CausViz: Visual Representations of Complex Causal Semantics Based on Theories of Perception

by

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A Thesis submitted to the Faculty of Graduate Studies of

The University of Manitoba

in partial fulfilment of the requirements of the degree of

DOCTOR OF PHILOSOPHY

Department of Computer Science

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Abstract

Michotte's theory of ampliation suggests that causal relationships are perceived by objects animated under appropriate spatiotemporal conditions. In this thesis I extend the theory of ampliation and propose that the immediate perception of complex causal relations is also dependent upon a set of structural and temporal rules. The thesis aims at achieving two main goals. The first goal is to define a taxonomy of semantics that describe different causal events in the environment. Ten semantics are defined in this thesis and divided into two main groups; simple causal semantics and complex causal semantics. Simple causal semantics describe basic semantics, which form the building blocks for more complex information and include causal amplification, causal dampening, causal strength, and causal multiplicity. Complex causal semantics are built by enhancing or combining one or more simple semantics and include additive causality, contradictive causality, fully-mediated causality, partially-mediated causality, threshold causality, and bidirectional causality. The second goal of this thesis is to design simple visual representations to describe the causal information. Three representation types were designed during the course of this research; static-graph, static-sequence, and animation. Nine experiments were also conducted to test the effectiveness of these representations. The first five experiments compared the static-graph and the animated representations through Memory Recall and Intuitiveness Evaluations tests. Results of these experiments suggest that animations were ~8% more accurate and performed ~9% faster than the static-graph representations. The last four experiments compared an enhanced static representation, called static-sequence, to the animations to test if sequential animation of causal relations had any influence on the superior performance of the animations in the previous experiments. Results of these experiments suggest that there was no significant difference in the performance of the static-sequence representations when compared to the static-graph representations. The results also suggest that the animations performed more accurately than their static counterparts mainly due to their intuitiveness. Overall our results show that animated diagrams that are designed based on perceptual rules such as those proposed by Michotte have the potential to facilitate comprehension of complex causal relations.

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Acknowledgments

I would first like to thank my advisor Dr. Pourang Irani, for his support, motivation, and guidance. I also thank Dr. Jason Leboe, my external committee member, and his students for providing me with invaluable help, advice, resources, and the use of his labs during my research. My internal committee members, Dr. Neil Arnason and Dr. David Scuse, have been extremely patient, understanding, and I am really grateful for their advice and critique. In all, my committee members have always been available to help me out and have provided tremendous support throughout my research. Thank you very much.

Several members of the department have been part of my support framework and without their help I would not have been able to complete my PhD goals. Firstly, I would like to thank our Administrative Assistant, Lynne Hermiston, who has always been helpful and has made time for me in her busy schedule. I would also like to thank the department's Systems Administrators Jeff Durston and Ken Drewniak, and my colleague, Erum Tanvir for helping me in conducting my experiments. In addition, I would like to thank the Department of Computer Science and the Department of Psychology for giving me access to a system where I could recruit participants for my research. I also thank NSERC and the University of Manitoba for awarding me with a fellowship and the UMGF grant, and various associations of the university for their travel grants and financial assistance towards this research.

No project is successful without the support of family and close friends. I thank my parents, Ramchand and Brinda Kadaba, my family, my husband's family, and the rest of my extended family and friends, here in Canada, and back home in India, for their love, support, and faith in me. Last, but certainly not the least, I thank my husband Parthiban Muthukumarasamy, for his encouragement, advice, and for always believing in me. Thank you all.

This thesis is dedicated to my grandparents and my father-in-law

Chapter 1

Introduction

Causal relations are deeply rooted in human reasoning and appear in many contexts. Cause-and-effect relationships are used for explaining natural phenomena (the iron will become red under the influence of fire), for describing common events (flipping the switch will turn on the lights), and for specifying and resolving research questions (do horror movies lead to aggressive behavior?). In most cases such relationships are intermeshed in the collection of information and data available to the user. To better comprehend cause-and-effect relationships, many visual representations, typically in the form of diagrams, have been developed and are being used extensively.

Causal graphs constitute the most common representation of cause-and-effect relationships. These are directed acyclic graphs, in which vertices denote variable features of a phenomenon and edges denote a direct causal claim between these features (Figure 1.1). These graphs have appeared in many forms: Feynman diagrams in physics [Veltman, 2001], Lombardi diagrams to explain secret deals and suspect relations [Lombardi et al., 2003], flowcharts to describe process flows within a system, and influence diagrams to represent the essential elements of a decision problem such as decisions, uncertainties, and objectives, and how they influence each other [Tweedie et al., 1995]. In all these variations, the causal graphs replace long verbose descriptions or complex mathematical formulations that describe events with their causes and effects.

Although node-link causal graphs provide information about cause-and-effect, in certain cases it can be very difficult to make credible causal inferences from linking lines and arrows [Zapata-Rivera et al., 1999]. They may produce many implicit and powerful assumptions, but they cannot convey the entire structure of the information to find out what is actually going on. In some instances, it is essential that the meaning or the semantic of the causal relationship be clearly revealed. For example, car manufacturers could understand better the quality of the tires being produced if a causal graph indicated that glass had a stronger influence than thorns in causing a flat tire; or that a flat tire has a larger impact on steering problems than it does on noise (Figure 1.1).

What seems to be lacking in the traditional forms of graphs is the capacity to convey different types of complex causal relations or semantics. Very little knowledge exists for properly visualizing complex causal relationships. Therefore the central question I address in my research is, "How do we make causal graphs more informative and carry precise meanings?" In an effort to answer this question, my research is divided into four components:

- **Component I (Creating a taxonomy of causal relations):** In the first

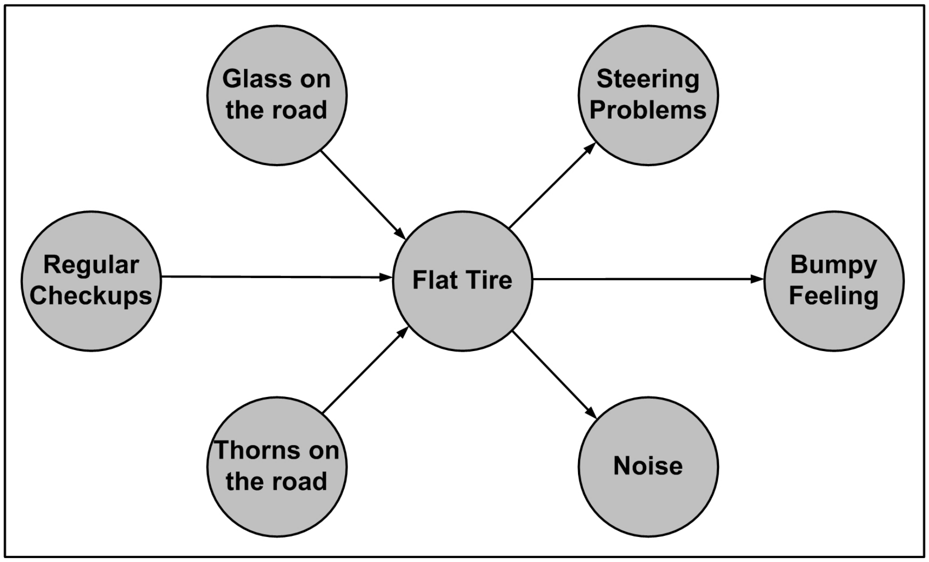

Figure 1.1: Causal graph describing causes and effects of a flat tire. Note that it is unclear whether there is positive or negative correlation between the influences and the target (flat tire), and also whether an influence is stronger or weaker than another.

component of my research, I have characterized causal semantics that exist with various types of data based on their occurrence, such as causes, effects, types of effect, and existence of mediators. These include semantics that are simple (such as causal amplification, causal dampening, causal strength, and causal multiplicity) and complex (such as additive causality, contradictive causality, fully-mediated causality, partially-mediated causality, threshold causality, and bidirectional causality).

- **Component II (Representing simple causal semantics):** In the second component of my research, I have conducted experiments to determine if there was any improvement in comprehension when causal relations were represented using static-graph images or animations based on theories of perception. In this component, I have analyzed the simple semantics I defined in Component I.

- **Component III (Representing and evaluating complex causal semantics):** In the third component of my research, I have conducted experiments, similar to those in Component II, to analyze the effect of static-graph and animations on the complex causal semantics defined in Component I.

- **Component IV (Comparing static-graph to static-sequence representations of causal semantics):** One of the main differences between the static-graph and animated representations tested in Components I and II was the method of representing the relations. The static-graph displayed all the causal relations in a scenario simultaneously, while in the animated representations, causal relations were isolated, shown one-at-a-time, and in sequence. Therefore, I was concerned whether animations performed differently from the static-graph representation because of this sequential presentation of relations, or because the animations themselves were superior. I decided to address this concern by enhancing the static-graph representation to sequentially present the static glyphs and renamed it the static-sequence representation. In this component, I focused on comparing the static-sequence representation to animations and to the older static-graph representation in order to determine if there was any difference in performance.

My thesis is laid out as follows. Chapters 2 and 3 describe previous research related to my thesis. These sections describes studies that have detailed the perceptual issues with using static and animated visualizations, studies that have focused on comparing static and animated techniques to elucidate complex information, and studies that have focused on developing techniques to efficiently perceive and visualize causal relations. Chapters 4 and 5 define the taxonomy of causal semantics that have been derived from this research, along with the structure of the causal relations, and visual representations of the causal events. Chapters 6, 7, 8, and 9 describe the experimental studies conducted during my research, followed by the conclusion in Chapter 10, which describes the inferences drawn from my studies and future work in the area of causal visualization.

Chapter 2

Related work on perceptual theories

Causality is defined as an event wherein one object (called the factor) influences a change in another object (called the target). For example, a person applies force, in the forward direction, to a stationary table and causes it to move. Causality is not constrained to Newton's laws of motion, and can be seen in every facet of life, such as in philosophy, medicine (Figure 2.1), law, chemistry, and computer science.

However, as my research focuses on employing static and animated representations to represent causal semantics, it is critical to understand the various issues that were

Figure 2.1: A simple causal graph showing factor (pollen), target (allergic reaction), and relation (directed line from factor to target).

considered during the course of my studies. As described in the next section, several researchers have suggested guidelines that can be followed while creating static or animated representations. Theories of perception can also enhance the effectiveness of new visualization and I will report on this related literature that supports, to a large extent, the research done here.

2.1 Issues in static perception

Our visual system has evolved to recognize complex objects effortlessly. Object recognition is achieved through a three stage process, each stage adds to the details collected in the previous stage, which finally combine to recognize the object accurately. This section describes issues encountered in the perception of static objects and the three-stage process of recognizing them.

2.1.1 Stage I - Feature processing

The first stage in object recognition constitutes feature processing, which is concerned with recognizing the primitive features of the objects such as contours, edges, and textures. These are the simple features that cause an object to stand out from its surrounding. Colors are distinguished by the color receptors in the eye and span the entire color spectrum. Features such as edges are recognized in order to distinguish between different faces; such as vertical, horizontal, and oblique faces of the object. Texture distinguishes the surface quality of the object, such as smooth, shiny, grainy, coarse, and rough. Figure 2.2 shows how a lamp is de-constructed to its basic attributes in the first stage of visual processing.

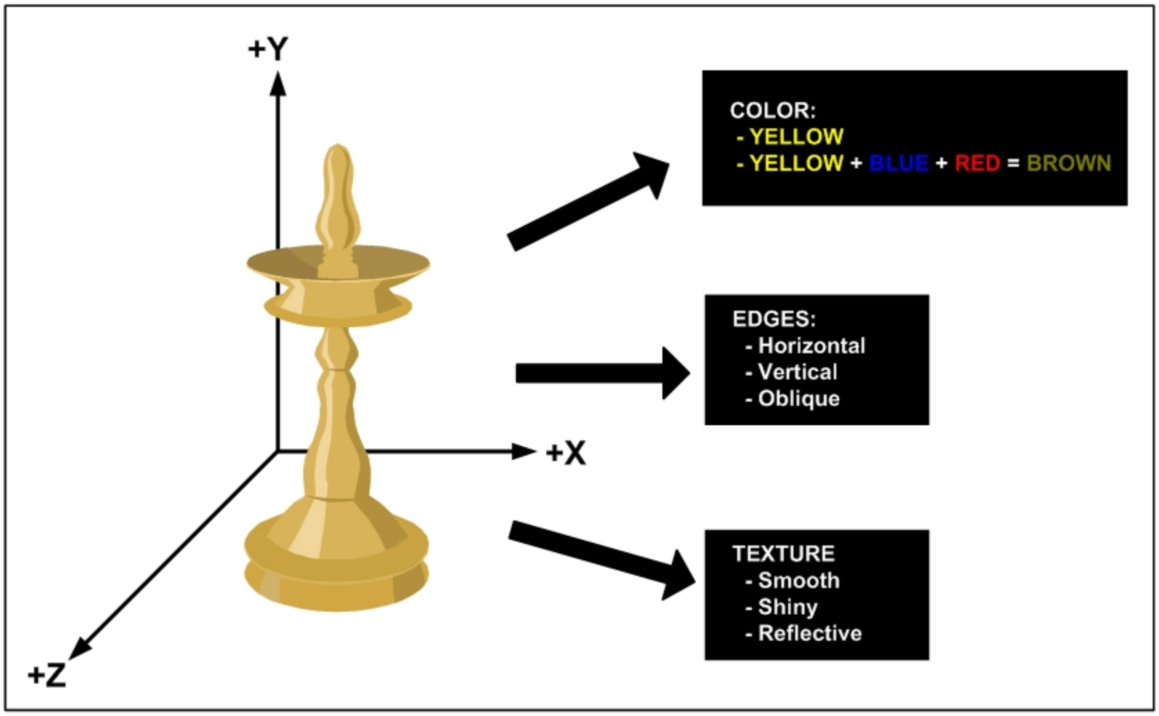

Figure 2.2: Image of a lamp showing color, edges, and texture information that is assimilated in the first stage of feature processing.

The feature processing stage also distinguishes objects through a general theory of the human visual system known as pre-attentive processing [Ware, 2003]. This theory states that certain features of the object are distinguished more easily than others because they "pop-out" from the background. Some of the pre-attentive features of an object include color, shape, orientation, length/size, grouping, and curvature variance. Studies [Ware, 2003] have shown that pre-attentive processing occurs unconsciously and subjects usually perform well in dense and sparse scenes.

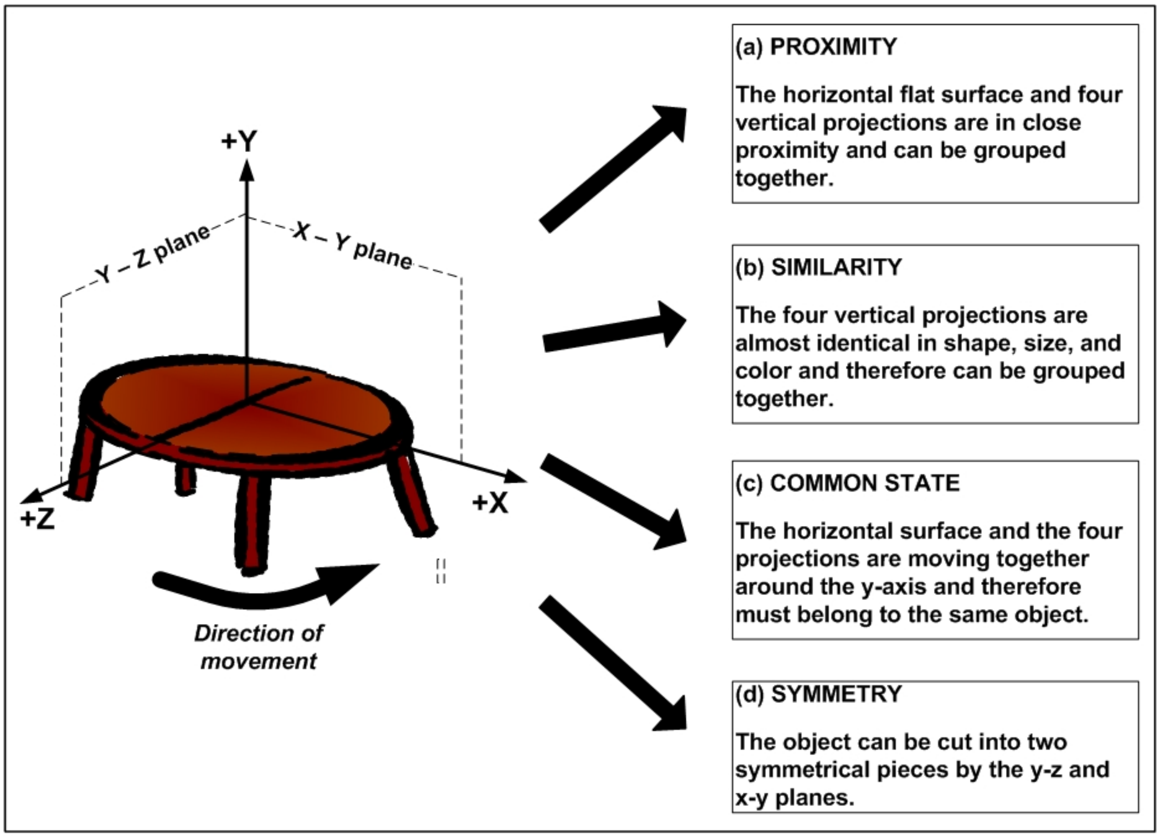

Figure 2.3: Second stage processing distinguishes features such as proximity, similarity, common state, and symmetry.

2.1.2 Stage II - Pattern matching

The second stage in object recognition constitutes pattern recognition, where objects are grouped together based on similarities and closeness in physical appearance [Ware, 2003]. This phenomenon of pattern matching is commonly explained by Gestalt's Laws of pattern perception. These laws describe features based on their closeness to one another (proximity), same shape (similarity), symmetrical along any of the axes (symmetry), and existence in the same state of rest or motion (common state). These laws are useful when attempting to create several groups of representations that retain their uniqueness, while being part of the whole.

2.1.3 Stage III - Object recognition

The third and final stage of object recognition is involved with categorizing the objects into recognizable classes, such as chair and table, in order to aid final recognition. Another important component of this stage is the recognition of three-dimensional properties of an object which help us provide depth to the image we currently have in our minds. Biederman [Biederman, 1987] proposed that simple three-dimensional glyphs can be used to visually represent complex constructs; he called this the *Geon Theory*.

Biederman [Biederman, 1987] generated a set of 36 glyphs or primitives that could be used individually or in combination to generate any complex object. The design of this objects were based on the concepts of collinearity, curvature, symmetry, parallelism, and co-termination of two-dimensional objects (Figure 2.4). In addition, Biedermann compared the effectiveness of the above concepts and suggested that collinearity is easily distinguishable when compared to curvature as it is easy for the human eye to assimilate linear and non-linear lines rather than lines with varying degrees of curvature. Beidermann also suggested that symmetry is a stronger distinguishing feature than parallelism as it retains its shape under both reflection and rotation and does not require changes in the view angle of the human eye. Finally, co-termination, which is concerned with the terminating edges of an object, is crucial as edges define the boundaries and shape, and thereby facilitate in object recognition. The results of these studies have been very useful in developing my causal visualiza-

Figure 2.4: Beiderman's Geon Theory describing features of an object that improve recognition such as (a) collinearity vs. (b) curvature, (c) symmetry vs. (d) parallelism, and (e) co-termination (redrawn based on [Biederman, 1987]).

tions. In particular, based on these results, the nodes and glyphs displayed in my causal graphs are symmetrical, with strong co-termination (no missing components), and connected by collinear lines, for easy comprehension.

Sekuler et al. [1988] conducted an extensive study into the perception of visual motion in dynamic scenarios. The findings of this and other studies are summarized below.

2.2 Issues in motion perception

2.2.1 Factors that effect the perception of motion

Several studies have also analyzed factors relating to motion perception such as motion detection, trajectory, direction, speed, and coherence. Some of these factors have been described below:

Detection of motion

Motion is normally perceived as the movement or displacement of an object over a period of time. Sekuler et al. [1988] state that motion can be described through a space-time graph, where the space-axis represents the distance that an object moved over the time-axis. More commonly, motion, according to the study by Lappin et al. [2001], is distinguished in terms of relativeness, i.e. the movement of one object with respect to the stationary nature of another, e.g. a train is viewed as moving relative to a person standing on the stationary railway platform. The authors state that human beings can recognize relative motion more accurately than pure visual motion, and in some cases cannot distinguish motion at all unless it is relative, e.g. a person in a moving train does not recognize the motion of another person sitting in an adjacent train moving at the same speed and in the same direction. Robson [1966] states that in many cases motion can bring the objects that are previously invisible into the line of sight. Therefore in order to categorize the amount of motion that is required to visually detect it, studies employ the usefulness of the *lower envelope principle* [Watson and Turano, 1995], which estimates the smallest number of neurons that are required to distinguish motion. Using computer technology, a more modern technique called the *random dot cinematogram* (RDC) is also popular in motion perception estimations. In the RDC technique, subjects are asked to distinguish the overall motion of a given set of dots. The percentage of dots moving in a particular direction is controlled and the remaining dots in the scene move in random directions (causing noise). Studies showed that subjects were able to recognize motion with as low as 5% of the dots moving in one direction [Blake and Aiba, 1998], which shows that human beings are able to distinguish object movements even in small degrees. Some studies also state that the detection of motion can be improved with the addition of visual cues, such as color, hue, and orientation, and by aiding visual attention [Croner and Albright, 1997; Raymon, 2000]. As suggested by these researches, the causal graphs in my studies are stationary, in order to provide a high contrast and maximize detection of the moving bullets that depict the causal information.

Detection of trajectory

Trajectory detection focuses on perceiving the direction of motion of a single object among several distractors. According to studies by Watamaniuk and McKee [1995], the visual system is quite adept at distinguishing single object movement, and an RDC testing of this ability showed that subjects were able to visually track motion even when only 0.4% of the dots were moving in the same direction. As mentioned in the previous subsection, in my visualizations, only the bullets describing causal information move. All other components of the causal graph are stationary, which reduces the number of distractions in the scene.

Discriminating direction, coherence, and speed of motion

Motion discrimination deals with recognizing the motion of an object along with discriminating changes in speed, direction or coherence of the motion. Studies by Watamaniuk et al. [1989] have shown that subjects are adept at discriminating changes in the direction of motion, even when in some cases the motion change is as small as $1°$ and a study by Gros et al. [1998] showed that directions such as up, down, left, and right were more easily assimilated when compared to directions such as oblique. Other studies [Bravo and Watamaniuk, 1995] state that motion as a whole can be used to aid object coherence, i.e. when several objects move in the same direction, perceptual grouping occurs and the moving objects are grouped into a coherent shape. The study states that speed of an object is normally perceived by measuring the distance an object traveled over a period of time. The study employs the use of Weber fractions (ratio of smallest increment in speed that can be reliably detected to the current speed of the body) to determine the smallest proportion of change of speed that can be perceived and states the range as low as $0.04 - 0.08$. In addition, research has also shown that discrimination of speed is reduced when the object is far away from the eye [Johnston and Wright, 1986] and also when the available light is less or dim [Gegenfurtner et al., 2000]. In my studies, the animated bullets mostly move in the same direction, either horizontally, vertically, or obliquely. In bidirectional causality, bullets move in one direction and then move in the opposite direction. In this case, the two motions are separated by a few seconds, in order to be able to discriminate between them easily. Perceptual grouping plays an important role in causal multiplicity, as information travels from more than one factor simultaneously, towards the target. In this situation, the motion is slow and easy to distinguish. Finally, the illumination is bright in order to enhance motion comprehension.

2.2.2 Analyzing motion

Several studies that test the effectiveness of visual systems employ the use of a basis model called the *ideal observer model* [Meeteren and Barlow, 1981]. This model can be used to design an ideal subject who knows all about the environment and is trained to perform accurately under the base conditions. When Watamaniuk [1993] applied this model in order to determine the effectiveness of the human eye in discerning visual motion, the ideal observer was designed as an observer who perceived the direction of the dots in an RDC by discerning the global direction of the display.

The ideal observer performed more accurately than humans when all the dots were moving in the same direction. This performance improved as the duration of the display increased, but stayed constant between durations of $100 - 500$ milliseconds. However, as the amount of randomness in the display was increased, the human observer performed more accurately (efficiency = 0.35, 70% accuracy) than the ideal observer. Studies into the limitations that effect motion perception attributed the ideal observer's inferior performance to the fact that it considers the entire display before making a decision, while the human observer views only parts of the display and hence is less distracted by the randomness in the rest of the display [Baddeley and Tripathy, 1998].

2.2.3 Recognizing object structures through motion

Koenderink [1986] has suggested that visual motion forms an important part in discerning the structures of objects. This visual motion is seen in the form of spatiotemporal changes in bodies and is termed optic flow. Optic flow helps the human body to distinguish between stationary and moving objects and also helps to make decisions with regard to speed, direction, and obstacles. Koenderink [1986] also states that movement can be broken down into four basic types: translation, isotropic expansion, rigid rotation, and shear, and any complex movement of the body is broken into combinations of these four components, each of which produce a unique optic flow.

A study by Kirschen et al. [2000] suggested that optic flow allows a subject to learn directions in a complex environment. However, for optic flow to be useful to the visual system, it should be smooth and easily perceptible. Kirschen et al. [2000] showed that when optic flow was limited, subjects took longer to learn their way around complex paths, than when optic flow was smooth and non-choppy. Another study by Lee and Kalmus [1980] stated that optic flow helps in avoiding collisions and is crucial to many species, such as birds, as errors due to irregular optic flow could be life-threatening (for example, when hunting or diving into water). The study of optic flow is of particular importance to my research, as I depend upon the intuitiveness of my animations in depicting the causal information. As a results, my animations are smooth, non-choppy, simple, and follow the principles of good optic flow.

2.2.4 Motion perception by the visual system

Sekuler et al. [1988] state that for a visual system to discern motion, the motion is broken down into its basic components such as direction, speed, and coherence. However, several issues arise when motion of an object becomes complex and requires further processing by the receptors in order to be accurately distinguished, e.g. when an object moves in a right-top oblique direction (combination of the basic directions of right and top). This section describes such issues as addressed by the authors [Sekuler et al., 1988]:

Sensitivity of direction

One common problem encountered by the visual system is the complex movements of an object in motion. According to Sekuler et al. [1988], receptors in the eye are tuned in specific directions. However, the question arises as to how these receptors distinguish and determine the direction of a moving object. Several models have been designed to describe the steps taken by the receptors to recognize motion. The Hassenstein-Reichardt model [Borst, 2000] suggests that the receptors use object displacement over small periods of time to perceive motion. Based on a mathematical calculation of the displacement, a positive difference means that the object is in motion in the same direction in which the receptor is tuned, and vice versa. Sekuler et al. [1988] state that, though very useful, this model is inadequate as it is unable to distinguish between smooth motion and motion that is shown as a sequence of still images (apparent motion). Another model by Watson et al. [1986] uses the concept of window of visibility to specify a limit to the amount of information that can be processed by a receptor. According to this model, object motion generates energy in the form of spectra, and only spectra that fall within the window of visibility can be processed by the receptor; any spectra falling outside the window is ignored. Therefore, based on this model, motion of two objects will appear identical if both of them generate the same spectra within the window. In order to address this problem, the animations I use in my causal visualizations are smooth, simple, and shows only what is necessary, without unnecessary distractions.

The correspondence problem

The second problem arises when the visual system encounters more than one object moving at the same time. Perception of motion states that each step in the motion of an object is perceived as a displacement of the object over a small period of time. Therefore, it can also be said that the visual system recognizes that a particular object has moved, by matching its new location (at the end of the time frame) to its old location (from the beginning of the time frame); which is quite simple when there is only one object under consideration. However, when two or more objects move at the same time, the visual system has to then match each object to their corresponding positions at the end of the time frame. The problem can increase exponentially as the number of objects increase (n objects $\longrightarrow$ n! matches) [Sekuler et al., 1988]. Dawson [1991] states that the visual system overcomes this problem by following three global principles that aid in matching the relocated objects accurately; the nearest neighbor principle that focuses on reducing the distance between successive displacements, the smoothness principle that focuses on reducing the abrupt changes in speed of the object over successive time frames in order to create smooth motion, and the element integrity principle that prevents objects from degenerating, appearing or splitting into several objects unnaturally. Another type of correspondence problem encountered by the visual system is what is termed as bistable motion sequences [Sekuler et al., 1988]. Such sequences occur when the visual system is confused by the interaction of intermingled moving patterns, for example two superimposed diagonally moving gratings (in opposite directions) can be seen as a series of superimposed moving diamond shapes. Hence, the visual system has to decide if the motion is of two gratings or of one diamond patterned grating. In this case the motion is bistable as the visual system shifts between the two ideas based on which image is dominating at that time [Kramer and Yantis, 1997]. As my causal relations sometimes show the influence of multiple factors on a target, I have tried to minimize the correspondence problem by making sure that the casual graph does not have overlapping nodes or causal paths, the animations are smooth and proceed in small steps, and the bullets are whole, do not change in shape or size, and do not split or degenerate unnaturally during movement.

The aperture problem

The third problem is encountered by the visual system when the size of the object in motion is larger than the size of the receptive field (also called the window or aperture), for example looking at a large object through a slit such that only a part of the object is visible at any given time. In this situation, depending on the direction of that particular visible piece of the object, the perception of the direction of motion could change [Wueger et al., 1996]. Wueger et al. [1996] also state that the shape of the aperture could have an impact on the perceived direction of motion, for example, an oblique line moving behind an L-shaped aperture is seen first to be moving down (along the vertical rib of the aperture) and then moving to the right (along the horizontal rib of the aperture). The main problem here is how the visual system discerns the correct type of motion from the small pieces of information that are presented to it. This is accomplished by perceiving the movements of the entire object as a whole and not by looking at the individual pieces of information collected by the receptors. Wueger et al. [1996] infer that the visual system seems to have a mechanism to integrate all the local pieces of information to form a global picture of motion. Therefore, if some receptors provide contradicting or incomplete information, the visual system is able to ignore them without much issue. Although this problem is currently not an issue in my research, I do realize that as the size of the causal graphs increase, it might not be possible to fit the entire graph within a given viewport. In such situations, additional interactive techniques such as zooming, re-ordering, and node selection might be useful and have been mentioned as part of my future work.

2.2.5 The aftereffects of motion

Sekuler et al. [1988] state a common example of motion aftereffects when a subject views a moving scene for a prolonged length of time and then views a stationary scene. The stationary scene is now perceived to be moving in the opposite direction, although it is in fact not moving at all! This phenomenon is termed motion aftereffect. Several models have again been designed to explain motion aftereffect. Some studies [Barlow and Hill, 1963; Sekuler and Ganz, 1963] have attributed this phenomenon to an imbalance in the use of receptors tuned to the direction of the object's motion. According to these studies, when viewing motion for a prolonged period of time, receptors in the direction of motion are overused and become tired. Therefore when the stimulus is removed, the receptors in the opposite direction (which are less used) provide stronger signals to the brain which in turn perceive motion in the opposite direction (called the ratio model). The distribution shift model [Mather, 1980] expands the ratio model to include a range of receptors (instead of only one) which work together to perceive direction of motion. According to the distribution shift model, motion aftereffects include all receptors in the general direction of motion and not only those that are tuned to that particular direction. Finally, newer models [Barlow, 1990] relate mutual inhibition properties of the receptors that influence the perception of direction in the visual system. According to the mutual inhibition models, receptors in opposite directions tend to inhibit each other and this inhibition builds up as the scene is viewed for a longer period of time. When the display is then removed the inhibition is still active and therefore motion is perceived in the opposite direction. Motion aftereffects have to be considered when designing animation sequences as they can counteract the detection of minute or quick changes in an event. For example, in my causal graphs nodes are placed as close as possible to each other such that the bullets travel short distances between them and motion aftereffects are reduced, while making sure that the information contained in the bullets is still clearly visible.

