifying key variables that may be obscure. This enhanced dialogue also sheds light on the decision-making complexities in agricultural operations, particularly in optimizing storage and processing to match market demands. Although both growers report having some access to predictive analytics tools, how those tools are integrated with their decision-making models and presenting the result of these analytics tools that remains a challenge. Drawing from cognitive science concepts and a deep analysis of visualization tools for decision-making, it is possible to develop strategies specifically tailored to enhance the decision-making processes for agricultural professionals like GA and MI. By leveraging insights into how cognitive capabilities interact with visual tools, these strategies can be designed to address the unique challenges GA and MI face in optimizing the matching of harvested sweet potatoes with market demand.

Potential Areas for Improvement

The existing decision-making practices of GA and MI provide a clear baseline for improvement through the introduction of visual decision-support tools that are based on cognitive theories. Currently, the process is heavily manual, relying on basic tools and the growers' intuition and experience. The introduction of Decision Intelligence (DI) and advanced visual tools aims to bridge this gap by providing a structured and systematic approach to decision-making. For example, the use of causal diagrams and interactive dashboards can help visualize the cause-and-effect relationships and provide actionable insights, thereby reducing reliance on intuition and minimizing cognitive load. This structured approach can also improve the clarity and accountability of decision documentation, aligning with cognitive science theories to support better decision-making processes.

In essence, the goal is to enhance the decision-making efficiency and effectiveness by integrating advanced visual tools that support all stages of the decision-making process, from information gathering and analysis to decision execution and monitoring. By addressing the limitations of the current tools, the proposed guidelines aim to provide GA and MI with a more comprehensive and user-centric decision-support system that aligns with their cognitive processes and decision-making needs.

Chapter 3.

Current Visualization Tools for Decision Making

What types of visualizations or visual tools are typically used for decision-making?

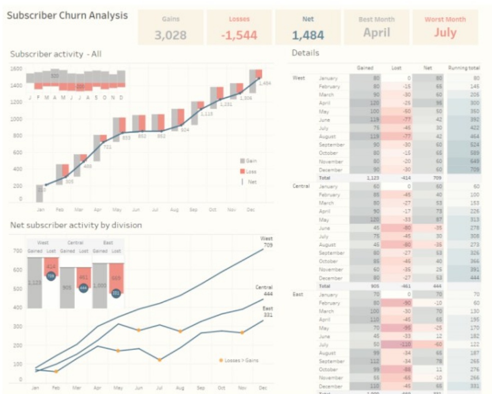
This chapter aims to answer RQ1, by providing an overview of visual tools and diagrams designed to support decision-making, such as dashboards and decision trees. While these tools significantly contribute to specific aspects of the decision-making process, they are often not designed to address the entire process comprehensively and can be improved upon (Oral et al., 2024). By examining their strengths and limitations, we can identify areas for enhancement and better support holistic decision-making.

3.1. Dashboards

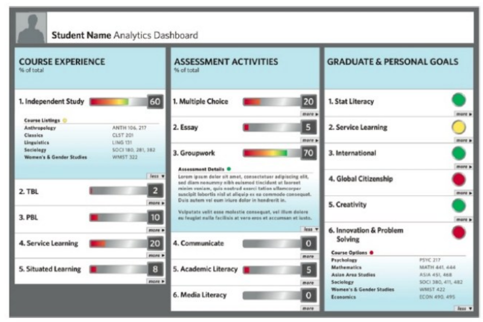
Having recognized the role of data visualizations, researchers and designers have been exploring optimization strategies for data presentation. Dashboards emerge as a key solution, enhancing decision-making in various sectors including business, education, and everyday life (Lea & Nah, 2013; Negash & Gray, 2008; Yigitbasoglu & Velcu, 2012). Yigitbasoglu and Velcu (2012, pp. 42) describe a dashboard as a "data driven decision support system", while Wexler et al. (2017) prefer a broader definition: "... a visual display of data used to monitor conditions and/or facilitate understanding."

3.1.1. Types and Purposes of Dashboards

Several studies on dashboards have suggested the diversity in dashboard definitions and their expanded use beyond original intentions leading to widespread adoption across different sectors (Sarikaya et al., 2019; Tory et al., 2021). The primary function of dashboards in decision-making contexts, according to Sarikaya et al. (2019, pp. 683), is to support a range of organizational tasks, although they are also used in non-decision-making contexts like education, communication, and social interaction. Sarikaya et al. (2019, pp. 683), considering the temporal aspects of decisions and the organizational tasks that are supported by dashboards, categorize decision support dashboards into three: strategic, offering support to generate insights for long term plans, tactical, assisting decision makers test and refine their tactics, and operational, utilized in the implementation and monitoring of established procedures with pre-tested and recognized metrics. Figure 3.1 presents examples of all three decision support dashboard types, as well as an example of a dashboard designed for social communication.



(a) Strategic Dashboard (DB001)



(b) Tactical Dashboard (DB106)

(c) Operational Dashboard (DB102)

(d) Social Dashboard (DB028)

Figure 3.1 Examples of four categories of dashboards.
Source: "What Do We Talk About When We Talk About Dashboards?" by A. Sarikaya, M. Correll, L. Bartram, M. Tory, D. Fisher, 2019, *IEEE Transactions on Visualization and Computer Graphics,* 25, pp. 684

Sarikaya et al. (2019, pp. 683) also discuss two main dashboard types, although in broad terms, given the often-blurry lines separating them: visual and functional. Visual dashboards are designed to aggregate multiple charts and numbers in a structured manner. Functional dashboards, on the other hand, facilitate interaction with the data and are dynamic by nature, as their design is driven largely by their purpose. Functional dashboards frequently update the data presented either through external data sources or user interaction (Sarikaya et al., 2019, pp. 683), a crucial feature for operational and organizational decision-making.

3.1.2. Use of Dashboards

Tory et al. (2021) categorized the goals of dashboard users into two: Conversation with Data, and Conversation Through and Around Data (pp. 29). Conversation with Data is further divided into levels based on purpose: “summarize, monitor, explain, predict, compare, lookup, experiment, find anomaly, and audit” (Tory et al., 2021, pp. 29). Conversation Through and Around Data includes other parties in the process and are also divided into sub-categories based on purpose: “discuss data, circulate, discuss tools, and document” (Tory et al., 2021, pp. 29). Tory and colleagues (2021) assert that the second category of dashboard use is not sufficiently supported by current dashboard tools, suggesting that new tools must facilitate the construction of narratives from the data.

Tory and colleagues (2021) conducted interviews with real dashboard users, which revealed that the linear model of the data analysis pipeline is not reflective of dashboard users’ tasks (pp. 33). In fact, they discovered a frequent tendency to switch to spreadsheets when building and interacting with dashboards (pp. 33). Dashboard users report using spreadsheets tools such as Excel to transform data and build new artifacts, to make better sense of the data, citing a certain sense of “materiality” of spreadsheets that offer direct interaction with data (Tory et al., 2021, pp. 33), a notion also reported by Dimara et al. (2017a) and Bartram et al. (2022).

Since dashboards are visual tools that display information that has already been processed, necessary cleaning and analysis phases are typically carried out before presentation. This processed data is then prepared into a visual format by data analysts or visualization specialists, making it accessible and interpretable for the end-user. Referred to as “encoding”, this step is crucial in conveying information. The effectiveness of a dashboard is gauged by its ability to support both the encoding and decoding of information swiftly and effectively (Yigitbasoglu and Velcu, 2012, p. 46). Simple visual stimuli, differentiated by shapes and colors (Goldstein, 2007; Tufte, 1983, pp. 77), often accompanied by textual stimuli, are often utilized for this purpose, given their facilitative nature to even untrained users (Yigitbasoglu & Velcu, 2012, pp. 46).

Interactivity helps users comprehend the impact of their decisions, making it crucial for the interaction to be as natural as possible, as complex interactions can confuse untrained users (Sarikaya et al., 2019). Interaction within the dashboard also allows users to control visibility of information according to their needs. This feature helps in managing the detail of information presented, ensuring it is tailored to suit the user's specific requirements (Yigitbasoglu & Velcu, 2012, p. 53-54). Interaction has also been shown to enhance user engagement and improve task performance (Nadj et al., 2020) and decision accuracy (Tang et al., 2014). However, as Sarikaya et al. (2019) note, the interaction must be well thought out and as aligned with the mental processes of the user as possible, without overwhelming the user.

3.1.3. Challenges in Dashboard Design

Design challenges for dashboards include accommodating diverse cognitive abilities and visualization literacy levels among users (Tory et al., 2021), reflecting on the importance of addressing individual differences of target users. A dashboard may be designed to serve the entirety of the population or a single individual, depending on its purpose. To further specify the intended audience, the "required visualization literacy" (Sarikaya et al., 2019, pp. 684) or "data literacy" (Tory et al., 2021, pp. 34) of the audience must be considered. Simpler visual tools, like bar or line charts, may be employed to aid understanding across a broad audience (Sarikaya et al., 2019, pp. 684).

The literature on the design and use of dashboards suggests that, although dashboards do support monitoring and lookup tasks, their design does not sufficiently support sensemaking (Srinavasan et al., 2021, pp. 28) or the construction of narratives for scenario-based analysis (Dimara et al., 2022). Other factors that limit the effectiveness of dashboards are organizational work practices. As an example, one dashboard user reported their colleagues' taking screenshots of dashboards and placing them into decks for sharing within the organization, because there wasn't a more efficient practice or tool (Tory et al., 2021, pp. 34).

It is critical that dashboards maintain balance, providing enough information to offer context without overwhelming the user with visual complexity, which increases cognitive load (Nowak & Bartram, 2023, pp. 932). In addition, designers of dashboards must consider aspects such as the end-user's individual abilities and preferences, the specific tasks they need to perform, their goals, their organization's size, authority, and work practices (Yigitbasoglu & Velcu, 2012, pp. 54). These factors dictate the selection of design features that best convey the necessary information to facilitate informed decision-making. A customizable, tailored approach would optimize the user's interaction with the dashboard, enhancing the likelihood of achieving the desired outcome (Abel et al., 2018).

3.2. Conceptual and Causal Diagrams

Conceptual diagrams are vital for structuring and visualizing abstract concepts, making complex information more accessible. These diagrams are instrumental in organizing information and highlighting the relationships between various elements, thereby enhancing understanding, and facilitating knowledge transfer (Ammirato et al., 2021).

By employing shapes such as arrows, circles, pyramids, and matrices, and integrating text, letters, and numbers, these diagrams effectively organize information and illustrate relationships. This comprehensive approach supports both qualitative and quantitative analyses, enabling the representation of both simple and complex business issues (Eppler & Burkhard, 2004). By breaking down intricate ideas into more manageable parts, conceptual diagrams make it easier for individuals to grasp and discuss these concepts. This simplification enhances cognitive processing by allowing the brain to focus on the core components and their relationships, which promotes better understanding and facilitates the transfer of knowledge. Conceptual diagrams are methodical and precise, focusing on codifying knowledge while also supporting its creation and sharing, distinguishing them from the more flexible and informal nature of sketches (Ammirato et al., 2021).

Causal diagrams, a specialized type of conceptual diagram, illustrate cause-and-effect relationships. These diagrams typically include nodes or items connected by lines or arrows that indicate how one element impacts another. This visualization technique is particularly effective for analyzing complex systems, predicting potential outcomes, and aiding in strategic decision-making. By clearly showing the connections and influences between different elements, causal diagrams help simplify complex information, making it more understandable and actionable. In business management, various forms of causal diagrams — such as decision trees, causal loop diagrams, and influence diagrams — are employed to organize information and clarify functional relationships within a system. This structured approach aids in identifying key issues and understanding the interdependencies within a business context, thereby supporting more informed decision-making processes (Eppler & Burkhard, 2004, 2007).

3.2.1. Decision Trees

Decision Trees, initially discussed as a decision-making tool by John F. Magee in 1964, are graphical representations of a decision, with connections that mimic the branching structure of a tree (Magee, 1964). These tools are prominently used as classifiers in machine learning (Kingsford & Salzberg, 2008, pp. 1012), and are also applicable to human in-the-loop decision-making processes (de Ville, 2013; Zylberberg, 2021). In a decision tree, each node, or question, branches into child nodes, which may lead to additional questions or involve specific calculations until a terminal node is reached (Shneiderman, 1996, pp. 338-339). This terminal node, also referred to as leaf, represents the end of a decision path and typically culminates in one or multiple potential outcomes, each weighted according to its likelihood. An illustration of a decision tree can be seen in Figure 3.2.

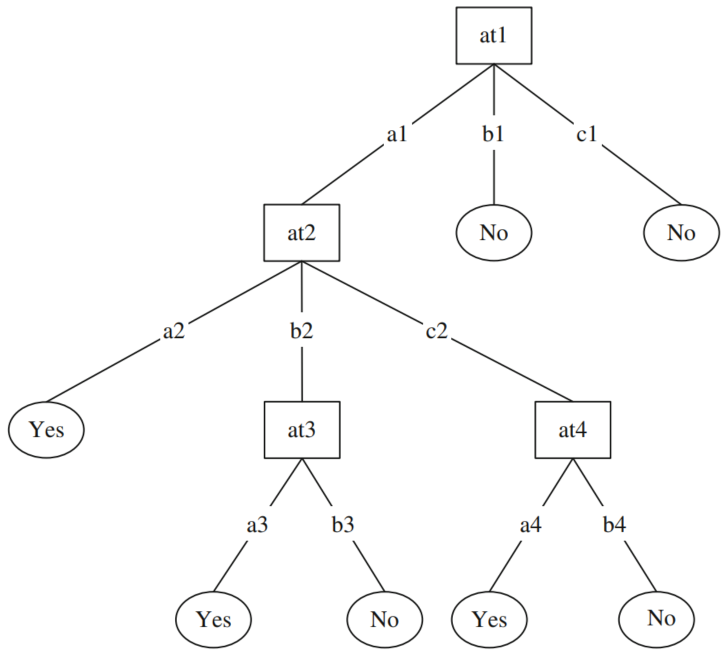


Figure 3.2 An example of a Decision Tree.
Source: "Decision trees: a recent overview" by S. B. Kotsiantis, 2013, pp. 263

Perhaps the most appealing attribute of decision trees is their inherent simplicity in communicating flow and the association between nodes (Kingsford & Salzberg, 2008). Often, the nodes within these trees pose straightforward Yes-No questions, creating a sequential flow through the successive connections from one node to another. Additionally, decision trees are highly versatile, capable of incorporating various types of data and analytical methods (Kingsford & Salzberg, 2008). Decision trees are also robust in the sense that they accommodate missing data within the decision process, which enhances their practicality in real-world scenarios where complete data may not always be available (Kingsford & Salzberg, 2008; de Ville, 2013).

Exploring further into the practical applications of decision trees, various researchers have innovated systems to enhance their utility and analytical capabilities. Barlow and Neville (2001) described and tested EMTree Results Viewer, displaying how decision trees can be used as a complementary visualization in a decision-support tool. Teoh and Ma (2003), pondering other use cases for decision trees and considering the task of knowledge discovery, developed the system PaintingClass, with the goal of easier construction and analysis of decision trees. Building on these frameworks, van den Elzen and van Wijk (2011) developed BaobabView as a new system that views and supports the process in three steps, named to reflect the botanical aspect of decision trees: grow, optimize, and prune. These advancements underscore the adaptability of decision trees in handling complex decision-making processes, serving as a foundation for continuous innovation in data visualization and analysis tools.

Decision trees often succeed in providing a clear visualization of the decision-making process, allowing users to easily trace the flow and sequence of decisions. This clarity is achieved through the use of lines that connect nodes, each representing factors that influence the decision process and its potential outcomes. Such a structured layout not only facilitates understanding but also aids in identifying the impact of various elements within the decision framework. However, despite these strengths, decision trees can become overly complex and unwieldy when dealing with large datasets or numerous variables. In addition, decision trees do not perfectly align with mental models of decision-makers, requiring further categorization of nodes that symbolize their role in the process. For instance, Klein (1993, pp. 139) reported that decision trees were not useful in depicting the rapid decision-making processes of firefighters, citing that their actions resembled reactions to extremely dynamic situations more than deliberate generation and evaluation of multiple options. This is mostly due to the type of decision, requiring rapid reactions to external stimuli. Thus, decision trees do not fully support users' need to compare and contrast alternative decisions.

3.2.2. Influence Diagrams

The pursuit of visually representing the structure of decision-making processes also led to the development of Influence Diagrams (ID), which highlight the effects of specific decisions on potential outcomes. Introduced by Howard and Matheson (2005), who suggested that decision trees did not allow representations of more complex problems, these diagrams were proposed as a more suitable alternative. Influence Diagrams typically visualize dependencies between variables (Howard & Matheson, 2005), a pivotal aspect of the decision-making process (Diez et al., 2017; Ford & Hegarty, 1984; Lunenburg, 2010).

Influence Diagrams allow for more intricate representations of decision-making processes, particularly useful in situations with high degrees of uncertainty (Suzic & Wallenius, 2005), and do so by differentiating the process into two levels: qualitative and quantitative (Bielza et al., 2010, pp. 354). The qualitative level is visually represented, while the quantitative level handles probability calculations and other modeling tasks (Bielza et al., 2010, pp. 354). A key feature of the qualitative level is its temporal sequence, or "total order" as Bielza and colleagues (2010, pp. 354) refer to it, essential for conveying the natural directionality in decision-making (Bielza et al., 2010, pp. 354). An example of a simple Influence Diagram is provided below (Figure 3.3):

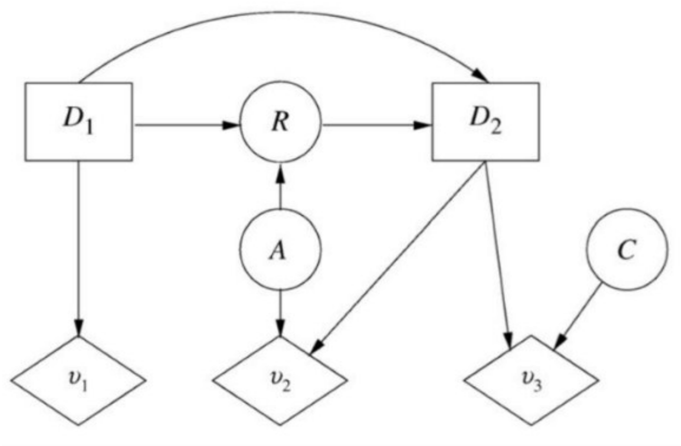


Figure 3.3 An example of an Influence Diagram
Source: "Modeling challenges with influence diagrams: Constructing probability and utility models" by C. Bielza, M. Gomez, P. P. Shenoy, 2010, *Decision Support Systems*, 49, pp. 355

Influence Diagrams consist of decision nodes (labeled D_1 and D_2 in 3.3), chance nodes (labeled A, C, and R in Figure 3.3), and value nodes (labeled v_1, v_2, and v_3 in Figure 3.3), which collectively assist the decision-making process by highlighting how different actions, variables and chance factors interact to influence the overall outcome (Bielza et al., 2010, pp. 354-355). These diagrams structure the analysis of decisions by weaving together both the direct and probabilistic impacts on outcomes. Additionally, their visual format helps map out the connections and flow of information, ensuring that each decision is informed by its potential impacts. The interlinked nature of these nodes supports an active exploration of various scenarios, making it a powerful tool for navigating decision analysis amidst uncertainty.

A significant shortcoming of influence diagrams is that they don't attempt to represent the causal structure of a domain (Hagmayer & Meder, 2013, pp. 45), as the connections within Influence Diagrams, represented by arcs between nodes, do not necessarily indicate causal relationships (Howard & Matheson, 2005). This means that the decisions modeled in influence diagrams do not inherently refer to causal interventions, limiting their utility in scenarios where understanding the causal dynamics is crucial for effective decision-making.

3.2.3. Sequential Decision Diagrams

Sequential Decision Diagrams (SDDs) are graphical tools used to depict the asymmetries often present in decision-making scenarios, specifically designed to enhance the modeling of such complexities within the broader framework Influence Diagrams (Bielza et al., 2011). SDDs provide a structured way to visualize how sequential decisions, environmental factors, and external influences interconnect to affect final outcomes. These diagrams are particularly useful in scenarios where decisions are not isolated but are contingent upon previous outcomes and current conditions (Bielza et al., 2011). Similar to Influence Diagrams, by employing a graphical layout, SDDs make it easier for decision-makers to comprehend and navigate through the intricacies of complex systems, ensuring that each decision is informed by a clear understanding of its potential impacts.

An example of an SDD is shown in Figure 3.4, which depicts the SDD for a reactor problem described in their study. In the reactor problem example, the SDD methodically shows how operational decisions — represented as nodes — affect the reactor's performance and safety, classified under value nodes (Bielza et al., 2011, pp. 231). This diagram highlights the influence of various operational and environmental variables, providing a clear view of how decisions cascade through the system. By visually representing these interactions, the SDD helps identify the most viable decision paths, thereby facilitating strategic planning in environments where decisions and their consequences are intricately linked.

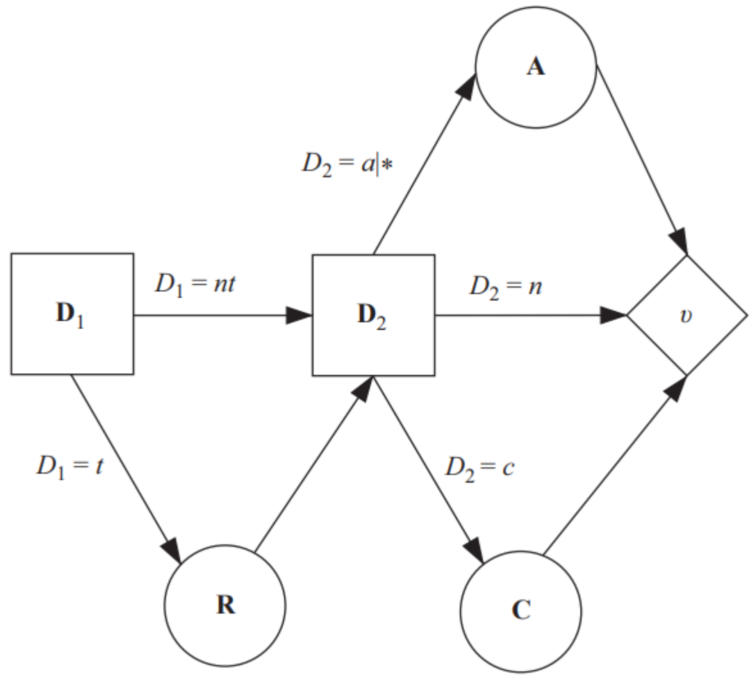


Figure 3.4 An example of a Sequential Decision Diagram
Source: "A review of representation issues and modeling challenges with influence diagrams" by C. Bielza, M. Gomez, P. P. Shenoy, 2011, *Omega,* pp. 231

While Sequential Decision Diagrams are valuable for analyzing complex decision-making sequences, a shortcoming also arises from their detailed focus on sequential and asymmetric decision paths (Bielza et al., 2011). This focus can sometimes obscure holistic understanding of a decision scenario. This limitation highlights the potential for misinterpretation or oversimplification of the decision-making environment, making it crucial to integrate these diagrams with other analytical tools to ensure a comprehensive analysis.

3.2.4. Causal Maps

Visualizing the decision-making processes and the flow of information that guides these decisions also led to the development of mapping techniques. The main idea behind causal maps was that the relationships between variables and how they interact to influence other variables and outcomes required visual representation for easier interpretation and collaboration (Montibeller & Belton, 2006). Causal maps originally were developed to assist in problem structuring (Montibeller & Belton, 2006) and have been shown to facilitate understanding of problem structures (Huff & Jenkins, 2002; Mingers & Rosenhead, 2004). An example is presented in Figure 3.5.

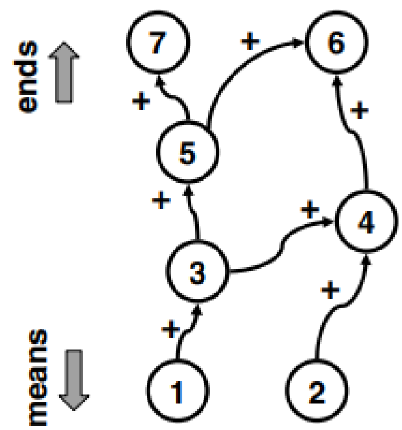


Figure 3.5 An example of a Causal Map
Source: "Causal maps and the evaluation of decision options—a review" by G. Montibeller and V. Belton, 2006, *Journal of the Operational Research Society*

Montibeller and Belton (2006) propose that causal maps can be effectively utilized to evaluate potential options within a decision-making process. Through an examination of various cases where causal maps have been employed to assess options, the authors highlight that the utility of a causal map hinges on several factors (Montibeller & Belton, 2006, pp. 789). Primarily, the purpose behind using a causal map is pivotal in determining its effectiveness, highlighting the importance of cognitive fit. Some may use causal maps to survey a wide array of options, whereas others might apply them to craft a comprehensive depiction of the process, delving into every pertinent factor and variable.

Building on this premise, the authors advocate for the application of causal maps in uncovering novel, previously unconsidered options, and in deliberating on the most suitable alternative (Montibeller & Belton, 2006, pp. 790). However, they caution that their conclusions are primarily drawn from clinical case studies and may be most pertinent to similar contexts, underscoring that while causal maps are valuable for structuring complex problems, their adaptability in diverse decision-making scenarios should be further explored (Montibeller & Belton, 2006, pp. 790).

3.2.5. Decision Mapping

Decision mapping incorporates a higher level of complexity compared to decision trees (Friedler et al., 1995, pp. 1755) by considering additional factors such as external influences, stakeholder opinions, and intended outcomes. Bouchart et al. (2002) developed a specialized decision mapping methodology for civil engineering, while also outlining its potential for broader applications. The authors highlight a gap in existing methods — namely, the absence of a comprehensive visual representation of decision-making processes that begins with data collection and progresses logically (Bouchart et al., 2002, pp. 189). They describe their Decision Mapping Methodology as an evolution of static Data Flow Diagrams typically used in Information Technology (IT) systems analysis, which they adapt into Information Flow Networks tailored for decision-making scenarios. In these networks, nodes represent individual actions and decisions, simplifying the interpretation of complex data flows (Bouchart et al., 2002, pp. 190; John et al., 2020).

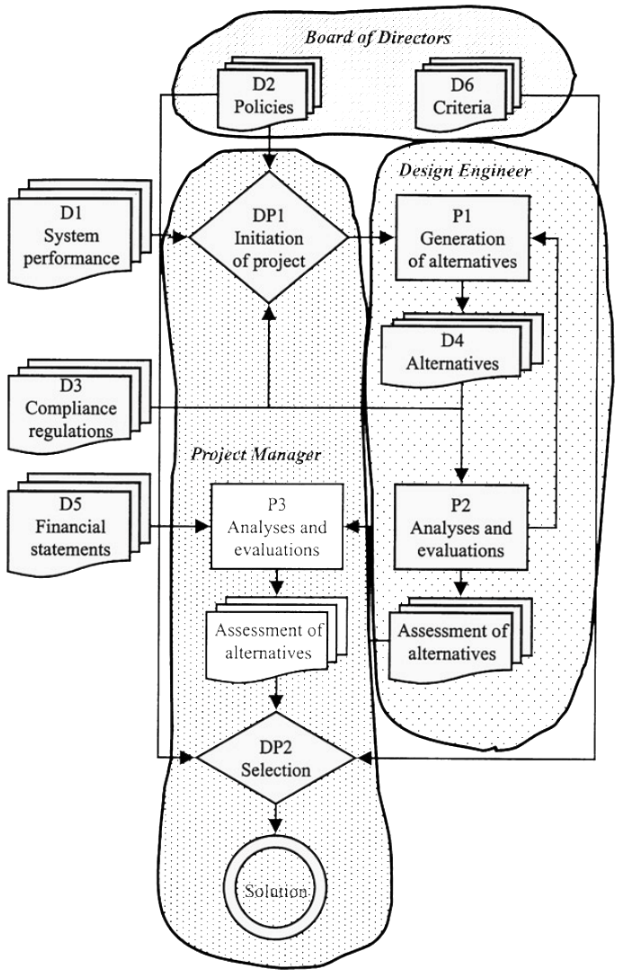


Figure 3.6 An example of a Decision Map (Information Flow Network and Thematic Decision Map)

Source: "Decision mapping: Understanding decision making processes" by F. J. Bouchart, D. J. Blackwood, P. W. Jowitt, 2002, *Civil Engineering and Environmental Systems,* 19, pp. 194

To enhance this methodology, Bouchart and colleagues propose integrating Thematic Decision Maps with Information Flow Networks (Figure 3.6), creating a dual system that highlights critical decision points to assist in prioritization and improve the overall efficiency of the decision-making process (Bouchart et al., 2002, pp. 193). This approach not only addresses external variables and the interests of different stakeholders but also enriches the decision-making process with a well-rounded perspective (Bouchart et al., 2002, pp. 206).

However, the complexity introduced by overlaying these two mapping techniques can pose significant challenges. Bouchart and colleagues note that this complexity might compromise the visual clarity and interpretability of the diagrams, particularly when cognitive differences between analysts and decision-makers are not adequately considered (Bouchart et al., 2002, pp. 195). Despite these challenges, decision mapping has been successfully applied in various fields; Friedler et al. (1995) demonstrated its utility in process synthesis and Comes et al. (2011) validated its effectiveness in managing complex decisions under conditions of high uncertainty. The insights derived from these applications have paved the way for further innovations in decision-making visualization tools, aiming to bolster their robustness and effectiveness.

3.2.6. Causal Loop Diagrams

Causal Loop Diagrams (CLDs) are pivotal visual tools that facilitate both qualitative and quantitative analysis in decision-making, as evidenced by numerous studies (Ammirato et al., 2021; Barnabè, 2011; Bottero et al. 2020; Dai et al., 2013; Iannone et al., 2015; Kotir et al., 2017; Lin et al., 2020; Prodanovic & Simonovic, 2007; Sendzimir et al., 2007). Taking a Systems Thinking – or System Dynamics (SD) perspective to decision making, the SD methodology typically employs CLDs alongside stock and flow diagrams (Figure 3.7) to provide structural insights into the system and represent its dynamic aspects. CLDs have been used to support strategic decision making (Barnabè, 2011), given their structured graphical representation of causal relationships within a decision process or system, as well as the often collaborative, meticulous, and time-consuming elicitation steps needed to strategize long-term decisions.

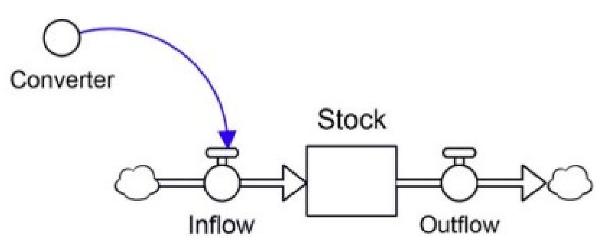


Figure 3.7 General structure of a stock and flow diagram
Source: "A System Dynamics Model and Analytic Network Process: An Integrated Approach to Investigate Urban Resilience" by M. Bottero, G. Datola, E. De Angelis, 2020, *Land*, 9, pp. 8

CLDs are instrumental in fostering causal reasoning by identifying necessary feedback loops and understanding their implications on system behavior (Iannone et al., 2015, pp. 1291; Lin et al., 2020, pp. 77). These diagrams assist in visualizing and improving mental models (Barbrook-Johnson & Penn, 2022, pp. 49) and incorporate various elements such as variables, delays, stocks, flows, and oriented arches, which illustrate positive or negative causal relationships, along with loops that are either self-reinforcing or self-correcting (Iannone et al., 2015, pp. 1291). Iannone et al. (2015) explore and visualize the challenges inherent in the fast-changing fashion industry, highlighting the dynamic complexity these systems encapsulate and the critical variables that need to be managed for effective system oversight (Figure 3.8).

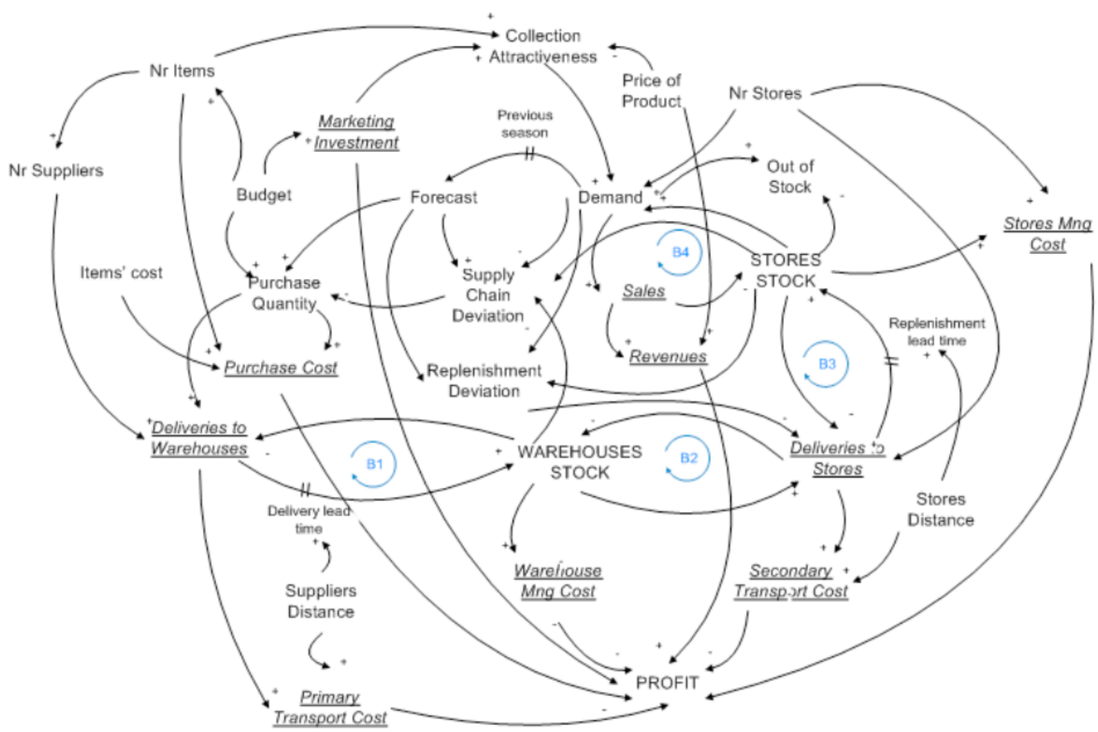


Figure 3.8 **An example of a Causal Loop Diagram depicting a supply chain system**

Source: "Modeling Fashion Retail Supply Chain through Causal Loop Diagram" by R. Iannone, G. Martino, S. Miranda, S. Riemma, 2015, *IFAC-PapersOnLine,* 48, pp. 1295

In another context, Inam and colleagues (2015) explored the application of CLDs in soil salinity management to enhance stakeholder engagement while reducing the need for large meetings. They proposed a qualitative approach to CLD construction, emphasizing a simplified process that does not require extensive pre-training. The authors presented a seven-step process for creating CLDs, beginning with problem definition.

The process of problem definition in stakeholder engagement begins with defining the problem theme, key variables, time horizon, and model boundaries, followed by developing reference modes and identifying stakeholder groups (Inam et al., 2015, pp. 254). Stakeholder analysis is then conducted based on roles such as decision-makers, users, and experts, prioritizing them according to their power and interest, which may change over time (Inam et al., 2015, pp. 254). Facilitators proceed to conduct interviews with potential stakeholders to understand their perspectives on the problem, laying the groundwork for constructing Causal Loop Diagrams (CLDs) with each stakeholder (Inam et al., 2015, pp. 253-254). These diagrams use color to differentiate variables and feedback loops, initially created with simple tools like Post-it notes and a whiteboard. This critical step engages stakeholders in deep critical thinking, prompting them to consider both short-term and long-term policies, evaluate their solutions, and identify potential obstacles (Bottero et al., 2020, pp. 18-19; Inam et al., 2015, pp. 254-255).

Once individual CLDs are created, they are digitized using tools like Vensim DSS to accurately represent identified variables and feedback loops (Inam et al., 2015, pp. 256). Facilitators synthesize these into a preliminary group CLD, which is then refined in a group stakeholder meeting. This meeting, sometimes lasting a full day, aims to finalize the group CLD through discussions and negotiations, marking conflicting opinions with question marks (Inam et al., 2015, pp. 256). While these qualitative CLDs cannot make quantitative inferences, they highlight key points needing further negotiation or research. The process concludes with preparing simple thematic sub-models of CLDs to address specific system components, such as agricultural, social, environmental, or economic aspects, facilitating targeted analysis and decision-making (Inam et al., 2015, pp. 256). The final CLD created by merging five sub-systems is presented as an example in Figure 3.9.

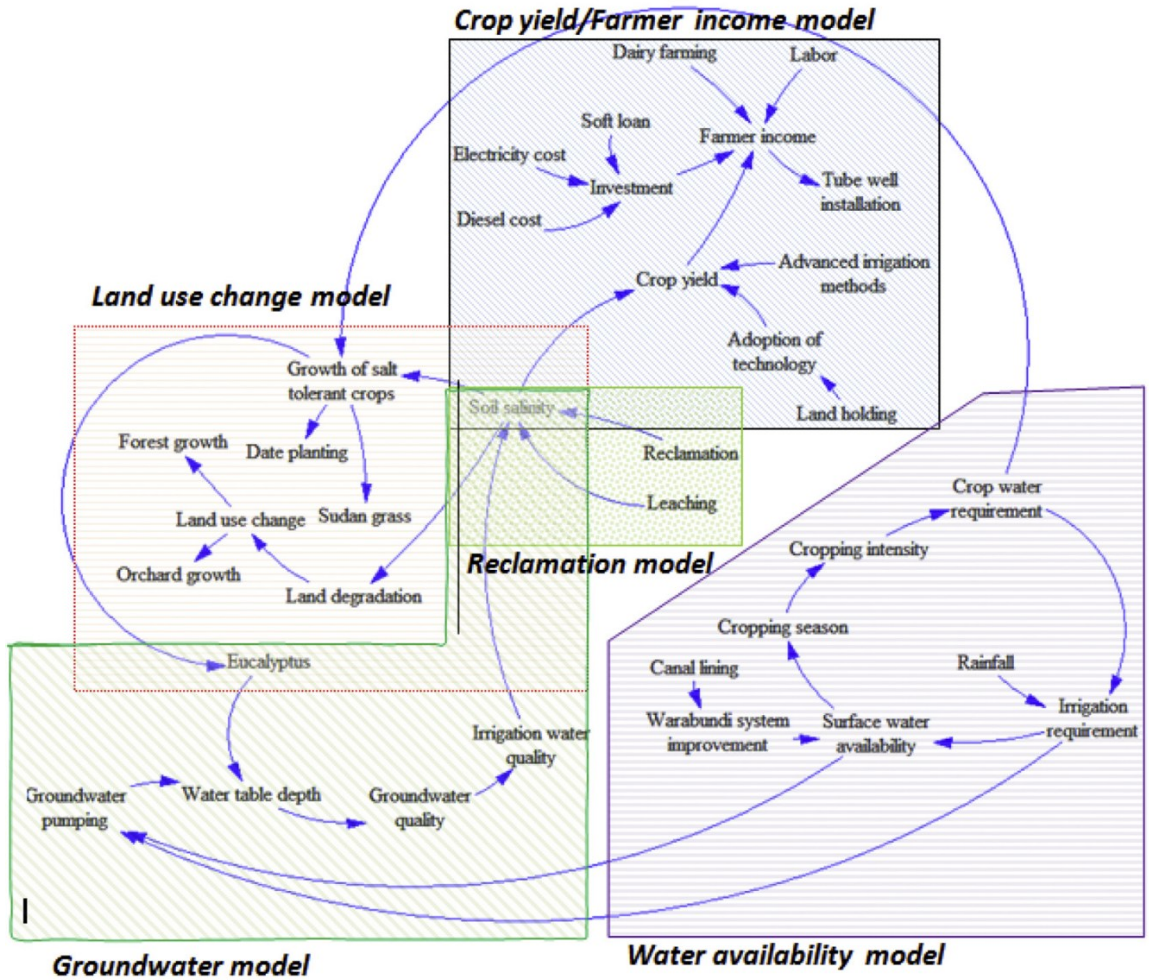


Figure 3.9 The merged group Causal Loop Diagram from Inam et al. (2015)
Source: "Using causal loop diagrams for the initialization of stakeholder engagement in soil salinity management in agricultural watersheds in developing countries: A case study in the Rechna Doab watershed, Pakistan" by A. Inam, J. Adamowski, J. Halbe, S. Prasher, 2015, *Journal of Environmental Management*, 152, pp. 266

While Causal Loop Diagrams (CLDs) are instrumental in organizing complex decision-making processes and providing valuable insights by visually representing system interdependencies, they possess several limitations that must be carefully considered (Currie et al., 2018, pp. 8; Lin et al., 2020, pp. 96). These diagrams often fail to capture the full spectrum of system behaviors and human rationality, leading to potential oversights in understanding intricate dynamics (Lin et al., 2020, pp. 96). The challenges extend to the static nature of CLDs, which may not adequately accommodate the dynamic changes typical in organizations, necessitating frequent updates to maintain relevance (Currie et al., 2018, pp. 8). Additionally, the process of parameterizing these models is complicated by cognitive constraints like the "curse of dimensionality," where increasing the number of dimensions can exponentially increase complexity, further complicating the model (Lin et al, 2020, pp. 96). The validity of these diagrams also heavily depends on the available data and expert interpretation, which can introduce biases and affect the reliability of the outcomes. These factors underscore the need for cautious application and continuous evaluation of CLDs in decision-making to mitigate their limitations and enhance their effectiveness.