2.2.6 Retention qualities of motion

Remembering motion

Several studies have analyzed participants' efficiency in remembering the motion of displayed objects. The study by Magnussen and Greenlee [1992] tested the ability of the participants to remember the velocity of a moving grating (grid of horizontal and vertical bars). In this study, the authors compared the ability of the subjects to match the velocity of a reference grating to a test grating by manipulating the time difference between the displays. Results of this study showed that subjects were able to retain the properties of the initial stimulus for up to 30 seconds. Another study by Blake et al. [1997] tested the ability of subjects to remember the direction of a given motion. Results of this study stated that subjects could remember the direction of motion for around 8 seconds of time and were not disturbed by the insertion of noise in the display. However, the studies also showed that increasing the number of directions in the display had adverse effects on the subjects' performance. The results of these studies are important to my research as my *Memory Recall* experiments test the retention and recall qualities of causal motion using animations.

Multiple object tracking

The retention qualities of motion are particularly important as the number of objects in the display increase and as the difficulty in matching the initial positions of objects to their respective final positions also increases. Pylyshyn and Storm [1998] suggested the FINST model that describes how participants track multiple objects. According to this model, the eyes of a person generally focus on one area of the scene, called the locus of visual attention. However, without moving their eyes, the authors state that it is possible to shift the locus of visual attention such that the eye can distinguish regions which were not visible previously. This is called pre-attentive processing and this is used very commonly to track multiple moving targets simultaneously. According to authors, FINST can be described as references to certain features of objects such that they stand out and can be tracked by the eye pre-attentively, independent of the position of the objects in the scene. A study by Allen et al. [2004] compared the ability of experts (radar controllers) and novices (undergraduate students) to track multiple moving objects in a scene. Overall, the experts were more accurate than the novices in the experiment, since the experts were trained in object tracking. The results of the experiment showed that both experts and participants could keep track of up to six targets, above which the error rate drastically increased. However, when an additional vocal task was added to the experiment, the performance of the novices (up to 2 objects) degraded more rapidly than the experts (up to 4 objects). A second theory proposed by Yantis [1992] states that subjects create perceptual groups, in the shape of virtual polygons, and use the relative positions with respect to the rest of the group to keep track of the moving targets. Yantis [1992]'s studies supported this theory and also showed that any breakage (crossing two edges of the virtual polygon) in this perceptual group had an adverse effect on the participant's performance. The results of the above studies are relevant to my research as my visualizations can be used to display multiple simultaneous causal effects. However, as the focus of my thesis is on creating the visual representations and testing their effectiveness, I have not focused on multiple object tracking in my studies and have limited the number of simultaneous animations to at most two items.

Uncertainty in direction

In situations where motion is not unambiguously visible, for example in low luminance, studies have shown that visual cues play an important role in influencing the perception of motion. Studies by Ball and Sekuler [1981] show that motion cues, such as oriented lines showing direction of motion, improved the performance of perceiving motion, when they directed the gaze of participant towards the same direction as that of the displayed objects. However, when the cues provided incorrect information (directed the gaze to a different direction than that of the displayed motion), then the performance of the subjects degraded to a greater degree than when no cues were given at all. In addition, the studies stated that the degradation in performance increased with increase in the difference between the actual and the cued direction. However, Ball and Sekuler [1981] also stated that the motion cues were useful only if they were presented at least 500 milliseconds before the actual display was shown. This showed that subjects need some time to process and comprehend the direction before being able to observe it in the display. Finally, studies by Alais and Blake [1999] tested the influence of attention in perceiving motion. Results of this study showed that as the participants were able to detect motion 3 times more accurately when paying attention than when they were distracted by other events in the scene. In my studies, I have tried to avoid uncertainly in direction of motion by using contrasting colors and by avoiding any lighting effects in the scene.

2.2.7 Information retrieval through motion

In order to evaluate the efficiency of motion in providing people with information, Bartram et al. [2003] analyzed the various advantages and disadvantages of motion cues in dynamic scenarios. In this study, the authors conducted a series of experiments to evaluate their hypotheses. In the first experiment, motion cues were compared against cues such as color and shape (as separate experiments), to determine the most effective among them. In these experiments, the participants were given a simple task to perform, which was replacing all the 0s by 1s, in a table containing the numbers 0 to 9. While the participant was concentrating on the given task, the rest of the screen outside of the table, which contained many objects, either moved or changed color or shape at sometime. The participant was asked to inform the system immediately when they saw any of the symbols outside the table area move. The error rates and response times were analyzed. The results of the experiment suggest that color and shape cues are not as effective as motion cues in providing dynamic information. Also the experimental results suggested that as the distance of the dynamic object moves away from the center of the eye, perception through color and shape reduces. I have extended these studies in my research by comparing the color and shape information presented in my static graphs to the motion information presented by the animated causal graphs.

2.2.8 Lessons learned from research on motion perception

In my causal designs I have endeavored to avoid the problems associated with motion perception, based on the above literature. For this reason, my animations are smooth, travel at constant speed, move with small displacements, do not appear or disappear without reason, and are fully visible within the same view port in order to ensure smooth optic flow, enhance sensitivity to direction of motion, and reduce correspondence and aperture problems. In addition, the suggestions on object magnification and optimum light requirements encourage accurate perception of motion direction and have been considered while creating my animated designs [Borst, 2000; Gegenfurtner et al., 2000; Kirschen et al., 2000; Watson et al., 1986; Wueger et al., 1996].The retention qualities of motion are also useful when designing dynamic displays as it provides us with the user's perspective of the animations [Magnussen and Greenlee, 1992; Blake et al., 1997]. Therefore, in order to enhance comprehension, intuitiveness and memory retention, each causal animation is repeated 3 times. Within a scenario, the causal relations are shown in sequence to reduce the number of simultaneous movements and thereby reduce visual overload. Rules for the animations are also strictly controlled, i.e. influence bullets move only from the factor to the target, so as to prevent uncertainty in the direction of movement that could have an adverse influence on user performance [Ball and Sekuler, 1981]. Table 2.1 below summarizes the lessons learned and their influence on the animations I have designed to represent my set of identified causal semantics.

#	**Suggestions from background research on motion perception**	**Influence of background work on my research**	**Reference chapter/ section**
1.	Relative motion and trajectory of objects is discernible easily when distractions/randomness in a scene are minimized	Nodes in the causal graphs are stationary in order to provide high contrast to the animated bullets, and to minimize unnecessary distractions	2.2.1

2.	Perceptual grouping will occur when several objects move simultaneously	This principle is employed in causal multiplicity scenarios, where objects move simultaneously from the factors to show combined effects on the target. In bidirectional causality, the motion of the bullet from the factor to the target is seperated by a few seconds before the return journey of the bullet, in order to enable discrimination between opposite directions of motion	2.2.1, 2.2.6
3.	Motion discrimination is reduced when the object is further away from the eye, and in poorly lit conditions	The causal graphs in my research are displayed clearly on a light background, with contrasting colors, and by avoiding any lighting effects in the scene	2.2.1, 2.2.6

4.	Smooth optic flow enhances the perception of motion and sensitivity to direction of motion	The causal animations are smooth, non-choppy, simple, and fully visible within the same viewport to ensure smooth optic flow	2.2.3
5.	Motion perception is reduced when objects move randomly, with abrupt speed variations, degenerate or overlap other objects in motion (The Correspondence Problem)	Causal graphs do not have overlapping nodes, animated bullets are whole and do not change shape, size, split, degenerate, appear or disappear without reason, or overlap other bullets during motion	2.2.4
6.	Motion perception is reduced if the objects are not fully visible within the viewport (The Aperture Problem)	In my research, the entire causal graph has been designed to fit within the given viewport. However, as the size of the graph increases, incorporation of additional interactive techniques such as zooming, re-ordering, and node selection will be required to help reduce the aperture problem	2.2.4

7.	Prolonged viewing and removal of an object in motion can cause perception of opposite directions of motion (aftereffects of motion)	The nodes in the causal graphs are placed as close as possible so that bullets travel short distances thereby reducing prolonged exposure to motion and motion aftereffects	2.2.5
8.	Retention qualities of motion are reduced as the number of animations in the scene increase	Since some scenarios can show multiple simultaneous animations, the animations are repeated 3 times to enable retention. In addition, the *Memory Recall* Experiments in my research test the retention qualities of motion.	2.2.6

Table 2.1: Summary of lessons learned from background research on motion perception and their application to my research.

Although this section provides useful suggestions for building my static and animated representations, it is also important to understand how a user perceives causal events, so that the representations I design are effective and describe these events accurately. Therefore the next section focuses on research that has studied causal perception in human beings and suggests general temporal rules for efficient identification of causality.

2.3 Guidelines for perceiving causality

David Hume [Nuttin, 1966] (18^{th} century philosopher) described the *Problem of Causation* as the existence of relations between time and space, which generate causal effects. In philosophy, causality is defined based on the actions of human beings. Human beings are the cause of actions, deeds, and thoughts, the results of which help shape their lives. God, on the other hand shapes the environment, by causing birth, death, and natural disasters. In chemistry, two chemicals when mixed can cause predicted (or unprecedented) reactions, for example hydrochloric acid reacts with the dyes in blue litmus paper and causes it to turn red. Sometimes, causality is unconsciously employed while determining the solution to a problem, such as heating water to create water vapor. In law, causality is critical to pronouncing fair judgment. For example, while determining why a person committed a crime, the causes, "it was in self-defense" or "it was premeditated" can result is very different legal outcomes. Most questions in the practice of law investigate why certain events occurred and what conclusions can be drawn from these investigations. Therefore, it is imperative to fully comprehend the true cause of events in order to dispense justice. In physics, gravity is held responsible for causing the apple to fall, or for causing tides in the oceans. In computer science, causality is transparent but is used to understand and debug process flows, for example the value in variable A causes an action on variable B. Consequently, causality is encountered in every field of information science.

Albert Michotte, a pioneer in the research on causality conducted a series of experiments to analyze the sensitivity of human beings to causal occurrences. Through his experiments he suggested a set of temporal guidelines that would enhance perception

Figure 2.5: A simple causal event where an object (L) moves towards another object (T), hits it, and causes it to move (reproduced from [Michotte and Thinés, 1963])

and aid the comprehension of causal information, as described in the next section.

Michotte's temporal rules for perceiving causality

Michotte's *theory of ampliation* suggests that we perceive or infer causality when a moving object strikes another and sets the latter into motion [Michotte and Thinés, 1963]. The causal inference is immediate upon presentation to our visual system.

The experiments developed by Michotte initially concentrated on mechanical causality. In the basic experiment, referred to as *launching*, subjects see two immobile rectangles (L and T) of different colors on a uniform white background. The experiment begins when the launcher (L) moves at a constant speed toward the target (T). When L reaches T, it stands still and the latter starts moving (Figure 2.5). Subjects, even though unaware of the purpose of the experiment, responded with descriptions, such as "L pushes T", "L launches T", or "L projects T", which were endowed with causal meaning.

Michotte carefully controlled various factors to determine the conditions under which causal inferences would be produced. *Temporal conditions* were one of the most contributing elements for appropriately perceiving launching. One such guideline suggests that the *time between impact and movement* of the target should be constrained to a maximum of 100 milliseconds. For delays beyond 150 milliseconds, the objects L and T appear to move independently [Michotte and Thinés, 1963].

Another guideline suggests that the *size and shape* of objects can vary significantly without depreciating causal inferences, as long as the objects are perceived as independent upon the point of impact. Thinés [1962] used triangular arrays of light spots and found that subject responses were not affected by a change in shape. Also when L and T are perceived to be created from different types of material (i.e. L is a light spot and T is a solid object) launching responses were still obtained [Michotte and Thinés, 1963].

Absolute speed restrictions on the launcher and target are also necessary for observing proper launching effects [Michotte and Thinés, 1963]. Velocities beyond 110 cm/sec are perceived as the launcher passing through the target *(tunnel effect)*. On the lower limit, velocities of either launcher or target below 3 cm/sec weakens the launching effect.

The *relative ratio of velocities* between L and T is considered important in maintaining causal inferences. The character of the causal structure is considered best when the movement of the target is slower than that of the launcher [Michotte and Thinés, 1963]. When the reverse is applied, very different responses are provided, in particular that of the target being autonomous in its movement.

Spatial information such as the *length of the paths* traveled by L and T should also be carefully manipulated. In essence the causal responses start to degrade once the path of the target extends beyond its radius of action, i.e. naively related to the velocity of both objects [Boyle, 1961; Yela, 1954]. After a certain length of path, which can be empirically determined, the target appears to be autonomous. Also, Copyrighted Image. Please refer to the referenced document

Figure 2.6: (a) A causal event showing a black 'caterpillar' hitting and causing a grey caterpillar to move and (b) a non-causal event showing the grey caterpillar moving before the black caterpillar hits it (redrawn based on [Schlottmann and Surian, 1999]).

the direction of movement of the launcher-target couple is critical in inferring the relations. Best results are achieved when the target's path follows the line of action created by the launcher.

In addition to determining the basic guidelines that contribute to causal perceptibility, researchers also studied the inherent behavioral characteristics of causality. Some such studies have tested the presence of causal perception in children as young as 9 months while others have tested the influence that a contextual causal event can have on non-causal events, as described below in the next two sub-sections.

Perception of causality in infants

Several studies show that causality is an innate quality of human beings and can be seen even in young children and infants [Schlottmann et al., 2002; Schlottmann and Surian, 1999]. One study tested the perception of causality in children as young as 9 months [Schlottmann and Surian, 1999]. In the first phase this study, one group of infants was shown a causal event consisting of a red square (the factor) hitting a green square (the target) and causing it to move (Figure 2.6.a). A second group of infants was shown a non-causal version of the same, wherein a delay was incorporated between the factor and target movement (Figure 2.6.b). In order to assist the infants in relating

Figure 2.7: Visual depictions of (a) physical causality, (b) non-causal event, and (c) psychological causality (redrawn based on [Schlottmann et al., 2002].

the images to real-life objects, the squares expanded and contracted, resembling a caterpillar in motion. In the second phase, the order of the events was reversed; the green square became the factor and the red square the target. The study compared attention spans of the infants in both phases. Analysis of "looking time" data showed that 78% of the infants looked longer at a reversed causal event than the 53% who looked longer at a reversed non-causal event. The study concluded that infants were able to perceive causality, which in turn enabled them to adapt to the reversed causal event.

Another study [Schlottmann et al., 2002] tested the ability of children between the ages of 3 to 9 years in perceiving causality. Two types of causal events were shown; physical and psychological. The physical causal event was visibly described by a ball (A) moving towards another ball (B), and B moving away after A touched it, generating the impression that "A caused B to move" (Figure 2.7.a). The psychological causal event was abstractly implied when a man (M1) ran towards another man (M2), and M2 starting running before M1 touched him, generating the impression that "M2 was running away from M1" or "M1 was chasing M2" (Figure 2.7.c). The non-causal event consisted of an image of a man walking alone to depict an independent event without any preceding causes or proceeding events (Figure 2.7.b). Schlottmann et al. [2002] stated that animated images and pictures were used to avoid the necessity of verbal reports, as prior experience showed that children were inconsistent and sometimes unable to provide descriptive reports of their thoughts due to undeveloped verbal skills [Schlottmann et al., 2002]. Participants were shown the three events and were asked to group them into causal and non-causal categories. The results of the study showed that all participants were able to comprehend psychological causality as they could relate it to real life events. Most of the participants also perceived physical causality, and predicted that the factor was going to cause movement in the target. Overall the results of this experiment showed that children were able to recognize causal events and were able to comprehend causal relationships between the factors and the targets.

Although these studies are not directly related to my research, several lessons can be learned from them. The studies show that causality can be recognized at a very young age and is used consistently in making judgements. The studies also show that visual cues are effective in showing the causal information. Finally, these studies show that different types of causality can be perceived using effective visualizations, such as a reversal event Schlottmann and Surian [1999], which inspires bidirectional causality in my taxonomy.

Perceiving causality through context

Several studies have extended Michotte's work to analyze the effect of a context environment in perceiving causality. Scholl and Nakayama [2001] tested the ability of a causal (context) event to influence participants' perception of a non-causal (test) event. The context event demonstrated an unambiguous causal event with A striking

Figure 2.8: Evaluating the influence of contextual causal events on non-causal events. (a) Launch event (causal), (b) pass event (non-causal), (c) pass event in the context of a launch event, and (d) pass event in the context of another non-causal event (redrawn from [Scholl and Nakayama, 2001].

B and causing B to move. The test event was similar but comprised of A overlapping B before B started moving and was mostly perceived as a *passing* event (A passes over B). Results of this study showed that participants were 100% accurate in recognizing the causal event and 10.7% accurate in perceiving the non-causal event as causal, when both the events were shown separately. However, when the test and context events were shown together, perception of the non-causal event as causal increased to 92.1%, which showed that the insertion of a causal event into the environment had a significant influence on the perception of causality (Figure 2.8).

Additional experiments by Scholl and Nakayama in this study manipulated the characteristics of the context event and tested the perception of causality in the test event. Some of the manipulated characteristics included changing the duration of display of the context event, including temporal asynchrony between the two events, and changing the direction of movement of the reference event. Results of the experiments showed that the context event should be shown at least 50 milliseconds before the test event for it to have any influence on the perception of causality. The results also stated that temporal asynchrony of more than 50 milliseconds between the points of impact (A hits/passes over B) of both events also had a significant influence on

Figure 2.9: Evaluating the influence of connected lines in the perception of causality. (a) Ambiguous causal event (above: test event, below: context event), (b) test and context events connected by a solid line, (c) gap between connecting line and events, and (d) removal of line as objects make contact (redrawn from [Choi and Scholl, 2004]).

reducing the perception of causality in the test event. Finally, the studies showed that directional phase has a large impact on the influence of the context event as the performance reduced by 50% when the direction of movement of the context event was exactly opposite to the direction of movement of the test event.

Another study by Choi and Scholl [2004] discussed the effectiveness of perceptual grouping in influencing causality. In this study, the authors analyzed the properties of connectedness, proximity, attention, and competing causal events in perceiving causality in non-causal events. The experimental design was similar to the one used by Scholl and Nakayama [2001] with the difference that the objects in the context event moved in the opposite direction to the objects in the test event, to reduce the perception of apparent causality. In the first experiment (effect of connectedness), the objects B of the test and context event were connected in three ways: (i) a line connecting the two 'B' objects, (ii) a line connecting, but not touching the two 'B' objects, and (iii) a line connecting the two 'B' objects, but disappears when each object A touches its respective object B. Participants showed the best performance (perceived causality) of 57.1% when a line connected the two objects (condition (i)) as shown in Figure 2.9.b. Preventing the connecting line from touching the objects (condition (ii)), as in Figure 2.9.c, slightly lowered the performance to 54.6% but this was considered insignificant. However, the study showed that performance was significantly reduced to 29.6% when the connecting line disappeared during the causal contact, as in condition (iii) (Figure 2.9.d). This experiment showed that perceptual grouping plays a significant role in improving the perception of causality; the stronger the grouping (such as a connecting line) the stronger the perception of causality. Choi and Scholl [2004] further tested their perceptual grouping theory by using proximity to create perceptual groups in the display. In the second experiment, a non-causal event was displayed in context with a group of causal events. Results of this study showed that when the context group moved along with the test event, the performance improved to 51.3% than when the context group remained stationary (9.2%). However, a change in the directional phase of the context caused a significant reduction in performance to 20.8%. This experiment showed that perceptual grouping can have an influence on the perception of causality in the test event, but similar to the previous study, a change in discrepancy in the direction of motion between the context and test events can reduce that perception. A follow up study also showed that varying the number of causal events in the context group did not have any significant influence, but varying the proximity of the context to the test event did affect the performance. The authors reasoned that the improvement in performance when the context is closer is attributed to the ease of comparisons, and therefore to the stronger influence of the causal event on the visual system. The results of this study are especially useful and have some implications on my research as my causal graphs use connected lines to show perceptual grouping between causal events and to indicate direction of causal information flow.

The above studies suggest that the identification of causal events are inherent in human understanding and certain temporal rules enhance the perception of causal relations. One of the main advantages of a causal relation is that is allows us to make experienced judgments and predictions on future events. The results of these studies are particularly useful as they show that visual cues, such as connecting lines, help establish context within the relation and improve the perception of causal events. Therefore, my causal graphs use connecting lines to establish the causal relationship between the factor and target, and the animated bullets move along these lines to show the influence of the factor on the target.

However, before representing a causal relation, it is also important to understand its true nature. This includes understanding the agents involved in the event and their physical and psychological connections with each other, without which errors in judgment are inevitable. Therefore the first step and efficient mode of perceiving and understanding a causal relation is by using a causal model, as described in the next section.

2.4 Perceiving causality through causal models

Causal models define the agents in a causal relationship as they are considered to be constant in nature as long as the causal relationship exists. In a real-life scenario, the *causes* and the *outcomes* form the agents of a causal relationship.

Causes are agents that instigate a causal event, called a factual event (in Fig-

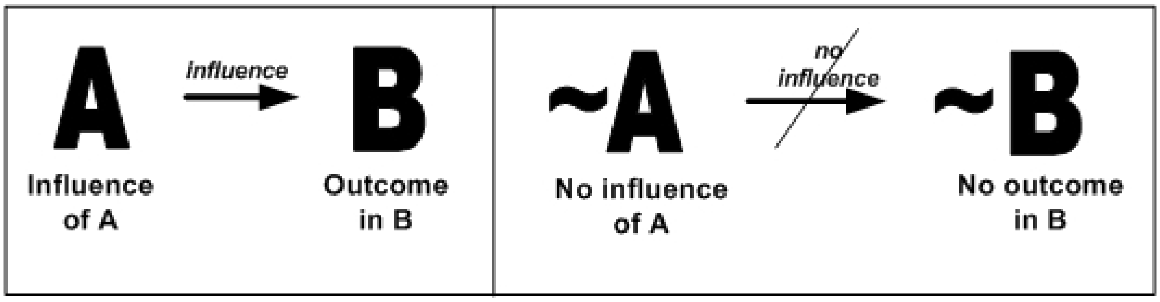

Figure 2.10: (a) Factual event - A causes an outcome in B and (b) Counterfactual event - Absence of influence in A results in an absence of outcome in B.

ure 2.10.a, A is a cause of the event). In addition to satisfying a factual event, Sloman [2005] suggests that causes should also satisfy a counterfactual definition, which states that a cause is an agent such that without it, the outcome would not have occurred (Figure 2.10.b). The importance of factual and counterfactual adequacy in a causal event can be demonstrated by a simple variant of a decision problem that we encounter in daily life. In this problem, Bob, a manager in Company A, is not happy with his employee Susan and decides to fire her. On the other hand Edward, who is the manager of company B, likes Susan's work and wants to hire her, with a higher pay and more employee benefits. Bob sets up a meeting with Susan in the evening (to break the sad news), but before the day is done, Susan receives a call from Edward offering her a job in his company. She accepts, and submits her resignation immediately. The question now is, "Who truly caused Susan to leave her job at Company A?" Did Bob fire her? Or did Edward offer her the better job? The obvious answer might be "Edward! That's what the problem statement declares!" However, on closer analysis we notice that there are actually two potential causes for this event, 'Bob firing Susan' and 'Edward hiring Susan'. The counterfactual argument would suggest that if Bob had not fired Susan, she would have still moved to a better job that Edward offered. So we can reason that Bob is not a true cause for this event, as he does not satisfy the counterfactual condition. However, Edward also does not satisfy this condition, because if he had not offered Susan a job, she would still have left Company A because Bob would have fired her. So, who then is the true cause? Either one or the other's influence was sufficient for Susan to leave her position with Company A, but unless we define the relationships between the three agents in this event, it is difficult to determine who might have been the true cause of the outcome. Mackie [1980] points out that it is not enough to simply look at the immediate cause for the event as there are relationships that exist, which might not be currently used but could effect the overall outcome. He therefore defined a cause as one that belongs to a larger set of sufficient conditions for the event to take place, called INUS (Insufficient itself for effect, but a Necessary part of an Unnecessary but Sufficient set of conditions) Sloman [2005].

In Susan's case, Edward's phone call is an existing condition (I), which is necessary (N) and is one of the set of conditions (U, S) for Susan to be fired. Therefore, we can say that Edward is a cause in this causal event. However, we cannot say the same for Bob, because he did not actually talk to Susan, so his conversation with Susan in not existing (∼I). Therefore, by process of elimination we can say that Edward was the true cause for Susan to leave her position in Company A.

Sloman [2005] suggests that causal models are useful because, in addition to providing a generic method of displaying these invariants, they allow us to assign values and view the outcome. Figure 2.11 describes Susan's problem. The advantage

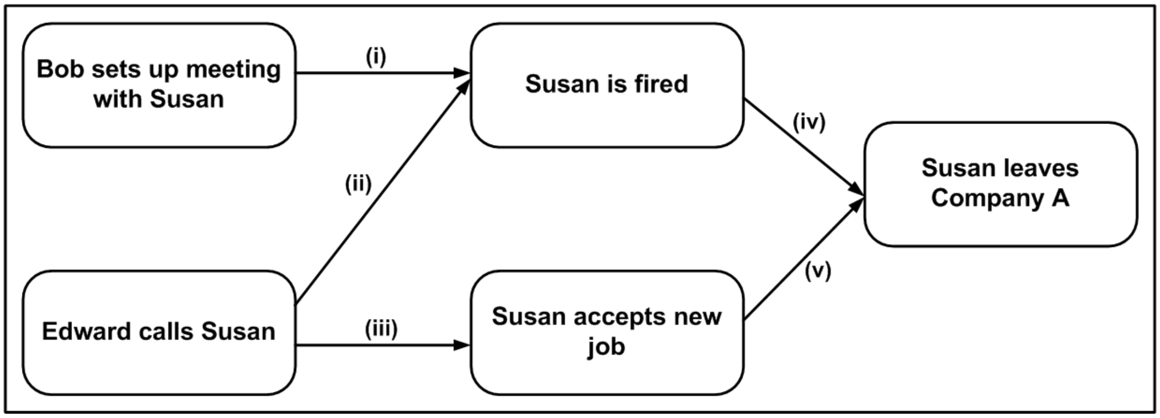

Figure 2.11: Causal model showing the decision problem of Susan leaving Company A; (i) Bob fires Susan, (ii) Edward offers job and prevents Bob from firing Susan, (iii) Edward offers Susan a job, (iv) Susan is fired and leaves Company A, and (v) Susan accepts new job and leaves Company A (words in italics indicate causal influence).

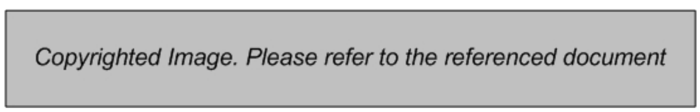

Figure 2.12: The three main components of a causal model (redrawn from [Sloman, 2005])

of a causal model can be seen here because it shows that in addition to Edward's phone call's relationship to Susan accepting the new job, his phone call is also related to Susan being fired. This is surprising, but logical because Edward calling Susan prevented her from being fired, hence the relation (Figure 2.11(ii)).

Sloman defined three critical parts to a causal model; the world, the probability distribution, and the graph. The world represents all the components of the causal system. For example, in Susan's case, the world consists of components such as Bob, Edward, Susan, phone calls, conversation, Susan leaving Company A, and Susan accepting a new job. The second part is the probability distribution, which provides information on the relationship between the invariants. For example, "Would Edward's offering a job have had any influence on Susan accepting it?" or "What remuneration would Edward have to offer for Susan to except his job?" Probability distributions are important in a causal model, as we cannot specify the exact value of a certain agent, but if we define the relation between the agents we can determine the outcome when we provide the input values. The third part of this model is the graph, which visually describes the components of the causal system and their interactions.

Sloman also defined several basic types of causal relations that are encountered in the environment:

- **Basic relation:** consists of one factor and one target. The factor influences and has an effect on the target. For example, cold virus (factor) causes cold in human beings (target) (Figure 2.13).

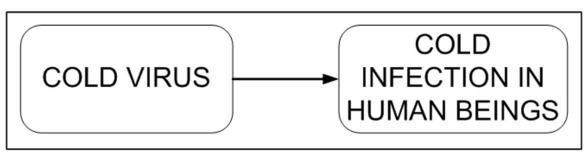

Figure 2.13: A basic causal relation showing cold virus causing a cold infection in human beings.

- **Causal chain:** represents indirect relations between the factor and target, with the presence of mediators. For example, cold virus (factor) is carried by one human (mediator) and infects another (target) (Figure 2.14).

- **Causal fork:** represents a relation of one factor to more than one target. For

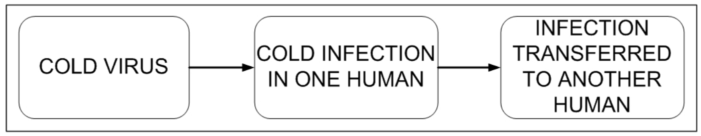

Figure 2.14: A causal chain showing the indirect influence of a factor on the final target.

example, cold virus (factor) causes fever (target 1) and headache (target 2) (Figure 2.15).

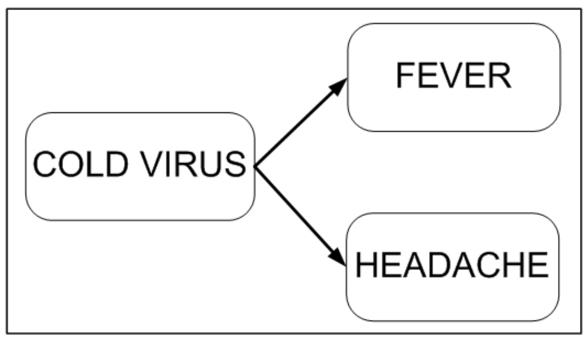

Figure 2.15: A causal fork showing the multiple influences of the cold virus.

- **Inverted fork:** represents a combination of more than one influence in a particular outcome. For example, cold virus (factor 1) and low immunity (factor 2) together cause cold in human beings (target) (Figure 2.16).

Causal models also help determine the outcome of a causal event. Every component has a state (or a set of states/values) and setting a component to a predetermined state is called *intervention*. Sloman suggests that in addition to displaying the relationships between components, causal models also help us understand how relationships change when a factor's state is intervened. Sloman explains that when a factor is given a pre-determined value, then all other relationships to its targets are

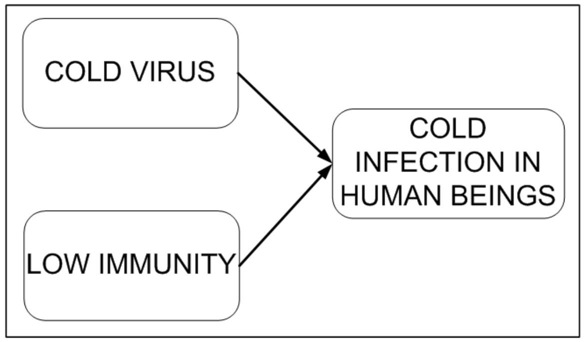

Figure 2.16: An inverted fork showing combined influences of multiple factors on the final target.

erased. For example, the problem statement declares that Edward does call Susan, so we set its value to 'YES'. In doing so, we see that Bob's relationship to the causal model is removed and can confidently say that Bob's setting up a meeting with Susan (or not) would have had no influence on Susan leaving Company A (Figure 2.17). Therefore Edward calling Susan is the only event that satisfies both the factual and the counterfactual conditions and must have been the true cause for Susan leaving the company.

In addition to determining the correct answer, causal models also help us eliminate the inaccurate options, such as Bob's involvement in the event. We can determine if Bob could have been the cause of Susan leaving Company A by setting Bob's values to 'YES'. Although now Edward cannot prevent Bob from firing Susan, he is still connected to the model and can exercise his influence by offering her a job (Figure 2.18). Therefore, we can infer that, although Bob satisfies the factual condition, he does not satisfy the counterfactual condition and cannot be considered a true cause.