3.2.7. Causal Decision Diagrams

Causal Decision Diagrams (CDDs) are a fundamental component of Decision Intelligence (DI), a framework increasingly recognized for its ability to bridge the gap between the extensive data resources available to organizations and the decision-makers who leverage this data for informed, precise decisions.

Decision Intelligence (DI)

Emphasized by notable entities like Gartner Incorporated, DI enhances decision-making processes by integrating data analysis with artificial intelligence to optimize outcomes (Gartner Inc., 2023). Dr. Lorien Pratt, a key figure in the development of DI, has significantly advanced its application and theoretical underpinnings in modern organizational settings (Pratt, 2019; Pratt and Malcolm, 2023; Pratt et al., 2023). A central principle of DI, particularly relevant in the context of CDDs, is the emphasis on structuring information around the decision to be made rather than the surrounding data, some of which may be irrelevant (Pratt, 2019). This approach highlights the importance of CDDs in creating a clear visual map of the causal relationships within a decision process, thereby simplifying the selection and integration of pertinent data and aiding decision-makers in navigating complex decision scenarios more effectively.

Decision Intelligence has gathered a lot of media and institutional attention given its promises to bridging the gap between abundant data, Artificial Intelligence platforms and reaching intended outcomes with informed decisions, not assumptions (Haider &

Tahseen, 2022). Google hired a Chief Decision Officer, who, in 2018, had already trained 17,000 employees in how to make better decisions considering Decision Intelligence (Byrne, 2018). Furthermore, on multiple occasions, Forbes discussed the potential of Decision Intelligence and even deemed it as big a revelation as Artificial Intelligence (Bornet, 2022; Emini, 2022).

Decision Intelligence (DI) offers three distinct levels of support: decision support, decision augmentation, and decision automation, each varying in the degree of assistance provided by computer or Artificial Intelligence systems (Pratt, 2019). This classification is analogous to how data-driven decision-making is categorized by the amount of data utilized (Buijsse et al., 2023). Decision support, the foundational level, utilizes basic computational tools and software, such as data analytics, to aid decision-makers (Pratt, 2019). The next level, decision augmentation, introduces more substantial computational input, often in the form of predictions and recommendations, enhancing the decision-maker's capabilities (Pratt, 2019). At the pinnacle, decision automation minimizes human input to oversight roles, with both decision-making and execution processes handled by artificial intelligence (Pratt, 2019). Recognizing the appropriate level of automation and human involvement is crucial, as different situations demand varied approaches.

Use of Causal Decision Diagrams in DI

At the core of DI, Causal Decision Diagrams offer a structured approach to visualize decision-making processes, incorporating causal reasoning. These diagrams are designed to systematically categorize decision-related variables into four main types: Actions (Levers), Intermediates, Externals, and Outcomes (Pratt, 2019). Actions, sometimes referred to as Levers, are the potential decisions (Pratt. 2019). Intermediates and Externals are factors that may affect the final section of the CDD, Outcomes, which refer to both intended and unintended outcomes. This is an important distinction, given that Decision Intelligence attempts to reveal as many difficult to predict or explicit factors in a decision-making process as possible (Pratt, 2019). An example CDD, for a relatively simple decision of what type of coffee to buy, is presented in Figure 3.10.

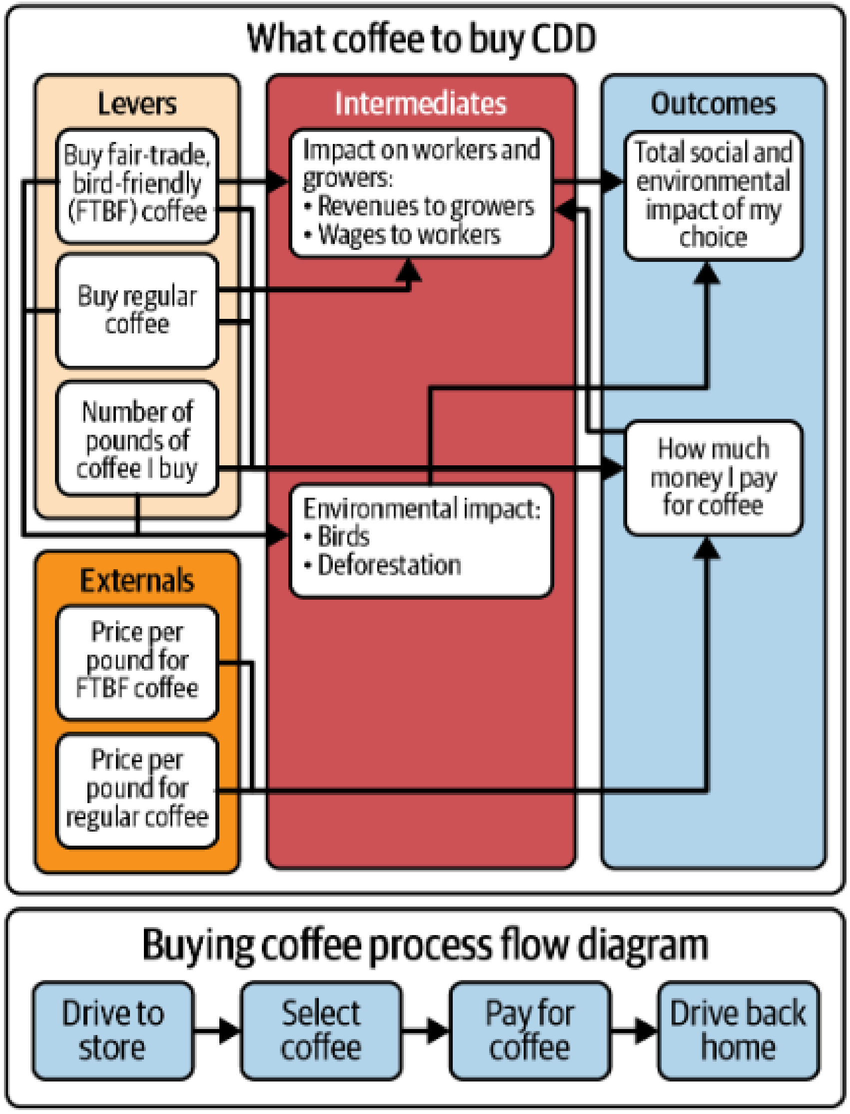


Figure 3.10 An example CDD, presenting a coffee-purchasing decision process. (The original figure was cropped to only include relevant information)
Source: "The decision intelligence handbook: practical steps for evidence-based decisions in a complex world" by L. Pratt and N. Malcolm, 2023

The Decision Intelligence (DI) process typically starts with defining the decision or problem at hand. Once the parameters and constraints of the decision are established, measurable outcomes are specified — for instance, aiming for a 20% increase in profits by the end of the year. These discussions often take on a negotiation-like quality (Zaimoglu et al., 2023), where potential actions that could influence the desired outcome are identified and assessed. Pratt (2019) notes that for the DI process to be effective, the decision-maker must have the necessary authority and resources to implement these actions. If these factors are beyond the control of the decision-makers, they should be classified as Externals.

The structure of the Causal Decision Diagram (CDD) is then outlined, with further details refined through continued discussion and deliberation. The four types of nodes — Actions, Intermediates, Externals, and Outcomes — are connected with lines and arrows to indicate directionality and causality. A critical phase involves brainstorming to generate and evaluate alternative actions or the impacts of actions, aiming to minimize unintended outcomes by clarifying the decision-making process, an extension of Second Order Thinking (Sunstein & Ullmann-Margalit, 1999). Pratt (2019) outlines two causal pathways within Decision Intelligence: the "why" chain, which traces the sequence from action to outcome, and the "how" chain, which maps the reverse direction from outcome back to action. These conceptual chains serve as useful tools for decision-makers, especially when encountering difficulties in pinpointing additional nodes or factors, enabling them to further elaborate on the decision-making trajectory. This step is essential for uncovering any previously overlooked actions, impacts, or potential outcomes and typically relies on multiple inputs from subject matter experts. The categorization suggested by Pratt (2019) helps in mapping out the decision-making landscape more clearly, providing a clear structure that aids stakeholders in understanding how various decisions impact organizational objectives and the external environment.

CDDs are particularly notable for their ability to make the causal connections within decision processes explicit. By visualizing how different actions can lead to various intermediate states and ultimately affect outcomes, these diagrams facilitate a deeper understanding of the causal pathways that support strategic decisions. This clarity is crucial for effective sensemaking, as it allows decision-makers to navigate complex scenarios by tracing the potential effects of their actions through the system. Visual cues, such as shapes representing nodes and lines with arrows representing causality and directionality, aid in instilling an insightful model of the decision, facilitating interpretation and adoption by the user. Moreover, the explicit representation of external factors within CDDs helps in anticipating and mitigating risks that could influence the decision outcomes.

DI systems are designed to be adaptive, accommodating the specific needs and preferences of users. Initially, users may engage these systems for basic visualization of decision processes. Over time, they can advance to integrating predictive models and eventually automating certain decisions. Pratt (2019) emphasizes that an optimal DI system should support iterative use, allowing decisions to be refined based on human feedback and the comparison of predicted outcomes with actual results. This iterative capability ensures that DI systems remain relevant and effective across various decision-making contexts.

Furthermore, the Intermediates and Externals components of Decision Intelligence emphasize the importance of unveiling both overt and covert factors that could impact decision-making. This approach mirrors the Decision Mapping methodology developed by Bouchart et al. (2002), which underscores the necessity of accounting for all activities and data — both seen and unseen — that might sway decisions. The proactive exploration of external factors is a growing trend across various decision visualization methodologies, reflecting a broader recognition of their critical influence. Addressing these often-overlooked external factors is crucial because they can significantly shape decision outcomes, making their identification and analysis an essential aspect of effective decision-making strategies. However, Pratt and colleagues (2023) also acknowledge that no model is perfectly accurate or complete, emphasizing the inherent uncertainty in decision-making processes and, by extension, the intrinsic imperfections of Causal Decision Diagrams (CDDs).

A significant challenge associated with CDDs, and decision diagrams more broadly, is their complexity, which can sometimes obstruct their practical utility, especially for users without a technical background (Diez et al., 2017, pp. 1-2). As the number of decision nodes and their interrelationships increase, the diagrams can become overly complex, making it difficult to extract clear insights without advanced analytical tools. This complexity can impede the effective communication and operational efficiency that CDDs aim to enhance, highlighting the need for careful design and potential simplifications to maintain their usability across different user groups.

To provide a comprehensive overview of the visualization tools discussed in this chapter, the following table summarizes their advantages and disadvantages.

Table 3.1 Visual diagrams and tools for decision-making discussed in Chapter 3

Diagram	Advantages	Disadvantages
Dashboards	Effective for monitoring and summarizing data.	Lack of support for construction of narratives and reporting.
Decision Trees	Provide clear, structured pathways for decisions.	May not indicate causal relationships clearly.
Influence Diagrams	Visualize dependencies between variables effectively.	Can become unwieldy with large datasets.
Sequential Decision Diagrams	Handle asymmetries in decision-making well.	Can obscure the holistic understanding of interconnected decisions.
Causal Maps	Excellent for structuring complex problems and identifying relationships.	May not always be suitable for all decision-making scenarios.
Decision Mapping	Incorporates external variables and stakeholder opinions.	Can become visually complex and hard to interpret.
Causal Loop Diagrams	Useful for understanding feedback loops and system behavior.	May require extensive elicitation and time-consuming construction.
Causal Decision Diagrams	Provide a structured way to represent decision-making processes and their outcomes.	Can be complex to construct and require detailed elicitation from stakeholders.

Chapter 4.

Cognitive Science Theories and Concepts

What are the cognitive processes a user goes through, or are relevant, when viewing a visualization and using it to make a decision?

This chapter aims to answer RQ2 by examining the intersection of cognitive science and decision-making processes through a scoping literature review. It delves into various theories to understand how decisions are conceptualized, made, and justified within cognitive frameworks. These theories provide insights into organizing decision-making processes, enabling the design of visualizations that effectively support and enhance decision outcomes.

4.1. Perception

For a visualization to impact a user's decision-making process, it must first be perceived by the user. Thus, understanding the role of perception in data visualization is crucial for enhancing decision-making effectiveness. Perception is fundamentally about how the human mind processes visual elements such as shapes, colors, lines, motions, and interactions, which are all integral to how decision-makers interpret and interact with visual data displays. This process directly influences how visual information is mentally structured and understood, facilitating a deeper comprehension of the data presented.

Early research in fields like Gestalt psychology has significantly influenced the development of principles for designing visual decision-making tools. Gestalt psychology introduces several key principles that guide our perception (Rock & Palmer, 1990): the law of proximity suggests that objects that are close to each other in space are perceived as a group, enhancing the organization of information, which can be critical for structuring user interfaces that group related data points together effectively. Further principles include the law of similarity, which suggests that items that look similar are considered part of the same group, useful for categorizing data visually; and the law of closure, where the mind completes incomplete figures to form a coherent image. This principle helps users understand complex diagrams more quickly by filling in missing parts, allowing for a smoother interaction with the data, ultimately facilitating quicker and more effective decision-making processes.

Building on this foundation, Bertin introduced methods to enhance data visualizations by adjusting size, color, and layout, significantly improving the clarity and impact of information presentation (Bertin & Berg, 1983). Size, for example, can be strategically utilized to highlight significant data trends or highlight outliers, directing the decision-maker's attention to critical information swiftly. Color differentiation not only segregates data into clear categories but also reduces the time it takes for users to identify relationships or discrepancies within the data, which is vital in environments where quick decision-making is essential. The thoughtful arrangement of information through effective layout practices helps in maintaining a logical flow, enabling decision-makers to follow complex data trails easily.

Research by Pineo & Ware (2012) illustrates how effective data visualization relies on alignment with these perceptual processes. For instance, their study highlights how visual elements that mimic natural patterns can enhance the perceptual processing of information. This alignment allows users to discern patterns and anomalies more readily within complex datasets, enhancing their ability to make informed decisions based on the visualization (Pineo & Ware, 2012). The design of these tools, therefore, must consider these perceptual traits to optimize how information is presented and processed.

The interaction between decision-makers and visualizations is inherently dynamic, where the perception of the entire display and its individual components occurs simultaneously. This dual perception process allows users to discern overarching trends and minute details within the same visual frame, thus enabling a comprehensive understanding of the data. Rind and colleagues (2013) highlight the importance of this aspect by demonstrating how layered visualizations that present data at varying levels of detail can enhance decision-making capabilities. These multi-layered visual tools are designed to cater to the perceptual strengths of the human mind, allowing decision-makers to effortlessly switch between global overviews and granular insights. This flexibility enhances the decision-makers' ability to interpret complex datasets effectively, ensuring that both broad patterns and specific anomalies are perceptible and informative (Rind et al., 2013).

The ultimate goal of leveraging perception in visualization design is to enable decision-makers to uncover and understand the underlying stories that the data seeks to tell. By effectively matching visual properties with perceptual abilities, designers can create tools that not only display data but also elucidate the deeper meanings and relationships inherent in the data. This approach ensures that decision-makers are not just consuming information but are actively engaging with it to derive actionable insights that are critical for making informed decisions.

4.1.1. Sensemaking

Once perception of the visualization takes place, users try to make sense of it. Sensemaking refers to "the deliberate effort to understand events" (Klein et al., 2007). It is instrumental for several purposes, such as foreseeing challenges, identifying issues, directing the search of information, and facilitating appropriate actions (Klein et al., 2007). Humans go through the sensemaking process when presented with visual stimuli and must integrate it into their mental model of decision-making (Klein et al., 2006; Lee et al., 2016).

Data Frame Theory

Gary Klein and colleagues (2007) introduced Data Frame Theory as a possible explanation of humans making sense of data and "adapt to the complex, dynamic, evolving situations" (pp. 114). Data Frame Theory posits that data is selected and analyzed based on the mental model of the individual, guiding how each variable relates to another (Figure 4.1). The authors refer to this as the "frame", which they suggest can take the form of a narrative story with temporal elements, a map with distance calculations, or a plan for sequential actions (Klein et al., 2007, pp. 118).