The above example illustrates that causal models help us determine the main

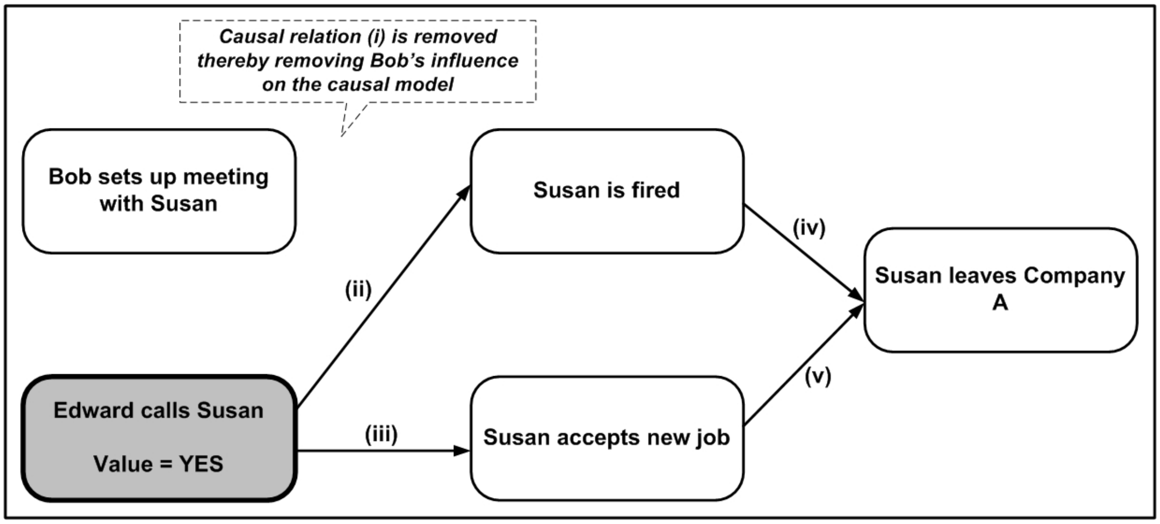

Figure 2.17: Relationship between 'Bob's meeting' and the causal model is removed when Edward intervenes by calling Susan.

components of a causal event by taking the environment and the context into consideration. The next step now is to visualize them such that they can communicate dynamic information and can be utilized to make causal predictions. Two common methods of representing such complex information are by using detailed images or by animating the information. However, the debate on which mode is better is long standing and has been described in the next section.

2.4.1 Lessons learned from studies on causal models

This section described studies on causal models, which is highly relevant to my current research. One of the most useful lessons that I learned is the importance of visualizing causal events as, along with describing obvious relationships between the factors, it also brings to light the hidden relations that influence the outcome of the

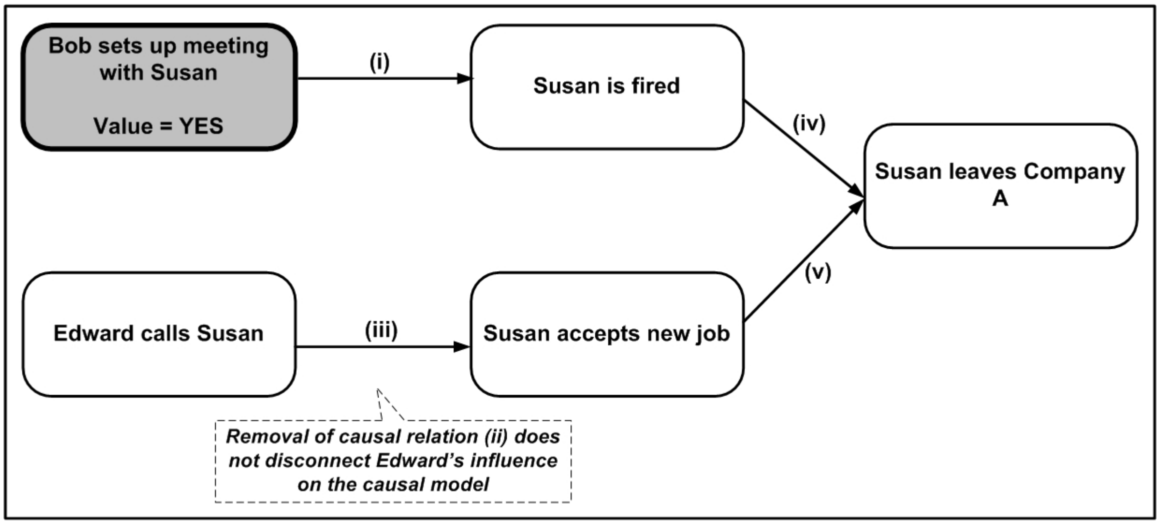

Figure 2.18: Although Bob intervenes and fires Susan, Edward's relationship to the causal model still exists.

event. The models also explain the theory behind causal judgements and explain the concept of factual (outcome is seen due to the existence of a factor's influence) and counterfactual (outcome is not seen due to the non-existence of the factor's influence) events, which are critical to distinguishing causal from non-causal events. The causal models also form the basis for several of the causal semantics used in my study, such as causal multiplicity and mediated causality. Finally, The studies describe the concept of intervention (specific input values that determine the value of the final outcome), which is critical to making judgements in real-life scenarios, and forms a major component of the graphs used in my experimental section.

2.5 Chapter Summary

This chapter focused on the perceptual issues in describing causal relations. The first section of this chapter described research on the perception of static and animated information. Studies show that static perception occurs in three steps starting with recognition of the basic features such as color, edges, texture, and pre-attentive ability [Ware, 2003], in the first step. The second step groups objects based on proximity, similarity, common state, and symmetry. Finally, the third step distinguishes the 3-dimensional properties of an object. Objects are also considered to be created from combinations of 36 geons, which aid in object conception and recognition through critical features such as collinearity, curvature, symmetry, parallelism, and co-termination [Biederman, 1987].

Several studies have also analyzed the features of motion that effect perception such as direction, coherence, speed, trajectory, transparency, sensitivity, retention, and aftereffects [Sekuler et al., 1988].

The second section of this chapter addresses causal representations and guidelines that enable the perception of causality. Studies have analyzed features such as speed, direction of movement, distance traveled, and relative ratio of velocities that distinguish a causal relation from a non-causal one [Michotte and Thinés, 1963]. Studies have shown that human beings use causal reasoning unconsciously when making decisions. This quality is inherent in children as young as 9 months [Schlottmann and Surian, 1999] and can influence the perception of non-causal events in the contextual environment [Scholl and Nakayama, 2001].

Finally, in order to harness the advantages of the extensive research that has been conducted in the area of visual perception, the last section of this chapter goes back to the basics and uses the concept of causal models to describe causal semantics that are inherent in the environment. In my research, I have identified a set of causal semantics and described the relationships using causal graphs. Some of my causal semantics include semantics described by Sloman [2005], such as causal chain and causal fork. However, Sloman has only defined these semantics to describe their causal structure and has not focused on their visual representation. My research goes into detail about the type and nature of the causal semantics, design details, and modes of construction.

This chapter mainly focussed on the basic concepts required to improve human perception of causal events. In addition, there are several studies that have designed visual representations for dynamic events and have analyzed them through user-experiments. However, before describing these studies it is also important to discuss a long-standing debate between research that supports the usage of animations for representing dynamic events and research that prefers the traditional format of static pictures and images. This debate is important to my research because my hypothesis supports the usage of animations to describe causal events and will compare these animations to equivalent static representations. Therefore, the next chapter will describe studies that support and refute the usage of animations followed by studies that have devised innovative methods of using animations to represent causal events.

Chapter 3

Related work on visualization techniques

3.1 Which is better: static or animation?

Several studies in the areas of information visualization and cognitive science have focused on determining which of the two basic visualization techniques, static diagrams or animations, are more efficient at displaying dynamic information. However, the results of these studies have not aided researchers in reaching a common consensus, as some state that static diagrams are less expensive and more descriptive while the others state that animations are more intuitive and therefore easier to comprehend. Nonetheless, surveying this debate is very interesting and provides useful guidelines for producing effective visualizations of complex information.

Figure 3.1: Sorting techniques were shown in the form of dynamic visualizations (a) insertion sort, (b) exchange sort, and (c) selection sort techniques (reproduced from [Baecker, 1998])

3.1.1 Studies reporting the benefits of animation

Intuitively, animations seem to be the most natural means of conveying dynamic information. Animations have been used effectively in several areas of information science such as in learning aids [Baecker and Marcus, 1998], to describe causal concepts [Ware et al., 1999; Elmqvist and Tsigas, 2003; Kadaba et al., 2007], to show real-time data [Ware et al., 2001], to display network flows [Jones and Yean, 1994], and to visualize audio data [Cosker et al., 2007]. While not many applications use visualizations for depicting temporal data, the ones that do, show positive results.

In the field of education, animations have frequently been used to describe general and complex computing concepts to students. Several studies have been employed to describe dynamic concepts such as algorithm design [Bryne et al., 1999], data structures [Becker and Beacham, 2001], and programming techniques [Stasko, 1997]. Analysis of such studies have shown that performance and response times improved significantly as the animations augmented students' interest and appreciation towards these difficult concepts. Several such studies have been described below.

Sorting out Sorting, by Baecker [1998] has been a very popular example of the efficiency of animations in describing complex dynamic concepts to students. The study focused on describing 9 basic sorting algorithms through a 30 minute video, by employing simple animated glyphs such as bars, nodes, connecting lines, and audio cues. The sorting algorithms in this study were divided into three categories; insertion sort, exchange sort, and selection sort. The insertion sort category consisted of the Linear Insertion Sort, Binary Insertion Sort, and Shell Sort techniques, which were animated using upright bars to represent the set of numbers being sorted (Figure 3.1.a). The height of the bar was proportional to the value of the number being represented and the student viewed a smooth animation of the bars being sorted according to the sorting technique being described. Baecker used animated glyphs as it was visually pleasing and easy for the students to match the heights of the bars to the numbers on the numerical scale. The exchange sort category consisted of Bubblesort, Shakersort, and Quicksort techniques. In this category, the animated glyphs were similar to the ones used to represent the insertion sort category, with the exception that they utilized horizontal bars instead of vertical ones in the animation (Figure 3.1.b). The selection sort category consisted of Straight Selection Sort, Tree Selection Sort, and Heap Sort techniques. The sorting techniques in this category were described using smooth animation of the nodes in a tree data structure (Figure 3.1.c). In all the animations, the bars and nodes smoothly changed position as the animation progressed, to represent the sorting of the numbers within the given set. Color schemes were also used to distinguish between different states of the simulation, objects were dimmed when they were not in context, and the speed of the animation was modified according to the complexity of the concept that was being described. An evaluation was conducted into the efficiency of the animation to improve comprehension, performance, and interest. Two groups of participants were tested; the first group received a clear textual description of the algorithms while the second group viewed the 30 minute sound film. Results of this study showed that both groups were able to understand the algorithms equally well, but the improvement in performance was more significant in the group that learnt the algorithms through their animated narratives.

A study by Stasko [1997], evaluated the efficiency of animations in teaching students to design computer algorithms. Stasko identified two main requirements for animations to be an effective learning aid. The first requirement was that the animations should be easy to create so that the students can build them without extensive training and the second requirement was that along with the final animation, the development process should also aid in learning the algorithm. Therefore, Stasko created the Samba system [Stasko, 1997], which is an interactive animation system with the main belief that students will be able to understand complex algorithms more accurately if they created them from the basics. Samba also allowed students to visualize their algorithms using animations, thereby giving them the opportunity to understand and correct their mistakes. Samba used a programming language consisting of ASCII commands that were text-based and simple to learn and implement. The primary mode of visualization was through animations of simple lines and polygons. The students were required to choose the representation that matched their algorithm from a list of bars, lines, circles, and tree structures. An additional feature of Samba was that the students were supplied with a series of “print” statements that gave them step-by-step descriptions of the execution during the animations. Another useful feature was that the students were allowed to interact with the animations and

Figure 3.2: Screenshot of a plane moving through a conical section to create hyperbolic curves (redrawn from [Sonnier and Hutton, 2004; Hutton, 2004])

control its speed so as to maximize the efficacy of the learning process. Stasko [1997] conducted a study to evaluate the Samba system. As part of the study, students were asked to use the Samba system to design animations for commonly taught algorithms such as quicksort and minimum spanning tree. In a post-course survey, over 80% of the students claimed that the animations were very valuable, fun, and helped them learn the concepts easily.

A similar study focused on teaching concepts in physics, mathematics, and computer science to undergraduate students. Sonnier and Hutton [2004] created animations with two goals in mind; to evaluate the efficiency of animations to complement textual or verbal descriptions, and to design a simple technique for developing animations for classroom use by students without a prior knowledge of programming concepts. The study consisted of animations to represent concepts in physics such as static and dynamic equilibrium, in mathematics such as algebraic equations, and in computer science such as sorting algorithms and digital logic. In the mathematical exercises, the animations consisted of numbers that smoothly "floated" to their respective positions in the algebraic equations. Simple animations such as moving boxes were used to show concepts of velocity and acceleration, while complex animations, with color, texture, and shading, were employed to show concepts such as movement of a plane through a conical section (Figure 3.2). Similar animations were also used to illustrate physics concepts such as projectile motion. In computer science, animations were used to elucidate concepts such as sorting algorithms and digital logic. A study was conducted where one group of students was given clear textual description of the problem and the other group was shown a visual representation of the same. Results of the study showed that high aptitude participants in both groups performed equally well. However, participants with low aptitude performed with significantly higher accuracies when the concepts were described using animations. Hence, the study concluded that, dynamic visualization helps in providing introductory information about complex concepts, especially as an online resource in distance education and to students with low spatial ability.

3.1.2 Studies reporting the negative effects of animation

Animations have become very popular for depicting dynamic information in the field of information science. While studies on animations have shown a significant improvement in comprehension and performance, several studies have also shown that static representations can be as useful, and in many cases less expensive, than animations in displaying the same information. Studies claiming the efficiency of static images have stated that animations can be broken down into a series of static images. If the static images are placed such that they show the critical events in the animation, then these images are as easy to comprehend as the animations. For example, if changes in an animation take place at large time intervals, static images might be more efficient in eliminating the uneventful parts of the animation and displaying only the critical events.

Figure 3.3: Usage of static lines to provide information, (a) Lines and objects to show geographical information, (b) bars to show quantitative values, and (c) arrows to show direction of motion (redrawn from [Tversky et al., 2000]).

Tversky et al. [2000] designed a set of schematic figures that intuitively represent complex information. The schema consisted of drawings such as lines, circles, and boxes which when taken in context could efficiently represent complex information without the need of a textual description. Tversky et al. [2000] stated that the main advantage of these figures lies in their simplicity, which make them effortless to construct and combine into more complex shapes. The ambiguity of these figures is also an advantage as they could be reused multiple times and interpreted differently depending upon the context. For example, a single line could depict a path on a map or a trend in a graph depending upon the context of representation. Similarly, four lines joined at the ends could represent an enclosed area or, if they overlap, could represent an intersection (Figure 3.3 (a) & (b)). Arrows are also important modes of representation as they enhance structural representations of an object and its functional properties. Results of a study showed that students preferred using arrows to reproduce the functional properties of a machine, given its textual description [Tversky et al., 2000]. This study provides insight into the usability of static glyphs and in my study I have used lines to show connectivity and relation between nodes in a causal graph.

Through their studies, Tversky et al. [2002] defined the *Congruence Principle* which states that the structure of the graphic being used should directly correspond to the structure of the information being represented. Animations can be said to conform to this principle as they are dynamic and therefore are the best choice to represent dynamic information. However, several studies [Reiber and Hannafin, 1988; Pane et al., 1996] refute this assumption as animations have not helped or in some cases even deterred information acquisition. Tversky et al. [2002] state that the reason animations are sometimes not as effective as their static counterparts is because they do not satisfy a second principle, called the *Apprehension Principle*. The Apprehension Principle states that, for a graphic to be effective, it should be easy to perceive and assimilate. Therefore, a highly complex animation, which requires a high degree of aptitude to be comprehended, might be as ineffective as a graphic that does not show the required information at all.

Morrison and Tversky [2001] defined the *Conceptual Congruence Hypothesis* which states that some types of media are specifically suited for displaying certain types of information. According to this hypothesis static information should be best represented by still images and motion information should be best represented by animations. Morrison and Tversky [2001] conducted a study to compare the static and dynamic versions of this theory. The study consisted of experiments which compared text, text+static, and text+animated representations of seven rules of movement. Results of the experiments showed that although there was significant improvement of visualization over textual descriptions, there was no significant difference between static and animated representations over performance, for participants of low and high spatial ability. The researchers concluded that the lack of significance could be attributed to the causal reasoning that was provided to the participants when the rules were explained. This reasoning holds for participants of low spatial ability in the second experiment who performed with higher accuracies in the text+static condition when compared the text-only condition. Participants with high spatial ability did not show any change in performance from the first experiment as they had the ability to visualize the rules without the help of static or animated displays.

Although animations are the more popular choice in pedagogy for depicting temporal data, a study by Lowe [2003] tried to understand why animations are not more accurate than static images in depicting complex information to novices. The study focused on teaching dynamic weather mapping to students and testing their ability to retain and utilize the information to make future predictions. The study consisted of two conditions; the control condition consisting of paper and verbal instructions and the animation condition consisting of interactive instructional animations. The results suggested that although influence of animations on a participant's predictions did provide more meteorologically accurate results, they did not show any significant improvement in performance between the control and animated instructions. This showed that the dynamics of complex animations may not be efficiently extracted and retained for integration into the participant's knowledge structure. Researchers theorized that this might be because the participants were only able to assimilate the major changes in the animation and neglected the minor but equally critical movements. Overall consensus of the study determined that animations should be created with the user in mind. Complex animations may be able to display all the information that being depicted, however, when such animations are used in the educational field, they should be tailored down so as to be instructional and beneficent.

Brogacz and Trafton [2005] conducted a study to determine, which of three representation types, a static picture, a sequence of static images or an animation, was preferred by meteorologists when making weather predictions. Participants were allowed to choose the display of choice which making their predictions. Each static picture described information regarding weather conditions using text, lines, and colors. The sequence of images consisted of these static pictures shown sequentially over a period of time. Finally, participants were also allowed to view an animation of a weather map showing weather changes over a given period of time. Participants' were asked to refer to their preferred weather models in order to generate flight information, such as departures and arrivals, using the information provided to them. Results of the study showed that the participants preferred looking at a sequence of images rather than the corresponding animation. However, results also showed that the forecasters used their expertise to convert these images into animations in their mind for the purpose of extracting dynamic information. This study concluded that animations are only useful if they provided more information than what was contained in the static images. However, this study was tested using experts and therefore cannot be generalized to users with low spatial ability.

The studies mentioned in this section infer that the efficiency of static and animated representations depends upon the scenario and the type of information being represented. As my causal semantics are dynamic, I hypothesize that animations would be more suited to the information that I will represent. However, due to the long-standing argument of static vs. animation, I have also designed static representations for the semantics and will be comparing them to the animated representations to determine which of them are more intuitive and improve participant accuracy rates and response times under user-testing.

Innovative research suggests that causality is an inherent behavior and can significantly influence human judgment, irrespective of age. However, as the complexities of causality are being understood, another area of main concern is in representing this information in order to augment comprehension. A number of visual representations have been designed to effectively visualize and display causal occurrences. While some studies utilize static images, lines, and glyphs to depict the information, others use colors and animation to highlight the causal events. The next section describes some of these traditional and modern forms of causal illustrations.

3.2 Visualizing causal relations

Causal graphs denote the most common and traditional representations of causal relationships. These are acyclic graphs comprised of vertices, which denote the factors and targets, and directed lines that denote the causal relationships between them. One major drawback with causal graphs is that it only shows basic information about the causal event and does not provide additional information about the agents involved in the relation. Therefore, it does not satisfactorily answer complex questions that can be asked about the nature or reason for the causal occurrence.

Hasse diagrams also constitute one of the earlier systems for showing causal concepts. They have been used for representing distributed systems [Rehn, 2004], parallel processes [Viennot, 1997], or any other type of information structure that consists of

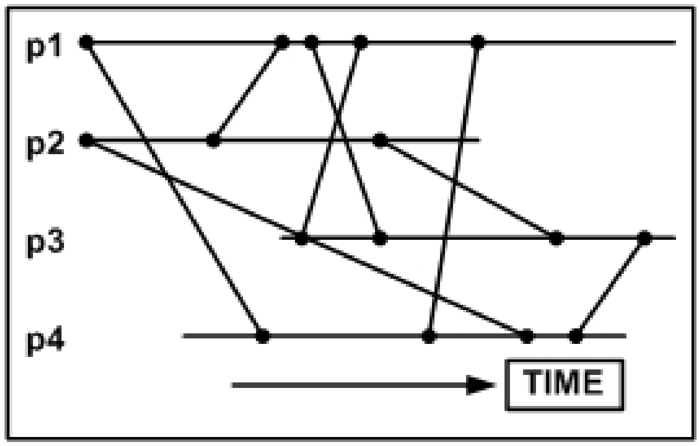

Figure 3.4: A simple Hasse diagrams showing processes p1 – p4 interacting with each other over a time frame.

causal events. In Hasse diagrams, processes are represented by parallel lines, while interactions between the processes are displayed by connecting lines and the time-line is represented from left-to-right (Figure 3.4). Hasse diagrams can be difficult to comprehend as the layout of the graph creates a large number of intersecting lines. Furthermore, to view the causal chain the user has to backtrack along the various edges. As with causal graphs, Hasse diagrams are not equipped to show causal semantics. The Hasse display also works on the principle that one factor is effecting one target and does not recognize multiple factors, targets, and mediators. Additionally, expanding a Hasse diagram would result in more clutter and make it difficult to visualize the causal relationships.

Another popular method of cause-effect analysis in project management scenarios are the Ishikawa or fish-bone diagrams [Ishikawa, 1991], which employ a static method of representing causal semantics. In Ishikawa diagrams the target is written at the right end of the "main bone" of the diagram, main causes are written as side bones

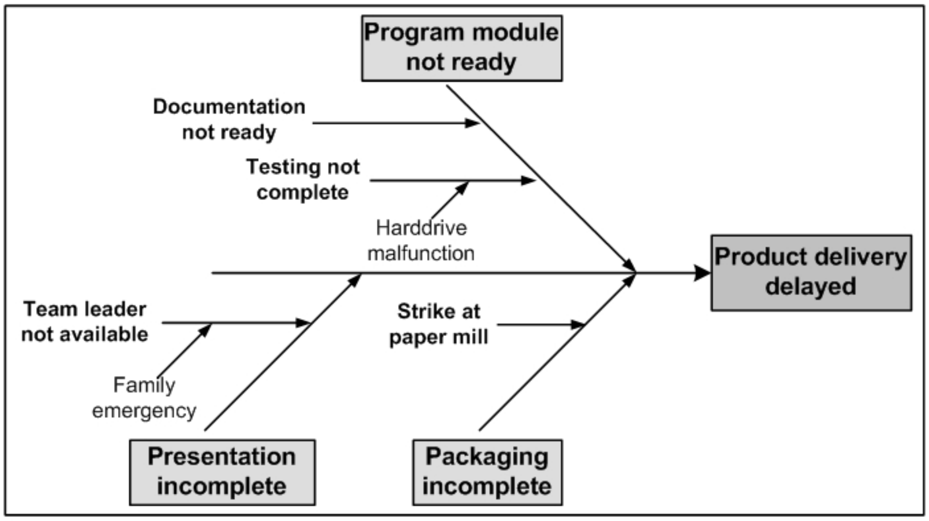

Figure 3.5: A sample Ishikawa fish-bone diagram showing factors and their relations to the final target.

off the main bone, indirect causes are written off of their respective side bones, and so on until the entire scenario is mapped out (Figure 3.5). This diagram allows for categorization of the factors and for describing indirect influences on the final target. However, it does not incorporate multiple targets or shared factors (factors directly or indirectly connected to more than one bone in the diagram) and is spatially limited in the number of events it can represent.

Flowcharts have also been popular for representing causal flows in information science. They have been used to show interactions between processes or to show a project management schedule [Bauer et al., 2006]. For example, Figure 3.6(a) shows a project development schedule, starting from client meetings to discuss project requirements and ending at packaging and delivering the finished product. Flowcharts utilize nodes of different shapes to show information such as start and end points, decision points, and input/output information. Directed lines show the sequence of

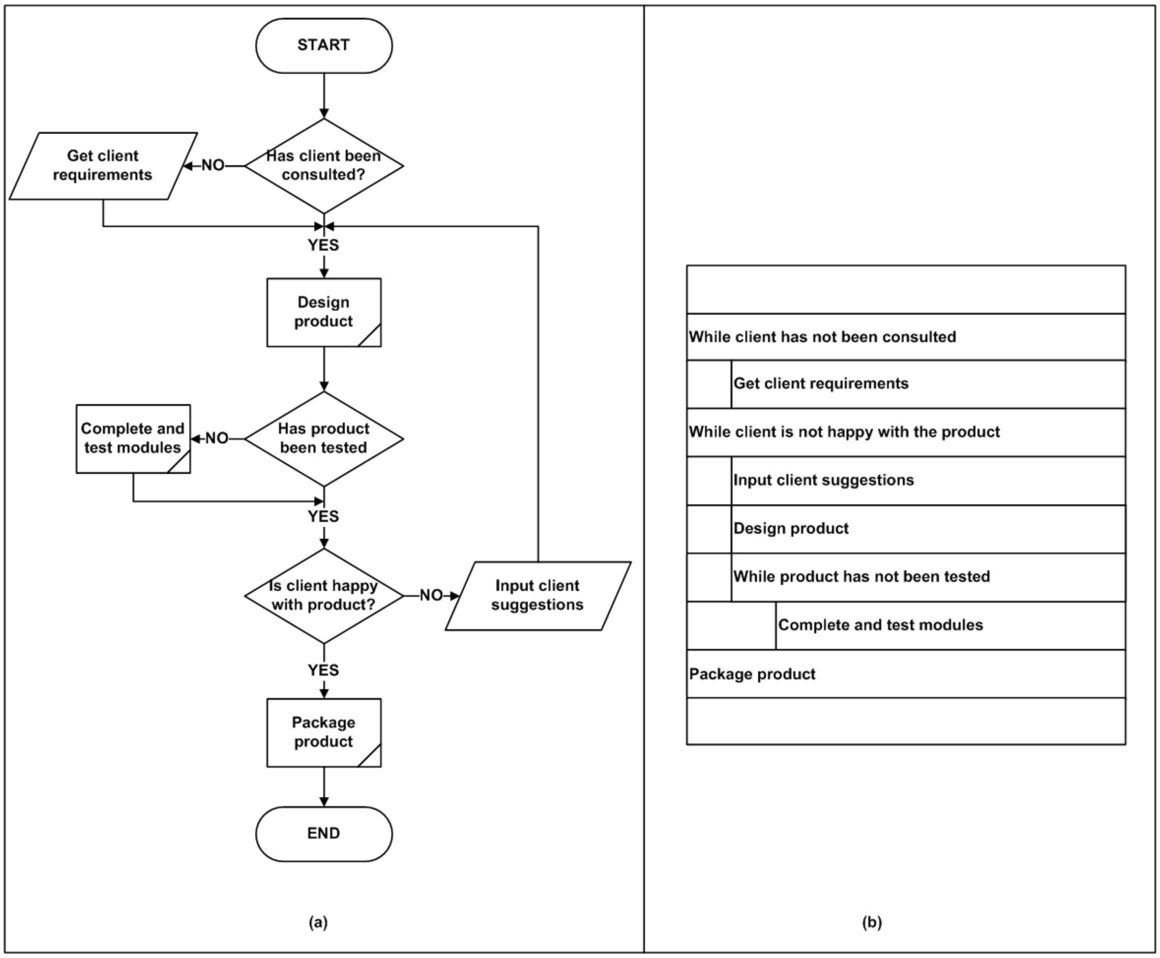

Figure 3.6: A product development process represented by (a) a flowchart and (b) a Nassi-Schneidermann diagram.

information flow. Although flowcharts allow multiple factors and targets and can be used to provide quantitative information, they are static and do not distinguish between various types of causal semantics, such as contradictive or mediated, and therefore are not a preferred choice when representing dynamic causal information.

Nassi-Schneidermann diagrams have also been used to graphically represent process flows in a system [Nassi and Shneiderman, 1973]. In this technique, the sys-

Figure 3.7: Newton's Cradle demonstration influence of a factor (the first ball) transferred through mediators (the intermidiate balls) and causing a change in the target (the last ball) (redrawn based on [Nassi and Shneiderman, 1973]).

tem is considered as a box with contains process interactions and decisions. Nassi-Schneidermann diagrams enable representation of information flows from factors to targets, single or multiple decision points, and start and end of process (Figure 3.6(b)). However, these diagrams also do not distinguish between different causal semantics or multiple factors and are inadequate in representing dynamic causal information.

Newton's Cradle also shows a nice representation of a causal relationship between a factor and a final target [Herrmann and Seitz, 1982]. In this setup, a series of pendulums are hung adjacent to each other, such that the ball of each pendulum just touches the ball of the adjacent pendulums. When the ball of the first pendulum is pulled away and released, it hits the ball of the adjacent pendulum, and transfers its momentum to the second ball. In this manner, the momentum of the first ball is passed through the pendulum series, until it is transferred to the final ball, causing it to swing outward, thus giving the impression that the first ball *caused* the last one to swing (as shown in Figure 3.7). This study is particularly interesting as it portrays a good example of mediated causality (described in 4.1.2), where causal information is transferred from the factor to the target through mediators.

Recent studies have used smooth animations to visualize causal events. Ware et al. [1999] designed a number of visual representations for showing causal information in

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Figure 3.8: Representing causal relations using VCV metaphors; (a) Pin-ball metaphor, (b) Prod metaphor, and (c) Wave metaphor (reproduced from [Ware et al., 1999]).

node-link diagrams. They defined a visual causal vector (VCV) that represented a causal relation between two entities. The VCV was tested using several metaphors (pin-ball, prod, and wave) that were designed with a number of spatiotemporal rules that are necessary for perceptually inferring causal effects [Ware et al., 1999]. In the pin-ball metaphor, a ball is released from an object and strikes another object and sets the latter into oscillatory motion (Figure 3.8 (a)). In the prod metaphor, a rod extends from the first object and sets the second object into oscillatory motion (Figure 3.8 (b)). Thirdly, in the wave metaphor a wave emerges from the first object and sets the second object into a "bobbing" motion, like a ball floating on the surface of water (Figure 3.8 (c)). Results from their study showed that the nature of the metaphor is less critical than the spatiotemporal rules that were used for showing the causal relations. Their results inspired some of the work presented in this research. In particular, I extended their results for depicting semantics that can provide rich descriptions of naturally occurring causal relationships.

Elmqvist and Tsigas [2004] designed the Growing-squares technique to depict causal dependencies between processes in a system. With Growing-squares, each process is given a unique color. When processes influence one another, their colors intermix in a checkered fashion over a time frame (Figure 3.9.a). Growing-squares

Figure 3.9: (a) Visualizing causality using Growing-squares technique; (i) Process P0 influences P1 (color of P0 (light grey) flows into P1 (white) in a checkered fashion) and (ii) Process P1 influences P2 (color of P1 (white and light grey) flows into P2 (dark grey)). (b) Visualization of a 3-process system using Growing-polygons; (i) P0 (black) influences P1 (dark grey) and (ii) P1 (black and dark grey) influences P2 (light grey). (Images redrawn from [Elmqvist and Tsigas, 2003, 2004]).

takes advantage of animation to show gradual increase and decrease of influences in a system. A user evaluation showed that users were significantly faster ($\sim$25%) in answering questions related to causal events using Growing-squares in comparison to Hasse diagrams [Elmqvist and Tsigas, 2004]. The evaluation also showed that users preferred the Growing-squares technique to Hasse diagrams. However, a significant redesign of the Growing-squares visualization would be necessary to incorporate additional causal semantics into the system.

Growing-polygons are an enhancement to the growing-squares technique [Elmqvist and Tsigas, 2003]. In this approach, each causal factor is represented by an n-sided polygon, having a color. Each polygon is further divided into sectors for each of the factors in the system. As one factor influences another, the color of the first flows into its respective sector of the second, representing the effect (Figure 3.9.b). The causal flow takes place over a timeframe. A user evaluation by [Elmqvist and Tsigas, 2003] showed that users were 58% faster and 21% more accurate in answering causal questions with Growing-polygons than with Hasse diagrams. Additionally, Growing-polygons is capable of showing certain types of semantics such as depicting two factors that have a simultaneous effect on one another. Similarly, Growing-polygons can depict properly the semantic of transitive/mediated causality, i.e. if A influences B and B influences C, then A influences C. However, significant modifications to the visualization is necessary in order to include semantics such as strong or weak causal factors, large or small causal outcomes, or threshold causality ("At least a certain amount of influence of A is needed to cause an outcome in B"; e.g. at least a certain amount of stress is needed to increase Flu symptoms).

While the representations described above have facilitated viewing causal relationships in a passive way, a number of systems have relied on some form of interactivity for showing causality. Spence and Tweedie [1998] designed the Attribute Explorer which allows users to adjust attribute values of objects in a scenario and incorporate responsive interaction to quickly provide results of user queries (within 0.1 seconds). The Influence Explorer [Tweedie et al., 1995] allows users to interactively inspect the influence of factors on different outcomes. The interaction is provided by means of slider bars that control the amount or range of influence of one factor on the effect. Neufeld et al. [2005] used a variation of the influence explorer in which the user is allowed to dynamically vary the values of the factors to show the amount of influence on the target. Such systems can be successfully used in situations that necessitate causal reasoning for making decisions. However, as neither method is equipped with the ability to depict various forms of causal semantics, these techniques cannot be used to distinguish between different types of causal events.

Yao's master's thesis constitutes a recent study of causal visualization [Yao, 2008].

This study aimed at testing the effectiveness of animations and motion cues in elucidating casual information in real-time scenarios, e.g. in maps. Yao also tested the effectiveness of mapping these visualizations onto existing displays. The study focused on testing temporal conditions, velocity, and target changes to generate the perception of causality. Results of their study concluded that animations are effective in describing the information and also suggested guidelines for effective perception of the causal events. Although this study is similar in context to my study, Yao has focussed on different aspects of causal visualization such as details of the animations. In contrast, my study focuses on the defining a taxonomy of causal semantics and then visualizing them using simple animations. Another difference between our studies is that Yao's study focuses on the general representation of the causal relation, while my study focuses on providing additional information such as type and quantity of influence and type and degree of effect. Notwithstanding these differences, this study suggests interesting guidelines which can be utilized while incorporating interactions into my visualizations and extending them for professional use.

3.3 Chapter Summary

This chapter describes two main categories of related research that has been the source of inspiration for my work: comparison of static and animated representations and visualizing causal relations.

Studies that have compared static and animated representations suggest that animations are useful in presenting dynamic information and have been successfully utilized in the areas of pedagogy [Baecker and Marcus, 1998; Bryne et al., 1999;

Dann et al., 2001], information science [Cosker et al., 2007], to describe complex information [Bodner and MacKenzie, 1997], and to design interactive graphical user interfaces [Harrison et al., 2011]. However, animations can quickly become complex and ineffective if they do not conform to the two design principles of *Congruence* and *Apprehension* [Tversky et al., 2002]. Researchers have compared static and animated representations in describing pedagogical concepts such as Newton's Laws of Motion [Reiber and Hannafin, 1988], programming languages [Pane et al., 1996], and computer algorithms [Bryne et al., 1999]. Results of these experiments have shown that carefully selected static images are as effective as animations in elucidating complex concepts. The studies have also suggested that the display medium should be chosen based on the spatial ability of the person viewing the information. However, these studies are not conclusive as they have focused on changes that are slow or far apart and can be adequately replaced by static images showing the critical moments. Therefore, since the debate has not yet been resolved on which representation type (static or animation) is more effective in describing dynamic information, I have designed and compared both static and animated representations for the set of causal semantics identified in my study.

Several studies have also designed animated techniques to describe interactions between causal components and have compared these techniques to traditional representations of causal relations [Elmqvist and Tsigas, 2004]. Although these techniques provide interesting and dynamic visualizations, they do not support categorization of the causal semantics and are inadequate in representing complex causal information.

In the next chapter I will apply the knowledge gained from the studies in chapters 2 and 3 to define the causal semantics that have been tested in my research. I will also describe the static and animated representations of these semantics and the steps that have been taken to construct them.

Chapter 4

Component I: Defining the basic structure of a causal relation

The work of Michotte and others suggests that certain spatiotemporal conditions favor the perception of causal phenomena. Hence, I reason that if I could map the semantics of causal systems onto a set of perceptual semantics, I could create visual diagrams that are more informative and descriptive. In addition, I could test the effectiveness of my visualizations by analyzing the accuracy rates and response times of viewers through perceptual user studies.

In order to achieve my goal, my research has been divided into four components:

- **Component I:** In this component I categorize the causal semantics based on their reasons for occurrence, the agents involved in the causal equation, and the outcomes they produce. This component concludes with perceptive visual designs to depict these semantics, as described in this chapter and in chapter 5.

- **Component II:** In addition to designing the causal representations it is crucial to test their effectiveness and usefulness in practice. Therefore, in this component, I test the intuitiveness of my representations in depicting simple causal semantics, using user studies. Chapter 6 describes the experiments conducted in this component of the research.

- **Component III:** In the third component I extend the user studies in Component II to test visual representations of more complex variations of the causal semantics, as described in chapter 7.

- **Component IV:** In the fourth, and last, component of my research, I endeavored to test the effectiveness of the animated representation by comparing it with an enhanced version of the static representation, as described in chapter 8.

Also, as an aid to understanding the various causal descriptions I now describe a simple scenario, which I will refer to, where needed, during the course of this chapter. *NOTE: The examples used here and throughout the thesis are not based on factual data. They have been used solely to define a theme for describing the different causal semantics.*

The scenario is as follows:

An ailment commonly affecting human beings is Influenza and can be described using the following *Flu* scenario. For instance, Cold Weather and Low Immunity together can cause an increase in the Flu. Medication can reduce Flu symptoms, and Medication and Taking Rest together also relieve the Flu. In the latter case, Medication has a stronger influence than Taking Rest on relieving Flu. Finally, Stress can cause Flu, which in turn can increase Stress.

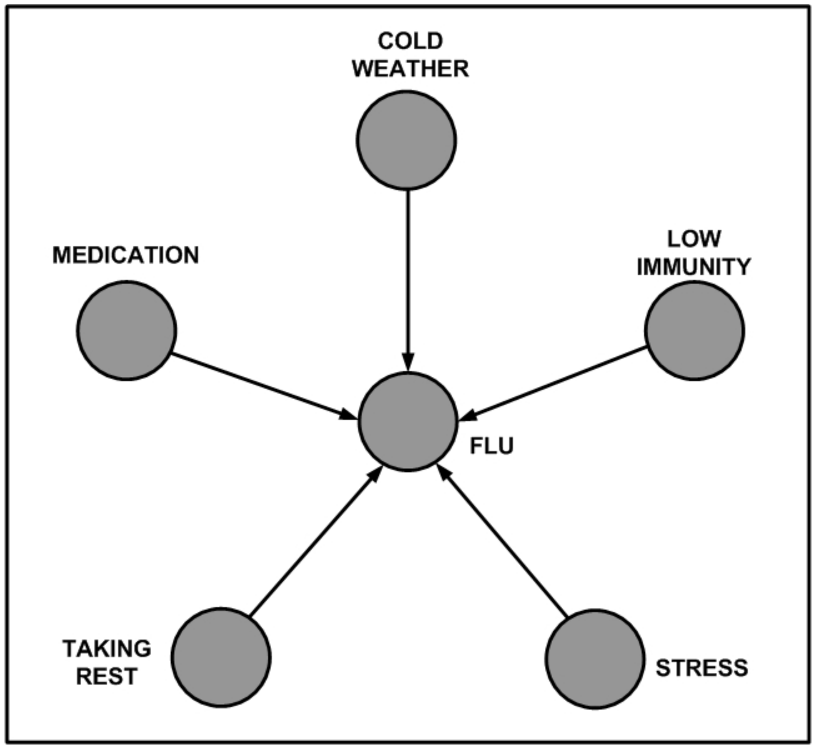

Figure 4.1: A causal-graph representation of the 'Flu' scenario. Arrows represent the direction of causal influence. Please note that the causal representations shown in this thesis are used only as an illustration of something that is understandable, and are not based on any scientific studies.

This scenario can be represented using a simple causal graph, as shown in Figure 4.1. However, this graph is inadequate in providing additional help when making medical judgments, such as "How much of medication do we need to cause a large decrease in Flu?" or "Is a small amount of Low Immunity enough to cause an increase in Flu Infection?" In order to answer such questions it is important to define different types of causal semantics and categorize them based on their behaviors.

4.1 Defining the causal semantics

As the focus of my research is to generate effective visual depictions of causal semantics, in this component I will describe the steps taken to define the semantics, create a taxonomy, and design the representations based on Michotte's temporal guidelines.

4.1.1 Step 1: Elementary units of a causal relation

The first step in designing visual representations for causal semantics is to connect them together to form causal relations. To achieve this goal it is important that the structure of a causal relation and the components that make up this relation are clearly defined. Hence I will now define a set of keywords that describe the main components of a causal relation:

- **Factor:** A factor is the cause in a relationship, and is displayed as a labeled circle. In the Flu scenario of Figure 4.1, *Cold Weather*, *Medication*, *Taking Rest*, *Stress*, and *Low Immunity* are all factors. In a directed causal graph, factors are distinguished as the nodes placed at the origin of their respective directed lines. As my causal graphs are undirected, in my static representation, the factor is the node surrounded by the influence glyphs and in the animation the factor is the node from which the bullet originates.

- **Target:** A target (or outcome) is the variable acted upon by a factor or by a combination of factors. In a directed causal graph, targets are placed as nodes at the destination of the connecting arrows, as shown in Figure 4.1. In this example, *Flu* is the target which is acted upon by the factors mentioned above. In my static representation, targets are the nodes by the side of the effect bars and in the animation the targets are the nodes at the destinations of the bullets.

- **Relation:** A relation signifies a causal action occurring between a factor(s) and the target and is represented as a directed line emerging from the factor to the target. However, my visual designs use undirected lines to depict causal relations in order to provide each node the option of switching between the status of factor or target based on the semantic being represented.

- **Influence:** A factor(s) can have a *positive or negative* and a *weak or strong* influence on the target. A positive influence is one that aims at causing an increase in the outcome and a negative influence is one that tries to decrease the outcome. For example, Cold Weather can have weak/strong and positive/negative influence on the Flu. However, this cannot be perceived from Figure 4.1, without extra textual descriptions. My representations use descriptive glyphs and bullets to depict a factor's influence.

- **Effect:** A target that is acted upon by a factor(s) can show a *weak* or *strong* and a *positive* or *negative* effect. A positive effect is inferred when an increase in the target seen and a negative effect is inferred when a decrease in the target is seen. As with depicting influence, type and quantity of effect are not depicted in a traditional causal graph. As with the influence, my representations utilize glyphs and target transformations to describe effects on a target.

The above keywords define the characteristics of a basic causal relation. Various combinations of one or more of the above can be made to generate causal semantics of different complexities, as described in the next subsection.

4.1.2 Step 2: Taxonomy of causal semantics

In order to consolidate the different varieties of causal semantics commonly perceived, it is necessary to organize these semantics based on their behavior in different scenarios. Therefore the second step of this phase focuses on defining a taxonomy of causal semantics that are inherent in the environment. These semantics can be grouped into two categories, simple and complex, based on the difficulty in representing and comprehending the causal relations (Figure 4.2).

Simple causal semantics

Simple causal semantics represent the building blocks of most causal relations. Four semantics fall under this category: Causal Amplification, Causal Dampening, Causal Strength, and Causal Multiplicity.

Causal Amplification

In abstract terms, causal amplification occurs when a factor is causing an increase in the target. For example, *Cold Weather* causes an increase in *Flu Infection* (Figure 4.3 (a)).

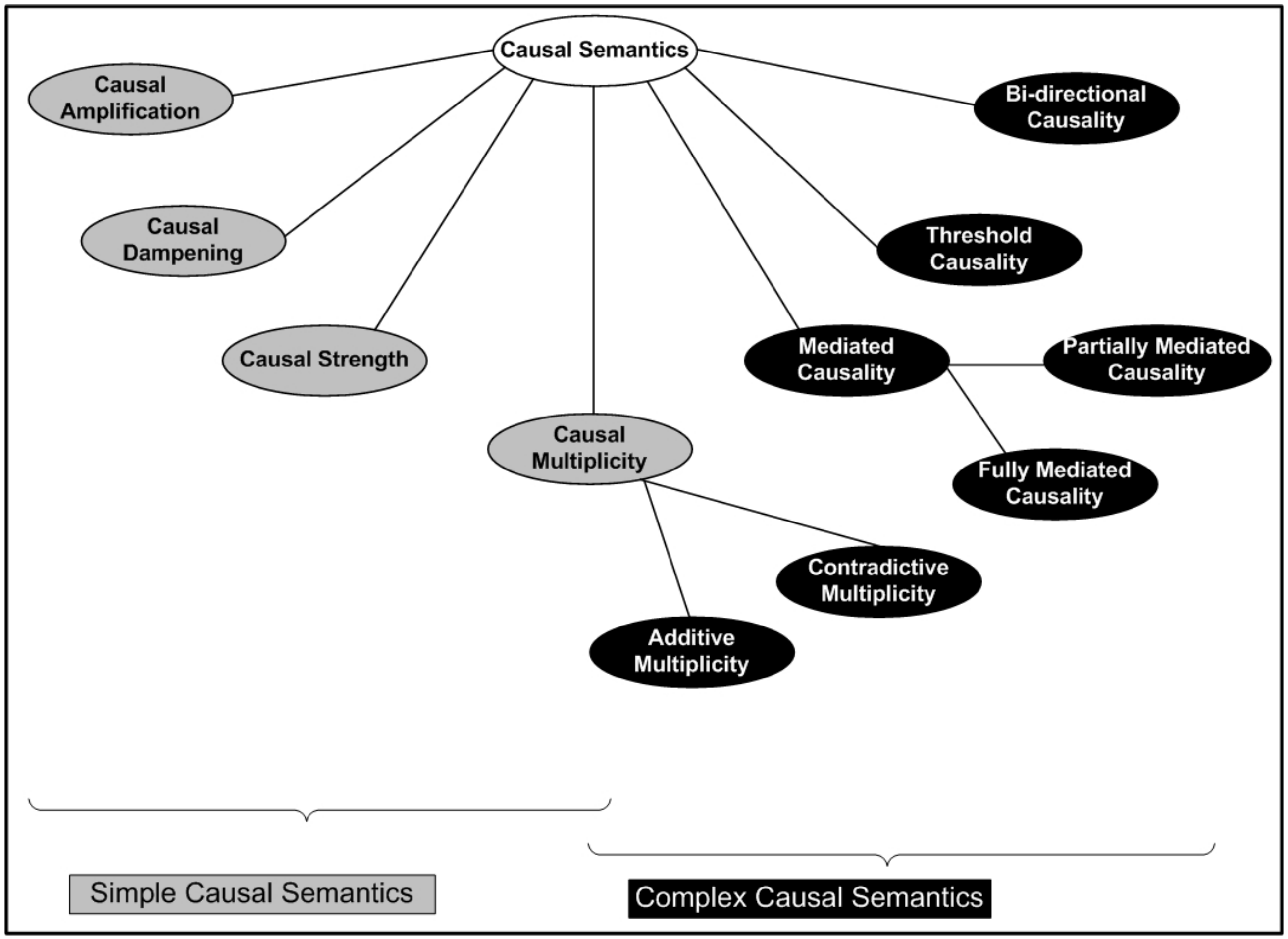

Figure 4.2: Classification of the causal semantics into groups based on their behavior.

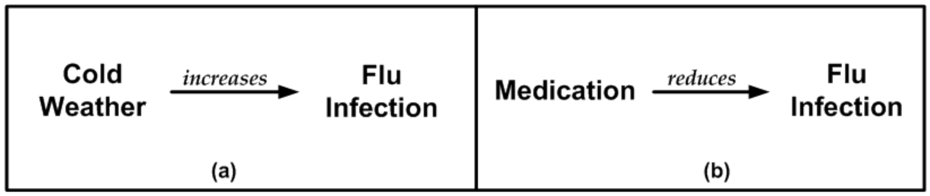

Figure 4.3: (a) Factor (Cold Weather) causes an increase in target (Flu Infection) - *Causal Amplification* and (b) Factor (Medication) causes a decrease in the target (Flu Infection) - *Causal Dampening*.

Causal Dampening

Causal dampening means that a factor is having an overall negative effect on a target. For example, causal dampening can explain physical phenomena such as lack of sunlight "decreases or dampens" the environmental temperature or, as shown in Figure 4.3 (b), taking *Medication* "reduces or decreases" *Flu Infection*.

Causal Strength

We talk about causal strength when a one factor is contributing more or less significantly to an outcome, when compared to another factor. As causal strength is defined in relative terms, it therefore exists only when there is more than one contributing factor, i.e. "stronger than" or "weaker than". For example, *Medication* has a stronger influence than *Taking Rest* on *Flu Infection* (Figure 4.4 (a)).

Causal Multiplicity

When two or more factors are contributing to the causal effect it is referred to as causal multiplicity. In this definition it is implicit that the effect is only present when all the factors are simultaneously influencing the target. In more concrete terms, causal multiplicity appears in many contexts such as *Medication* and *Taking*

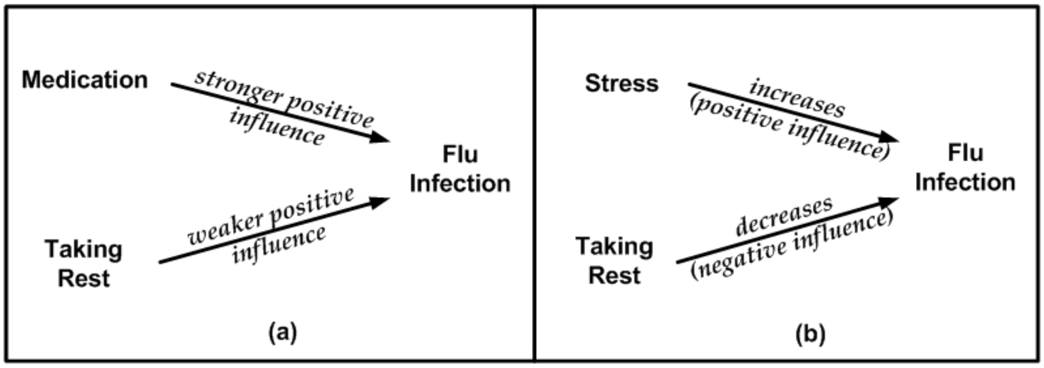

Figure 4.4: Factor (Medication) and factor (Taking Rest) have positive influences on the target (Flu Infection) - *Additive Causality*; One factor (Medication) has a stronger influence than another factor (Taking Rest) on the target (Flu Infection) - *Causal Strength* and (b) Factor (Stress) has a positive influence while factor (Taking Rest) has a negative influence on the target (Flu Infection) - *Contradictive Causality*.

Rest together have a combined effect on *Flu Infection* (Figure 4.4 (a)), two processes causing a deadlock in distributed systems or the opinions of two people having a combined influence on the final decision.

Complex causal semantics

Complex causal semantics are combinations or modifications of the simple semantics. Six semantics fall under this group: Additive Causality, Contradictive Causality, Fully-mediated Causality, Partially-mediated Causality, Threshold Causality, and Bidirectional Causality.

Additive and Contradictive Causality

Based on the type of influences of the factors (positive or negative), *Causal Multiplicity* can be further divided into two sub-categories:

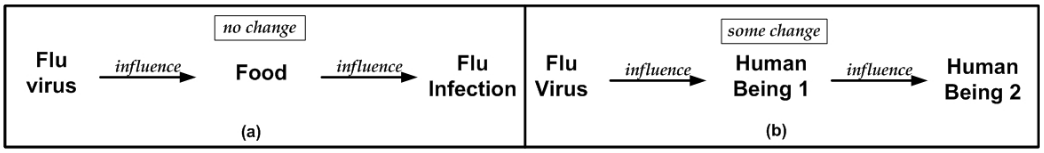

Figure 4.5: (a) Factor (Flu Virus) is carried by mediator (Food) and causes change in the target (Flu Infection); the mediator (Food) is not affected during this transfer - *Fully-mediated Causality* and (b) Factor (Flu Virus) infects the mediator (Human Being 1) who in turn passes it on to the target (Human Being 2) - *Partially-mediated Causality*.

Additive Causality

Additive causality occurs when every factor has the same type of influence (positive or negative) and the final effect is a summation of these influences. For example, both *Medication* and *Taking Rest* have negative influences and will "sum up" to cause a decrease in *Flu Infection* (Figure 4.4 (a)).

Contradictive Causality

Contradictive causality occurs when factors have opposing influences on the target. In this event the final effect will depend upon the strongest influence. For example, *Stress* increases Flu Infection (positive influence) while *Taking Rest* decreases Flu Infection (negative influence) and the remaining outcome of the *Flu Infection* depends upon which factor is stronger (Figure 4.4 (b)).

Fully-mediated and Partially-mediated causality

Mediated Causality is said to occur when a factor indirectly influences the target. In this type of causality, there is no direct contact between the initial factor and the final target; nonetheless, influence of the factor on the outcome is perceived. Based on the behavior of the mediator two types of mediated causality can be defined:

Fully-mediated causality

Fully-mediated causality is perceived when the mediator acts purely as an intermediate agent to pass on the influence of the main agent to the target, without itself being affected in any way. For instance, *Flu Virus* is carried by *Food*, which when ingested causes *Flu Infection*. The mediator (Food) is not affected by the factor and simply passes on the factor's influence to the target, thereby depicting fully-mediated causality (Figure 4.5 (a)).

Partially-mediated causality

In partially-mediated causality, the mediator is affected by the main agent in addition to passing on the influence to the target. As traditional causal graphs do not show changes in the components of a causal relation, therefore it is difficult to distinguish this type of causality from fully-mediated causality using traditional techniques. For example, the *Flu Virus* infects a *Human Being* who in turn transmits the virus to another *Human Being* (Figure 4.5 (b)). Along with transmitting the virus, the first human being is also affected by the virus, which is perceived as partially-mediated causality. In addition, in this type of causality, there is also a possibility that the influence is modified (amplified or dampened) before it is eventually transmitted to the target.

Threshold causality

Many cases exist where the strength of a causal influence is not adequate to generate a significant change in the outcome. Threshold causality is seen when an agent requires equal to or more than a given minimum strength in order to influence

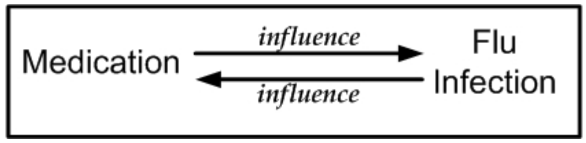

Figure 4.6: Medication causes a change in Infection and in turn Infection causes a change in Medication - *Bidirectional Causality*.

the outcome. For example, only a large amount of *Stress* can influence a change in *Flu Infection*, while a small influence of Stress is inadequate to show a causal effect. Traditional causal graphs do not show changes in the factors or targets and therefore cannot represent threshold causality.

Bidirectional causality

In abstract terms, bidirectional causality is perceived when the agent and the outcome influence each other. For example, *Medication* can reduce *Flu Infection*, and as *Flu Infection* reduces the *Medication* intake is also reduced (Figure 4.6).

The above 10 semantics represent many of the general causal events that we experience in our lives. Now that these semantics have been defined the next step is to determine the manner of representing these relations along with the information they would display. In order to achieve this goal it is important to define the composition, or structure, of a causal relation; as has been described in the next subsection.

4.1.3 Step 3: Define the structure of a causal relation

A causal relation can be defined in terms of categories, component types, semantics, and quantifiers.

As shown in Figure 4.7, each causal relation is composed of three main categories;

antecedents, intermediates, and consequents.

Antecedents are the intimidators of the causal relation and consist of one component type, the *factor*. Each factor in turn is described using two semantics - *quantity* and *type*. Quantity is the amount of influence present in the relationship and contains two pieces of quantifier information (small or large). Type describes the nature of the influence and also contains two pieces of quantifier information (positive or negative).

Intermediates are the auxiliary components that are seen only in certain types of causal relations. Two component types of intermediates are commonly seen - mediators and thresholds. *Mediators* are encountered in fully-mediated and partially-mediated causal relationships and can have different types of semantic information connected to them depending upon their current role in the relation. When a mediator is involved in a fully-mediated causal relation, it is dormant and does not take an active part in the event; therefore it does not have any semantic information attached to it. However, in a partially-mediated causal relation, the mediator is initially the *intermediate target* (influenced by the factor), containing the semantic information, *quantity* (quantifier information: large or small) and *degree* (quantifier information: increase or decrease), and later becomes the *intermediate factor* (passes on influence to target), containing the semantic information, *quantity* (quantifier information: large or small) and *type* (quantifier information: positive or negative). The other type of intermediate component type is *threshold*, which is used to control a factor's influence in the causal relation. A threshold is attached to a factor and contains two pieces of semantic information, *quantity* (quantifier information: small or large) and *type* (quantifier information: positive or negative). Influence of a factor must equal or surpass the threshold in order to affect the outcome.

Consequents are the outcomes of a causal relation and consist of one type of component, the *target*. Although a causal relation can have one or more targets, in my research, each causal relation consists of only one target containing two pieces of semantic information, *quantity* (quantifier information: small or large) and *degree* (quantifier information: increase or decrease).

Based on the structure in Figure 4.7 causal relations can now be built and visually designed. These causal relations may be constructed as causal statements, where the path of the statement consists of one or more components in the three sections (antecedents, intermediates, and consequents) of the causal structure. It is also not necessary for each causal statement to consist of all the semantic information in every section, i.e. the causal statement can be constructed based on any of the paths shown in Figure 4.8. The following are examples of the different types of causal relations represented using causal paths:

- **Causal Amplification:** "Cold Weather causes a large increase in Flu Infection" is constructed as START $\longrightarrow$ 4 (No influence quantifiers) $\longrightarrow$ 10 (Factor: *Cold Weather*) $\longrightarrow$ 21 (No Intermediates) $\longrightarrow$ 22 (Target: *Flu Infection*) $\longrightarrow$ 32 (Quantity : *large*) $\longrightarrow$ 33 (Degree: *increase*) $\longrightarrow$ 37 (END).

- **Causal Dampening:** "Medication causes a large decrease in Flu Infection" is constructed as START $\longrightarrow$ 4 (No Influence quantifiers) $\longrightarrow$ 10 (Factor: *Medication*) $\longrightarrow$ 21 (No Intermediates) $\longrightarrow$ 22 (Target: *Flu Infection*) $\longrightarrow$ 32 (Quantity: *large*) $\longrightarrow$ 33 (Degree: *decrease*) $\longrightarrow$ 37 (END).

- **Causal Strength:** "Medication has a large influence while Taking Rest has a small influence on Flu Infection" is constructed as START $\longrightarrow$ 2, 2 (Quantity (commas separate information from multiple factors): *large*, *small*) $\longrightarrow$ 8, 8 (Factor: *Medication*, *Taking Rest*) $\longrightarrow$ 21, 21 (No Intermediates for either factor) $\longrightarrow$ 22 (Target: *Flu Infection*) $\longrightarrow$ 38 (No effect quantifiers) $\longrightarrow$ 39 (END).

- **Causal Multiplicity:** "Medication and Taking Rest together influence Flu Infection" is constructed as START $\longrightarrow$ 4, 4 $\longrightarrow$ 10, 10 (Factor: *Medication*, *Taking Rest*) $\longrightarrow$ 21, 21 $\longrightarrow$ 22 (Target: *Flu Infection*) $\longrightarrow$ 38 $\longrightarrow$ 39 (END).

- **Additive causality:** "The negative influence of Medication and the negative influence of Taking Rest combine to decrease Flu Infection" is constructed as START $\longrightarrow$ 1, 1 (Type: *negative*, *negative*) $\longrightarrow$ 7, 7 (Factor: *Medication*, *Taking Rest*) $\longrightarrow$ 21, 21 (No intermediates) $\longrightarrow$ 22 (Target: *Flu Infection*) $\longrightarrow$ 36 (Degree: *decrease*) $\longrightarrow$ 37 (END).

- **Contradictive causality:** "The positive influence of Stress and the negative influence of Taking Rest together combine to increase Flu Infection" is constructed as START $\longrightarrow$ 1, 1 (Type: *positive*, *negative*) $\longrightarrow$ 7, 7 (Factor: *Stress*, *Taking Rest*) $\longrightarrow$ 21, 21 (No intermediates) $\longrightarrow$ 22 (Target: *Flu Infection*) $\longrightarrow$ 36 (Degree: *increase*) $\longrightarrow$ 37 (END).

- **Fully-mediated causality:** "Flu Virus is carried through Food and causes Flu Infection" is constructed as START $\longrightarrow$ 4 (No influence quantifiers) $\longrightarrow$ 10 (Factor: *Flu Virus*) $\longrightarrow$ 11 (Mediator: *Food*) $\longrightarrow$ 12 (No mediator quantifiers) $\longrightarrow$ 22 (Target: *Flu Infection*) $\longrightarrow$ 38 (No effect quantifiers) $\longrightarrow$ 39 (END).

- **Partially-mediated causality:** "A small positive amount of Flu Virus causes a small increase of Flu Infection in Human Being 1 and consequently a large positive amount of Flu Virus transmitted by Human Being 1 causes a large increase in Flu Infection in Human Being 2" is constructed as START $\longrightarrow$ 2 (Quantity: *small*) $\longrightarrow$ 5 (Type: *positive*) $\longrightarrow$ 7 (Factor: *Flu Virus*) $\longrightarrow$ 11 (Mediator: *Human Being 1*) $\longrightarrow$ 14 (Quantity: *small*) $\longrightarrow$ 17 (Degree: *increase*) $\longrightarrow$ 15 (Mediator: *Human Being 1*) $\longrightarrow$ 14 (Quantity: *large*) $\longrightarrow$ 16 (Type: *positive*) $\longrightarrow$ 18 (Target: *Human Being 2*) $\longrightarrow$ 32 (Quantity: *large*) $\longrightarrow$ 33 (Degree: *increase*) $\longrightarrow$ 37 (END).

- **Threshold causality:** "At least a large positive amount of Stress is needed for influence, therefore a small positive influence of Stress causes no change in Flu Infection" is constructed as START $\longrightarrow$ 2 (Quantity: *small*) $\longrightarrow$ 5 (Type: *positive*) $\longrightarrow$ 7 (Factor: *Stress*) $\longrightarrow$ 23 (Threshold factor: *Stress*) $\longrightarrow$ 25 (Threshold quantity: *large*) $\longrightarrow$ 27 (Threshold type: *positive*) $\longrightarrow$ 29 (Target: *Flu Infection*) $\longrightarrow$ 32 (No change in quantity) $\longrightarrow$ 33 (No change in degree) $\longrightarrow$ 37 (END).