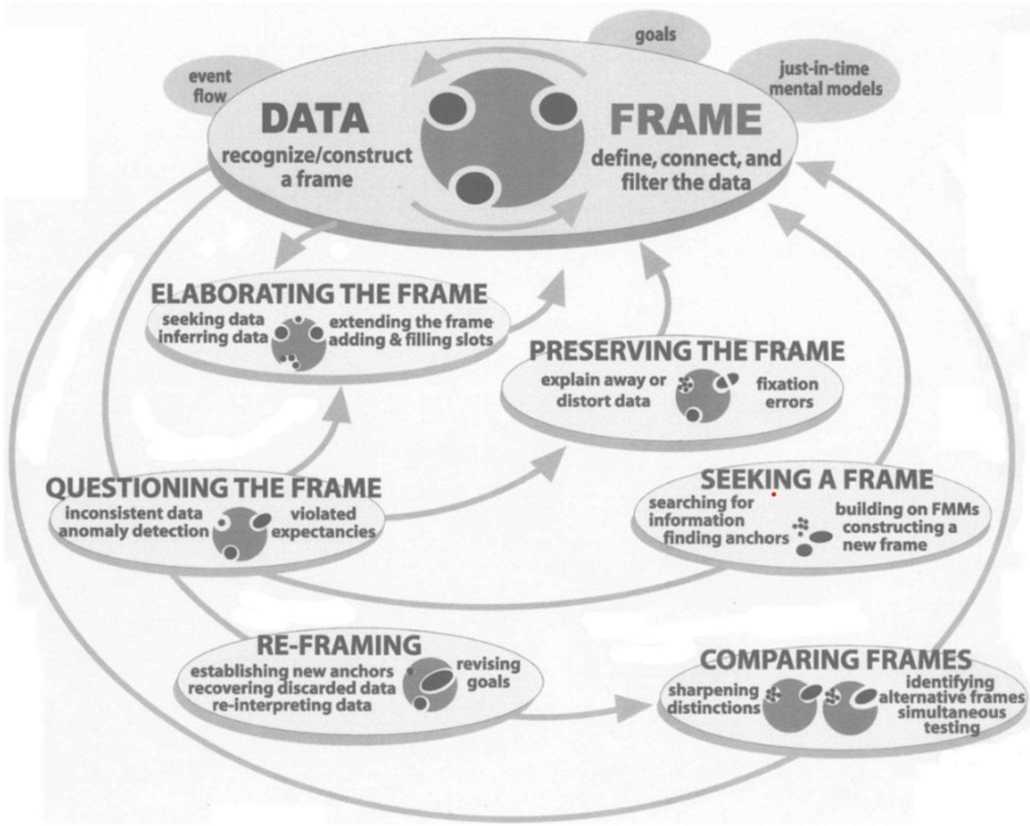


Figure 4.1 The Data Frame Theory, as presented by Klein et al. (2017)
Source: "A data-frame theory of sensemaking" by G. Klein, J. K. Phillips, E. L. Rall, D. Peluso, 2007, *Expertise out of Context: Proceedings of the Sixth International Conference on Naturalistic Decision Making*, pp. 133

The Data Frame Theory suggests neither the data nor the frame comes first, they interchangeably affect each other: the data helps shape the frame and the frame in turn helps filter and analyze the data. In other words, "once the frame becomes clear, so do the data" (Klein et al., 2007, pp. 118). When humans are given a novel situation, several key variables, at most three or four (Klein & Crandall, 1995) are automatically identified and act as "key anchors" (Klein et al., 2007, pp. 122-123). These key anchors are essential in constructing the initial frame, through which data is interpreted.

Once a frame is constructed, abductive reasoning is utilized to make inferences and logical deductions. In instances where the frame is insufficient, inaccurate, or incomprehensive, it is iteratively readjusted and reapplied. In some cases, multiple frames are constructed and compared against one another (Klein et al., 2007, pp. 139), sometimes up to three (Klein et al., 2007, pp. 140). The sensemaking process is concluded when the relevant data is identified and the frame is deemed valid, unless the individual believes there is potential benefit in continuing (Klein et al., 2007, pp. 126).

It is also important to note that the number of potential frames available to an individual varies vastly given their expertise. Although both experts and novices employ a similar sensemaking process designed around finding cause-and-effect relationships between identified variables, experts simply have access to more domain knowledge, which leads to both a higher number and higher quality of inferences (Klein et al., 2007, pp. 127). The sensemaking process may also take different forms based on the domain of expertise the individual possesses (Klein et al., 2007, pp. 132; Klein et al., 2017), as well as workload, level of fatigue and level of commitment (Klein et al., 2007, pp. 134-135).

Through the explanation of the Data Frame Theory, Klein and colleagues (2006, 2007) suggest that sensemaking is a process of iterative framing, making adjustments as the individual deems necessary. Without a frame, even the most accurate and appropriately analyzed data may not inform an individual to its full extent. Thus, when visualizing data or processes for use in decision-making, one must aid the sensemaking process of the decision-maker, so that it supports the construction, and readjustment, if necessary, of a frame.

Information Foraging

Reflecting on the role of visual analytics in decision-making contexts necessitates sufficient understanding of the interaction dynamics involved. Here, the sense-making model developed by Pirolli and Card (1999) offers a crucial framework for interpreting how decision-makers engage with visual systems through iterative refinement processes. This dynamic is aptly captured in Pirolli and Card’s (1995) sense-making model, which describes an iterative loop of information gathering, synthesis, and conclusion drawing.

In this model, a user begins with an information-rich environment. The process of “foraging” involves navigating through visual data to identify relevant pieces – a principle grounded in their initial exploration of how people search for information (Pirolli & Card, 1995). Once relevant data are identified, the sense-making process transitions to the “analysis phase”, where data are organized and interpreted to form insights (Pirolli & Card, 1999). This supports the cognitive work of constructing a coherent narrative from the data. The ability to customize views and focus on different aspects of the data mirrors the model's description of refining insights through analysis.

The "decision-making phase" is where synthesized knowledge is applied to form conclusions and make informed decisions (Pirolli and Card, 1999). This involves presenting the information in ways that align with the decision-making needs. Often decision-makers do not carry out a deliberate generation of alternatives to evaluate when structuring a problem, most likely due to time constraints and overwhelming amount of data (Pirolli & Card, 2005). This challenge may be addressed through visual tools that support the generation and comparison of alternative hypotheses and scenarios, offloading as much of these representations from the mind to a visual display. Thus, design features should facilitate not just the consumption of information but also the application of insights in practical decision-making scenarios.

Incorporating the framework from Pirolli and Card (1995, 1999, 2005) into the discussion, it emphasizes the importance of interaction in the cognitive development of decision processes. It highlights how effective visual analytics systems are not just about data presentation but about fostering an interactive environment where data is not only seen but engaged with – enabling users to move through cycles of exploration, insight generation, and decision application iteratively (Lee et al., 2016). This approach aligns with the broader goals of visual analytics, where the aim is not only to present data but to transform it into actionable intelligence through a well-supported cognitive journey.

Gisting

Exploring a largely unexplored task within visual analytics, Nowak and Bartram define "gisting" as gathering the overall essence of the situation, providing a preview of what items or information will be searched, therefore expediting the detection of items of interest (2023, pp. 925). Gisting is a crucial cognitive bridge between the observation of raw data and the synthesis of information into actionable insights. This process involves rapidly extracting the essence or the 'gist' of the data, which is integral to both causal reasoning and decision-making, particularly in environments characterized by complexity, uncertainty, or ambiguity.

Gisting is not merely about summarizing; it is about distilling the core themes or patterns from a wealth of information at a glance (Nowak & Bartram, 2023, pp. 925). This process relies heavily on the analyst's ability to assimilate and interpret high volumes of data swiftly, identifying overarching narratives or key anomalies that inform further inquiry or decision-making. It is a higher-order cognitive process that combines elements of perception, memory, and attention to filter and focus on what is most relevant from a potentially overwhelming stream of data inputs.

Decision-making processes, particularly under conditions of uncertainty or ambiguity, are enhanced by effective gisting. In dynamic decision-making environments, where timely responses are crucial, gisting enables decision-makers to quickly get up to speed with the situation at hand, as Nowak and Bartram (2023) illustrate with the use of visual analytics in avalanche forecasting. This rapid comprehension helps in setting priorities and preparing for potential scenarios, forming a basis upon which more detailed analyses and informed decisions can be made.

In the context of causal reasoning, gisting facilitates the formation of initial hypotheses or mental models about the relationships within the data. Once the initial gist is understood, analysts can dig deeper into the data to validate or refute their initial interpretations, refine their models of causation, and explore complex interdependencies without the bias of getting lost in minute details initially. For instance, in emergency management or business intelligence, understanding the gist of a sudden change in data patterns can prompt immediate and necessary actions, such as reallocating resources or adjusting strategies in response to an emerging threat or opportunity.

The importance of gisting in causal reasoning and decision-making necessitates that visual analytics tools are designed to support this cognitive process effectively. Nowak and Bartram's work (2023) emphasizes the need for visualizations that support the ambiguous nature of sensemaking by encouraging reflection, provoking alternative interpretations, and enabling users to quickly and effectively process vast amounts of data to identify critical insights. This approach underlines the necessity for design strategies that include the use of visual summaries that highlight key data trends or anomalies, the integration of interactive features that allow users to easily drill down from general overviews to specific raw data points, and the implementation of adaptive user interfaces that adjust the level of detail presented based on the user's tasks and preferences.

4.2. Recognition

After interpreting the graphic elements of displayed patterns, decision-makers begin the recognition process by matching these elements with visual memories stored in their minds (Ltifi et al., 2020), a comparison fundamental to understanding and interpreting the data presented. Zheng et al. (2016) discuss how the recognition process involves not just a simple recall but a complex pairing with various appearances of the display, such as changes in size, orientation, and lighting (Ltifi et al., 2020), which can significantly affect the interpretation of visual data.

The nature of these representations is such that they can evoke multiple interpretations, underscoring the importance of designing visualizations that are clear yet flexible enough to be understood under various conditions. Recognizable elements within these patterns play a crucial role in enhancing their memorability. According to Borkin et al. (2016), the more distinct and easily identifiable these elements are, the more likely they are to be remembered by the viewer. For instance, distinct color contrasts or unusual shapes can stand out more in the cognitive process, making them more memorable and easier to recognize in future contexts. Borkin and colleagues provide examples of how visualizations designed with these principles in mind not only aid in immediate recognition but also ensure that key information is recalled accurately when needed, thereby supporting effective decision-making (Borkin et al., 2016).

This exploration into the recognition phase highlights the interplay between human cognitive capabilities and effective visualization design. Ensuring that visualizations align with perceptual and cognitive patterns not only enhances the immediate understanding of data but also supports the long-term retention and recall of critical information, facilitating a more informed decision-making process.

4.3. Reasoning

4.3.1. Reasoning about Correlation, Causation, Association

Causal reasoning is a fundamental pillar of human cognition, essential for navigating and understanding the complexities of the world. It underlines our ability to discover relationships between causes and effects, guiding our predictions, diagnoses, and decisions. This cognitive ability allows individuals to plan actions and solve problems by leveraging an understanding of cause-effect dynamics (Sloman, 2005; Waldmann, 2017). Although philosophers have long studied causal reasoning, offering profound theoretical insights, it has also been categorized as merely a facet of broader cognitive abilities like logical thinking or associative learning, rather than a distinct domain (Hagmayer & Waldmann, 2002; Waldmann & Hagmayer, 2013).

Alternate Theories of Causality

Starting all the way from philosopher David Hume, who argued that causal relationships are simply illusions we deduce from our observations (Hume, 1748), causality and causal reasoning has long been the subject of debate. Associative theories have explained such relationships as covariation (Waldmann & Hagmayer, 1992). Dividing events into cues and outcomes, these models focus on the temporal nature of these factors as the differentiator. However, research over the past two decades has shown that these theories fail to include directionality (Waldmann & Holyoak, 1992), which is a critical component of causality, as well as explaining the distinction between causal and non-causal triggers (Cheng, 1997).

Logical theories categorize causal reasoning as a sub-category of deductive reasoning. Mental Model Theory of Causation (Goldvarg & Johnson-Laird, 2001) assumes a deterministic approach to causality and asserts that humans develop mental models of the potential relationships between factor elements. Expanding Hume's perspective (1748), these cause-and-effect elements are also differentiated through temporal priority. However, this introduces problems, given that according to Mental Model Theory of Causation, causation (A causes B) would be modeled the same as co-occurrence (if A, then B) (Waldmann & Hagmayer, 2013). Similar to associative theories, logical theories also fail to address causal directionality (Waldmann & Hagmayer, 2013).

A third group of alternative theories that attempted to explain causal reasoning as part of a non-causal framework were probabilistic. Probabilistic theories do refer to cause and effect directionality within covariations, although in a strictly statistical manner, somewhat paving the way for the development of causal theories (Waldmann & Hagmayer, 2013). One of the leaders of attempting to condense causal relationships within probabilistic theories was H. H. Kelley (1973), who posited that humans go through an internal statistical analysis process, reminiscent of an Analysis of Variance (ANOVA), helping to infer causal relationships. However, as one may postulate, this internal analysis is subject to computational limitations of the human mind, especially given the complexity of real-life problems with multiple, often confounding, causes (Waldmann & Hagmayer, 2013).

Causal Reasoning in Cognitive Science

In the realm of cognitive psychology, causal reasoning has emerged as a critical area of study, particularly in how it enables humans to predict and influence their environments. This competency involves not only understanding the sequences and consequences of events but also applying this knowledge to effect change and anticipate future outcomes. Historically, while causal reasoning has been a subject of philosophical inquiry, its practical implications in everyday human actions — such as how we relate actions to outcomes — have only recently been emphasized in psychological research. These insights reveal that our interactions with the world are heavily predicated on our interpretations of causality, which inform our actions and decisions in profound ways (Sloman, 2005; Waldmann, 2017).

Causal relationships have long been depicted through visual mediums, from philosophy (Reichenbach, 1956) to the realms of data mining and artificial intelligence, where they form the basis of Bayes net theory (Pearl, 1988, 2009; Spirtes et al., 1993).

However, Waldmann and Hagmayer (2013) argue that Bayes net theory is not fully applicable to psychology, preferring instead to frame it within a broader "Causal Model" context (Figure 4.2). In the graphical representation of causal relationships, the use of arrows is critical, as they not only signify causality but also directionality. Additionally, the design of these representations must account for human sensitivity to causal power (Buehner & May, 2003; Hagmayer et al., 2007) and causal structure (Hagmayer & Meder, 2013; Rehder, 2003; Rehder & Hastie, 2001), both of which are essential for accurately conveying the dynamics of causal interactions.

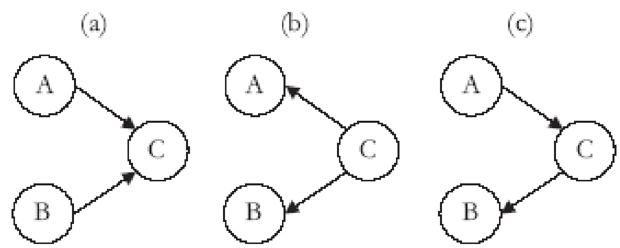


Figure 4.2 Examples of causal models (common effect, common cause, and causal chain model)
Source: “Causal Reasoning” by M. R. Waldmann and Y. Hagmayer, 2013, *The Oxford Handbook of Cognitive Psychology*

Waldmann (1996) highlights that causal reasoning often leverages prior knowledge in a top-down manner, where hypotheses are formulated based on variables like prior experiences, interventions, and the sequence of events. Although the temporal sequence — where causes precede effects — is traditionally paramount in causal reasoning, prior knowledge can sometimes take precedence, potentially overriding chronological considerations if it is deemed relevant and reliable (Waldmann & Hagmayer, 2013). This integration of prior knowledge, however, presents challenges, as it requires careful judgment about when and how to allow this knowledge to supersede observed temporal sequences based on confidence in its applicability and efficacy.

The interplay of prior knowledge with causal reasoning is particularly relevant in complex decision-making frameworks, where decisions are not isolated but are part of a hierarchical structure of multiple, often simultaneous decisions. Zylberberg et al. (2021) investigates this complexity by studying how individuals navigate through hierarchical decision processes. Their research, which combines perceptual decision-making with hierarchical and counterfactual reasoning, demonstrates how earlier decisions, and the confidence placed in them, significantly influence subsequent choices. This finding illustrates the pivotal role of causal reasoning in structuring complex decision-making scenarios into a sequence of interlinked decisions, where each step is informed by the outcomes and understandings derived from previous ones (Zylberberg et al., 2021).

4.3.2. Causal Reasoning and Decision Making

Causal reasoning fundamentally shapes how individuals engage with complicated decision-making processes by providing a framework through which to understand and manipulate environmental and systemic variables. This cognitive process enables decision-makers to anticipate outcomes and tailor their strategies, accordingly, making it a critical component of effective decision-making across various domains.

Research by Hagmayer and Sloman (2009) underscores the preference that individuals have for causal mechanisms over statistical correlations in decision-making. They illustrate that decision-makers not only seek to understand causal relationships but also strive to influence outcomes directly by manipulating variables they identify as causal agents. This approach to decision-making highlights a cognitive preference towards causality, suggesting that decision-makers are proactive agents who utilize causal understanding to shape their environment effectively (Hagmayer & Sloman, 2009). Akin to Klein's (Klein, 1993; Klein et al., 2017) perspective, Hagmayer and Sloman (2009, pp. 34) posit that if an expert possesses sufficient knowledge given the circumstances, the causal reasoning process is not required for sensemaking, and actions are taken immediately.

Furthering this perspective, Hagmayer and Meder (2013) explore how causal beliefs about the world guide the generation of hypotheses and the planning of actions, particularly in settings characterized by uncertainty. Their findings reveal that causal knowledge is not passively applied but actively used to construct potential interventions and predict their effects, thus enhancing the decision-making process (Hagmayer & Meder, 2013). This active use of causal reasoning is crucial in environments where outcomes are not immediately apparent, requiring decision-makers to rely on their understanding of causal dynamics to navigate uncertainty and achieve desired outcomes.

The insights provided by these studies enrich our understanding of the pivotal role of causal reasoning in decision-making. Understanding the causal structure of a problem allows individuals to not only predict consequences more accurately but also adapt their strategies to align with evolving conditions. This dynamic approach to decision-making, grounded in causal reasoning, offers substantial advantages in complex scenarios where outcomes depend on the interplay of multiple factors, and simple correlations do not suffice for making informed decisions (Hagmayer & Sloman, 2009; Hagmayer & Meder, 2013). By emphasizing the proactive and dynamic utilization of causal knowledge, they highlight how integral causal reasoning is to navigating complex decision-making landscapes effectively.

Causal-Explanation-Based Decision-Making Framework

The Causal-Explanation-Based Decision-Making (CDM) Framework provides a comprehensive method for leveraging causal reasoning in complex decision-making scenarios, particularly within clinical contexts (Hagmayer & Witteman, 2017). This framework systematically incorporates causal analysis to optimize the outcomes of interventions. By grounding decision-making in causal reasoning, the framework enhances the predictability and effectiveness of interventions, offering a structured pathway through the often-chaotic landscape of clinical decision-making.

The initial steps of the CDM Framework involve a meticulous preparation process that sets the stage for informed decision-making. Step one involves deciding whether a causal analysis could potentially improve decision outcomes, a determination that is critical as it dictates the applicability of the entire framework to the specific decision scenario (Hagmayer & Witteman, 2017, pp. 116-119). If a causal analysis is deemed beneficial, step two progresses to developing a detailed causal explanation for the identified problem (Hagmayer & Witteman, 2017, pp. 119-121). This causal mapping not only aids in understanding the problem more thoroughly but also serves as the foundation for subsequent interventions. Step three then evaluates the utility of possible interventions that could be applied based on the developed causal explanation (Hagmayer & Witteman, 2017, pp. 121-122). This evaluation is crucial as it ensures that any selected intervention is backed by a robust causal rationale, thereby increasing the likelihood of its success.

Step four of the CDM Framework involves the selection and implementation of an intervention that has been deemed most suitable based on the thorough causal analysis conducted in the preceding steps (Hagmayer & Witteman, 2017, pp. 122-123). This step is particularly critical because it encapsulates the decision-making process where interventions are not just chosen based on causal efficacy but also on the basis of maximizing expected utility (Nozick, 1994). Expected utility in this context refers to the comprehensive evaluation of potential outcomes, both positive and negative, weighed by their likelihood and the value or impact they hold for the patient or situation. However, it is essential to recognize that Expected Utility Theory is not the only framework for comprehending decision-making under uncertainty.

Kahneman and Tversky's (1979) Prospect Theory provides an alternative perspective, suggesting that individuals assign different values to gains and losses, resulting in decisions that diverge from those anticipated by traditional utility theories. This theory emphasizes that individuals are more significantly impacted by losses than by equivalent gains, a phenomenon known as "loss aversion." It also explains how the perceived probability of outcomes can be distorted by the decision-maker's perception, influencing their decisions in risk-laden situations.

The intervention chosen in Step 4 of the CDM framework must be supported by robust causal inferences, ensuring that it is not only actionable and appropriate within the specific context but also optimizes the balance between benefits and risks. This optimization is crucial, particularly in complex or high-stakes clinical environments where the consequences of decisions can significantly impact patient outcomes, or organizations where decisions can result in the loss of financial value and therefore, jobs (Mariano & Baker, 2024). Furthermore, this step's focus on expected utility emphasizes the need for decisions to be made with a deep understanding of their probable impacts, enhancing the decision-making process's overall integrity and effectiveness.