- **Bidirectional causality:** "Medication causes a small decrease in Flu Infection and in turn Flu Infection causes a large decrease in Medication" is constructed as START $\longrightarrow$ 4 (No influence quantifiers) $\longrightarrow$ 10 (Factor: *Medication*) $\longrightarrow$ 21 (No intermediates) $\longrightarrow$ 22 (Target: *Flu Infection*) $\longrightarrow$ 32 (Quantity: *small*) $\longrightarrow$ 33 (Degree: *decrease*) $\longrightarrow$ 37 (END) $\longrightarrow$ 39 (No influence quantifiers) $\longrightarrow$ 38 (Factor: *Flu Infection*) $\longrightarrow$ 22 (No Intermediates) $\longrightarrow$ 21 (Target: *Stress*) $\longrightarrow$ 8 (Quantity: *large*) $\longrightarrow$ 6 (Degree: *decrease*) $\longrightarrow$ 3 (START).

With the definition of the structure of a causal statement and the causal semantics that are encountered in the environment, it is now possible to capture these semantics using a variety of representations, as described below. The next chapter will focus on applying this design to generate simple static and animated representations of the causal semantics, which constitute the final step of **Component I** of my research.

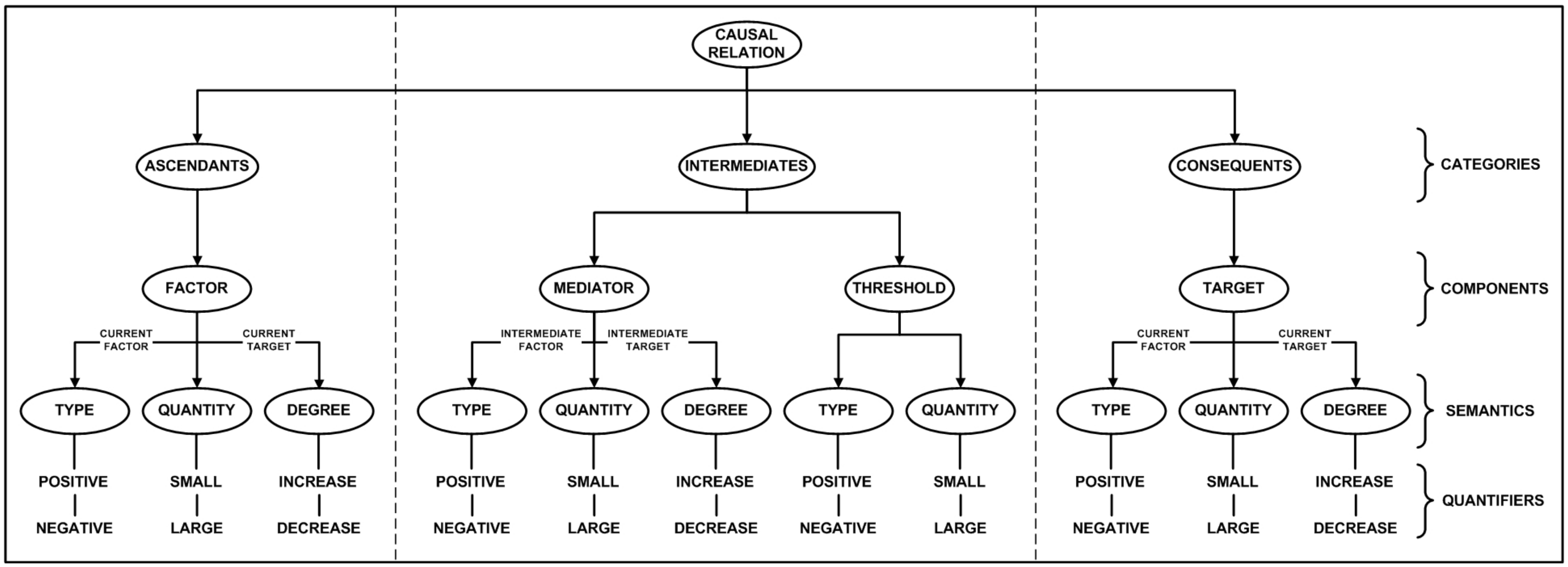

Figure 4.7: Structure of a causal relation showing categories, component types, semantics, and quantifier information.

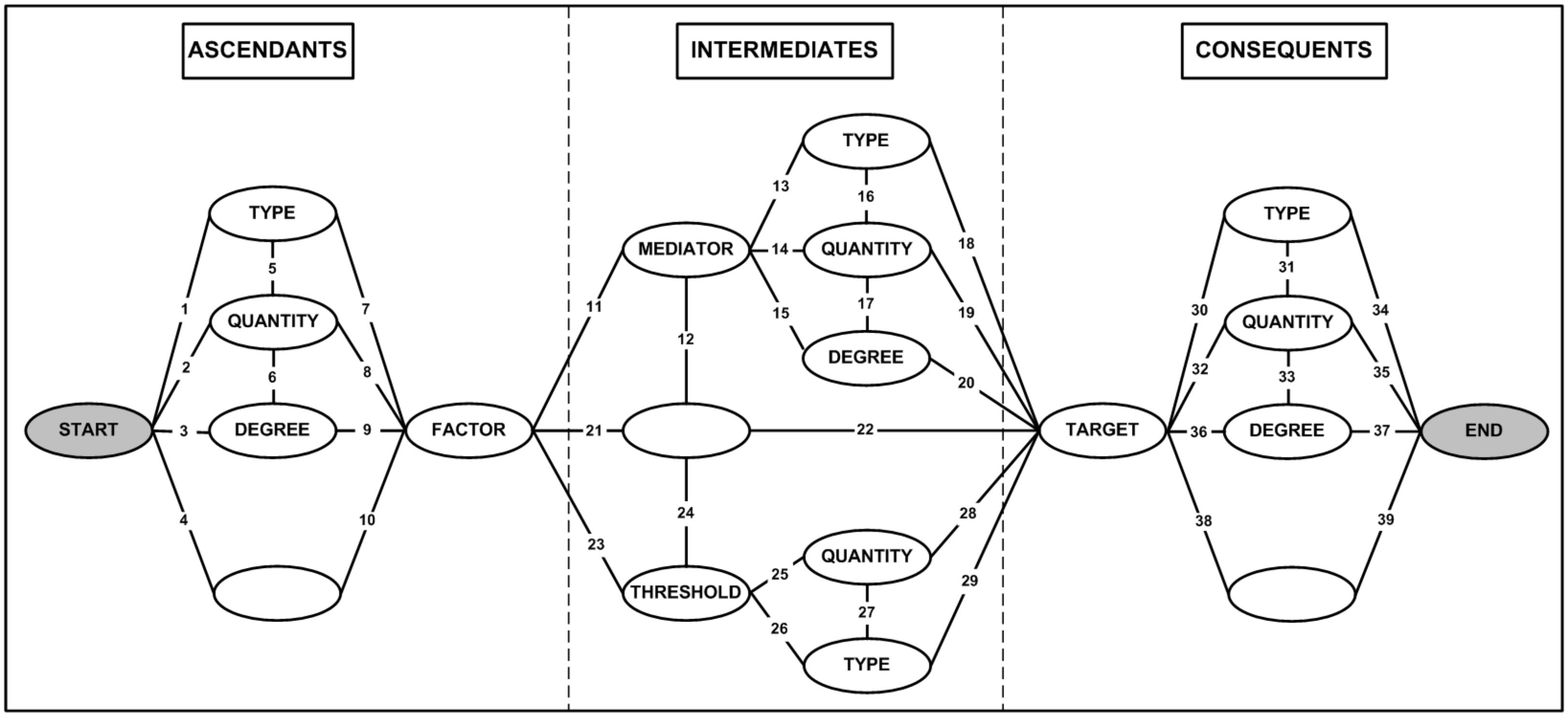

Figure 4.8: Path of a causal relation. Nodes depict the components of a relation and connecting lines represent the paths that can be taken to construct the relation.

4.2 Chapter Summary

This chapter focuses on the definition and representation of causal semantics commonly encountered in the environment, which constitutes half of the first component of my research.

At the beginning of this chapter, I defined the terms factor, target, relation, influence, and effect, which will be utilized throughout the rest of the study to describe various constituents of a causal relation. These constituents are the building blocks of any causal relation and can exist in different combinations depending upon the behavior of the causal semantic and its environment.

Upon defining the basic terms that describe a causal relation, the next step focused on defining the causal semantics. I categorized the semantics into two main groups. The first group is called *simple causal semantics* and comprises of basic causal information such as amplification, dampening, strength, and multiplicity. The second group is called *complex causal semantics* and consists of causal information created by enhancing, modifying or combining the simple semantics. This group includes additive and contradictive causality, which are enhancements of causal multiplicity, fully-mediated and threshold causality, which are modifications of causal amplification and/or dampening, and partially-mediated and bidirectional causality, which are combinations of two or more causal events. I feel that the above semantics represent many of the causal events that we come across regularly. In addition, several of these semantics have been inspired (though not always explicitly identified) from background research on causal models (described in section 2.4) and causal animations (described in section 3.2), as summarized in table 4.1 below.

#	**Causal Semantic**	**Related research on causal models**	**Related research on causal visualizations**
1.	Causal Amplification	A type of *basic relation* where a factor has an effect on an outcome	The VCV metaphors have been a main source of inspiration for some of the basic representations of my research. The property of a ball, a prod, or a wave setting the target into motion by hitting it has inspired my use of bullets originating from the factor and hitting the target to show influence of the factor on the target. Also, in the VCV metaphors, the target is set in motion to show an effect. In my representations, the target is set into motion (expansion/contraction) to show effect, and in some cases (e.g. threshold causality) the target remains stationary to show that the factor's influence was not strong enough to cause an effect
2.	Causal Dampening	A type of *basic relation* where a factor has an effect on an outcome	-

3.	Causal Strength	Comparing two *basic relations* where influence of one factor is compared to the influence of another factor, on the outcome	-
4.	Causal Multiplicity	*Inverted fork* where an outcome is influenced by more than one factor	This is inspired from the Growing Squares and Growing Polygons technique, where the color of the factor flows into and inter-mixes with the target. In the next step the two colors (from both factors) flow into the third, thus showing causal multiplicity. Although I do not use the technique of color inter-mixing, influences from my factor "intermix" and have a combined effect on the outcome

5.	Additive Causality	A type of *inverted fork* where an outcome is influenced by more than one factor, but both factors have similar type of influences (positive or negative)	-
6.	Contradictive Causality	A type of *inverted fork* where an outcome is influenced by more than one factor, but both factors have contradicting type of influences (one has a positive influence and other has a negative influence)	-

7.	Fully-mediated Causality	A type of *causal chain* where influence of the factor is transferred wholly through the mediator to the outcome	Fish-bone diagrams intuitively represent mediated causality by the structuring auxiliary effects as branches of the main effect. I have used the same principle in connecting nodes that would have only a mediated effect on the final outcome
8.	Partially-mediated Causality	A type of *causal chain* where influence of the factor is transferred partially through the mediator to the outcome	Similar to above, I have used the Fish-bone diagram's principle in connecting nodes that would only have indirect influences on the final outcome
9.	Threshold Causality	A type of *basic relation* where a factor needs a certain minimum amount of influence to have an effect on the outcome	The wave metaphor of the VCV metaphors inspired my design for Threshold causality, where the only the presence of a wave (or in my case a certain minimum value) causes a bobbing effect on the outcome, otherwise the target is not influenced by the factor

10.	Bidirectional Causality	A combination of two *basic relations* wherein the factor and target interchange roles	In Newton's Cradle, the first pendulum (initial factor) swings and passes on the influence (through mediators) to the last pendulum (outcome), which swings outward. However, since the outcome is also a pendulum, it will eventually swing back and hit its adjacent pendulum thus passing back the influence to the first pendulum, inspiring bidirectional causality

Table 4.1: Table summarizing inspiration drawn from background research on causal models and causal visualizations in identifying my taxonomy of causal semantics.

In order to determine a standard for creating the causal relation I also defined its structure as consisting of three main categories; antecedents, intermediates, and consequents. Each causal relation is made up of at least one antecedent and one consequent which represent the cause and outcome of any event. Intermediates, on the other hand, are optional and are seen in only certain types of relations. In addition to describing these three main categories, each part can also be given additional semantic information and quantifier information, such as quantity or type, which aid in answering more complex and detailed questions about the event. Also, this structure can be clearly defined using a causal path, which details the different options available in each part of the causal relation. Each path represents a unique causal equation and eventually, the combination of the antecedents, intermediates, and consequents, along with the additional information attached to them, determines the final structure of the causal relation.

The next chapter focuses on the second half of this component of my research, applies knowledge gained from prior research in this area, and also utilizes the causal structure and paths described in this chapter to generate designs that are intuitive and can be easily comprehended.

Chapter 5

Designing the visual representations

In Section 3.1, I described several studies that have been conducted to determine which representation (static or animated) is more suited for representing dynamic information. The common consensus of these studies is that the type of representation should be chosen based on the type of information being displayed and the type of people trying to access this information. In addition, Tversky et al. [2002] suggest that adherence to the two design principles of Congruence and Apprehension will enhance comprehension of the information being displayed. As my research involves describing dynamic causal information, I hypothesized that this type of information would be more accurately represented and perceived faster using simple and effective animations. However, in order to be fair to prior research comparing static and animated techniques, I have also designed static representations for my causal semantics and have compared them to animations of the same.

This section describes my static and animated designs along with their detailed depictions of the causal semantics.

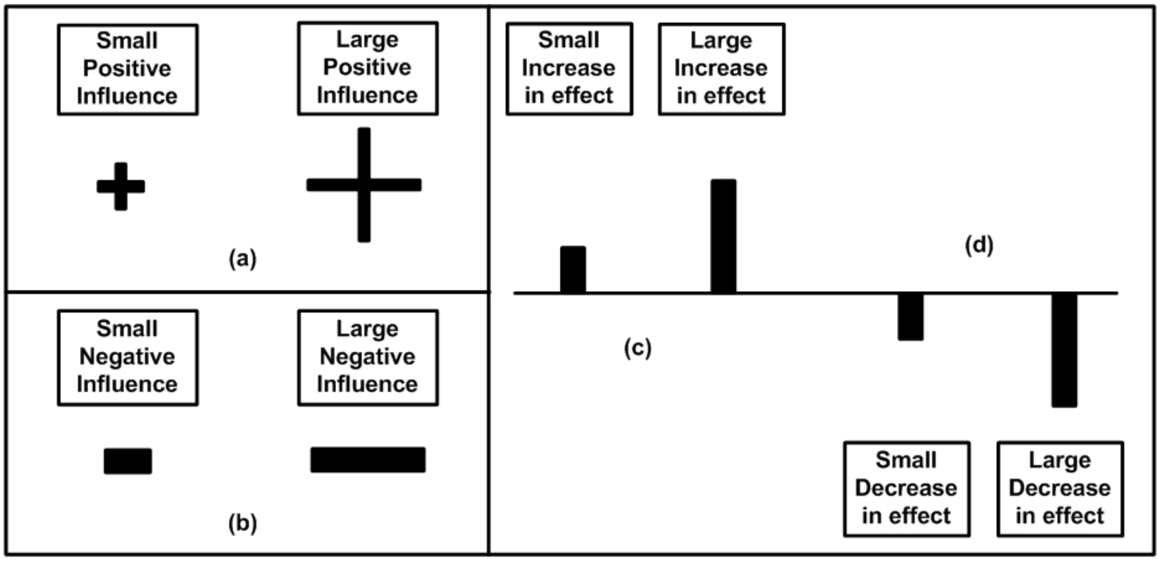

Figure 5.1: Static glyphs representing semantic information such as (a) small and large positive influence, (b) small and large negative influence, (c) small and large increase in effect, and (d) small and large decrease in effect.

5.1 Static design using node-link diagrams and glyphs

The static design enhances traditional causal graphs with additional visual encodings. Factors and targets are denoted using nodes and connected using lines, in order to create perceptual groups between the factor and target, which in turn will help improve the perception of causality [Choi and Scholl, 2004]. A positive influence is denoted by a plus glyph (+) (Figure 5.1 (a)) and a negative influence is denoted by a minus glyph (−) (Figure 5.1 (b)), attached to its respective factor. The size of the glyph depicts the strength of the influence. Near the target, a series of bars are placed to show type and degree of effect. Bars along the positive y-axis depict an increase in the effect (Figure 5.1 (c)) while bars along the negative y-axis depict a

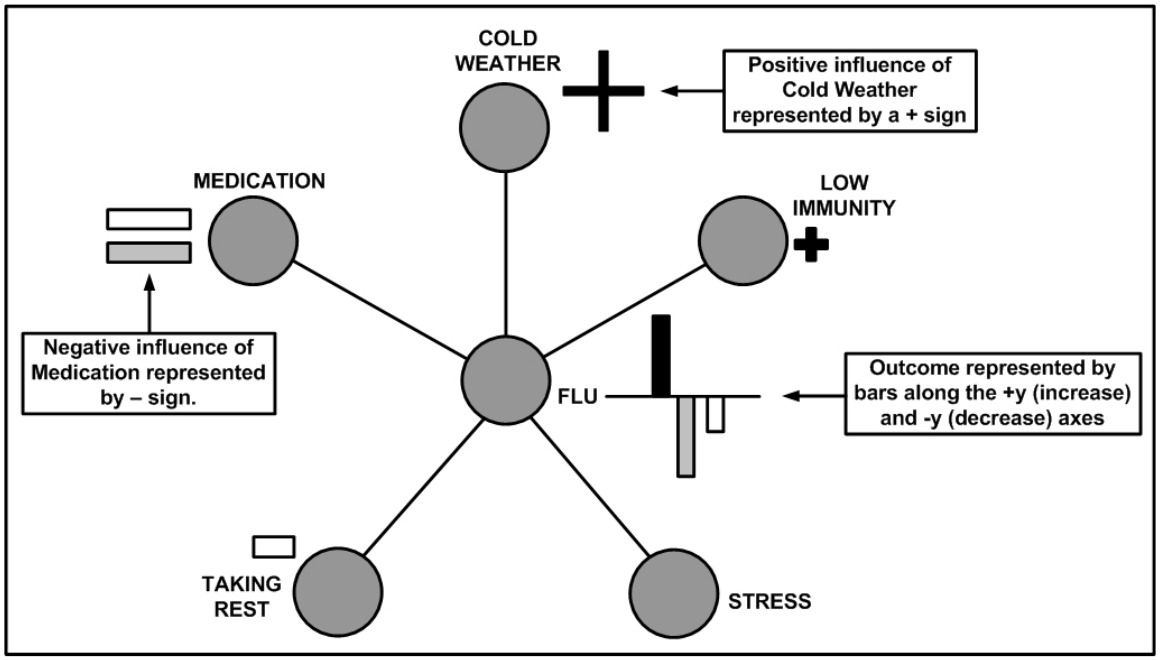

Figure 5.2: Static representation of the Flu scenario using nodes (factors, targets), connecting lines (relations), and glyphs (influences, effects). Three causal relations are represented here distinguished by their unique colors (black, grey, and white).

decrease in the effect (Figure 5.1 (d)). The sizes of bars depict small or large degree of effect. Finally, in a scenario containing more than one causal relation the order of the bars depicts the order in which the causal events take place and the events are distinguished from one another through their unique colors i.e. glyphs of the same color (influences and effect) belong to the same causal relation.

Some causal relations from the *Flu* scenario are depicted in Figure 5.2 using the static representation. As the order of the target bars denote the order the causal events, we can state the scenario in the following manner; Cold Weather and Low Immunity have positive influences on the Flu and a large positive amount of Cold

Weather together with a small positive amount of Low Immunity cause a large increase in the Flu (glyph color: *black*). Medication has a negative influence on the Flu and a large negative amount of Medication causes a large decrease in the Flu (glyph color: *grey*). Taking Rest also has a negative influence on the Flu and a large negative amount of Medication together with a small negative amount of Taking Rest cause a small decrease in the Flu (glyph color: *white*).

5.2 Animated design using moving bullets and smooth target transformations

The animated design uses simple animations and Michotte's *Theory of Ampliation* [Michotte and Thinés, 1963] to generate the sensation of causal interactions between the factors and the target. This design is also an extension of the traditional causal graph and depicts factors and the target using nodes that are connected by undirected lines. Influences on the target are displayed by the smooth movement of bullets from their respective factors to the target, along their connecting lines. Plus (+) and minus (−) glyphs within each bullet depict the type of influence (positive or negative) and the size of the bullet denotes the quantity of influence currently involved in the causal equation (Figure 5.3 (a) and (b)). Also, the bullets travel at a speed of **~5 cm/sec**, which is in keeping with Michotte's *absolute speed of the factor* guideline that suggests that causality is perceived only when an object's speed is between the range of **3 cm/sec** and **110 cm/sec** (Figure 5.4 (a)).

The type of effect is depicted by a change in target size. An increase in size

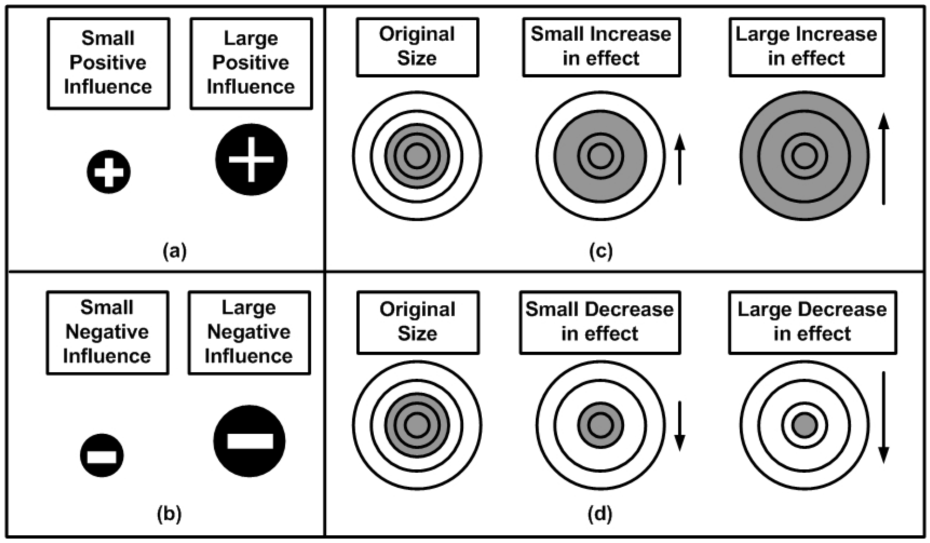

Figure 5.3: Animated glyphs representing semantic information such as (a) small and large positive influence, (b) small and large negative influence, (c) small and large increase in outcome, and (d) small and large decrease in outcome *(concentric circles were displayed to aid in judging the magnitude of target change, arrows were not shown in the experiment).*

denotes an increase in the outcome while a decrease in size denotes a decrease in the outcome. In addition, the degree of effect is depicted by the size to which the target transforms. Although the target does not "move" as described in Michotte's experiment, its transformation in size is also a type of movement. Therefore I followed Michotte's *relative ratio of velocities* guideline which suggests that the target should move slower than its factor and constricted my target transformation speed to ~**1.7 cm/sec** (Figure 5.4 (b)). Although the speed of the target falls below the *absolute speed of factor* range suggested by Michotte, through an informal evaluation, I determined that target transformations at speeds larger than ~1.7 cm/sec hindered

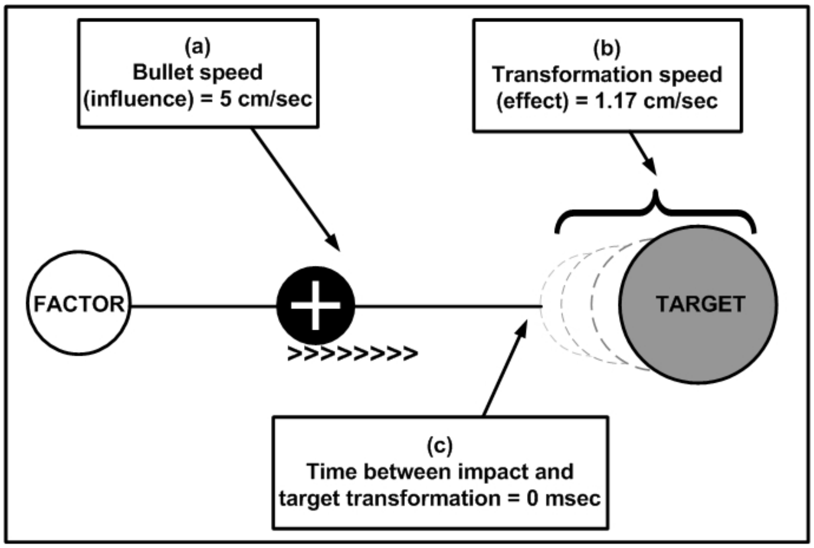

Figure 5.4: Description of the spatiotemporal guidelines that were employed to build the animated representations.

information acquisition.

Finally, Michotte also suggested that that *time between impact and movement* should be below 110 milliseconds. In order to retain a strong causal context in the visualizations, I have not incorporated any delay (**0 milliseconds**) between the bullets hitting the target and the target transformation (Figure 5.4 (c)).

Figure 5.5 describes one causal event in the Flu scenario using my animated design. In this event, factors Cold Weather and Low Immunity together influence the outcome (the Flu) as bullets from these nodes travel simultaneously towards the target. Secondly, both factors have positive influences on the Flu, which is depicted by the plus (+) signs within their respective bullets and thirdly, the sizes of the bullets suggest that Cold Weather has a large influence (Figure 5.5 (a)) while Low Immunity has a small influence on the Flu (Figure 5.5 (b)). When these bullets hit the target,

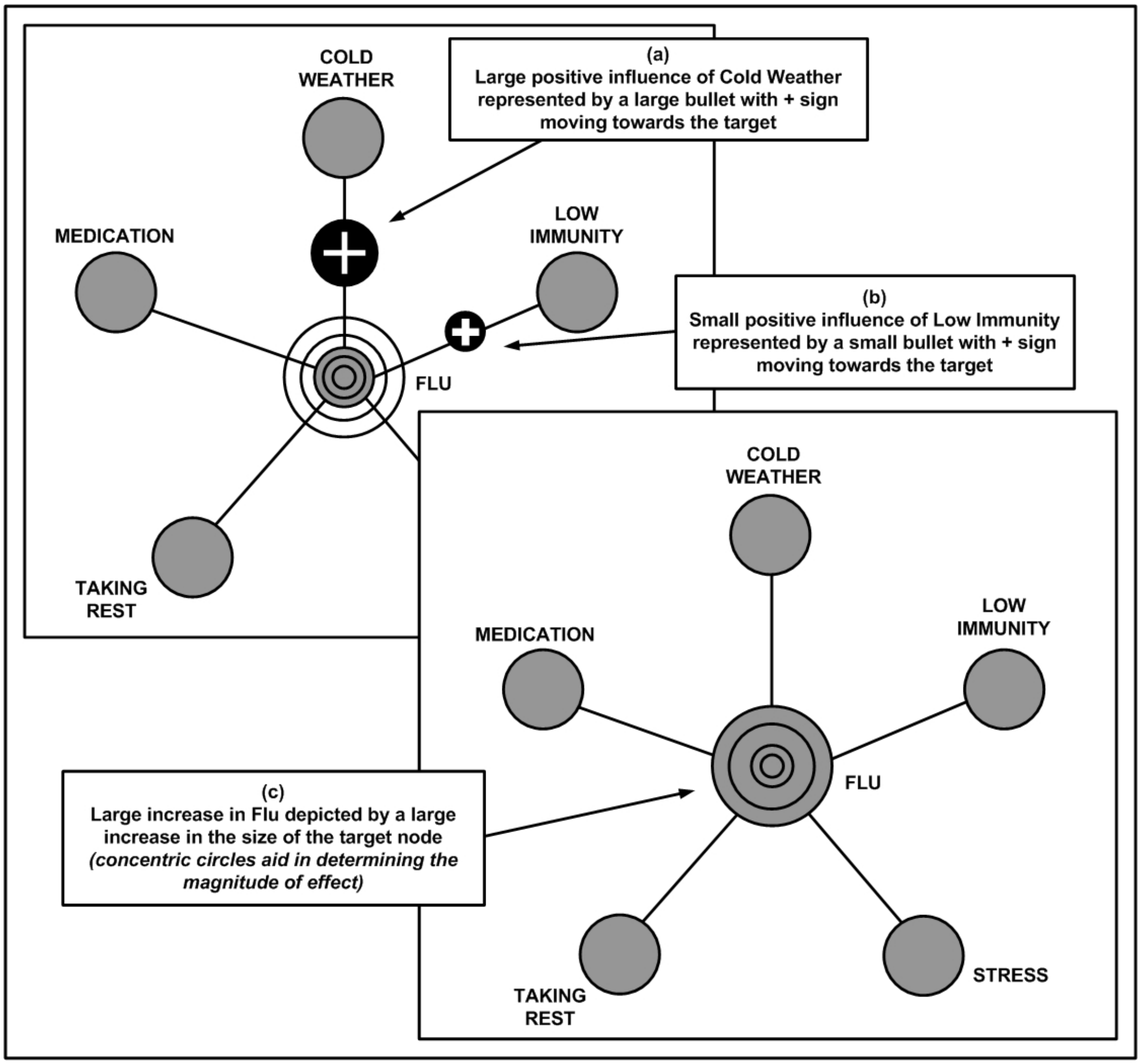

Figure 5.5: Animated representation of the Flu scenario using nodes (factors, targets), connecting lines (relations), animated bullets (influences), and target transformations (outcomes).

the target is smoothly transformed to show the outcome. Concentric circles have been placed as guides around the target node to aid in distinguishing between small and large changes in the target. In this scenario, the above factors cause a large increase

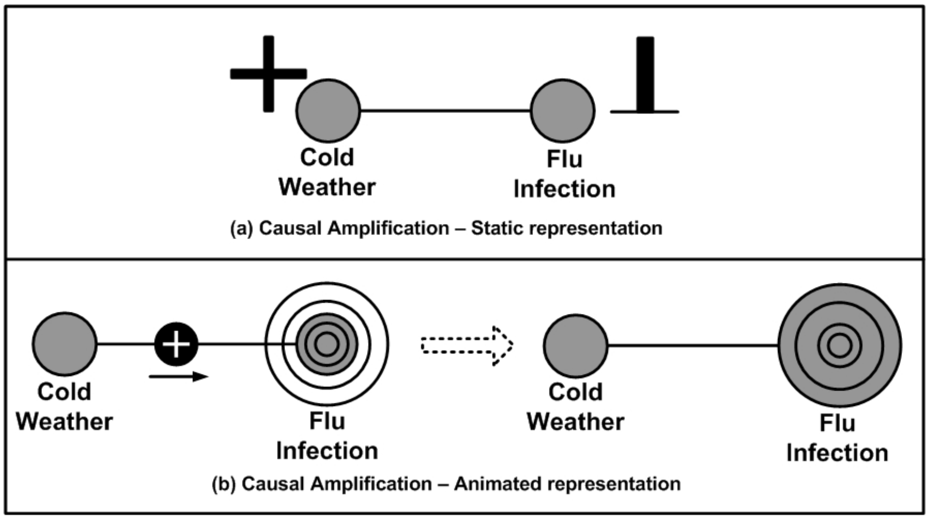

Figure 5.6: A large positive influence of factor (Cold Weather) causes a large increase in outcome (Flu Infection) - *Causal Amplification* (arrows were not shown during experiment).

in the outcome depicted by the large increase in the size of the Flu node (Figure 5.5 (c)).

In this subsection I focused on designing simple static and animated representations for general causal events. In the next subsection, I have utilized these designs to generate visual representations for each of my complex causal semantics.

5.3 Static and animated representations of causal semantics

5.3.1 Causal Amplification

Causal amplification is seen when the factor influences an increase in the outcome. The influence is depicted by a plus glyph (+) next to the factor in the static representation and by a bullet (containing a + glyph) moving from the factor to the target in the animated representation. The effect in the static representation is described by upright bars next to the target and in the animated representation is depicted by an increase in the size of the target at a constant speed of ∼1.17 cm/sec. For example, in Figure 5.6, Cold Weather causes an increase in Flu Infection, thus denoting *causal amplification*.

5.3.2 Causal Dampening

Causal Dampening is perceived when a factor causes a decrease in the outcome. The influence is depicted by a minus glyph (−) next to the factor in the static representation and by a bullet (containing a − glyph) moving from the factor to the target in the animated representation. The effect in the static representation is suggested by an inverted bar next to the target and depicted in the animated representation by a decrease in the size of the target node at a constant speed of ∼1.17 cm/sec. For example, in Figure 5.7, Medication causes a decrease in Flu Infection, thus denoting *causal dampening*.

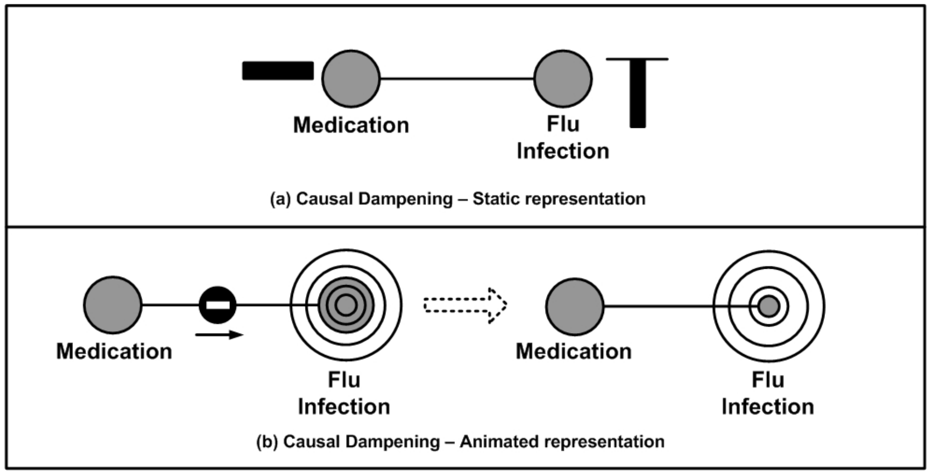

Figure 5.7: A large negative influence factor (Medication) causes a large decrease in outcome (Flu Infection) - *Causal Dampening*.

5.3.3 Causal Strength

Causal strength distinguishes between strong and weak factors in the relation and is depicted by the size of the corresponding glyphs. The small and large influences are depicted by the size of the plus (+) and minus (−) glyphs in the static representation and by the size of the bullets in the animated representation. In addition, in the animated representation, the bullets travel from the factors to the target at a speed of ∼5 cm/sec and the target transforms at the rate of ∼1.17 cm/sec. For example, in Figure 5.8, Medication has a large influence, which is stronger than the small influence of Taking Rest, on Flu Infection thus showing *causal strength*.

5.3.4 Additive Causality

Additive causality is a type of causal multiplicity in which all the factors in the causal relation have the same type of influence, and the outcome is simply the sum of

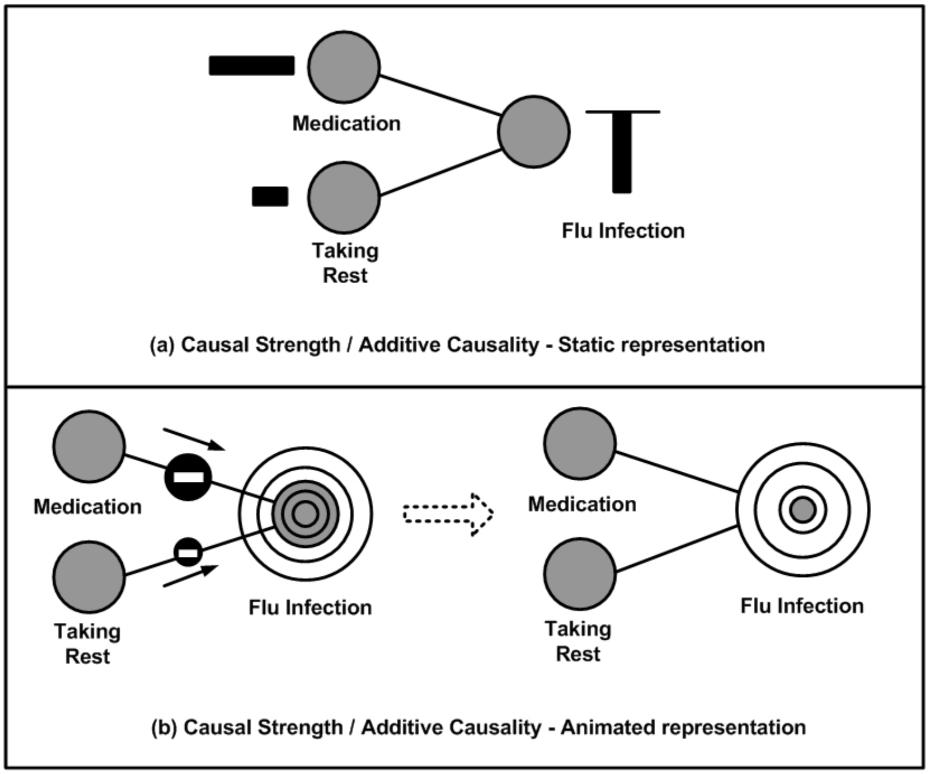

Figure 5.8: Factor (Medication) has a large negative influence and factor (Taking Rest) has a small negative influence and together they cause a large decrease in the outcome (Flu Infection) - *Additive causality.* Factor (Medication) has a stronger influence than factor (Taking Rest) on the outcome (Flu Infection) - *Causal Strength.*

all these influences. In the static representation all the factors have the same glyphs next to their respective nodes (all positive or all negative) while in the animated representation each factor sends a bullet with the same sign (+ or −) towards the target at a speed of ~5 cm/sec. For example, in Figure 5.8, Medication and Taking Rest are both positive influences and have a combined influence on Flu Infection, thus depicting *additive causality.*

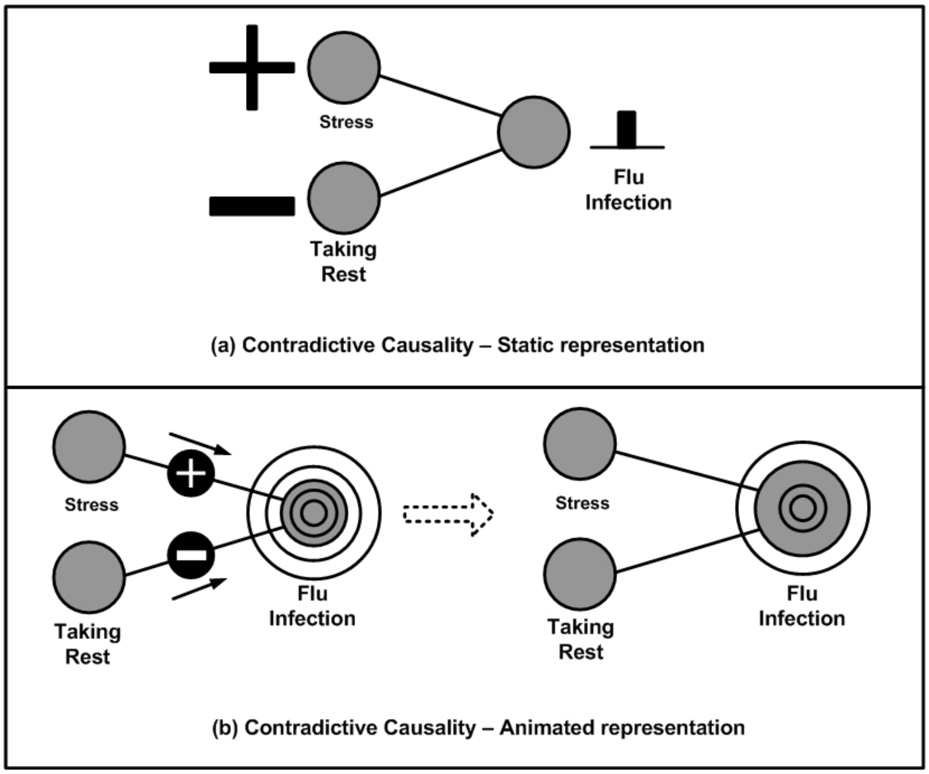

Figure 5.9: Factor (Stress) has a large positive influence and factor (Taking Rest) has a large negative influence and together they cause a small increase in the outcome (Flu Infection) - *Contradictive Causality.*

5.3.5 Contradictive Causality

Contradictive causality is also a type of causal multiplicity wherein factors have opposing influences and the final outcome depends on the strongest of these influences. In the static representation, the type of glyph (+ and $-$) and the size of these glyphs (small or large) determine the influences, while the size of the upright or inverted bars next to the target determine the type and degree of effect. In the animated representation, bullets of different sizes (small or large) and of opposing types (positive and negative) travel at a speed of $\sim$5 cm/sec towards the target, and the target

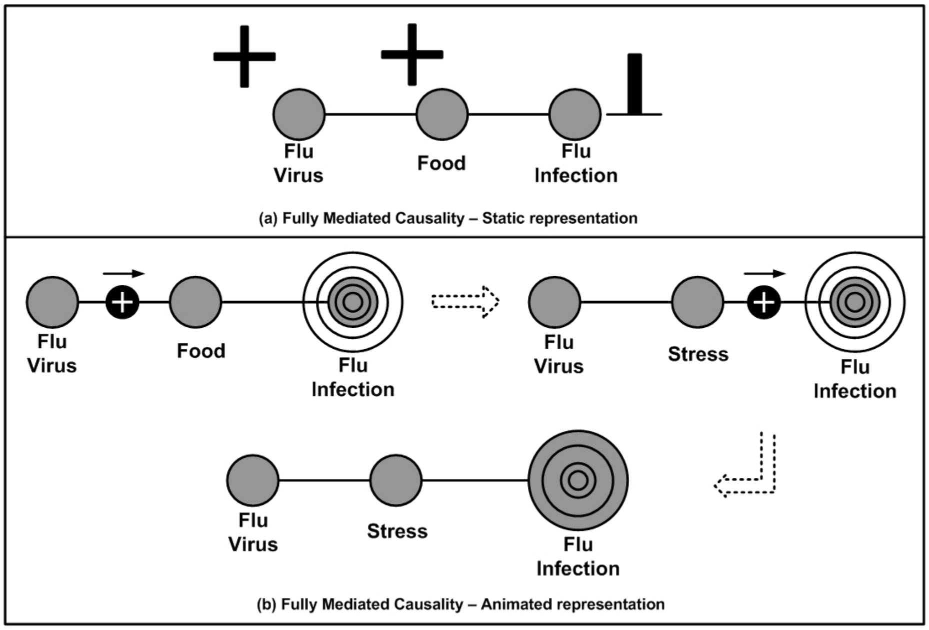

Figure 5.10: Large positive influence of factor (Flu Virus) is carried through a mediator (Food) and causes an large increase in the outcome (Flu Infection) - *Fully Mediated Causality.*

transforms (increases or decreases) based on the stronger of the influence at a speed of ∼1.17 cm/sec. For example, in Figure 5.9, Stress has a positive influence while Taking Rest has a negative influence on Flu Infection. However, the positive influence of Stress is stronger than the negative influence of Taking Rest and therefore the final outcome (Flu Infection) is slightly increased, depicting *contradictive causality.*

5.3.6 Fully-mediated Causality

Fully-mediated causality is the first type of mediated causality where the mediator simply passes the influence from the factor to the target without itself getting involved in the event. In the static representation, the mediator does not show any change (no bars next to the mediator) and passes on the factor's influence glyph to the target, where effect is shown using upright or inverted bars. In the animated representation, the influence bullet travels from the factor and *passes through* the mediator to the target, at a constant speed of ~5 cm/sec. Target transformation occurs at the rate of ~1.17 cm/sec to show the effect. For example, in Figure 5.10, the influence of the Flu Virus is passed through Food to cause a change in Flu Infection, thus depicting *fully mediated causality*.

5.3.7 Partially-mediated Causality

Partially-mediated causality is the second type of mediated causality where the mediator is affected by the main agent in addition to passing on the influence to the target. In this semantic the mediator can assume one of two states: the *intermediate target* when it is affected by the factor's influence and the *intermediate factor* when it passes on the influence to the target. In the static representation, change in the intermediate target is represented by upright (increase) or inverted (decrease) bars and influence of the intermediate factor is represented by positive (+) or negative (−) glyphs. In addition, the bars and glyphs next to the mediator are connected with dotted lines to show that they are part of the same causal event and also to reinforce their order of occurrence within the event. In the animated representation, bullets of different sizes (small or large) containing type information (positive or negative) travel from the factors to the intermediate target at a speed of ~5 cm/sec. Upon reaching the intermediate target, this target is transformed (increase or decrease) at a speed of ~1.17 cm/sec to small or large degrees, based on the factor's influence.

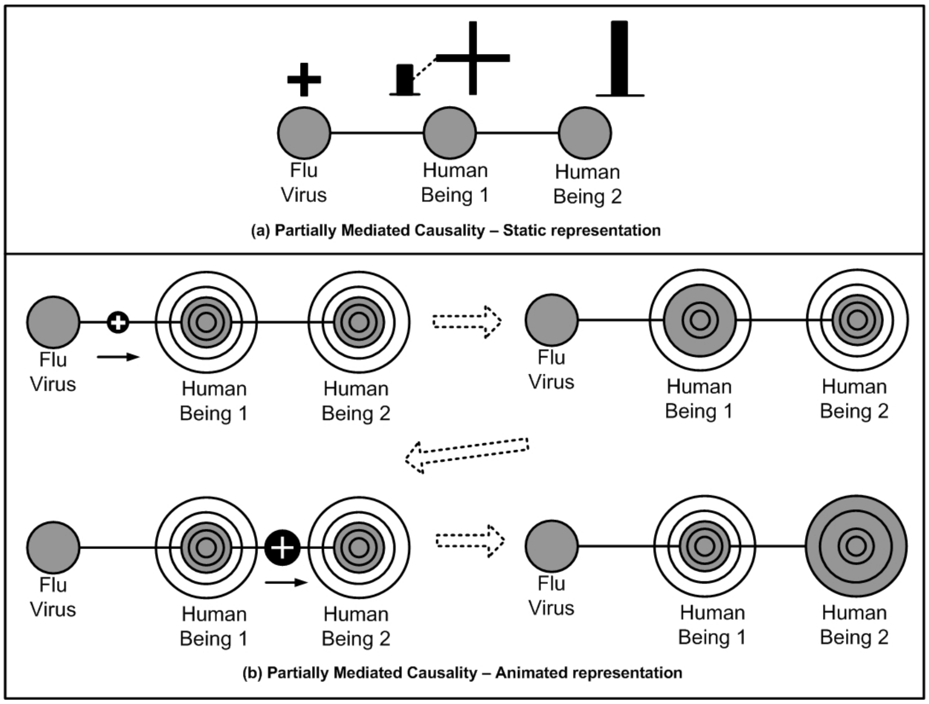

Figure 5.11: Small positive influence of factor (Flu Virus) causes a small increase in the mediator (Human Being 1) and a large positive influence of the mediator (Human Being 1) causes a large increase in outcome (Human Being 2) - *Partially-mediated Causality.*

The intermediate target then becomes the intermediate factor and sends positive or negative influence bullets, of small or large size, to the final target at a speed of ~5 cm/sec and transforms the final target at a speed of ~1.17 cm/sec. For example, in Figure 5.11, influence of the Flu Virus is causes a change in Human Being 1, and in turn the influence of Human Being 1 causes a change in Human Being 2.

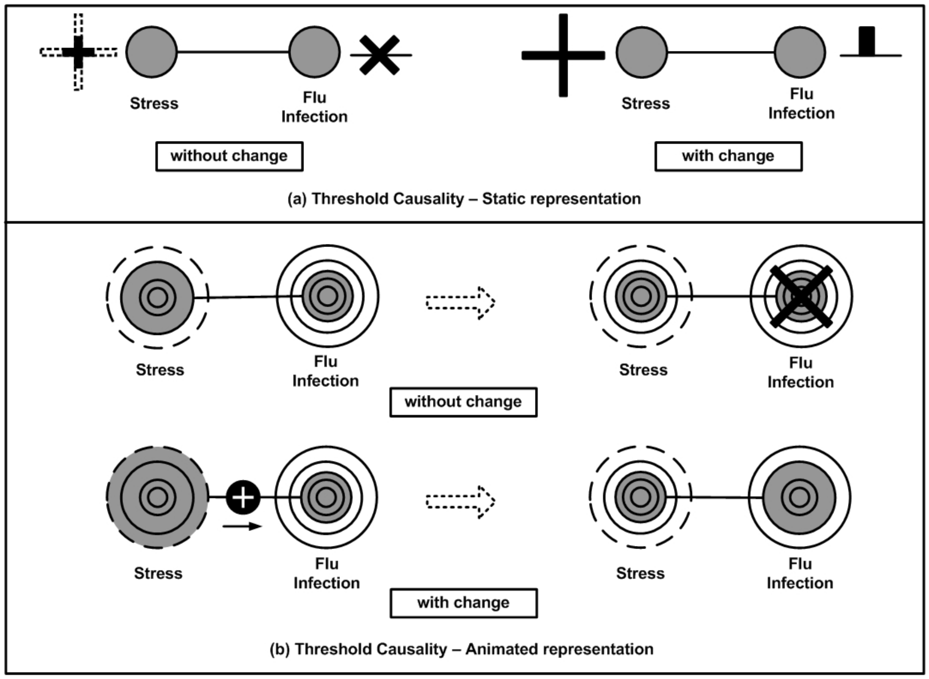

Figure 5.12: At least a large amount of factor (Stress) is needed to cause a change in the outcome (Flu Infection), therefore a small amount of Stress does not cause a change in Flu Infection but a large amount of Stress causes a small increase in Flu Infection.

5.3.8 Threshold Causality

Threshold causality allows constraints to be placed on factors that are trying to influence an outcome. In the static representation, the threshold influence is depicted by a dotted glyph superimposed upon the influence glyph. Shape and size of the dotted glyph denote the type and amount of influence required to cause a change in the target. When a factor(s) influence reaches or surpasses the threshold, the effect is seen by upright or inverted bars next to the target. However, if the factor's influence is less than the threshold, then a cross glyph next to the target depicts that there is no change in the outcome. In the animated representation, the threshold is depicted by a concentric dotted circle around the factor's node. The size of the dotted circle depicts the threshold influence. Initially, the factor increases in size equal to its amount of influence, at a rate of ∼1.17 cm/sec, i.e. for a small influence the factor size increases by small amount and for a large influence the factor size increases by a large amount. During this increase, if the factor size equals or surpasses the dotted threshold, then a bullet (with the size and glyph of the factor's influence) is sent, at a speed of ∼5 cm/sec, towards the target (transformation rate = ∼1.17 cm/sec), showing that the factor is influencing the outcome. However, if the factor does not touch the dotted line when it transforms, then no outcome is seen in the target and a cross glyph (on the target node) depicts the absence of a causal action. For example, in Figure 5.12, at least a large positive amount of influence of Stress is required to cause a change in Flu Infection; therefore a small positive amount of Stress does not cause any change in Flu Infection (without change), but a large amount of Stress causes a small increase in Flu Infection (with change).

5.3.9 Bidirectional Causality

Bidirectional causality illustrates the dual-state property of factors and targets in some causal scenarios. In this semantic, a factor influences the target and in return, the target causes a change in the factor. The static representation utilizes connected bars and glyphs to show influences and effects belonging to the same causal event. These glyphs are dotted lines and are placed from left to right, in the order of occurrence within the event. In the animated representation, the influence bullet

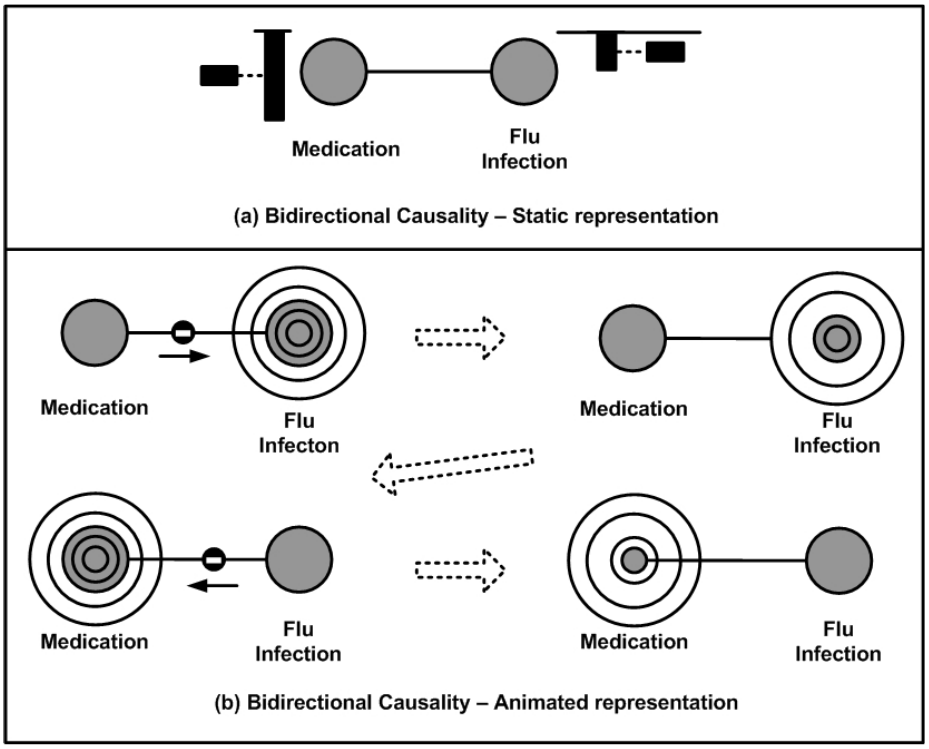

Figure 5.13: A small negative amount of factor (Medication) causes a small decrease in the outcome (Flu Infection) and in reverse; a small negative amount of Flu Infection causes a large reduction in Medication.

travels from the factor and causes a change in the target, depicting the first half of the bidirectional causal event. On completing the first half, the target now becomes the *new factor* and sends its influence bullet to the old factor (now the *new target*) causing a change and completing the second half of the bidirectional causal event. For example, in Figure 5.13, Medication has a small negative influence and causes a small decrease in Flu Infection, and in turn a small negative influence of Flu Infection causes a large decrease in Medication.

The above sections outline my static and animated representations for the causal semantics. I will now conclude this chapter with a short summary.

5.4 Chapter Summary

This chapter focuses on the second half of **Component I** of my research and is aimed at applying my background research on causal visualizations to design static and animated representations for the two groups of causal semantics. I adhered to Tversky et al. [2002]'s Congruence and Apprehension guidelines in order to create visual illustrations that are simple and relevant to the information being described. My causal relations are represented using traditional graphs, wherein the factors and targets are displayed as nodes and the relation is defined by connecting lines. In the static representation additional information is provided through simple glyphs that depict the influences and effects. In the animated representation, the same information is displayed using animated bullets (influence) and target node distortions (effect). Finally, the causal semantics are distinguished from each other by their unique structure and combination of the glyphs or animations.

In the remaining components of my research, I have focused on evaluating my casual visualizations in a user-environment, through a series of experiments. In these experiments I have provided users with my causal representations and have asked them to perform simple and specific tasks or answer questions based on the information given to them. The next section provides detailed descriptions along with the analysis of the data collected during these experiments.

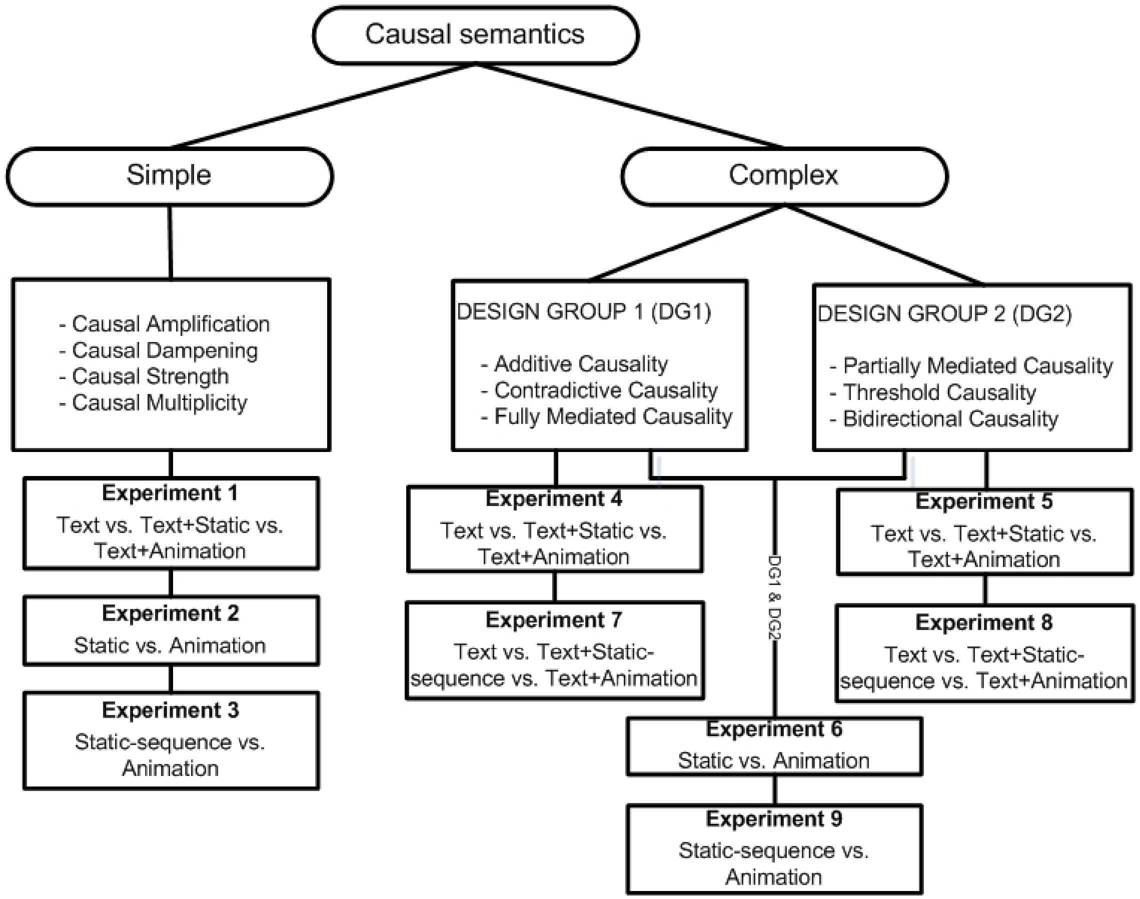

Figure 5.14: Division of the semantics into groups for experimental purposes.

Chapter 6

Component II: Analyzing visual representations of simple causal semantics - Experiments 1 and 2

Chapters 4 and 5 short listed 10 causal semantics that we encounter in everyday life. In order to limit the amount of information presented to the participants and to simplify the experimental evaluations, these semantics have been divided into two groups, *simple causal semantics* and *complex causal semantics*. This chapter focuses on analyzing the simple causal semantics, which consist of basic causal information such as causal amplification, causal dampening, causal strength, and causal multiplicity. Chapter 7 will focus on analyzing the complex causal semantics, containing causal information that have been constructed using combinations of the simple semantics and divided into two sub-groups; *design group 1* consisting of additive causality, contradictive causality, and fully-mediated causality, and *design group 2* consisting of partially-mediated causality, threshold causality, and bidirectional causality. Figure 5.14 outlines the semantic groups along with their respective experiments.

6.1 Experiment 1 - Comparing the effectiveness of text, static-graph, and animated visualizations of causal semantics *(published in Infovis'07)*

The goal of this experiment is to evaluate the two different types of visualizations designed to depict causal semantics. My hypotheses are as follows:

- **Hypothesis 1:** Participants will perform the recall tasks with higher accuracy rates when the causal relations are enhanced with visualizations, when compared to a textual description of the information.

- **Hypothesis 2:** Participants will perform more accurately and with faster response times when the causal relations are enhanced with animated (vs. static-graph) visualizations.

6.1.1 Method

Participants

Forty-four undergraduate psychology students of a local university participated in this experiment. The age of the students varied from 23 – 30 years. None of the students had any formal training with computers, perceptual visualizations and/or causal relations. The participants also had good English language skills, normal to corrected vision, and did not suffer from a history of color blindness (established through Ishihara's color blindness test [Ishihara, 1917]), which was required to distinguish between the various colors displayed during the experiment.

Materials

The experiment comprised of three methods for representing simple causal relations. These relations were displayed as text, static-graphs, and animations. The text representation was provided in the form of an English passage, printed on an 8" × 11" paper. The static-graph representation displayed the causal relations as still images, created using Microsoft Visio®, while the animations were created using Macromedia Flash™. The static-graphs and the animations were run on a Windows XP computer and projected onto a 60" × 60" screen. The visualizations were projected with a 1024 × 768 pixel screen resolution.

Design

The experiment consisted of a 3 × 2 within-subject design. The two independent variables were: Representation Type and Statement Type.

Representation type

Three types of representations were shown to the participants: Text, Static-graph, and Animation.

- **Text:** In this representation type, the participants were provided with passages, based on randomly selected topics, to read for a limited amount of time. Each passage consisted of 10 relations in total; 5 positive and 5 negative. The positive and negative relations were separated from each other in separate paragraphs with distinct titles. Each sentence in a paragraph described one causal relation.

- **Static-graph:** In this representation type, the participants were shown the static description of the semantics, projected onto a screen. The graphs described causal relations using + and − glyphs, bars, and connecting lines. Colors were used to connect the influences with the effects. Upright or inverted bars of varying sizes, near the target, depicted the type and magnitude of effect and varying sizes of + and − signs, near the factors, were used to describe the strength and quantity of influence. The causal relations depicted were identical to the relations described in the text representation and all 10 causal relations were shown simultaneously for a limited amount of time.

- **Animation:** In this representation type, the participants were shown an animation, projected onto a screen. The quantity of influence was depicted by animated bullets of different sizes, while the magnitude of effect was depicted by the expanding and shrinking of the targets to varying sizes. The causal relations depicted were identical to the relations described in the text representation. In addition, each causal relation was isolated, displayed in sequence, and clearly defined by a 3 second gap.

Statement type

At the completion of each trial, the participants were given a set of causal relations and were asked to identify whether they had seen these relations during the trial. The statements that the participants were asked to match were of two types:

- **Correct:** A correct statement was one where all the components of the given relation matched a relation visualized during the trial. For this statement the participant would need to enter a "Correct" response to get a point.

- **Incorrect:** An incorrect statement was one that partially matched a relation that was displayed during the trial. The participant would need to select "Incorrect" and provide the accurate statement, as recalled from the visualization, to get a point. Partially correct responses were awarded partial scores (maximum score = 1).

The representation types were fully counterbalanced using a Latin square design. Each participant viewed three of six passages, with one passage per condition. Each questionnaire consisted of 14 questions, with 7 questions of each statement type. The statement types were randomly distributed within the questionnaire. Overall, with 44 participants, 3 experimental conditions (text-only, text + static-graph, text + animation), and 14 questions per condition, a total of 1848 responses were collected for analysis.

Tasks

The experiment consisted of three conditions; text-only, text + static-graph and text + animation. The participants were given two tasks to perform. The first task was the *memorization* task where the participants read and/or viewed the causal relations, and memorized as many as they could within a given time period. Depending upon the condition, the memorization task of the participant varied slightly. In the text-only condition, the participants read the given passage for 4 minutes and then filled the next 4 minutes by performing simple filler tasks such as connecting a sequence of dots. This was chiefly done to standardize the length of each condition of the experiment. In the text + static-graph condition, the participants first read the given passage for 4 minutes to memorize the causal relations. They then viewed the static representation for the next 4 minutes to support what was read previously. Similarly, in the text + animated condition, the participants first read the given passage for 4 minutes and then viewed the corresponding animation for the next 4 minutes. As the length of the animation was only 60 seconds, it was repeated four times to fill the 4 minute slot.