Following the implementation of the chosen intervention, step five involves a critical re-evaluation of the causal model based on the outcomes achieved (Hagmayer & Witteman, 2017, pp. 124-125). This reassessment allows for the empirical feedback necessary to refine the decision-making process, ensuring that it remains responsive to new insights and results. By rigorously assessing and reporting the consequences of the intervention, decision-makers can ensure that their actions remain aligned with the latest clinical evidence and practice standards, thereby maintaining the dynamic and responsive nature of the decision-making process within clinical settings.

Although causal reasoning and causal theory help describe the process carried out by humans when making decisions, they are inherently subject to biases and assumptions. Hagmayer and Waldmann (2002) showed that temporal assumptions regarding the cause-and-effect variables within a system can drastically influence how causal relationships are identified and judged, by determining which statistical indicators are deemed appropriate for establishing causality. If viewed from an organizational decision-making perspective, this results in individual decision processes and mental models that do not align with one another.

This integration of hierarchical decision processes and the strategic use of prior knowledge within causal reasoning frameworks underscores the need for tools and approaches that can adeptly handle the distinctions of both temporal dynamics and experiential insights. It highlights the essential nature of confidence and knowledge in shaping the pathways through which decisions unfold, ultimately influencing the efficacy and outcomes of the decision-making process.

4.4. Role of Working Memory in Decision Making

Working memory, the cognitive system that holds and manipulates information for a brief period of time, is fundamentally connected to the concept of cognitive load, which signifies the total mental effort required by working memory. Understanding the interplay between cognitive load and working memory is fundamental for the design of effective visualization tools in decision-making contexts. Cognitive load refers to the total mental effort required to process information within working memory, and it is classified into three distinct types: intrinsic, extraneous, and germane (Orru & Longo, 2019; Sweller, 1988; Sweller, 2011). Intrinsic load relates to the inherent complexity of the information itself, such as predictive sales data, field inventory levels, cold storage inventory, and confirmed orders in sweet potato packing. This complexity is usually fixed and cannot be easily modified (Sweller, 2011, pp. 57). Extraneous load, however, is generated by the way information is presented. Reducing extraneous load through clear, user-centered visualizations and by eliminating unnecessary data or processes allows users to process information more efficiently (Sweller, 2011, pp. 63). This enables users to concentrate their cognitive resources on understanding and analyzing data rather than interpreting its presentation, or decoding. Germane load refers to the mental effort invested in processing and comprehending information, which can be optimized by designing tools that facilitate the creation and automation of cognitive schemas (Paas & Van Merriënboer, 1994; Sweller, 2011). Schemas are mental frameworks that help in organizing and interpreting information, thereby supporting deeper understanding and learning. Effective visualization tools should not only present data clearly, in an attempt to reduce extraneous load, but also encourage the development and refinement of these schemas, thereby enhancing users' ability to process and retain complex information, enabling more informed and effective decision-making (Paas et al., 2003).

4.4.1. Working Memory and Dual-Process Models

Addressing the gaps in previous research on how visualizations aid decision-making, Padilla and colleagues (2018) explored the well-known dual-process model of decision-making, bearing similarity to Kahneman's System 1 and System 2 thinking (Morewedge & Kahneman, 2010). This model outlines two distinct types of cognitive processes: Type 1 for rapid, simple decisions, and Type 2 for slower, more complex decisions (Padilla et al., 2018, pp. 2). While some researchers support this clear distinction, others, such as Evans (2008), have argued for the boundaries between these types to be more ambiguous (Padilla et al., 2018, pp. 3). A significant contribution from Padilla et al., is their proposed model (illustrated in Figure 4.3), which integrates the role of working memory and cognitive load in decision-making. According to their findings, Type 1 decisions require less working memory due to their simplicity, whereas Type 2 decisions consume more working memory resources, due to their complexity (Padilla et al., 2018). Furthermore, working memory is essential for keeping track of conceptual questions and synthesizing messages from visual stimuli, which directly impacts decision-making and behavior (Figure 4.3). This model underscores the importance of considering working memory in the design of decision-support visualizations, aiming to enhance their effectiveness.

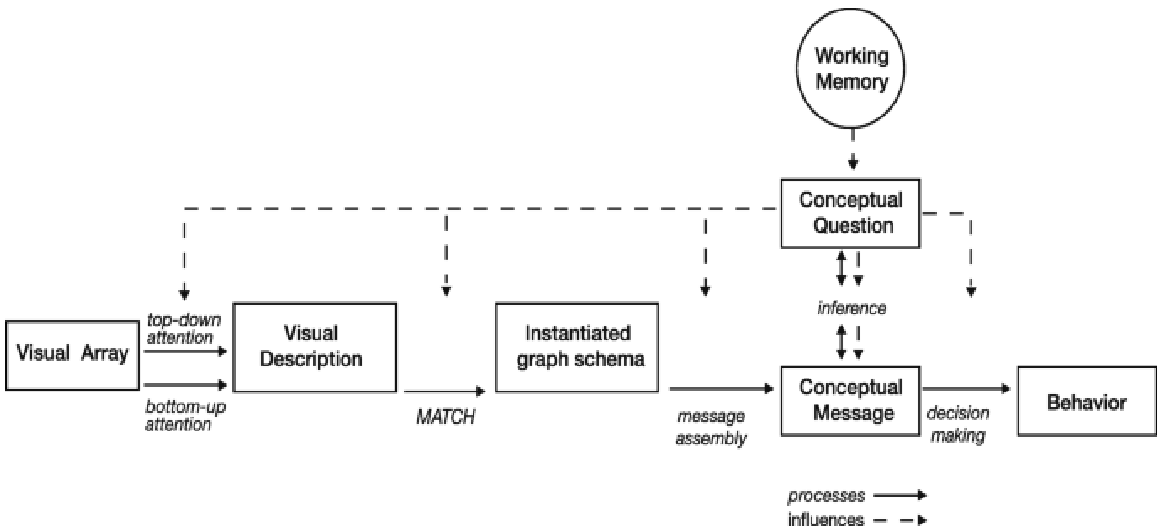


Figure 4.3 The model proposed by Padilla and colleagues (2018), which shows how working memory plays a role in visualization decision making

Source: "Decision making with visualizations: a cognitive framework across disciplines" by L. M. Padilla, S. H. Creem-Regehr, M. Hegarty, J. K. Stefanucci, 2018, *Cognitive Research: Principles and Implications*, pp. 5

In their exploration of working memory's impact on decision-making, Fletcher, Marks, and Hine (2011) demonstrate that individuals with higher Working Memory Capacity (WMC) exhibit superior performance in tasks that demand logical reasoning and syllogistic deductions, showing the impact of WMC utilization on reasoning ability. This higher capacity allows them to better retain and manipulate multiple pieces of information simultaneously, enhancing their ability to follow complex argument structures and arrive at correct conclusions more consistently. Furthermore, these individuals show greater resistance to common cognitive biases associated with probabilistic reasoning, such as the gambler's fallacy, where a person might incorrectly assume that past random events affect future probabilities (Fletcher et al., 2011). The ability to avoid such biases is crucial in high-stakes decision-making environments where erroneous assumptions can lead to significant consequences. These findings illuminate the critical role of working memory in the cognitive processes that drive rational decision-making, underscoring the necessity to utilize it effectively and not overload it with redundant information (Fletcher et al., 2011).

In the context of sweet potato packing, both GA and MI need to constantly monitor and interpret visual cues from predictive sales data, inventory levels in the fields, cold storage inventory, and confirmed current or future orders to make strategic decisions. Visualization tools can assist their working memory by allowing them to manage multiple scenarios based on metrics such as profit (revenue - cost). By offloading some of the cognitive burden involved in tracking these scenarios, these tools free up mental capacity for higher-level reasoning and comparison, allowing users to identify potential biases in the process. This enables GA and MI to visually compare various strategies and outcomes, focusing on in-depth analysis and making more informed decisions to maximize utility.

4.5. Cognitive Fit Theory

Cognitive Fit Theory, initially introduced by Vessey and Galletta in the early 1990s (Vessey, 1991; Vessey and Galletta, 1991), posits that decision-making effectiveness is significantly enhanced when there is a congruence between the information presentation format and the cognitive demands of the task (Nuamah et al., 2020). This theory, rooted in information processing principles, argues that the quality and speed of decisions are optimized when the presentation style aligns with the cognitive processes required by the task, a concept known as 'cognitive fit'. Shaft and Vessey (2006) propose that matching internal and external representations with the problem-solving task helps create a mental representation that improves problem-solving. This framework has gained substantial traction in fields like management information systems and decision support systems, where the design of optimal interfaces can significantly influence user outcomes.

The theory classifies tasks into two primary types: spatial and symbolic (Vessey and Galletta, 1991, pp. 68-69). Each type benefits differently from the specific modes of information representation. Spatial tasks, which involve the visualization and manipulation of spatial information, are better supported by graphical representations that highlight relationships through visual means, such as charts and maps. Conversely, symbolic tasks, which rely on the processing and understanding of numerical or textual data, are more effectively executed with tabular representations where data can be organized and examined in a structured format. This classification of task and representation type emphasizes the importance of aligning cognitive demands with the appropriate visual aids to optimize decision-making efficiency.

Cognitive Fit Theory aligns closely with established cognitive science paradigms by emphasizing the critical role of working memory in decision-making. The theory posits that decision-making efficacy is greatly enhanced when the format of information presentation is congruent with the cognitive requirements of the task (Vessey and Galletta, 1991, pp. 65-68). This congruence reduces cognitive load, allowing for a more efficient use of working memory. This relationship is particularly relevant to Pirolli and Card's sensemaking model (1995, 1999), which focuses on how individuals organize and process information to make sense of complex data. By optimizing the match between task demands and information format, Cognitive Fit Theory supports the sensemaking process, enabling more effective navigation through information and aiding the decision-maker in reaching conclusions with greater clarity and speed.

Building on Cognitive Fit Theory, Bina et al. (2023) demonstrate how modern visualization techniques such as interactive dashboards and augmented reality can optimize decision-making by ensuring a cognitive fit between the user and data presentation. They detail how dashboards, by clearly distinguishing between data trends and anomalies, empower decision-makers to rapidly adjust operational strategies based on real-time insights. This alignment of information format with the user's cognitive processes is essential, as it significantly reduces cognitive load and leads to faster, more precise decisions (Bina et al., 2023). Furthermore, the application of augmented reality in visualization overlays complex datasets onto physical environments, enhancing spatial context comprehension and matching the data presentation with the decision-maker's innate perceptual abilities.

Bina et al. (2023) also explore how certain evolutionary traits, such as the capability to recognize faces and emotions quickly, illustrate the benefits of integrating cognitive theories in visualization design. The geon theory, which focuses on object recognition based on geometric ions, or geons, suggests that simple, easily recognizable shapes form the basis of visual perception (Biederman, 1987). Applying this theory to 3-D surface graphs, where navigation is dependent on recognizing shapes and patterns, can enhance the speed and accuracy of data interpretation. However, the effectiveness of these evolutionary-derived capabilities in navigating these visual representations is specific to particular tasks. This clear understanding underscores the need to tailor visualization tools to specific decision-making contexts, ensuring they align with both the cognitive fit and the innate perceptual skills shaped by evolutionary processes.

It is evident that the Cognitive Fit Theory not only facilitates a deeper understanding of how different tasks benefit from tailored visualizations but also highlights the practical implications for designing decision support systems. For spatial tasks, graphical displays can enhance comprehension and pattern recognition, speeding up the decision process by presenting information in a way that is immediately interpretable (Joshi et al., 2012). For symbolic tasks, tables facilitate detailed comparison and straightforward access to specific data points, thereby supporting thorough analysis and precise decision-making. This understanding of task-specific information presentation is pivotal in developing effective tools for a wide array of decision-making scenarios, ensuring that the cognitive resources of the user are optimally employed (Hammond et al., 1987, pp. 767).

This evolving landscape of visualization tools emphasizes the need for interfaces that not only display data but also facilitate understanding of complex information systems. This approach ensures that visualization tools are not merely informative but are instrumental in enhancing decision-making efficiency and effectiveness.

4.6. Bounded Rationality Theory

Bounded rationality is a theory that suggests individuals operate within the constraints of limited information, time, and cognitive limitations when making decisions

(Hochbaum & Levin, 2006; Lunenburg, 2010; Sent, 2018; Simon, 1955). This theory acknowledges that decision-makers often must make quick, yet well-considered choices based on their limited understanding of a situation (Arend, 2002). It also indicates that individuals employ heuristics to resolve decision problems, thereby underscoring the importance of accounting for personal variations in knowledge visualization and decision-making processes (Hochbaum & Levin, 2006, pp. 161).

Originating from the work of Herbert A. Simon (1955), bounded rationality contests the notion of absolute rationality that is often assumed in models of economic and political behavior. Instead of striving for the optimal solution, individuals sometimes settle for a satisfactory one that meets their adequacy criteria. This approach reflects the practical difficulties individuals face, such as the complexity of the situation and the finite resources available for processing information, positing that humans do not carry out a comprehensive cost-and-benefit analysis and simply satisfice once an optimal solution is identified (Campitelli & Gobert, 2010). Simon's analogy of a pair of scissors, with one blade symbolizing human cognitive limitations and the other representing the environmental structure, demonstrates how people leverage environmental cues to navigate their cognitive constraints (Gigerenzer & Selten, 2002). An everyday example of bounded rationality in action is a diner in a restaurant who makes a hasty food choice under the pressure of a waiting server, indicating that the decision was influenced more by situational constraints than by a thorough evaluation of all available options.

The theory of bounded rationality is enriched by the exploration of heuristics, which individuals rely on to make decisions under uncertainty. Traditional rational choice theory suggests that decisions are made through an exhaustive optimization process; however, the reality often involves using heuristics that simplify decision-making. Anchoring and adjustment is a heuristic where initial information or values serve as an 'anchor', and subsequent judgments are adjusted based on this anchor, despite the relevance or additional incoming data (Zenko et al., 2016). This can lead to biases if the anchor is based on irrelevant information. Similarly, the availability heuristic causes individuals to overestimate the probability of events that are more memorable or vivid, while the representativeness heuristic leads to judgments based on how much a scenario resembles a typical case, often neglecting important statistical details such as base rates or sample sizes.

The collaborative research of Daniel Kahneman and Amos Tversky further explores the implications of bounded rationality, particularly in the field of psychology (Kahneman, 2003a, 2003b; Tversky & Kahneman, 1974, 1986). Unlike Simon, who primarily focused on the theoretical aspects of decision-making limitations due to cognitive constraints, Kahneman and Tversky provided empirical evidence illustrating specific biases and heuristics that people routinely employ. Their work extensively documented phenomena such as the framing effect (Tversky & Kahneman, 1986), where the way information is presented significantly influences decisions, and loss aversion, where the fear of losses predominates over the potential for equivalent gains. By highlighting these cognitive biases, Kahneman and Tversky shifted the focus from purely theoretical models of decision-making to more practical, observable behaviors that reflect the imperfections and irregularities of human reasoning. Their contributions have profoundly influenced not only psychology but also economics, leading to the development of behavioral economics, which integrates psychological insights into economic theory.

Understanding bounded rationality is crucial when designing visualizations for decision-making. Visual tools must account for human cognitive limits and aim to present information in ways that align with mental processes. Effective visualizations can help mitigate biases introduced by heuristics like availability and representativeness by clearly presenting statistical information and contextual data that might not be immediately evident. By accommodating the cognitive styles outlined in bounded rationality theory, visualizations can enhance decision-making efficiency and accuracy, making complex information more accessible and comprehensible for decision-makers navigating complicated scenarios.

4.7. Toulmin’s Argumentation Model

Stephen Toulmin's model, introduced in his 1958 work "The Uses of Argument," provides a structured framework for evaluating arguments, that reflects real-world complexities, paralleling the Socratic method's rigorous, dialogue-based inquiry. The Socratic method enhances understanding through a continuous cycle of probing questions that uncover underlying logic, similar to how Toulmin's framework critically examines reasoning and context. Both methods emphasize adapting to the situation at hand, recognizing that the relevance and standards of reasoning can vary depending on the context.

Continuing this analysis, Toulmin critiques the narrow scope of contemporary formal logic (1958), which often fails to capture the subtleties of everyday argumentation. He advocates for a contextual approach where the standards of reasoning are tailored to the specific issues being addressed, broadening the applicability of logical analysis, and aligning it with the practical, real-world application of philosophical inquiry (Figure 4.5). This captures the dynamic and varied nature of how arguments are constructed and understood in different contexts. The effectiveness of Toulmin's model has been displayed by numerous researchers, both in the general domain of decision making (Fox & Modgil, 2006; Reed & Rowe, 2005; Rieke & Sillars, 1975), as well fields requiring robust justification of decisions (Polacsek et al., 2018), as it allows for standards that reflect the complexities of specific contexts.

Toulmin's model systematically outlines six components of an argument: claim, data, warrant, backing, qualifier, and rebuttal (Bubakr &. Baker, 2020; Rubin & Benbasat, 2023; pp. 22:4-5; Toulmin, 1958; van Eemeren et al., 2014). The claim in Toulmin's model is the primary assertion or conclusion being argued for, supported by data which provides the factual basis. The warrant then acts as the logical link that connects this data to the claim, establishing the grounds on which the claim is deemed valid. To further solidify the warrant, backing is used to clarify the conditions under which the warrant holds, enhancing the argument's strength by detailing its operational framework. The qualifier modifies the scope of the claim, indicating the degree of certainty and setting boundaries on its general applicability, which manages expectations and maintains integrity. Lastly, the rebuttal addresses potential objections to the claim, highlighting scenarios where the argument might not hold true. The basic structure of Toulmin's model is presented in Figure 4.4 and the representation of an argument in the form of Toulmin's model is presented in Figure 4.5.

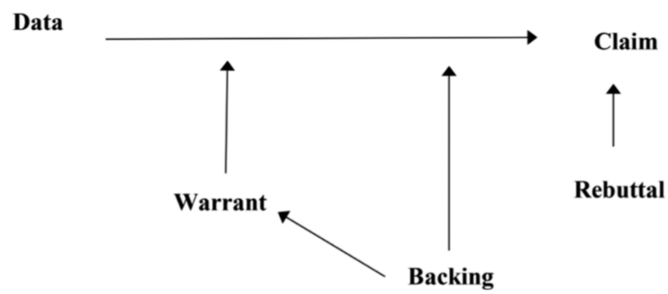


Figure 4.4 Basic structure of Toulmin's model of argumentation
Source: "Using Toulmin's Argumentation Model to Enhance Trust in Analytics-Based Advice Giving Systems" by E. Rubin and I. Benbasat, 2023, *ACM Transactions on Management Information Systems*, 14, pp. 22:5

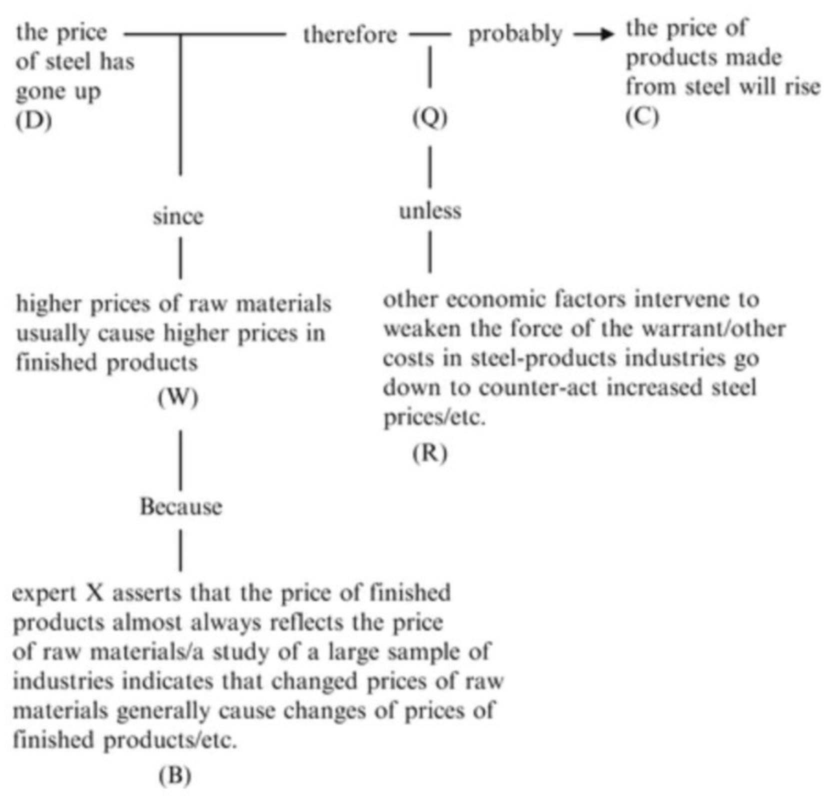


Figure 4.5 Example of an argument represented in Toulmin's model
Source: "Toulmin's Model of Argumentation" by F. H. van Eemeren, B. Gartssen, E. C. W. Krabbe, A. F. Henkemans, B. Verheij, J. H. M. Wagemans, 2014, *Handbook of Argumentation Theory*

Toulmin's model offers a structured methodology of causal reasoning to trace how conclusions are drawn from data, elucidating the underlying assumptions (warrants) and conditions (qualifiers and rebuttals) that justify these conclusions. This detailed breakdown enhances transparency, allowing decision-makers and stakeholders to explore the causal pathways that lead to certain decisions. Such clarity is crucial for validating the logical soundness of decisions, ensuring they are based on solid reasoning and are defensible under scrutiny.