The second task was the *recall* task wherein the participants determined if a given set of relations were Correct or Incorrect (as described above), within a 5 minute timeframe.

Procedure

The experiment was conducted in three stages. The first stage comprised of a color blindness test [Ishihara, 1917] to ensure that the participants could distinguish the colors in the static-graph. The second stage consisted of a 20 minute training session, which included a detailed description of the representation and statement types to the participants. The participants were also shown examples of the text, static-graph, and animated representations and quizzed in order to ensure that they had understood the representations accurately. They were also shown a sample questionnaire and instructed on how to record their responses. The third stage comprised of the final experiment wherein the experimental conditions were randomly assigned and time constraints were strictly enforced. Upon completing the viewing task of each condition, the participants were given 5 minutes to answer a questionnaire. At the end of 5 minutes, the participants were asked to stop answering and move on to the next condition. On completing all three conditions, the participants were asked to record their individual opinions of the representations and the experimental procedure in an informal questionnaire.

The study captured the number of correct responses that the participants gave in each of the conditions. They were given a maximum score of 1 for each correct answer they provided. If the participants answered only parts of the answer correctly, they were awarded a corresponding fraction of the maximum score. As this experiment was a paper-based study, response times were not recorded or analyzed.

6.1.2 Results and Discussion

Following the procedure described in the Method (6.1.1) section, I first computed the proportion of accurate responses made by each participant in each of the experimental conditions. These data were then submitted to a 3 × 2 repeated-measures Analysis of Variance (ANOVA), treating representation type (text-only vs. text + static-graph vs. text + animated) and statement type (correct vs. incorrect-with-corrections) as within-participant factors. Table 6.1 summarizes the overall analysis of the results, along with a summarization of the mean values for the factors showing significance in Table 6.2.

This analysis revealed a main effect of representation type, $F(2, 86) = 6.76, MSe = .035, p < .005$. The basis for this main effect was that participants were more accu-

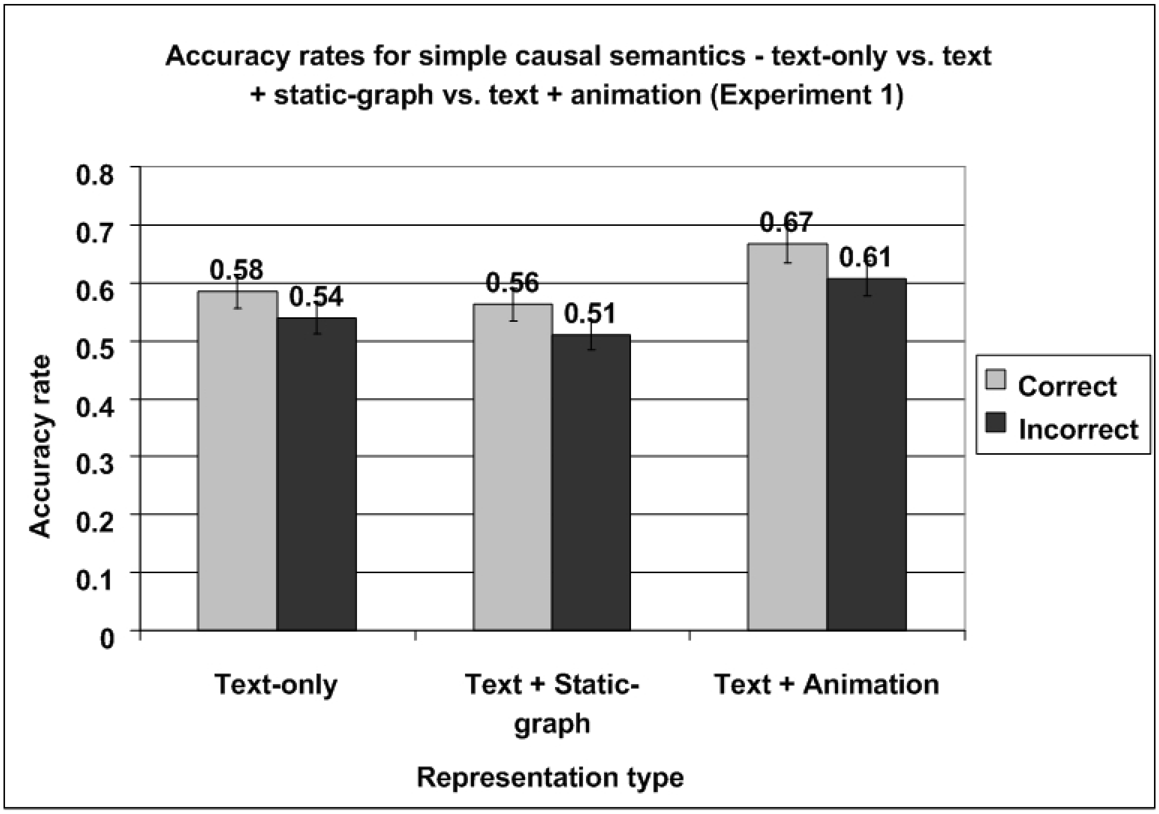

Figure 6.1: Accuracy rate for 'Correct' and 'Incorrect' statements of representation types: (a) text-only, (b) text + static-graph, (c) text + animation (the ±5% error bars represent the 95% confidence intervals for the mean).

rate in making judgments about causal relationships in the text + animated condition than in the other two conditions. Specifically, participants made ~8% more accurate responses in the text + animated condition than in the text-only condition (.64 vs. .56), $F(1, 43) = 7.79, MSe = .031, p < .01$, and they made ~10% more accurate responses in the text + animated condition than in the text + static-graph condition (.64 vs. .54), $F(1, 43) = 11.01, MSe = .040, p < .005$ (Figure 6.1).

There was no reliable difference in response accuracy between the text-only and

Factor	**Accuracy rate**	**Response time**
Representation type (F1)	**Significance**	Not tested
Response type (F2)	No significance	Not tested
F1 × F2 interaction	No significance	Not tested

Table 6.1: Summary of analysis of accuracy rates showing significant results (in bold), for Experiment 1: Simple causal semantics, Representation type(F1): *Text-only vs. Text+Static-graph vs. Text+Animation*, Response type(F2): *Correct vs. Incorrect-with-corrections*, Memory Recall Experiment.

Factor		**Accuracy rate** (↓ = % less accuracy than highest accuracy value for factor(in bold)
Representation type (F1)	**Text-only**	.562 (∼13% ↓)
	Text + Static-graph	.537 (∼18% ↓)
	Text + Animation	**.637**

Table 6.2: Summary of accuracy rates for factors showing significance in the analysis of Experiment 1 results. *NOTE: Highest accuracy rate for each factor is highlighted in bold and ↓ shows reduction in accuracy rate when compared to the highest accuracy rate for the factor.*

text + static-graph conditions, $F < 1$. Moreover, the main effect of statement type was not reliable ($p > .05$), which suggests that participants were able to identify correct and incorrect statements with similar accuracy, with both representation types. Finally, the effect of presenting an animated diagram on response accuracy did not depend on whether the test statement was correct or incorrect (representation type $\times$ statement type interaction, $F < 1$).

An analysis of the informal questionnaires also showed interesting results. More participants (∼67%) agreed that visual enhancements do improve memory and help in recall tasks. However, a considerable number (∼33%) of participants did not agree and were quite content with reading the passages only; this can be attributed to their superior memorizing abilities or to their inexperience in viewing computer visualizations. When asked to compare between the static and animated images, the participants were noncommittal as to which technique was preferred. Based on the task, they claimed either the static images or the animations to be more accurate and interesting. More participants (∼60%) agreed that the animations were useful in the memorization task, when compared to the static images. However, many claimed (∼59%) that it was easier to view the strengths of the influences with the static images. Finally, a major observation during the experiment was that pure animation constrained the participants to a fixed order and did not give any room for intellectual exploration.

Summary of Experiment 1 analysis

- Participants performed with ∼8% higher accuracy in comprehending the causal information in the text + animated condition, compared to the text-only condition, and with ∼10% more accuracy when compared to the text + static-graph condition.

- Informal questionnaires suggested that participants were divided in their preference of the representation types, based on the given task. ∼60% of participants agreed that animations improved comprehension and memory retention, while ∼59% preferred the glyphs of the static representation for understanding a factor's influence.

The results of this experiment partially concur with both my hypotheses and show that visualizations do help in improving recall of causal passages (*Hypothesis 1*). However this improvement was shown only by the animations. I think the reason the static-graph representations did not prove very effective was because it is quite difficult to adequately distinguish between the different colors displayed. On-screen clutter was another problem adversely affecting this representation. Finally, even though the effects (bars next to the target) described the timeline of the causal relations, on-screen clutter reduced any semblance of order in the influences (+ and − signs) which made the task extremely tedious. Figure 6.1 shows a decrease (albeit insignificant) in the accuracy rate when the causal relations were enhanced using static images.

The results also show that my animations performed with higher accuracy rates than the static images (*Hypothesis 2*). I think this is because the animations did not depend on colors and showed only one relation at a time. I also infer that designing my representations based on Michotte's guidelines contributed to the higher accuracy rates with the animations. The results also showed that the participants were able to distinguish correct and incorrect relations more accurately in this condition. Two drawbacks of this representation were noticed during the evaluation. One drawback was that the sequential nature of the animation did not allow skipping to a required relation, which can be overcome by allowing interactions with the animations. A second drawback was that the absolute sizes of the influences (bullet size) or the effects (degree of expansion or shrinking of the target) were not easily distinguishable and only relative judgments were possible. This problem can be overcome by adding legends as guides to compare the given information in order to determine its magnitude.

Overall, the results of this experiment showed that participants were able to perceive the causal relations more accurately when the textual passages were complemented with static-graph and animated representations. However, I was unable to conclude from the experiment whether the static-graph and animated representations can naturally and intuitively elicit comprehension of causal relations. Furthermore, I could not infer from my results whether one type of representation is more accurate than the other for showing the selected set of semantics. As a result, Experiment 2 (section 6.2) aimed at directly comparing the effectiveness of the static-graph and animated representations in describing causal relations, without the aid of textual descriptions.

6.2 Experiment 2 - Comparing static-graph and animated representations of simple causal semantics *(published in Infovis'07)*

The goal of this experiment was to compare the effectiveness of my static-graph and animated representations in describing causal relations. I was interested in identifying whether representations for complex semantics based on Michotte's rules of perceiving causality would elicit accurate and rapid responses. My hypotheses for this experiment were as follows:

- **Hypothesis 1:** Participants will perform the recall tasks more accurately when the causal relations are depicted using animations, when compared to a textual description of the information.
- **Hypothesis 2:** Participants will be able to respond faster when the causal relations are depicted using animations.

6.2.1 Method

Participants

108 undergraduate psychology students of a local university participated in this experiment. None of the participants had performed the previous experiment and were not familiar with the objectives of this study. The participants satisfied the same selection criteria as in Experiment 1 (section 6.1.1) (age, no color blindness, normal to corrected vision, no prior experience with causal graphs).

Materials

The experiment consisted of two major conditions for representing the relations; static-graph and animations. The experiment was generated as a .NET program with the embedded static-graph and animated Macromedia Flash™ files. Individual copies of the program were executed on a Windows XP computer and displayed on a 17" Dell monitor with a 1024×768 pixel screen resolution.

Design

The experiment consisted of a 2×4 within subject design, with two independent variables: Representation Type and Statement Type.

Representation type

Two types of representations were shown to the participants: Static-graph and Animation.

- **Static-graph:** In this representation type, the participants were shown a static graph that contained about 1 – 2 causal relations. The graphs were kept simple in order to identify whether subjects were able to intuitively capture the concepts presented in the atomic relationships. The main difference between the static-graphs used in this experiment and in Experiment 1 was that the + and − symbols were replaced by square (■) glyphs as the factor's influence type was not tested in this study. However, the size of the square glyph represented the strength of the influence and colors were used to distinguish between different causal relations.

- **Animation:** In this representation type, the participants were shown an animation which contained about 1 – 2 causal relations. The features of the animation were similar to the previous experiment. Also, the animated syntax was maintained on a comparable level to the static-graph syntax with the exception of applying Michotte's rule in the animated case, and replacing those with descriptive glyphs and symbols in the static-graph case.

Statement type

At the end of each trial, the participants were shown a statement based on the relation(s) they viewed. In order to isolate and test the effectiveness of various components of my representations, the participants were asked to correctly match four types of statements that were created from my initial set of semantics:

- **Type of outcome(S1):** Statement type S1 tested the ability of the participant to distinguish between positive and negative outcomes in the causal relation. During the experiment, the outcome of the causal relation was represented by upright/inverted bars near the target in the static-graph and by expansion/shrinking of the target in the animations.

- **Strength of influence(S2):** Statement type S2 tested the ability of the participants to comprehend the amount of influence a factor had on the target. In the experiment, the strength of influence was depicted as varying sizes of the square (■) glyphs in the static-graph representation and as small and large bullets in the animations.

- **Magnitude of outcome(S3):** Statement type S3 tested the ability of the participant to comprehend the magnitude of the outcome when a factor influences a target. The magnitude of the outcome was displayed as varying sizes of upright or inverted bars in the static-graph condition and in the animated representations the targets would expand or shrink to varying to sizes.

- **Combination of components(S4):** Statement type S4 tested the ability of the participant to identify all the constituent elements of a causal relation, such as strength of the influence and type and magnitude of outcome. This type of statement was the most complex and evaluated the overall effectiveness of the static-graph and animated representations in displaying the causal information.

Tasks

The experiment consisted of multiple random trials of the static-graph and animated relations. As in the previous experiment, the experiment comprised of two tasks; *memorization* and *recall*. In the *memorization* task the participant was shown the causal relations for a pre-determined length of time (9 seconds per causal relation). Within this period the subject was asked to carefully view all the possible relationships that existed. In the *recall* task, the participant was shown a statement, based on the relations that were just viewed. For example, they would be presented with a relation (concerning Malaria Infection) and a statement such as “Female mosquitoes have a positive effect on malaria”. The participant was asked to hit one of two keys on the keyboard (B = ‘Yes’ or N = ‘No’; the ‘B’ key was taped with a ‘Y’) depending on whether the given statement exactly matched the displayed relation or not. The participants were asked to respond as quickly and accurately as possible and, upon providing an answer, were automatically directed to the next trial.

The trials were fully counterbalanced using a Latin square design. Each trial was based on a random selection of 1 of 12 topics, with one statement per trial. The experiment consisted of 96 trials in total, divided into 6 sessions. Overall, with 108 participants, 6 sessions, 2 representation types (static-graph and animations) per session, 4 statement types per representation (S1, S2, S3, and S4), and 2 response types (Yes and No) per statement, a total of 10368 responses were collected for analysis.

Procedure

The experiment was conducted in two phases. In the *training* phase the participants were asked to self-train themselves by running a sample program consisting of the static-graph, animations, and statements that were similar to what would be displayed during the experiment. The participant was given the opportunity to run the sample program as many times as desired, with only technical help from the experimenter.

After completing the training phase, the participants were asked to commence the *experiment* phase. Each trial was timed and at the end of each session, the timers were paused to allow the participant to take a break if preferred.

6.2.2 Results and Discussion

The main variables of interest in this experiment were the accuracy of the users' responses and the completion times in responding to a given statement. Each accurate

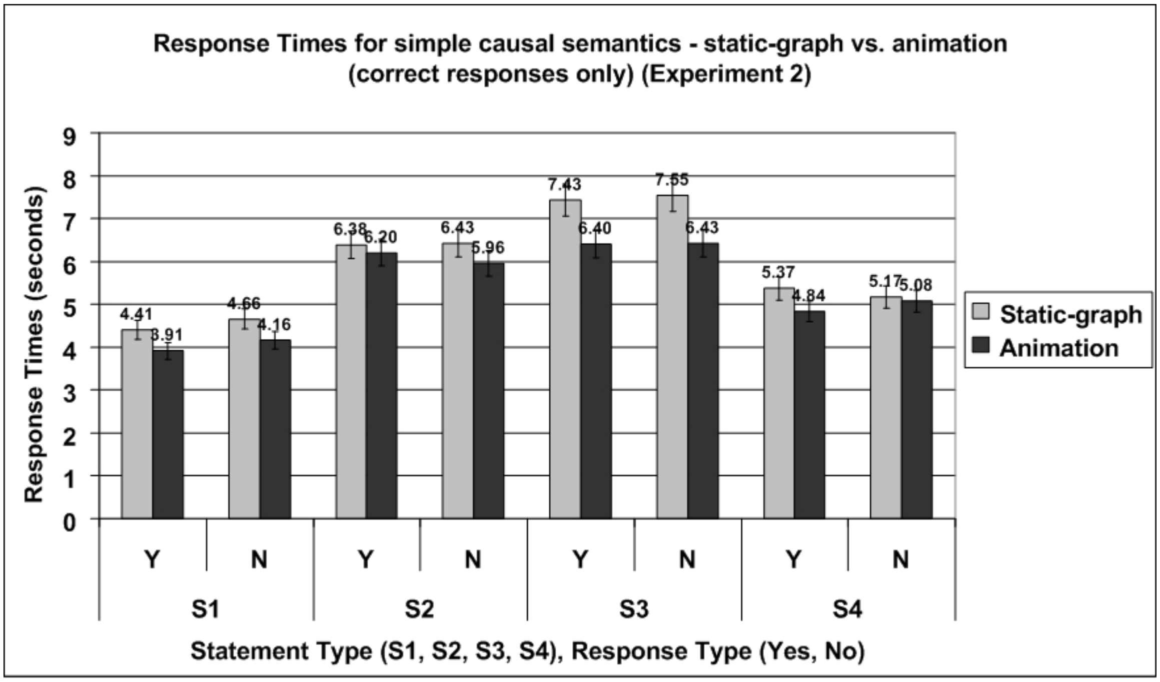

Figure 6.2: Response times for static-graph and animated representations of statement types: S1(type of outcome), S2(strength of influence), S3(magnitude of outcome), S4(combination of components) and response types: Y(yes), N(no) (±5% error bars depict the 95% confidence intervals for the means).

response of the participant was awarded 1 point. The analysis for response times only considered accurate responses.

The participants' data was analyzed using a 2 × 4 × 2 repeated-measures Analysis of Variance (ANOVA), treating representation type (static-graph vs. animated), statement type (type of effect(S1) vs. strength of influence(S2) vs. magnitude of outcome(S3) vs. combination of components(S4)), and response type ('Yes' vs. 'No') as within-participant factors. Table 6.3 summarizes the overall analysis of the results, along with a summarization of the mean values for the factors showing significance in Table 6.4.

Factor	**Accuracy rate**	**Response time**
Representation type (F1)	No significance	**Significance**
Semantic type (F2)	**Significance**	**Significance**
Response type (F3)	No significance	No significance
F1 $\times$ F2 interaction	No significance	**Significance**
F1 $\times$ F3 interaction	No significance	No significance
F2 $\times$ F3 interaction	**Significance**	No significance
F1 $\times$ F2 $\times$ F3 interaction	**Significance**	No significance

Table 6.3: Summary of analysis showing significant results (in bold), for Experiment 2: Simple causal semantics, Representation type(F1): *Static-graph vs. Animation*, Semantic type(F2): *Type of effect(S1) vs. Strength of influence(S2) vs. Magnitude of outcome(S3) vs. Combination of components(S4)* , Response type(F3): *Yes vs. No*, Intuitiveness Evaluation Experiment.

Analysis of the response times revealed a main effect of representation condition, $F(1, 107) = 107.529, MSe = 1.219, p < .001$. The basis for this main effect was that participants were ~9% quicker in making judgments about causal semantics in the animated condition than in the static-graph condition (5.37 seconds vs. 5.92 seconds). This improvement in response times using animations suggests that the intuitiveness of the animated representations enabled the participants to comprehend the causal information described, and quickly identify matches or discrepancies between the relation and statement during the *recall task*.

This analysis also revealed a main effect of statement type, $F(3, 321) = 273.543, MSe = 2.212, p < .001$. The basis for this main effect was that participants were faster in responding to statement type S1 (4.28 seconds) than to statements S4 (5.11 seconds), S2 (6.22 seconds), and S3 (6.95 seconds), as shown in Figure 6.2. This suggests that statement type S1 (type of effect) was easiest to recall, as the method of representing the semantic information using increase/decrease of the target size was intuitive and could be easily related by the participants to the type of effect.

Finally, the analysis revealed significant interaction between representation and statement types, $F(3, 321) = 11.431, MSe = 1.225, p < 0.001$. A detailed analysis suggests that participants were ∼6%, $F(1, 107) = 27.706, MSe = .954, p < 0.001$, faster with the static-graph representation than with the animations for statement type S1, ∼5%, $F(1, 107) = 10.848, MSe = 1.037, p < .005$ and ∼14%, $F(1, 107) = 62.667, MSe = 1.995, p < 0.001$ faster with animations than with the static-graph representation for statement types S2 and S3 respectively, and ∼10%, $F(1, 107) = 17.481, MSe = .869, p < .001$ faster with the animations for statement type S4 ('Yes' responses only). These results suggest that participants were generally faster with the animations than with the static-graph representation and that this difference was more prominent as the complexity of the causal statement increased.

A repeated-measures ANOVA on the accuracy rates did not reveal any significant difference between representation types $F(1, 107) = 3.044, MSe = 0.025, p > 0.05$, ∼82.8% for static-graph and ∼84.3% for animations. This high accuracy rate, along

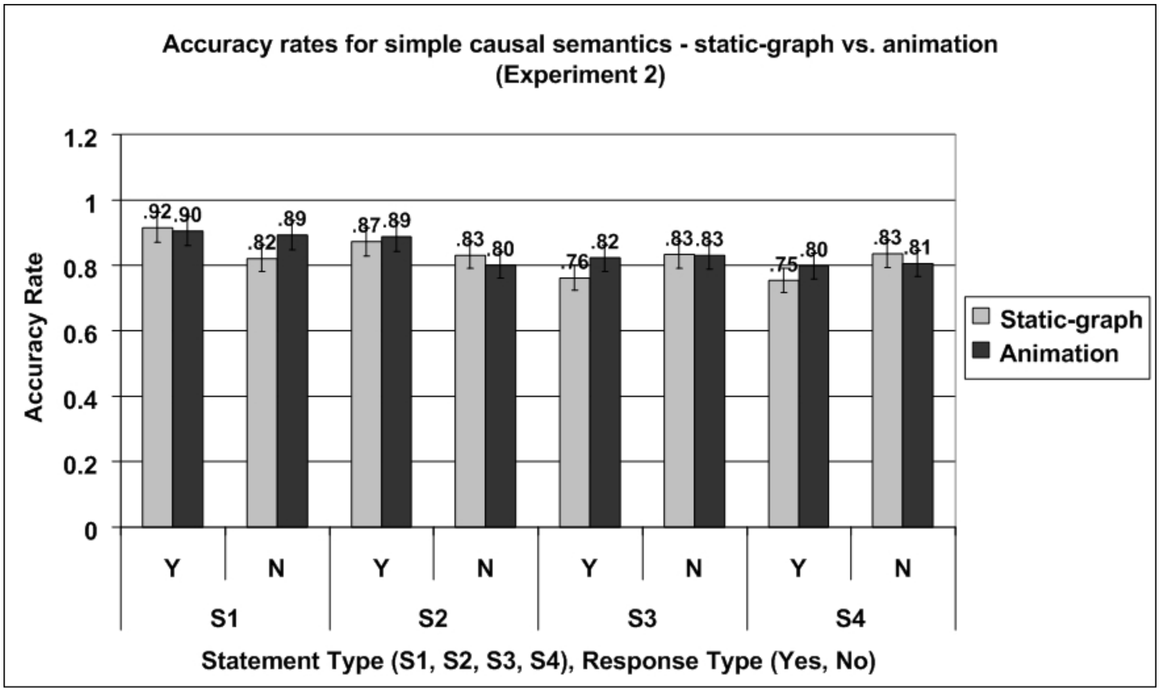

Figure 6.3: Accuracy rate for static-graph and animated representations of statement types: S1(type of outcome), S2(strength of influence), S3(magnitude of outcome), S4(combination of components) and response types: Y(yes), N(no) (±5% error bars depict the 95% confidence intervals for the means).

with no difference between the major conditions is particularly noteworthy as it suggests that both representations captured or represented the semantics with equivalent efficiency. However, the analysis revealed a main effect of statement type $F(3, 321) = 22.644, MSe = 0.028, p < 0.001$. The means suggest that accuracy rates were lower on statements of type S3 (∼81.2%) and S4 (∼79.8%) in comparison to S1 (∼88.3%) and S2 (∼84.8%), which in turn suggests that participant performance might improve if legends are provided for comparison (Figure 6.3). The analysis also showed significant interaction between statement type and response type

$F(3, 321) = 14.540, MSe = 0.025, p < 0.001$ and between all three factors (representation, statement, and response types) $F(3, 321) = 7.260, MSe = 0.019, p < 0.001$, which suggests that participant accuracy was dependant upon the condition that was presented. A more detailed analysis of these interactions showed that animations performed with ~8%, $F(1, 107) = 6.821, MSe = 0.029, p < 0.05$, higher accuracy rates in displaying the magnitude of outcome (S3) and with ~6%, $F(1, 107) = 4.810, MSe = .022, p < .05$, higher accuracy rates in displaying the overall causal statement (S4), than the static-graph representation, in recognizing correct matches between relation and statement (response type 'Yes'). Animations also performed with ~8%, $F(1, 107) = 11.620, MSe = .023, p < .005$, higher accuracy rates than the static-graph representation in recognizing mismatches between the relation and statement, when displaying type of outcome (S1).

Summary of Experiment 2

Summarizing the results of this experiment:

- Participants made ~9% quicker judgments when the causal information was presented using animations and took longest to comprehend the magnitude of outcome (S3).

- Participants were ~5% (S2), ~14% (S3), and ~10% (S4, 'Yes' responses only) faster with animations than with the static-graph representation.

- Participants performed with ~8% higher accuracy rates with animations in displaying the magnitude of outcome (S3), the overall causal statement (S4), and type of outcome (S1, 'No' responses only).

- Participants were more accurate in recognizing type of outcome (accuracy rate = ∼88.3%) and magnitude of influence (accuracy rate = ∼84.8%) than in recognizing the magnitude of outcome (accuracy rate = ∼81.2%). However, this performance can be improved by the addition of legends.

Overall, the results of this experiment partially concurred with my hypotheses and showed that the static-graph and animated visualizations can be used to efficiently describe the simple causal semantics. An analysis of the accuracy rates showed that although participants performed equally well with both representations, animations performed with significantly higher accuracy rates than the static-graph representation in representing statements S1, S3, and S4 (partial concurrence with *Hypothesis 1*). Overall response times were also significantly lower when the causal semantics were represented using animations, fully concurring with *Hypothesis 2*.

Experiments 1 and 2 comprise my analysis of the visualizations representing simple causal semantics. This concludes the second component of my research. The next component focuses on conducting similar analysis on the set of complex causal semantics, as described in the next chapter.

Factor		**Accuracy rate** (↓ = % less accuracy than highest accuracy value for factor(in bold)	**Response time** (↑ = % more time than lowest response time value for factor(in bold)
Representation type (F1)	**Static-graph**	-	5.924 seconds (∼9% ↑)
	Animation	-	**5.373 seconds**
Semantic type (F2)	**Type of effect (S1)**	**.883**	**4.284 seconds**
	Strength of influence (S2)	.848 (∼4% ↓)	6.244 seconds (∼31% ↑)
	Magnitude of outcome (S3)	.812 (∼8% ↓)	6.953 seconds (∼38% ↑)
	Combination of components (S4)	.798 (∼9% ↓)	5.113 seconds (∼16% ↑)

Table 6.4: Summary of accuracy rates and response times for factors showing significance in the analysis of Experiment 2 results. *NOTE: Highest accuracy rate and lowest response time for each factor are highlighted in bold. The ↓ arrow shows reduction in accuracy rate when compared to the highest accuracy rate for the factor and the ↑ arrow shows increase in response time when compared to the lowest response time for the factor.*

Chapter 7

Component III: Analyzing visual representations of complex causal semantics - Experiments 3, 4, and 5

In the previous chapter, I tested the efficacy of the static and animated visualizations in representing simple causal semantics. Results of those experiments determined that the comprehension of simple causal relations improved when they were depicted using animations. Therefore, I decided to extend the same techniques to the rest of the identified causal semantics, from Chapter 5.

In order to limit the amount of information displayed to the participant, the complex causal semantics were divided into two groups, with three semantics per group:

- **Design-Group 1 (DG1):** This group consisted of causal semantics such as additive causality, contradictive causality, and fully-mediated causality. The semantics of this group extended the concept of causal multiplicity by increasing the complexity of the simple causal relations, such as "one factor influences the target" to "one *or more* factors influence the target" and by providing additional information such as the type of influence and mediators.

- **Design-Group 2 (DG2):** This second group of semantics pushed the boundaries of causal relations to include complex notions such as multiple targets (partially-mediated causality), triggered factors (threshold causality), and bi-state nodes (bidirectional causality).

The complex semantics of DG1 and DG2 were analyzed separately in experiments 3 and 4 respectively, using a Memory Recall test. Finally, Experiment 5 combined the two design groups and tested the semantics through an Intuitiveness analysis of the visual representations. These experiments have been described below.

7.1 Experiment 3 - Comparing text, static-graph, and animated representations of Design-group 1 causal semantics

The goal of this experiment was to evaluate the effectiveness of the static-graph and animated visualizations, over text-only representations of the complex causal semantics. The causal semantics that I tested in this experiment were additive, contradictive, and partially-mediated causalities. As in Experiment 1 (section 6.1), my hypotheses were as follows:

- **Hypothesis 1:** Participants will perform the recall tasks with higher accuracy rates and lower response times when the causal relations are enhanced with visual representations, when compared to a textual description of the information.

- **Hypothesis 2:** Participants will perform more accurately and with faster response times when the causal relations are enhanced with animated (vs. static-graph) visualizations.

7.1.1 Method

Participants

27 undergraduate psychology students of a local university, between the ages of 20 – 30 years, participated in this experiment. None of the students had any formal training with computers, perceptual visualizations or causal relations. The participants also had good English language skills, normal to corrected vision, and did not suffer from a history of color blindness (as established by Ishihara's color blindness test [Ishihara, 1917]).

Materials

As in Experiment 1, the causal relations were displayed as text, static graphs, and animations. The text representation consisted of a series of one-line statements of the causal relations, while the static graphs and animated visualizations were created using Macromedia Flash™. Contrary to the materials used in Experiment 1, all three representations were embedded as flash movies in a .NET program and executed on a

Windows XP computer, chiefly to record response times in addition to the accuracies. The visualizations were displayed on a 17" monitor with a 1024 × 768 pixel screen resolution.

Design

The experiment consisted of a 3 × 2 within subject design. Two independent variables were identified: Representation Type and Statement Type.

Representation type

- **Text:** In the text representation, the participants were provided with passages consisting of 3 positive and 3 negative causal relations, which they were asked to read for a given amount of time.

- **Static-graph:** In the static-graph representation, the causal relations were represented using + and − glyphs, bars, connecting lines, and colors. All the causal relations were displayed simultaneously. Sizes of the glyphs and bars were changed to depict differing magnitudes of influences and outcomes.

- **Animation:** In the animated representation, the participants were shown animations consisting of nodes, moving bullets (containing + and − glyphs to depict type of influence), and target transformations. Bullet and target sizes were smoothly modified to depict type and magnitude of influences and outcomes.