Diagramming these components in Toulmin's model involves using arrows to indicate the directionality of support and influence among the argument's elements (Reed et al., 2007). These arrows serve as visual cues that guide the viewer through the flow of reasoning, from data to claim through warrants, much like how arrows in causal diagrams signify the direction of causality. This visual method not only aids in understanding the logical structure of the argument but also highlights the relationships between the components, making it easier to see how data supports the claim, how warrants justify the connection, and how qualifiers and rebuttals modify or challenge the argument's main assertion.

Despite the effectiveness of this approach in illustrating argument flows and structure, early representations of Toulmin's model in diagrams did not encapsulate nodes within circular or square shapes, a practice that helps in collapsing complex information into single, easily navigable nodes. Decisions that have a large number of nodes may benefit from Shneiderman's (1996) "overview first, zoom and filter, details on demand" mantra. Incorporating especially the "details on demand" mantra into Toulmin's model of argumentation, the nodes could be more effectively identified and arranged if they are encapsulated. By containing textual elements within shapes, the visual representation conforms to Gestalt principles such as proximity and closure, which suggest that elements grouped together within a defined area are perceived as a collective whole, this encapsulation may facilitate cognitive processing by reducing the effort needed to interpret and navigate between disparate pieces of information, thereby enhancing the overall comprehensibility of the argument structure. As such, incorporating these principles into diagrammatic representations of Toulmin's model could further aid in reducing cognitive load and improving the clarity and effectiveness of visual argument analysis.

To synthesize the cognitive science theories discussed and their relevance to the development of guidelines presented in Chapter 6, Table 4.1 outlines each concept, provides a brief description, and explains how it informs the design and functionality of visualization tools.

Table 4.1 Cognitive Science concepts and theories covered in Chapter 4

Topic	Description	Implications
Sensemaking	Effort to understand events and integrate them into a coherent mental model.	Align visualization tools with users' natural cognitive processes, facilitating data interpretation and decision-making.
Data Frame Theory	Organizing and interpreting information based on iterative frames.	Design visualizations that enable the user to iteratively seek patterns, developing or specifying the 'frame' with each iteration.
Information Foraging	Navigating through visual data to identify relevant pieces, organize them into coherent insights.	Guide the design of interactive visualizations to enable efficient navigation and retrieval of relevant data, enhancing decision efficiency.
Gisting	Extracting the essence or main point of information.	Design visualizations that quickly convey key insights, reducing cognitive load and aiding rapid decision-making.
Recognition	Identifying patterns in data through matching visual elements with stored visual memories.	Create visualizations that highlight significant patterns, making it easier for users to detect trends and anomalies, and make informed decisions.
Reasoning	Understanding cause-and-effect relationships.	Integrate causal diagrams to help users understand the implications of their choices and anticipate outcomes, enhancing strategic decision-making.
Working Memory	Holding and manipulating information temporarily.	Develop visualizations that allow scenario exploration and comparison, offloading this typically-mental process.
Cognitive Fit Theory	Matching visualization tools to tasks and cognitive styles.	Customize visualization tools to align with specific tasks and users' mental models, improving usability and decision-making effectiveness.
Bounded Rationality Theory	Making decisions with limited information and capacity.	Inform users about the factors considered in decisions through a causal diagram prepared through multi-stakeholder elicitation.
Toulmin's Argumentation Model	Structuring and evaluating arguments in decision-making.	Designs tools that support structured argumentation and logical reasoning, helping users construct and evaluate arguments to justify their decisions.

Chapter 5.

Literature Review

What types of visualizations have been developed and published in academic journals in the past 15 years, and how do such visualizations address the process of decision-making, beyond analytics and data?

This chapter outlines the methodology used to answer RQ3 by systematically searching, retrieving, and analyzing relevant literature on recently published visualization tools. The process includes defining keywords, selecting appropriate databases, applying inclusion and exclusion criteria, and conducting a thorough analysis of the filtered literature. This structured approach ensures a comprehensive review of the most relevant and current visualization tools to understand their effectiveness and potential for improvement.

5.1. Methodology

5.1.1. Search Criteria

The main literature search was conducted in April 2024. A second search was conducted on June 15, 2024, to include any recently published articles that may be pertinent. The main search was conducted on PubMed and Science Direct, and "“decision” “visualization tool” “agriculture”" was used as the search prompt, in order to better filter the results.

Given that PubMed and ScienceDirect are not exhaustive databases (Shariff et al., 2013; Shultz, 2007), secondary searches were conducted on Google Scholar. The following keywords were used for the complementary searches: “decision visualization”, “organizational decision making”, “technology decision making visual”, “decision diagrams”, “causal reasoning decision making”, “causal loop diagram decision”, “causal decision diagrams”, “visual decision argumentation”. The following keywords were also initially utilized, however did not result in any relative literature: “causal visual expression”, “causal visualization”, “causality visualization”.

5.1.2. Filtering Process

Only literature published in English were included, and a filter was set to only include literature published in the last 15 years (2009 - 2024). Review papers were excluded in both searches. The search on PubMed resulted in a total of 86 papers, whereas the ScienceDirect search resulted in 590 papers. Duplicate papers and review papers with no new tool or method contributions were excluded. The remaining papers were manually filtered, excluding ones that don’t contain a visualization tool for decision-making. 13 papers, found through the complementary Google Scholar searches, that fit the selection criteria and were deemed relevant were included in the analysis. The complementary searches were carefully filtered to leave out grey literature, a known shortcoming of Google Scholar given its “full-text searching” feature (Shultz, 2007).

Following the initial scan of the titles of papers, the analysis continued with an overview of the Abstracts. From the filtered literature, a secondary selection was conducted based on whether a paper presented or discussed a visualization method or tool for decision-making. Literature that discussed sense-making from visualizations for decision-making purposes, as well as visualizations that attempt to capture or support causal argumentation were also selected, given they fit the inclusion criteria. Figure 5.1 presents the flow diagram of the literature search and filtering process.

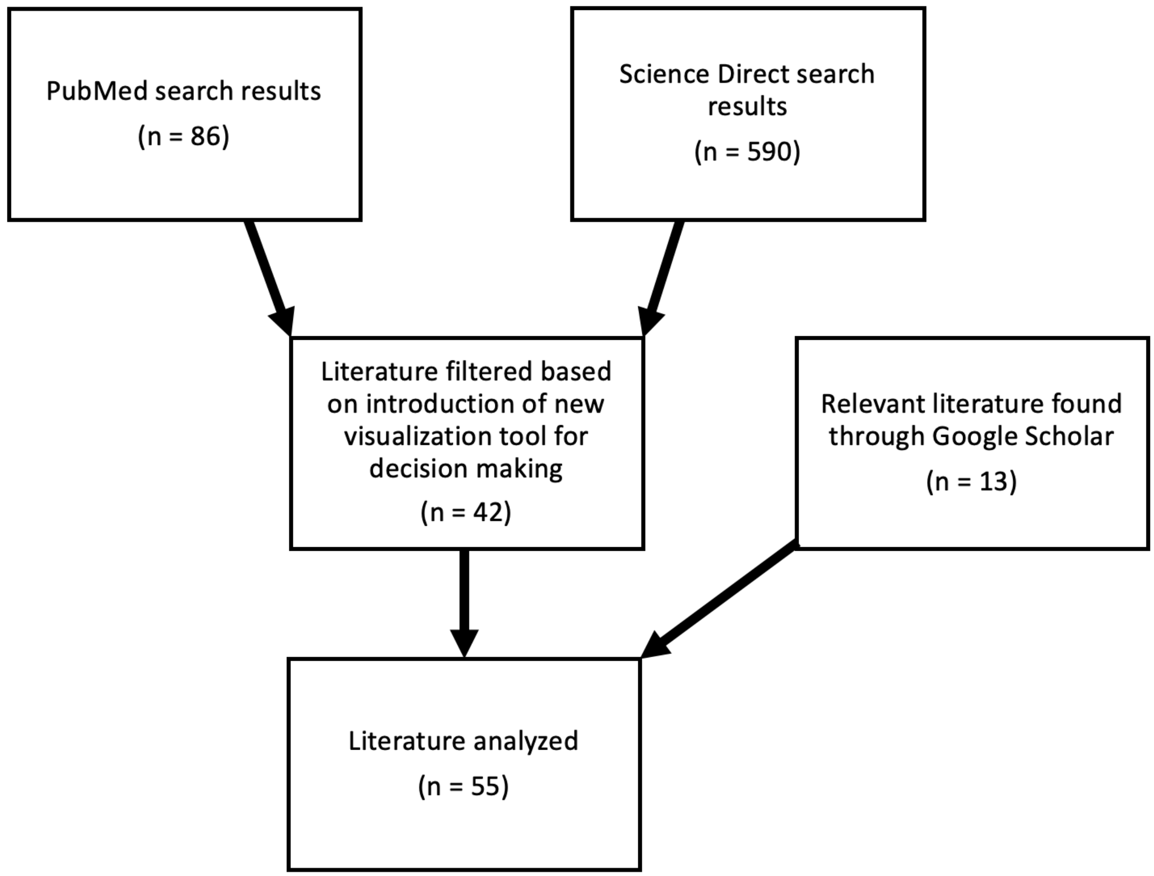


Figure 5.1 Flow diagram of the literature search, filtering, and results

5.1.3. Data Coding and Analysis

The reviewed papers were categorized based on the following variables:

Relative Field or Industry

For example: Healthcare, Business, Finance, Agriculture, General

Data Visualization Used

For example: scatter plot, line chart, decision tree, Influence Diagram, novel visualization (developed by the authors), multiple.

Interactivity (Yes/No)

Definition: Interactivity refers to the degree to which users can manipulate and engage with the visualization tool. This includes features that allow users to explore data through actions such as clicking, dragging, filtering, and zooming, enabling a dynamic and user-driven exploration of information.

Decision Flow (Yes/No)

Definition: Decision flow refers to the structured sequence and logic of steps that users follow within the visualization tool to arrive at a decision. It involves the visualization's ability to guide users through the decision-making process in a coherent and logical manner, supporting both linear and non-linear decision pathways.

Causality (Yes/No)

Definition: Causality in visualization tools denotes the capability to represent cause-and-effect relationships within the data. This includes visual elements that help users understand how different variables interact and influence one another, facilitating insights into the underlying causal mechanisms that drive observed outcomes.

Temporality (Yes/No)

Definition: Temporality involves the inclusion of time-sensitive data or processes within the visualization. This aspect ensures that users can view and analyze data over different time periods, understanding trends, changes, and the impact of time on various data points.

5.1.4. Methodological Limitations

The diverse academic fields and subjects covered in these studies, along with the varied nature of data visualization tools, made achieving uniformity in methodologies and outcome measures challenging. This variability underscores the highly purpose-driven nature of visualization tools. The current study sought to identify commonalities among these tools by examining key variables, attempting to categorize them as accurately as possible. However, it is important to note that these categories often lack distinct boundaries. For instance, while one visualization tool may feature highly advanced interactivity, another might only offer basic click interactions. This variability illustrates the spectrum of interactivity and other features within visualization tools.

This review has a specific focus on visualizations that aim to assist the flow of the decision-making process, and not visual analytics tools that merely provide outputs that direct a decision-maker. Thus, it purposefully overlooks the analytics portion of visual analytics, which inherently means the exclusion of studies discussing the data analytics or data modelling aspects from the discussion section. Analytics tools are essential for decision-making, such as the use of predictive and prescriptive analytics to simulate the outcomes of specific actions and optimize resources accordingly (Groot et al., 2012). However, given that the purpose of this review is to take on a psychological and cognitive perspective of this process, methods specifically designed for data transformation and analytics are not considered.

5.2. Results

The complete table listing the details of all of the 55 literature identified in the literature search is presented in Appendix A – "Results of the systematic literature review" (Table A.1). Table 5.1 shows the distribution of the reviewed visualization tools based on what specific industry they were designed for, if applicable. Figure 5.2 presents the publication frequency of the reviewed literature, and the distribution of the reviewed literature based on the four identified criteria (interactivity, decision flow, causality, and temporality) is presented in Figure 5.3.

Table 5.1 Results of the literature search, categorized by field of study.

Industry	Publications
agriculture	14
bioinformatics	1
city planning	1
emergency management	1
environmental	9
general	9
healthcare	16
operations	1
public health	1
supply chain	1
transportation	1

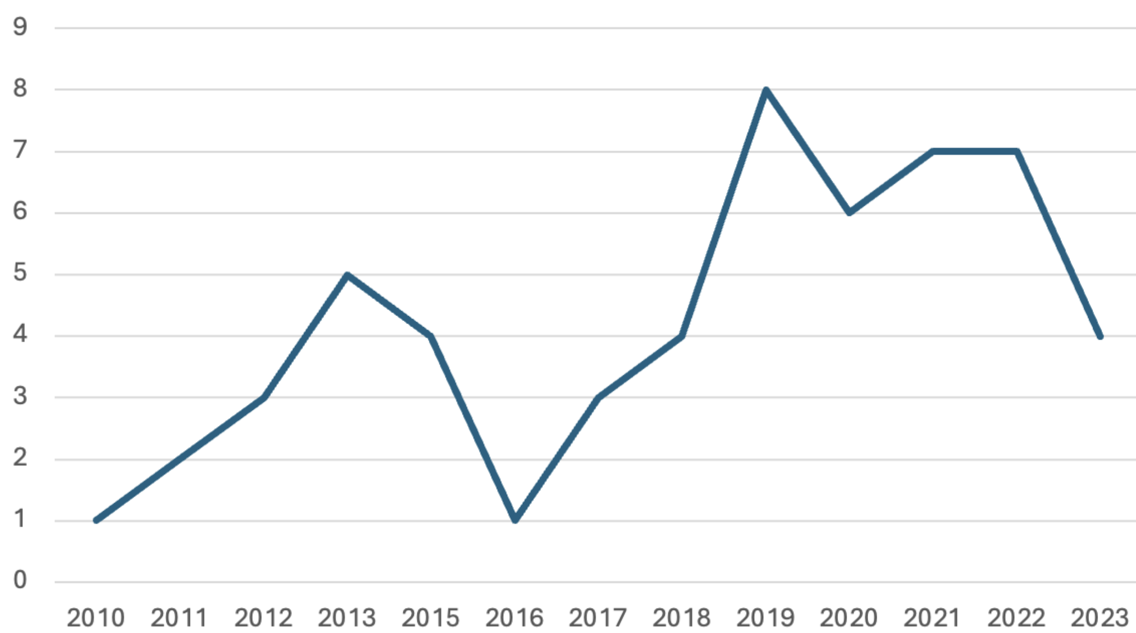


Figure 5.2 Line chart showing the frequency of the publications

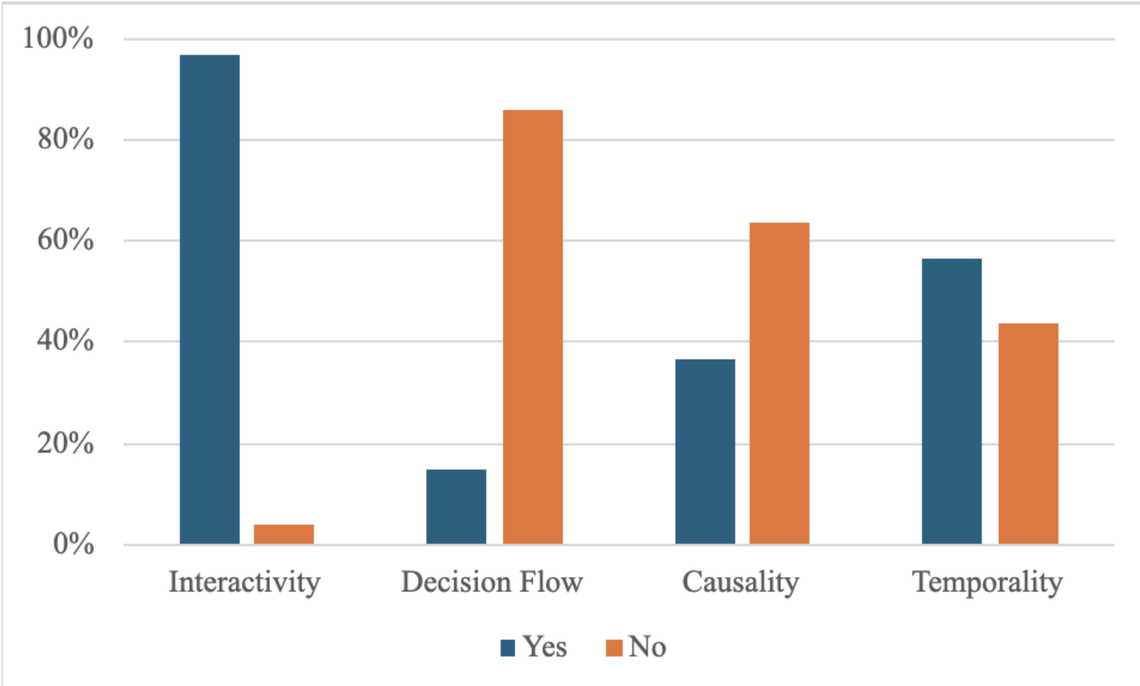


Figure 5.3 The distribution of the reviewed literature based on the four identified criteria.

From the 55 reviewed visualization tools, only four satisfied all four criteria that we were initially looking for: interactivity, decision flow, causality, and temporality. Interaction is without a doubt the most common feature among these visualization tools designed for decision making, given that only two out of the 55 did not support continuous interaction. Consideration of the temporal aspect of decisions was present in 31 of the 55 visualization tools, and although some tools' specific use-cases did not require a temporal aspect, there were some that did fail to implement it. Healthcare decision-making tools that were mainly designed for diagnostics or patient monitoring were found to be more likely to possess temporal features that allowed the user to compare current condition with historical data (Forsman et al., 2013; Hargrave et al., 2018; Mandell et al., 2022; Shee et al., 2021). 20 of the 55 visualization tools were designed to support causal reasoning, and only 8 out of the 55 considered the flow and process of decision making, going beyond the presentation and visualization of data (Barnabè, 2011; Diez et al., 2017; Elwyn & Vermunt, 2020; Hargrave et al., 2018; Hu et al., 2022; Lim et al., 2012; Srinavasan et al., 2021; van den Elzen & van Wijk, 2011). These findings further support the research gap identified earlier in the thesis. Although all of these visualization tools designed for decision making are inherently complex in one way or another, they largely fall short of addressing the perceptual and cognitive needs of decision-makers, as well as facilitating intricate and iterative process of reasoning in decision-making.

The four visualization tools that were found to address all four of these features varied in the specific visualizations they employed. For example, OpenMarkov (Diez et al., 2017) is an open-source tool that facilitates the creation and evaluation of Markov Influence Diagrams through multiple iterations and refinements. One could take inspiration from Diez and colleagues (2017) and develop a similar tool for the creation and evaluation of more structured causal diagrams for decision-making, such as Causal Loop Diagrams (CLD) and Causal Decision Diagrams (CDD). Hu and colleagues (2022) took advantage of multiple visualization methods in developing ADAM, such as decision trees and geospatial representations of data, to support supply chain optimization decisions. The authors suggest that hiding the computational features of the tool, as well as the decision trees, behind closed doors allows less-experienced users to be able to utilize the tool more effectively (Hu et al., 2022, pp. 7), and instead only present geospatial data to the users. Supporting Cognitive Fit Theory, only presenting visual aids that align with the user's task and preferences, in other words, not presenting certain elements of the visualization tool to certain users, may increase performance.

BN IGRT, developed by Hargrave et al. (2022) found Bayesian Networks, matched with medical imaging results, to be the best method of visualizing the associative and causal relationships in the vast amount of data needed to be processed in medical decision-making, Hargrave and colleagues (2022) prefer color hue as a differentiator between the nodes in the Bayesian Network visualization, as well as using color hue to encode the small bar graphs within each node. Lim and colleagues (2012) introduced a new method of visualization, which they referred to as "process visualization", in their paper discussing their novel decision-making tool, PSS Board. Although this visualization, which resembles a process map incorporated into a table with labeled columns and rows to depict stages in the process, is reported to be useful in operational management, it does not integrate data to the analyzed process and thus does not address the analytics portion of visual analytics in decision-making. This highlights the need for a visualization tool that not only supports the depiction and evaluation of the decision process, along with the essential nodes such as actions and outcomes, but also integrates quantitative data that allows either mental or computer-based simulation of potential decisions.

Chapter 6.

Guidelines for Designing Visual Decision-Support Tools

This chapter consolidates insights from earlier discussions to construct guidelines, designed to enhance the decision-making processes in sweet potato packing, and is meant to address RQ4:

What are the design opportunities (for visualization design) created by considering sensemaking and cognitive science theories?

Understanding how visualization tools can support and enhance decision-making processes in sweet potato packing operations is crucial. This chapter synthesizes concepts, insights, and findings from previous chapters to explore advanced visualization strategies that can support GA and MI by generating and evaluating decision alternatives, customizing data presentation, and integrating dual-screen visualization approaches. By focusing on improving tool functionality and design, the guidelines support operational decisions, such as maximum utility decision (Wang & Ruhe, 2008), for professionals like GA and MI.

As highlighted by Dimara et al. (2022) and Morewedge and Kahneman (2010), merely understanding data is insufficient for sound decision-making. Decision-makers engage in an evaluative step driven by reasoning, an aspect often overlooked by traditional visualization tools that focus predominantly on numeric outputs. These guidelines aim to bridge this gap, positing that visualization tools in sweet potato packing must facilitate a greater understanding of the causal relationships between potential actions and their consequences, ensuring decisions are informed by both immediate data and strategic foresight.

6.1. Dual-Screen Visualization Approach

The insight generated from this study emphasizes the significance of both causal diagrams and dashboards, serving separate yet crucial purposes. Thus, developing a dual-screen visualization approach that takes advantage of the strengths of both tools may significantly enhance decision-making support tools. Giving users the ability to switch between these two types of visualizations — one representing the decision process and its factors, and the other visualizing relative data — creates a more robust decision support tool. This dual-screen approach accommodates the user's mental decision-making process, leveraging their causal reasoning and sensemaking abilities.

The findings also highlight the need for visual tools to present these causal relationships clearly. Integrating Shneiderman's (1996) "overview first, zoom and filter, details on demand" mantra into the design can facilitate this understanding. Providing an initial overview of all fields and orders allows users to grasp the broad context of their decision-making environment. The zoom and filter capabilities enable users to focus on specific criteria such as size or order date, allowing them to delve into detailed aspects of the data that are most pertinent to their decisions. This functionality helps users identify and explore the causal relationships between different variables by focusing on specific subsets of data while maintaining an understanding of the overall context. This approach is particularly useful in complex scenarios where users need to isolate specific factors without losing sight of the overall system dynamics.

6.1.1. Causal Diagram Screen

Using causal diagrams within these guidelines allows users to visualize the pre-defined cause-and-effect relationships comprehensively. These diagrams can illustrate how changes in order sizes impact storage costs and harvesting decisions, providing a comprehensive view of the decision-making landscape. By switching to the causal diagram, users can clearly see the cause-and-effect relationships and the impact of various factors on their decisions. When users need to "zoom out," they can see the broader causal network and understand how higher-level factors interconnect, facilitating a holistic view of the system.

Elicitation of the Causal Diagram

The elicitation of these causal diagrams is crucial to their effectiveness. In both Causal Loop Diagrams (CLDs) and Causal Decision Diagrams (CDDs), the elicitation process is meticulously detailed, highlighting its significance. Typically, this involves identifying key stakeholders and conducting interviews with them either individually or in groups. These interviews are essential for stakeholders to define problems, identify and evaluate potential solutions, and pinpoint critical internal and external factors. Through these discussions, stakeholders can decide on individual nodes of the causal diagram. This diagram serves as a visual representation of the decision process and its influencing factors, providing a valuable reference for decision-makers when exploring scenarios through the data visualization dashboard.

The elicitation process not only helps in gathering comprehensive insights but also fosters collaboration among stakeholders. By engaging stakeholders in the development of the causal diagram, the process ensures that all relevant perspectives are considered, and the resulting diagram accurately reflects the complexities of the decision environment. This collaborative approach is vital for creating a decision support tool that is both accurate and widely accepted by its users. The causal diagram thus becomes a central component of the decision support system, capturing the relationships between different factors and guiding decision-makers as they navigate through various scenarios.

Example of Implementation

Figure 2.4 presents the decision objective described in the case study, in the structure of a Causal Decision Diagram. The two action items represent the choices GA and MI have, consisting of either selecting a field for harvesting or directly allocating potatoes from cold storage to fulfill incoming orders. Their goal is to maximize the profit generated from their operations, which is typically an equation of maximizing the revenue generated through fulfilling as many orders, as accurately as possible, as well as minimizing the costs incurred from the use of cold storage. Intermediates represent intermediary processes and variables in this decision, which GA and MI have some control over, whereas Externals represent external factors over which GA and MI have no say.

Lines connecting each node to another related node represent dependencies and directionality in the process. Once a decision is presented to the decision-maker in a structured diagram that is aligned with their mental decision model, it may allow the decision-maker to offload some of the information from their Working Memory Capacity, potentially resulting in more capacity to be allocated to reasoning tasks.

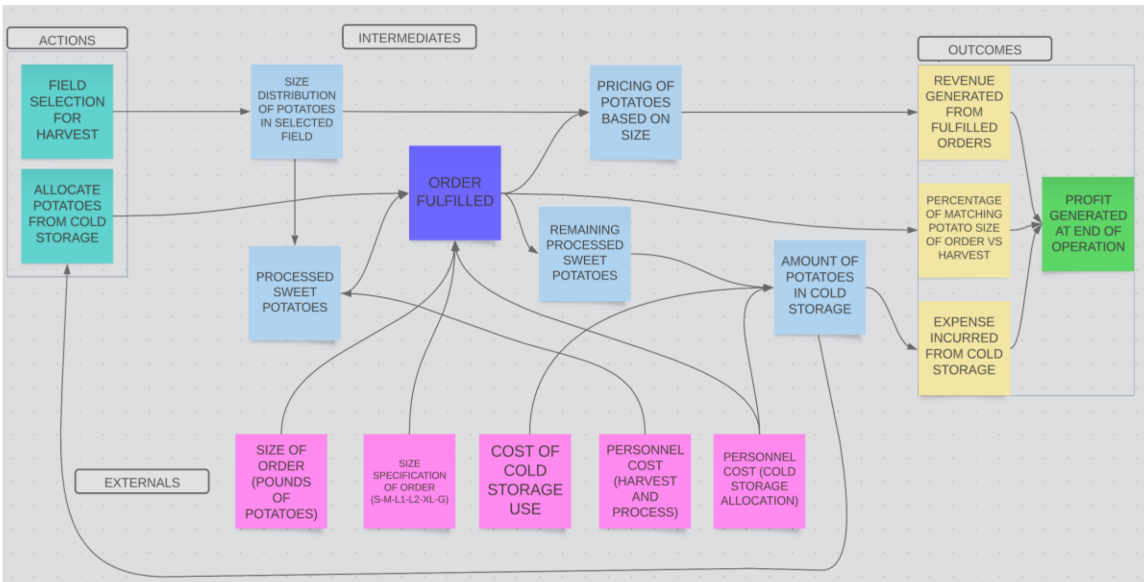


Figure 6.1 Causal Decision Diagram of the decision presented in the Case Study

6.1.2. Data Visualization Dashboard Screen

Meanwhile, the data visualization dashboard supports the information foraging process, where users iteratively seek and use information to make well-informed decisions. The dashboard provides detailed quantitative insights, allowing users to drill down into specific data points when needed, as well as perform detailed analyses that inform specific decision points. This combination ensures that users have a comprehensive understanding of both the broader context and the finer details of their decisions.

This layered approach supports both high-level overviews and detailed examinations, enhancing users' ability to analyze and understand complex causal relationships within their decision-making processes. By integrating these visual tools, users can shift seamlessly between different levels of detail, ensuring that they can both identify key causal factors and understand their broader implications. This dual capability is essential for making informed, strategic decisions in dynamic and multifaceted environments such as sweet potato packing.

6.2. Scenario Exploration Support

6.2.1. Generation of Alternatives

The findings of this study also highlight the importance of generating a range of feasible alternatives to support effective decision-making. When it comes to rapid decisions, humans tend to employ what Kahneman (2003a, 2003b) refers to as System 1 thinking, which does not support conscious generation and evaluation of alternatives. However, decisions that have potentially costly consequences require deliberate analysis and the identification of possible alternative action items, through causal reasoning.

Visualization tools can facilitate this process by presenting data in ways that highlight possible courses of action, symbolizing cause-and-effect relationships and aligning with principles discussed in Cognitive Fit Theory (Vessey & Galletta, 1991). Interactive dashboards with capabilities for multiple what-if scenario simulations can be particularly useful. For example, tools that simulate the consequences of harvesting a new field to fulfill an order based on actual or predicted incoming orders may provide immediate visual feedback. This approach allows GA and MI to explore various operational scenarios, visually presenting the potential outcomes of different decisions.

The findings also emphasize the importance of keeping track of these generated alternatives and presenting them back to the user in an easily interpretable manner. Visualization tools should support iterative exploration by organizing and displaying the explored scenarios without adding cognitive load. This can be achieved by categorizing scenarios based on key metrics and outcomes, using visual elements such as color-coded bars or line graphs to differentiate between various options. By maintaining a clear and accessible record of all considered alternatives, users can quickly compare and contrast different strategies, enhancing their ability to make informed decisions. This aligns with insights from information foraging theory (Pirolli & Card, 1995, 1999, 2005), emphasizing the importance of iterative exploration and structuring information in an easily navigable manner to facilitate the iterative exploration.

6.2.2. Evaluation of Alternatives

Once alternative viable decision paths have been identified, the decision-maker must compare and analyze them. Evaluating generated alternatives based on various criteria is essential for effective decision-making. Visualization tools can support this evaluation process by providing clear and detailed insights into the implications of each alternative. For instance, users can benefit from features that track explored scenarios and allow for side-by-side comparisons. Comparing projected revenue and costs of various decision paths, considering factors like storage costs incurred at the end of the day and shipping timelines, provides a comprehensive view of the trade-offs involved.

The research highlights the need for effectively monitoring and presenting various alternatives to users in a comprehensible format. It is crucial for visualization tools to support repeated exploration by systematically arranging and showcasing the scenarios that have been examined. Enabling users to save and retrieve different scenarios allows for continuous refinement of strategies. This feature not only supports the iterative nature of decision-making but also aids in documenting the decision-making process, providing a valuable reference for future decisions.

Furthermore, providing users the flexibility to select which metrics they will compare across different scenarios is crucial. This customization ensures that the decision-making process aligns with the specific priorities and goals of the user. For instance, one user might prioritize minimizing costs, while another might focus on maximizing revenue or reducing storage time. Allowing users to hierarchically order alternative decision paths based on selected metrics can further streamline the evaluation process. By ranking options according to the most critical factors, users can quickly identify the most promising strategies and make well-informed choices.

At this stage, decision-makers begin to develop a clearer understanding of which alternatives are more favorable. The evaluation process is critical as it ultimately determines which decision will be selected and implemented. Visualization tools play a pivotal role by providing a comprehensive view of the potential outcomes, enabling decision-makers to compare alternatives based on key metrics. This thorough evaluation helps ensure that the chosen decision aligns with strategic goals and operational constraints, leading to more effective and informed decision-making.

6.2.3. Implementation

Enabling users to save and compare different scenarios allows for a deeper analysis of potential outcomes. By implementing a history panel, users can review key metrics for each scenario side by side. Implementing this feature involves creating a user interface that supports the storage of various scenarios, allowing users to revisit and compare them easily. This history panel can be designed to display key metrics such as projected revenue, costs, and resource utilization for each saved scenario. Users can interact with these metrics, adjusting variables as needed and observing the changes in real-time.

Real-Time Variable Input

Real-time variable input can be effectively implemented through the use of interactive elements such as drag and drop. For instance, users could have the ability to drop draggable box-like assets that represent orders of varying sizes onto input fields, which would immediately show the remaining sweet potatoes that need to be sent to storage. Stacked horizontal bar charts could be used to represent the distribution of sweet potatoes in inventory, and additional charts representing the remaining sweet potatoes after an order is fulfilled could be generated, providing the user an idea of the inventory that must be sent to cold storage, or sent out in a following order on the same day.

As users modify these inputs, the system should provide immediate visual feedback, updating graphs, charts, or other visual representations to reflect the changes. Immediate visual feedback aids understanding and reduces cognitive load by making the consequences of each action clear and easy to comprehend. This dynamic interaction ensures that users can see the direct impact of their adjustments, facilitating a deeper understanding of how each variable influences the overall decision-making process.

Automated Financial Simulations

To quickly calculate and visualize the real-time variable changes during scenario exploration, models can be developed to calculate potential revenue and costs based on user inputs. In the context of sweet potato packing, users need to decide whether to harvest a new field to fulfill an order or utilize sweet potatoes from cold storage. Harvesting a new field may incur cold storage costs later on, while using stored sweet potatoes may mean sending higher quality sweet potatoes to fulfill an order for a lower quality. For example, when GA or MI input data about incoming orders or decide to allocate sweet potatoes from either new fields or cold storage, the system can immediately update and display the associated revenue and end-of-day cold storage costs. This feature is crucial for highlighting the financial trade-offs between different operational strategies.

Temporal Aspect

Incorporating a temporal aspect into decision-support tools is also essential for providing a complete understanding of the decision-making landscape. Time-related data features help decision-makers visualize the impact of their actions over time. To implement this feature, the visualization tool can include a "date line" that remains fixed, while time progresses toward it. As orders are fulfilled and time passes, the current date moves closer to the "date line," visually indicating when sweet potatoes need to be moved to cold storage. This line can be color-coded to represent different stages, such as a red line for when sweet potatoes exceed the optimal period, incurring cold storage costs. Such visual cues help users quickly understand the temporal implications of their decisions.

For GA and MI, understanding the temporal aspect is crucial. If they cannot ship sweet potatoes on the same day they are processed, these potatoes must go into cold storage, incurring daily costs. By incorporating a "date line," the tool can show how approaching this line leads to increased storage costs, enabling GA and MI to make more timely decisions. They can simulate various scenarios, such as delaying an order or prioritizing certain shipments, and immediately see the financial implications of these choices. This approach helps in reducing cognitive load by making the temporal aspects of decisions explicit, allowing for more strategic planning and efficient resource management.

In the context of GA and MI, the scenario exploration feature would be particularly valuable. By saving and comparing scenarios, they can assess which option is more cost-effective and aligns better with their operational goals. This approach not only enhances decision-making accuracy but also provides a clear record of considered alternatives, supporting informed and strategic planning.

User-Specific Customizability

The findings of this study also underscore the necessity of user-specific customizability of visualization tools. The effectiveness of visualization tools in supporting decision-making processes can be significantly enhanced by tailoring them to the specific needs and preferences of different users. By offering customizable options, these tools can cater to various levels of expertise and task requirements, ensuring that each user can effectively engage with and utilize the information presented.

For example, GA and MI have different backgrounds; GA has a more robust understanding of business terms and processes. Tools that can layer historical sales data, current market trends, and predictive analytics would potentially enable GA to make informed decisions about when to release potatoes from storage to meet market demand effectively. GA might prefer a detailed, data-rich interface with multiple filters and utilize the causal diagram that depicts the decision process. For GA, features could include advanced filters, customizable color schemes, and high data granularity. These tools can enable GA to perform in-depth analyses, identify trends, and make strategic decisions based on comprehensive data insights. Annotation tools can further aid in documenting insights and sharing them with the team.

On the other hand, MI is a more practice-driven, old-school farmer and packer, and might benefit from a simpler, clearer layout that simulates his potential decisions. Interfaces designed for MI should emphasize clarity, perhaps through dashboards that highlight key operational metrics such as current stock levels, upcoming orders, and storage conditions. These interfaces would enable MI to make quick, rapid decisions based on clear, visual cues that reduce cognitive load while still allowing access to more detailed data if needed. Options could include customizable color schemes and annotation features, ensuring that the tool is accessible and useful to all users, regardless of their background or expertise. Simplified visualizations with clear, bold graphics and minimal text can help MI quickly grasp essential information without feeling overwhelmed. Features like customizable color schemes can also help MI differentiate between key variables, enhancing their understanding and engagement with the data.

6.3. Incorporating Toulmin’s Model of Argumentation

In organizations, particularly for management, it is crucial that decisions are presented logically and transparently. Toulmin's model facilitates this by ensuring that each part of the decision-making process is documented and logically connected. This model, which emphasizes logical structuring and evidence-based reasoning, ensures that decisions are well-supported and clearly communicated. For senior management, this method provides a clear, detailed rationale for each decision, supporting better understanding, adoption, and implementation across the organization.

Incorporating Toulmin's model of argumentation within the decision-making framework provides a robust structure for documenting and reporting decisions. This structure makes it easier to review decisions and as it organizes complex decisions into distinct, manageable parts. This methodical breakdown ensures that each aspect of the decision is explicitly stated and supported by relevant evidence and reasoning. As a result, the decision's logic is clear and transparent. This clarity is crucial in ensuring that all team members and senior management are on the same page regarding the rationale behind a decision, which enhances communication and reduces misunderstandings.

Toulmin's model incorporates six key components: Claim, Data, Warrant, Backing, Qualifier, and Rebuttal. By structuring decisions using these components, the clarity and trackability of decision-making processes are significantly enhanced. For instance, the provided figure illustrates a structured argument for designing visualization tools to support causal reasoning and sensemaking in decision-making (Figure 6.1).

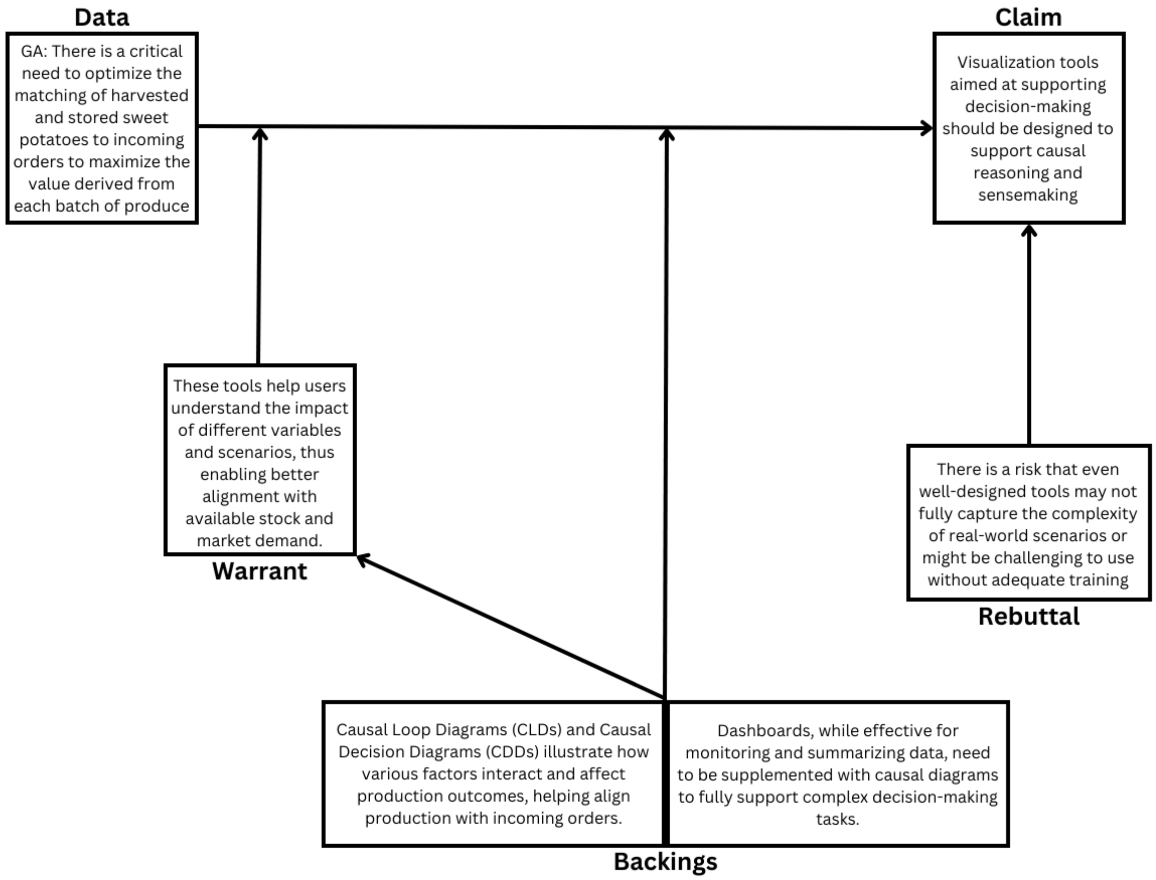


Figure 6.2 The claim – or decision – that visualization tools should be designed to support causal reasoning and sensemaking, presented in the structure of Toulmin's Model of Argumentation.

Trackability is another major benefit of using Toulmin's model. By documenting each component of the decision-making process, it becomes straightforward to trace how a decision was reached and to review the supporting evidence and reasoning. This documentation provides a clear audit trail that can be invaluable for future reference, evaluation, and learning. For example, if a decision's outcomes need to be reviewed, the organization can look back at the specific data and warrants that led to the initial decision, assessing whether the reasoning was sound or if different data might lead to a better outcome in the future.

Furthermore, Toulmin's model helps in systematically addressing potential challenges and counterarguments, which enhances the robustness of the decision-making process. By explicitly considering and documenting rebuttals, decision-makers can anticipate objections and plan for them, which strengthens the overall decision.

6.3.1. Implementation

Implementing Toulmin's model in a visualization tool designed to support decision-making can be achieved by integrating features that systematically guide users through each component of the model. The tool could include a structured interface where users input the Claim, Data, Warrant, Backing, Qualifier, and Rebuttal for each decision. For example, when entering data, users can attach relevant evidence and supporting documents directly into the tool, ensuring that all supporting data is easily accessible and visually connected to the claim. Interactive elements such as drag-and-drop functionality for data and automated prompts for warrants and backings can help users logically connect their evidence to their claims, reinforcing the decision's rationale.

Furthermore, the visualization tool can enhance clarity and communication by generating visual summaries and reports based on the Toulmin structure. For instance, the tool could automatically create flowcharts or mind maps that illustrate the logical flow from data to claim, making it easier for senior management to review and understand the decision-making process. These visual summaries can highlight key points and potential rebuttals, providing a comprehensive overview that facilitates thorough evaluation and feedback. By incorporating these features, the tool ensures that all decisions are systematically documented and visually communicated, enhancing transparency and accountability in the decision-making process.

Incorporating Toulmin's model in structuring decisions fosters a disciplined, transparent, and accountable decision-making process. By ensuring that all essential components are considered and documented, this model facilitates clearer communication, easier review, and effective learning. It provides systematic structuring, thorough documentation, and transparent communication, which improves senior management's ability to review, understand, and endorse decisions. Ultimately, this leads to better-supported decisions and a more resilient decision-making process. By embedding

Toulmin's model into their practices, organizations can achieve greater consistency, accountability, and effectiveness in decision-making.

In summary, the integration of advanced visualization strategies can significantly enhance decision-making processes in sweet potato packing operations. By implementing a dual-screen visualization approach, generating and evaluating alternatives, and utilizing Toulmin's Model of Argumentation to document decisions, these tools can support GA and MI in making informed and efficient decisions.

Chapter 7.

Conclusion

This thesis has provided a comprehensive analysis of how visualization tools can assist decision-making processes, specifically within the context of a sweet potato packing operation. By integrating cognitive science theories and evaluating existing visualization tools, this research addresses the critical need for comprehensive tools that facilitate every stage of the decision-making process, ensuring a coherent flow and enhancing causal reasoning.

7.1. Discussion and Contributions

Three literature reviews were conducted to scope the cognitive science theories and the typically used visualization tools for decision-making, as well as recently published visualization tools designed to support decision-making. The insight generated from the reviewed literature overwhelmingly suggests the lack of tools that support all stages of decision making, guiding the decision-maker through the process in a flow, assisting causal reasoning.

A key contribution of the guidelines discussed in this thesis is development of a dual-screen visualization tool. This suggestion incorporates both qualitative and quantitative elements to support effective decision-making. It allows users to visualize the entire decision process, manipulate variables, and simulate various scenarios, providing immediate feedback on potential outcomes.

The research also proposes the use of Toulmin's model of argumentation to structure and report decisions. This model offers a clear and logical framework that enhances the transparency and trackability of decision-making processes. By breaking down decisions into components such as claims, data, warrants, backings, qualifiers, and rebuttals, Toulmin's model ensures that each part of the decision is well-supported and logically connected. This structured approach facilitates thorough reviews and effective communication of decisions to senior management.

The study also underlines the importance of integrating temporal aspects into decision-making tools. The inclusion of features such as a "date line" to track cold storage costs helps decision-makers understand the time-sensitive nature of their decisions and manage their resources more efficiently. This approach aligns with the findings that highlight the need for tools that can handle the dynamic and sequential nature of decision-making in agricultural operations.

Moreover, this thesis emphasizes the importance of customizable and user-centered interfaces that cater to users with varying levels of expertise and preferences. Customizable features ensure that the tool is accessible and useful to all users, regardless of their expertise. This adaptability is crucial in ensuring that the tool is not underutilized due to a mismatch with user needs and expectations.

In conclusion, this thesis contributes to the field by providing comprehensive reviews and guidelines for designing visual decision-support tools that are based on cognitive theories and frameworks, addressing existing gaps in decision-support tools and lays the groundwork for future research and development. The implications of this research extend beyond the sweet potato packing industry. The principles and guidelines developed in this study can be applied to various organizational contexts, where decision-making involves complex, dynamic, and time-sensitive variables.

7.2. Limitations and Future Work

The use of visualizations in decision making is at times a double-edged sword. Although charts or visualizations have been used to facilitate sensemaking and reasoning in the context of decision making, they may also misguide users if not designed properly or appropriately (Cairo, 2019). For example, misrepresenting the sizes of symbols that depict quantitative variables (Cairo, 2019, pp. 53-59) or ineffectively visualizing uncertain or missing information (Cairo, 2019, pp. 135-142), may result in misinterpretation of the variables' impact. Charts may also suggest misleading patterns, and thus, a thorough simulation of how the user is expected to interact with the visualization (Cairo, 2019, pp. 153-169). Thus, if visualizations are not designed with these potential issues in mind, they may cause more harm than good in decision-making.

7.2.1. Limitations of the Guidelines

One significant limitation of this study is that the proposed guidelines has not undergone empirical testing. To address this, future research should begin by developing comprehensive evaluation criteria that can accurately measure the effectiveness of the suggestions. Additionally, it is crucial to establish a baseline for a control group, which will serve as a benchmark for comparison. This comparison will enable researchers to assess the impact of the suggestions more precisely. Conducting such comparative analysis is essential for validating the guidelines' utility and identifying areas where it can be further refined and improved. This rigorous approach will ensure that the suggestions are robust, practical, and capable of enhancing decision-making processes in real-world settings.

One of the pillars of the presented guidelines is customizability of the interface and contents on the visualization tool's screen. Given the differences in their backgrounds, it is proposed that the same decision can be presented differently to GA and MI, depending on user background, goals, and preferences. However, such customizations typically occur in the design stages, thus it is not always possible for designers to accommodate each and every user. This presents a possible technological limitation to the suggested guidelines. Future studies could attempt to this through machine learning to better understand user preferences and change the interface accordingly, on the go.

Other limitations may arise from the subjective nature of the human mind. For example, biases, namely Confirmation Bias (Pirolli & Card, 2005), may eliminate any value gained from a decision support tool if the outcome is inaccurate or leads to unintended consequences. Furthermore, decision making processes are often impacted by the mental state of the decision maker, such as stress (Giovanniello et al, 2023; Heereman & Walla, 2011) and motivation (Eisbach et al, 2023). This is important because the effectiveness of the visualizations designed with these guidelines in mind, is inherently dependent on individual factors. Future work could attempt to address this issue by developing frameworks on how to diagnose and address such individual factors.

Finally, the findings also emphasize the importance of iterative user testing to refine these interfaces. Incorporating feedback loops to continuously improve the user interface ensures that the visualization tools remain relevant and effective over time. Conducting user testing with GA and MI to simplify navigation, improve data readability, and ensure critical functions are easily accessible may significantly enhance the user experience. Another method of refining the visualization tool based on user background and preferences could be carried out in real-time, utilizing Large Language Models (LLMs) Machine Learning (ML). In this example, users could train the model through supervised learning, providing feedback through a LLM chatbot, which later could be switched to an unsupervised learning model, depending on whether the desired accuracy is achieved. Future studies could look to develop this feature, potentially eliminating the need for constant user feedback.

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Appendix. Results of the Systematic Literature Review

#	Tool Name	Industry	Authors	Year	Journal/Venue	Database	Interactivity	Decision Flow	Data Viz	Causality	Temporal
1	CloViz-IMDC	healthcare	Shee et al.	2021	JCO Clin Cancer Inform	PubMed	yes	no	parallel coordinate plots	no	yes
2	Sys Viz Tool	healthcare	Mandell et al.	2022	Annu IEEE Syst Conf	PubMed	yes	no	scatter plot	no	yes
3	ClinicalPath	healthcare	Linhares et al.	2023	IEEE Trans on Vis and CG	PubMed	yes	no	line charts	no	yes
4	EHR Viz Tool	healthcare	Cohen et al	2022	Annals of Family Medicine	PubMed	no	no	line charts	no	yes
5	Goal Board	healthcare	Elwyn et al.	2019	Journal of Patient Experience	PubMed	yes	yes	diagram	yes	no
6	BN IGRT	healthcare	Hargrave et al.	2018	Int J Med Phy Res and Practice	PubMed	yes	yes	bayesian network	yes	yes
7	Forsman et al	healthcare	Forsman et al.	2013	Inform Health Soc Care	PubMed	yes	no	line charts	no	yes
8	ImputEHR	healthcare	Zhou & Saghapour	2021	Frontiers in Genetics	PubMed	yes	no	scatter plot	no	no
9	Origami plot	healthcare	Duan et al.	2023	Journal of Clinical Epidemiology	PubMed	yes	no	radar chart	no	no
10	ISOFAST	agriculture	Laurent et al.	2020	Research Synthesis Methods	PubMed	yes	no	multiple (scatter, line)	yes	yes
11	SPHERE	healthcare	Foraker et al.	2015	eGEMS	PubMed	yes	no	bar chart	no	yes
12	Sibyl	healthcare	Zytek et al.	2021	IEEE Trans on Vis and CG	PubMed	yes	no	multiple (scatter, line)	no	no
13	Leskens et al	city planning	Leskens et al.	2017	Mitigation Adaptation Str Glob Change	PubMed	yes	no	3d simulation	yes	yes

#	Tool Name	Industry	Authors	Year	Journal/Venue	Database	Interactivity	Decision Flow	Data Viz	Causality	Temporal
14	Pedimap	agriculture	Rathnayake et al.	2020	Scientific Reports	PubMed	yes	no	multiple (scatter, line)	no	yes
15	ToxPi	bioinformatics	Reif et al.	2013	Bioinformatics	PubMed	yes	no	multiple (scatter, line)	no	no
16	MER visualization	healthcare	Waschk et al.	2021	Annu Int Conf IEEE Eng Med Biol Soc	PubMed	yes	no	spectogram	no	yes
17	Causality Explorer	general	Xie et al.	2021	IEEE Trans on Vis and CG	PubMed	yes	no	bar chart	yes	yes
18	Janssen et al.	healthcare	Janssen et al.	2020	Journal of Medical Internet Research	PubMed	yes	no	bar chart	no	no
19	Knowledge Plot	healthcare	Brynne et al.	2013	Journal of Translational Medicine	PubMed	yes	no	multiple (scatter, line)	yes	no
20	DCPairs	general	Dimara et al.	2017b	EuroVis	GoogleS	yes	no	pairs plot	no	no
21	WeightLifter	general	Pajer et al.	2016	IEEE Trans on Vis and CG	GoogleS	yes	no	multiple (specto, line, bar)	yes	no
22	Outcome-Explorer	general	Hoque & Mueller	2021	IEEE Trans on Vis and CG	GoogleS	yes	no	multiple (scatter, line)	yes	yes
23	Kokciyan et al.	healthcare	Kokciyan et al.	2019	Studies in Health Technology and Informatics	GoogleS	yes	no	multiple (scatter, line)	no	no
24	BaobabView	general	van den Elzen & van Wijk	2011	IEEE Conference on VAST	GoogleS	yes	yes	decision tree	yes	no
25	OpenMarkov	healthcare	Diez et al.	2017	Medical Decision Making	GoogleS	yes	yes	influence diagram	yes	yes

#	Tool Name	Industry	Authors	Year	Journal/Venue	Database	Interactivity	Decision Flow	Data Viz	Causality	Temporal
26	SD-based BSC	general	Barnabè	2011	International Journal of Productivity and Performance Management	GoogleS	yes	yes	causal loop diagram	yes	no
27	DataBreeze	general	Srinavasan et al	2021	IEEE Trans on Vis and CG	GoogleS	yes	yes	multiple (scatter, line, custom)	no	no
28	Nexus_SDM	agriculture	Laspiodu et al	2020	Science of the Total Environment	SD	yes	no	sankey, chord	no	yes
29	Pi-VAT	agriculture	Deval et al	2022	Journal of Hydology	SD	yes	no	multiple (line, bar, custom)	no	yes
30	MED-GOLD	agriculture	Terrado et al	2023	Climate Services	SD	yes	no	dashboard (with map)	no	yes
31	Parasol	environmental	Raseman et al	2019	Environmental Modelling & Software	SD	yes	no	parallel coordinate plots	no	no
32	SOMERSET-P	environmental	Guay & Waub	2019	EURO Journal on Decision Processes	SD	yes	no	GAIA plot	yes	no
33	LandCaRe DSS	agriculture	Wenkel et al	2013	Journal of Environmental Management	SD	yes	no	line charts	no	yes
34	Casteletti et al	agriculture	Casteletti et al	2010	Environmental Modelling & Software	SD	no	no	decision map	no	yes
35	Kadiyala et al	agriculture	Kadiyala et al	2015	Science of the Total Environment	SD	yes	no	multiple (line, bar, geospatial)	no	yes
36	mySense	agriculture	Morais et al	2019	Computers and Electronics in Agriculture	SD	yes	no	line charts	no	yes
37	ITALLIC	agriculture	Onsongo et al	2022	Computers and Electronics in Agriculture	SD	yes	no	geospatial	no	yes

#	Tool Name	Industry	Authors	Year	Journal/Venue	Database	Interactivity	Decision Flow	Data Viz	Causality	Temporal
38	ESP-VT	environmental	Drakou et al	2015	Ecosystem Services	SD	yes	no	geospatial	no	yes
39	Hydrographs	environmental	Cole et al	2023	Computers and Chemical Engineering	SD	yes	no	geospatial	yes	no
40	ESPRES	environmental	Udias et al	2020	Science of the Total Environment	SD	yes	no	multiple (scatter, bar, geospatial)	yes	no
41	ADAM	supply chain	Hu et al	2022	Computers and Chemical Engineering	SD	yes	yes	multiple (decision tree, geospatial)	yes	yes
42	rivervis	environmental	Mao et al	2019	Computers and Geosciences	SD	yes	no	multiple (matrix and bar)	no	no
43	Crop Monitor	agriculture	Becker-Reshef et al	2019	Global Food Security	SD	yes	no	multiple (geospatial and pie)	no	no
44	CropPhenology	agriculture	Araya et al	2018	Ecological Informatics	SD	yes	no	geospatial	no	yes
45	GeospatialVR	environmental	Sermet & Demir	2022	Computers and Geosciences	SD	yes	no	geospatial	yes	yes
46	SMETool	agriculture	Jarray et al	2022	Environmental Modelling & Software	SD	yes	no	multiple (line and geospatial)	no	yes
47	GVS	environmental	Cox et al	2013	Journal of Hydology	SD	yes	no	multiple (line and geospatial)	no	yes
48	Knotted-line	transportation	Zhao et al	2019	Journal of Computer Languages	SD	yes	no	"knotted-line"	no	yes
49	Lin et al	environmental	Lin et al	2015	Environmental Modelling & Software	SD	yes	no	multiple (geospatial and pie)	no	yes
50	PSS Board	operations	Lim et al	2012	Journal of Cleaner Production	SD	yes	yes	"process visualization" (table)	yes	yes

#	Tool Name	Industry	Authors	Year	Journal/Venue	Database	Interactivity	Decision Flow	Data Viz	Causality	Temporal
51	Zhang et al	emergency mgmt	Zhang et al	2019	International Journal of Digital Earth	GoogleS	yes	no	geospatial	yes	no
52	FarmDESIGN	agriculture	Groot et al	2012	Agricultural Systems	GoogleS	yes	no	influence diagram	yes	no
53	GeoVis	public health	Joshi et al	2012	Technology and Health Care	GoogleS	yes	no	geospatial	no	no
54	PaletteViz	general	Talukder & Deb	2020	IEEE Computational Intelligence Magazine	GoogleS	yes	no	3D scatter plots	yes	no
55	moGrams	general	Trawinski et al	2018	IEEE Transactions on Cybernetics	GoogleS	yes	no	decision tree	no	no