Statement type

As in Experiment 1, at the completion of each trial, the participants were given a set of causal statements and asked to match the statements to the relations shown during the trial. Two types of causal statements were presented:

- **Correct:** A correct statement was one where all the components (strength and direction of influences and strength and direction of effects) of the given statement exactly matched a relation provided during the current trial. For this statement the participant had to enter a “Correct” response to get a point.

- **Incorrect:** An incorrect statement is one where the given statement partially matched a relation that was presented during to the trial. For this statement, the participant had to select “Incorrect” and, in addition, correct the statement by recalling the original statement from memory, to get the full score. Fractional scores were also awarded to participants who were able to partially correct this type of statement.

Tasks

The experiment tested three conditions; text-only, text + static-graph and text + animation. The participants were given two tasks to perform: Memorization and Recall.

- **Memorization:** In this task, the participants were asked to read/view the causal relations and to memorize as many of them as possible within the given time. In the text-only condition, the participants were asked to read the given passage for $1^1/_2$ minutes and then were asked to fill the next $1^1/_2$ minutes with simple tasks that were not related to the experiment, such as connecting a sequence of dots. The tasks in the text + static-graph and text + animation condition were similar wherein the participants were asked to view the text for 1½ minutes and then view a corresponding graph (in the text + static-graph condition) or animation (in the text + animation condition) for the next 1½ minutes. As the length of the animation was only 30 seconds, the animation was repeated 3 times to fill the 1½ minute slot.

- **Recall task:** In the recall task, the participants were asked to respond to questions based on the relations they just read/viewed. Participant responses were limited to "Correct" or "Incorrect" (with corrections) and were required to answer all questions within an 8 minute timeframe.

The representation types were fully counterbalanced using a Latin square design. Each participant viewed 3 of 12 topics, with one topic per condition. The questionnaire for each condition consisted of 6 questions, with 3 questions of each statement type (i.e. 3 correct and 3 incorrect statements). The statements were randomly distributed within the questionnaire. Overall, with 27 participants, 3 conditions, and 6 questions per condition, a total of 486 responses were collected for analysis.

Procedure

The experiment was conducted in two stages. The first stage consisted of a training session that explained the concept of causal relations and their modes of representation. The participants were also allowed to practice on a sample version of the experiment. The second stage consisted of the main experiment wherein experimental conditions were randomly assigned and time constraints strictly enforced. At the completion of each condition, the participants were asked to answer a questionnaire within a time limit of 8 minutes. The program captured the responses and response times for each of the questions. The participants were given a maximum score of 1 for a correct response and a minimum score of 0 for an incorrect response. If a participant answered only parts of a question correctly, they were awarded a corresponding fraction of the maximum score.

7.1.2 Results and Discussion

Following the procedure described in the Method section, two values were recorded for each answer given by a participant: accuracy and response times. These data were then submitted to a 3 × 2 × 3 repeated-measures ANOVA treating semantic type (fully-mediated vs. additive vs. contradictive), statement type (correct vs. incorrect-with-corrections), and representation type (text-only vs. text + static vs. text + animation) as within-subject factors. Table 7.1 summarizes the overall analysis of the results, along with a summarization of the mean values for the factors showing significance in Table 7.2.

The analysis of the accuracy points showed a main effect of response type with $F(1, 26) = 34.464, MSe = .177p < 0.001$. A comparison of the means showed that participants were ∼31% (.720 vs. .496) more effective in recognizing that a given statement accurately described the displayed causal relation than in determining that the given statement and relation did not match. The reason for this significance can to attributed to the fact that participants were able to recall a statement that matched,

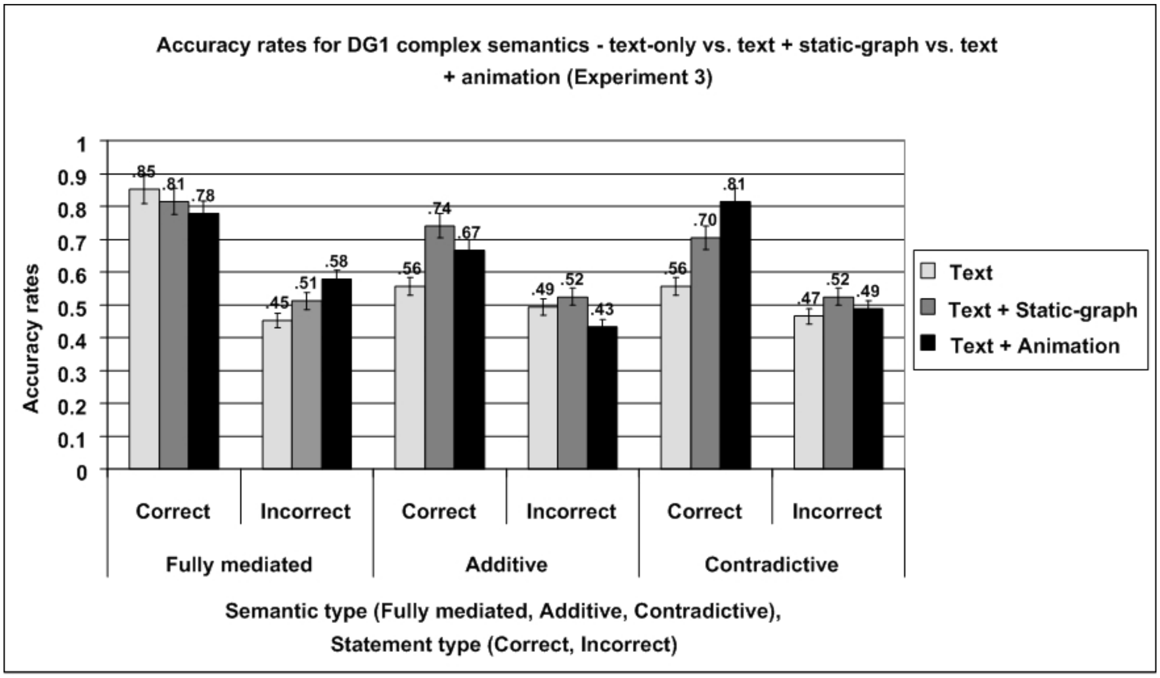

Figure 7.1: Accuracy rate for text-only, text + static-graph, and text + animated representations of DG1 complex semantics: fully-mediated causality, additive causality, contradictive causality and statement types: correct, incorrect (±5% error bars depict the 95% confidence intervals for the means).

but were less accurate in providing the correct causal information when there was a discrepancy between the given relations and statement.

The analysis did not show a main effect of semantic type ($p > .05$), which could be attributed to the number of relations that were presented during the *memorization task* (2 relations per semantic = 6 in total were presented in each experimental condition).

Also the analysis did not show reliable significance between representation types ($p > 0.05$), which suggests that the semantics were equally depicted by each of the

Factor	**Accuracy rate**	**Response time**
Representation type (F1)	No significance	No significance
Semantic type (F2)	No significance	**Significance**
Response type (F3)	**Significance**	**Significance**
F1 $\times$ F2 interaction	No significance	No significance
F1 $\times$ F3 interaction	No significance	No significance
F2 $\times$ F3 interaction	No significance	No significance
F1 $\times$ F2 $\times$ F3 interaction	No significance	No significance

Table 7.1: Summary of analysis showing significant results (in bold), for Experiment 3: Complex causal semantics, DG1, Representation type(F1): *Text-only vs. Text+Static-graph vs. Text+Animation*, Semantic type(F2): *Additive causality vs. Contradictive causality vs. Fully-mediated causality*, Response type(F3): *Correct vs. Incorrect-with-corrections*, Memory Recall Experiment.

three representations. This inference is logical because additive and contradictive causality are essentially a modification of causal multiplicity and show similar factor and target information (see section 4). Fully-mediated causality is also similar and only shows factor and target information, as there is no change in the mediator when it is influenced by the factor. Figure 7.1 compares the accuracy rates for ‘Correct’ and ‘Incorrect’ statements for DG1 of the complex causal semantics.

An analysis of the response times showed a main effect of semantic type $F(2, 52) =$

Factor		**Accuracy rate** (↓ = % less accuracy than highest accuracy value for factor(in bold)	**Response time** (↑ = % more time than lowest response time value for factor(in bold)
Semantic type (F2)	**Additive causality**	-	12.752 seconds (∼24% ↑)
	Contradictive causality	-	12.822 seconds (∼25% ↑)
	Fully-mediated causality	-	**9.636 seconds**
Response type (F3)	**Correct**	**.720**	**10.097 seconds**
	Incorrect-with-corrections	.496 (∼27% ↓)	13.376 seconds (∼24% ↑)

Table 7.2: Summary of accuracy rates and response times for factors showing significance in the analysis of Experiment 3 results. *NOTE: Highest accuracy rate and lowest response time for each factor are highlighted in bold. The ↓ arrow shows reduction in accuracy rate when compared to the highest accuracy rate for the factor and the ↑ arrow shows increase in response time when compared to the lowest response time for the factor.*

$11.152, MSe = 48.098, p < .001$. A comparison of the means showed that participants were ∼25% faster in responding to questions about fully-mediated causality (9.636

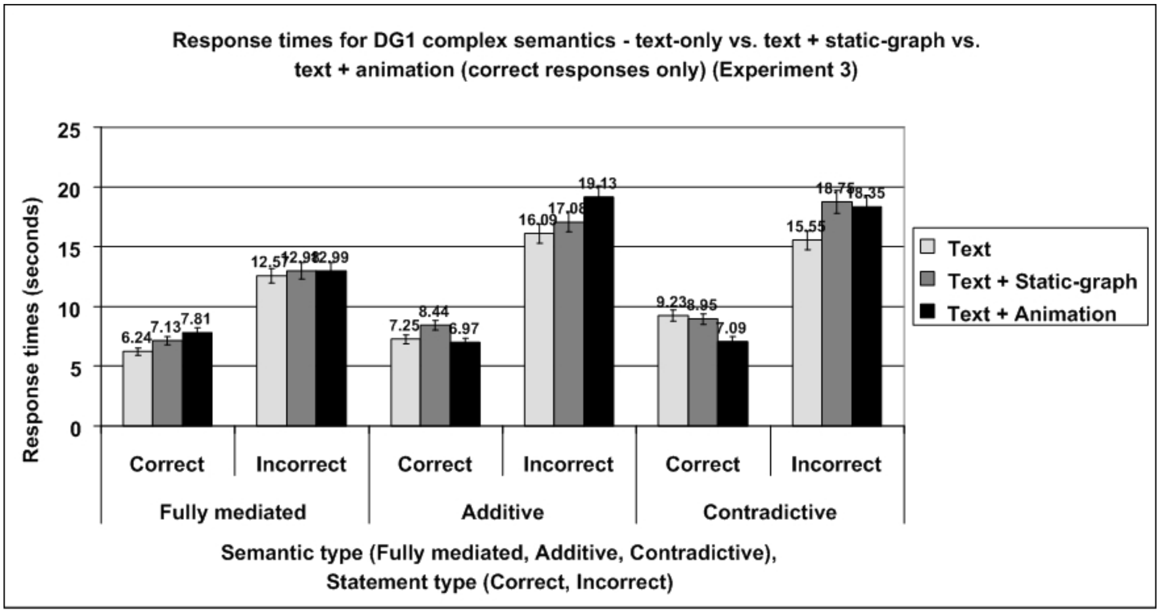

Figure 7.2: Response times for text-only, text + static-graph, and text + animated representations of DG1 complex semantics: fully-mediated causality, additive causality, contradictive causality and statement types: correct, incorrect ($\pm 5\%$ error bars depict the 95% confidence intervals for the means).

seconds) than additive (12.752 seconds) or contradictive causality (12.822 seconds). The reason for this might be related to the number of factors that affected the target in each of these relations; fully-mediated = 1 factor + 1 mediator (inactive), additive = 2 factors, contradictive = 2 factors. The analysis also showed a main effect of response type $F(1, 26) = 62.490, MSe = 20.901, p < 0.001$ and a comparison of the means showed that participants were faster (10.097 seconds vs. 13.376 seconds) in recognizing a match between the given relation and the statement, than in recognizing a mismatch, which again is expected as it was easier to recall the correct statement than to rectify an incorrect one by providing the correct causal information. The analysis did not show a reliable effect of representation type $F(2, 52) = .485, MSe = 45.244, p > 0.5$, which suggested that all three representations required the similar amount of attention and recall while matching the statements (Figure 7.2).

Summary of Experiment 3

The above results aid in the following inferences:

- Participants were more ~31% accurate and took less time in recognizing a match between the given statement and relation rather than in correcting a mismatch. This can be attributed to the memory power of the participant itself and to the difficulty in providing the correct causal information, when the relation and statement did not match.

- Fully-mediated causality was recalled faster than additive (~24%) or contradictive causality (~25%). The faster response time could be attributed to the fact that even though fully-mediated causality had two factors, one of them was an inactive mediator and did not contribute to the information described in the relation and hence, must have been generally ignored.

- Significance was not seen between the accuracy rates or response times for the three representation types, which suggests that the causal semantics were equally depicted by each of the representations.

The static and animated representations did not show significant improvement in accuracy rates or response times than their textual counterparts, and hence do not concur with *Hypothesis 1*. One reason for this could be attributed to the method of presenting the statements for comparison. The statements were presented in text form and therefore might be easier to match to a textual representation of the causal relations. The fact that the static and animated representations did not perform any worse than the text-only representation could be noted as encouraging as participants viewed the visual representation after they read the textual representation, which should have caused a distraction and decrease in performance.

Also, animations did not show significant improvement in accuracy rates or response times when compared to the static-graph representations, which shows non-concurrence with *Hypothesis 2*. The insignificant improvement in performance that was seen with the animations could be attributed to: (a) simplicity of the semantics presented in this experiment or (b) difficulty in remembering large amounts of information. If cause (a) had influence on the results of this experiment, it would interesting to test if the visual representations show any improvement in accuracy rates or response times when the complexity of the semantics is increased, as studied in Experiment 4 section 7.2 below, while cause (b) has been tested in Experiment 5 (section 7.3), by reducing the number of relations to be memorized and testing the intuitiveness of the static-graph and animated representations.

7.2 Experiment 4 - Comparing text, static-graph, and animated representations of Design-Group 2 causal semantics

The goal of this experiment was to evaluate the efficiency of static and animated visualizations, over text-only representations of DG2 complex causal semantics. The causal semantics that I tested in this experiment were partially-mediated causality, threshold causality, and bidirectional causality. As in Experiment 1 (section 6.1), my hypotheses were as follows:

- **Hypothesis 1:** Participants will perform the recall tasks with higher accuracy rates when the causal relations are enhanced with visualizations, when compared to a textual description of the information.
- **Hypothesis 2:** Participants will perform more accurately and with faster response times when the causal relations are enhanced with animated (vs. static-graph) visualizations.

7.2.1 Method

Participants

40 undergraduate psychology students, between the ages of 20 and 30 years, participated in this experiment. Participants satisfied the required criteria of good English language skills, normal to corrected vision, and passed Ishihara's test for color blindness [Ishihara, 1917].

Materials

As in the previous experiment, the visualizations were displayed through a .NET program with embedded Macromedia Flash™ files, in a Windows XP environment. The visualizations were displayed on a 17" monitor with a 1024 × 768 pixel screen resolution.

Design

The experiment was conducted using a 3 × 2 within subject design. Two independent variables were identified: Representation Type and Statement Type.

- **Representation type:** Three types of representations were shown to the participants; Text (lines of textual descriptions), Static-graph (graphical representation), and Animation (smooth animation and sequential display of causal relation).

- **Statement type:** At the end of each trial, the participants were asked to respond to a set of questions, divided equally into two categories; Correct (where all the components of the statement matched a given causal relation), and Incorrect (where only *some* of the components of the statement matched the given causal relation).

Tasks

The experiment tested three conditions; text-only, text + static-graph and text + animation. The participants were given two tasks to perform: Memorization and Recall.

- **Memorization:** In this task, the participant was initially asked to read the given passage of causal relations for 1½ minutes and was then asked to view the corresponding visualization for the next 1½ minute, except in the text-only condition where they performed a filler task (connect-the-dots) to supplement the lack of visualization. As in the other experiments, the 30 second long animation was repeated 3 times to fill the 1½ minute timeslot.

- **Recall:** In this task, the participants were asked to recognize relations that they read/viewed. Participant responses were limited to "Correct" or "Incorrect" (with corrections in case they deemed a relation to be incorrectly stated) responses within an 8 minute timeframe.

The representation types were fully counterbalanced using a Latin square design. Three topics were randomly picked from a list of twelve and each questionnaire consisted of 6 questions (3 correct and 3 incorrect). Overall with 40 participants, 3 conditions, and 6 questions per condition, a total of 720 responses were collected for analysis.

Procedure

Participants were allowed to practice on a sample version of the experiment until they were comfortable with the tasks. During the experiment, participant responses and response times were recorded. The participant was given a score of 1 for a correct response, a score of 0 for each completely incorrect response, and a fraction of the maximum score for a partially correct response.

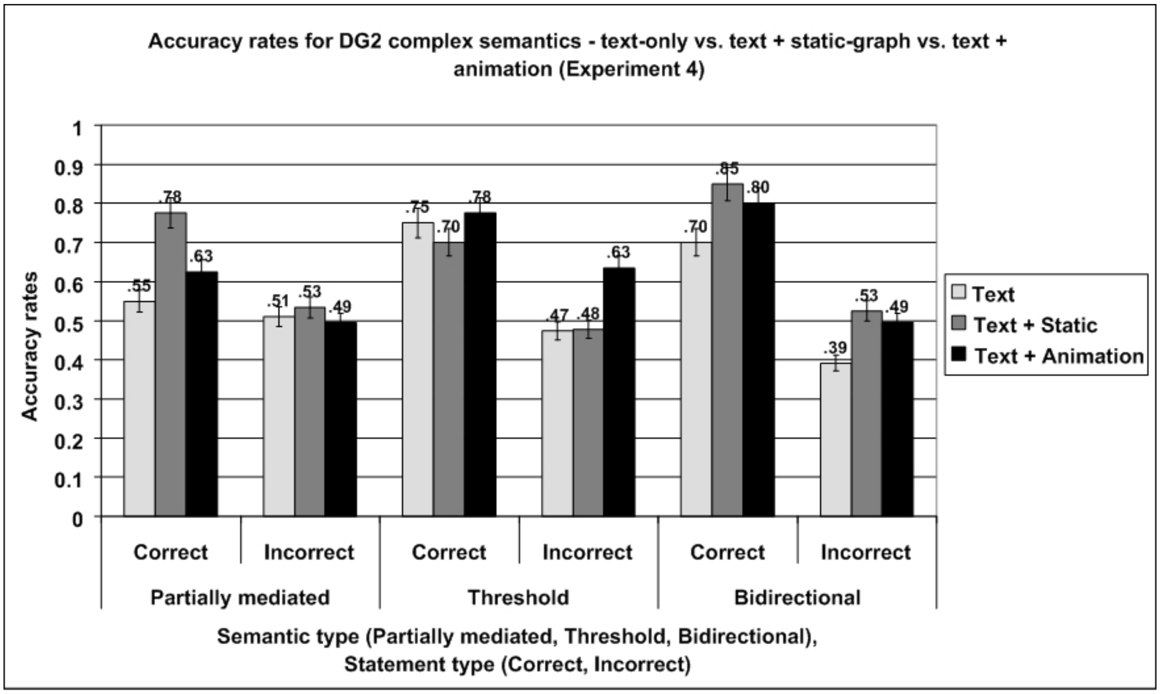

Figure 7.3: Accuracy rates for text-only, text + static-graph, and text + animated representations of DG1 complex semantics: partially-mediated causality, threshold causality, bidirectional causality and statement types: correct, incorrect (±5% error bars depict the 95% confidence intervals for the means).

7.2.2 Results and Discussion

As in Experiment 3 (section 7.1), two values were recorded for each answer given by a participant: accuracy and response time. The data were then submitted to a $3 \times 2 \times 3$ repeated-measures Analysis Of Variance (ANOVA) treating semantic type (partially-mediated vs. threshold vs. bidirectional), statement type (correct vs. incorrect-with-corrections), and representation type (text-only vs. text + static-graph vs. text + animation) as within-subject factors. Table 7.3 summarizes the overall analysis of the results, along with a summarization of the mean values for the factors showing significance in Table 7.4.

Factor	**Accuracy rate**	**Response time**
Representation type (F1)	No significance	No significance
Semantic type (F2)	No significance	**Significance**
Response type (F3)	**Significance**	**Significance**
F1 × F2 interaction	No significance	No significance
F1 × F3 interaction	No significance	No significance
F2 × F3 interaction	**Significance**	No significance
F1 × F2 × F3 interaction	No significance	No significance

Table 7.3: Summary of analysis showing significant results (in bold), for Experiment 4: Complex causal semantics, DG2, Representation type(F1): *Text-only vs. Text+Static-graph vs. Text+Animation*, Semantic type(F2): *Partially-mediated causality vs. Threshold causality vs. Bidirectional causality*, Response type(F3): *Correct vs. Incorrect-with-corrections*, Memory Recall Experiment.

An analysis of the accuracy points showed a main effect of response type $F(1, 39) = 40.394, MSe = 8.8, p < 0.001$ and a comparison of the means showed that participants were ∼31% more effective in matching relations to statements than in recognizing a mismatch. This difference can be attributed to the memory power of the participants and also to the number of relations that the participants were asked to memorize (6 relations) and recall while providing the correct causal information for the incorrect

Factor		**Accuracy rate** (↓ = % less accuracy than highest accuracy value for factor(in bold)	**Response time** (↑ = % more time than lowest response time value for factor(in bold)
Semantic type (F2)	**Partially-mediated causality**	-	14.760 seconds (∼14% ↑)
	Threshold causality	-	**12.703 seconds**
	Bidirectional causality	-	15.721 seconds (∼19% ↑)
Response type (F3)	**Correct**	**.725**	**11.790 seconds**
	Incorrect-with-corrections	.504 (∼30% ↓)	16.999 seconds (∼30% ↑)

Table 7.4: Summary of accuracy rates and response times for factors showing significance in the analysis of Experiment 4 results. *NOTE: Highest accuracy rate and lowest response time for each factor are highlighted in bold. The ↓ arrow shows reduction in accuracy rate when compared to the highest accuracy rate for the factor and the ↑ arrow shows increase in response time when compared to the lowest response time for the factor.*

statements.

The analysis did not show a significance in representation type ($p > 0.05$), which suggests that the semantics were equally depicted in all three representation conditions (Figure 7.3). The analysis also showed significant interaction between semantic and statement types. A 3×3 repeated-measures ANOVA for each response type treating semantic type and representation type as within-subject factors suggests that there is no significance between the performances of the semantics for the 'Incorrect' responses. However, analysis of the results for the 'Correct' responses suggests a main effect of semantic type, $F(2, 78) = 3.440, MSe = .162, p < .05$. Comparison of the means reveal that participants were most accurate in responding to bidirectional causality statements (mean = .783), ∼5% less accurate with threshold causality, and ∼17% less accurate with partially-mediated causality. These results suggest that the reason participants were able to comprehend bidirectional causality best could be attributed to the change in direction of the causal action (factor→target and factor←target); a unique feature that causes it to stand out from the other semantics. Figure 7.3 compares accuracy rates for the 'Correct' and 'Incorrect' responses across the three representation types.

An analysis of the response times showed a main effect of semantic $F(2, 78) = 7.539, MSe = 570.55, p < 0.005$ and statement type $F(1, 39) = 53.132, MSe = 91.898, p < 0.001$. A comparison of the means of the semantic showed that participants were able to recall threshold relations ∼19% faster than bidirectional relations and ∼13% faster than partially-mediated relations, since the threshold relation had less information (one factor and one target) to memorize and recall than the partially-

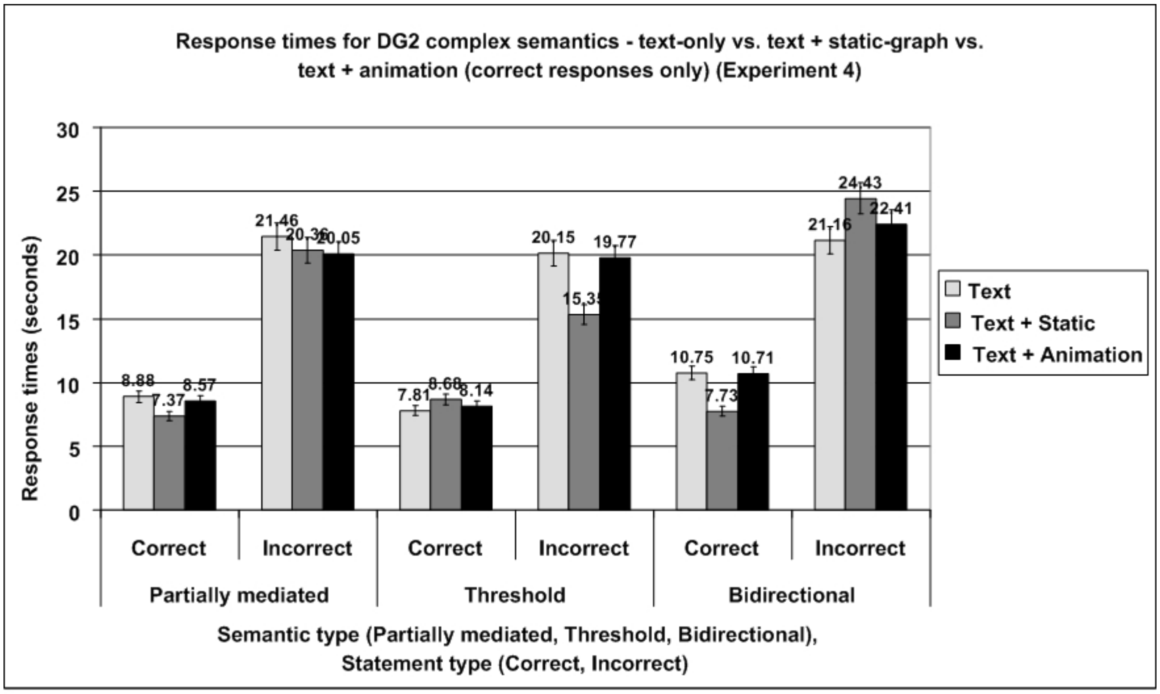

Figure 7.4: Response times for text-only, text + static-graph, and text + animated representations of DG1 complex semantics: partially-mediated causality, threshold causality, bidirectional causality and statement types: correct, incorrect (±5% error bars depict the 95% confidence level intervals for the means).

mediated and bidirectional causality relations. A comparison of the means for the statement type showed that participants took ∼31% less time to recall and respond to correct matches between the relations and the statements than in recognizing and correcting a mismatch, which as with Experiment 3 can be attributed to the number of relations provided and the difficulty in providing the correct information in case of a mismatch between the given relation and statement. Figure 7.4 shows the response times for 'Correct' and 'Incorrect' statements for DG2 complex causal semantics.

Summary of Experiment 4

From the above results, I can infer the following:

- Participants were more accurate (∼31%) and responded faster (∼31%) when recognizing that a given statement matched the displayed relation than in recognizing a mismatch.

- Results also reveal that participants were more accurate in responding to bidirectional causality statements, but also took the most time in providing answers to these statements. This suggests that bidirectional causality was easier to comprehend due to its uniqueness (two-way flow of information), but also consumed more time as it contradicted Michotte's rules of linearity in causal motion (described in 2.3).

The analysis did not show a main effect of representation type, which shows non-concurrence with *Hypothesis 1*. The lack of significance can be attributed to the manner of presenting the statements (using text representation) which closely matched the manner of representing the causal relation in the text-only condition. The analysis also did not show any significance between the static-graph and animated visualizations (non-concurrence with *Hypothesis 2*) which could be attributed to the large number of relations that the participant was asked to view and memorize each time (6 per condition). Therefore, a direct comparison of the static-graph and animated representations might be necessary to determine their intuitiveness in describing the causal semantics, which has been conducted in the next section (Experiment 5).

7.3 Experiment 5 - Comparing static-graph and animated representations of complex causal semantics *(published in APGV'09)*

The goal of this experiment was to compare the effectiveness of my static-graph and animated representations in describing complex causal relations. Contrary to the previous experiments in this subsection, the two design groups were combined and all six complex causal semantics were incorporated in this experiment: additive causality, contradictive causality, fully-mediated causality, partially-mediated causality, threshold causality, and bidirectional causality. As a follow up to the previous experiments, this experiment aimed at testing the intuitiveness of the static-graph and animations in describing the causal information, in the absence of a textual description. The hypotheses for this experiment were as follows:

- **Hypothesis 1:** Participants will perform the recall tasks more accurately when the causal relations are described using animations, when compared to a textual description of the information.

- **Hypothesis 2:** Participants will respond faster when the causal relations are depicted as animations.

7.3.1 Method

Participants

49 undergraduate psychology students of a local university, between the ages of 20 and 30 years, participated in this experiment. The participants satisfied the same selection criteria as in the previous experiments (age, no color blindness, normal to corrected vision, no prior experience with causal graphs).

Materials

As in the previous experiments, this experiment was executed as a .NET program with embedded static-graph and animated Macromedia Flash™ files. Individual copies of the program were executed on a Windows XP computer and displayed on a 17" Dell monitor with a 1024 × 768 pixel screen resolution.

Design

The experiment comprised of a 2 × 6 within subject design. Two independent variables were identified: Representation Type and Semantic Type.

Representation type

Two types of representations were shown to the participants: Static-graph and Animation.

- **Static-graph:** In this representation type, the participants were shown a static graph with 1 – 2 causal relations. In the case where 2 causal relations were shown, both the relations were shown simultaneously and colors were used to differentiate between the relations. In addition, color and +/− glyphs were used to depict influences, and upright and inverted bars were used to depict outcomes. Size of the glyphs and the bars were varied to show small and large amounts of influence or outcome.

- **Animation:** In this representation type, the participants were shown an animation which contained about 1 or 2 causal relations, ordered sequentially. As in the animated representations of the previous experiments, the causal relations were visualized using animated factors, bullets, and targets.

Statement type

At the completion of each trial, the participants were shown a statement based on the relation(s) they viewed and were asked to correctly match six types of statements, with each statement depicting one type of complex causal semantic; additive causality (S1), contradictive causality (S2), fully-mediated causality (S3), partially-mediated causality (S4), threshold causality (S5), and bidirectional causality (S6).

Tasks

This experiment consisted of two main tasks:

- **Memorization:** In this task, the participants were shown and asked to memorize either a static or an animated causal relation for 9 seconds.

- **Recall:** In this task, the participants were presented with a statement and asked to match it to one of the relations shown in the memorization task. If the statement exactly matched the information provided in the memorization task the participants were required to respond 'Yes' ('B' key on the keyboard) in order to score a point. Similarly, if the statement did not exactly match the previously given information the participant was required to respond 'No' ('N' key on the keyboard), in order to score the point.

The trials were fully counterbalanced using a Latin square design. Each trial was based on a random selection of 1 of 12 topics, with one statement per trial. The experiment consisted of 120 trials in total, divided into 5 sessions. Overall, with 49 participants, 5 sessions, 2 representation types (static-graph and animations) per session, 6 statement types per representation (additive, contradictive, fully-mediated, partially-mediated, threshold, and bidirectional), and 2 response types (Yes and No) per statement type, a total of 5880 responses were collected for analysis.

Procedure

The experiment was divided into two phases. In the *training* phase, the participant was asked to practice on a sample version of the program, while in the *experiment* phase, participant responses and response times were recorded for each trial. At the end of each session, timers were paused and the participants were allowed to take a break if required.

7.3.2 Results and Discussion

Following the procedure described in the method section, two values were recorded for each answer provided by the participant; accuracy points and response time. These data were then submitted to a 2 $\times$ 6 $\times$ 2 repeated-measures Analysis of Variance (ANOVA) treating representation type (static-graph vs. animation), semantic type

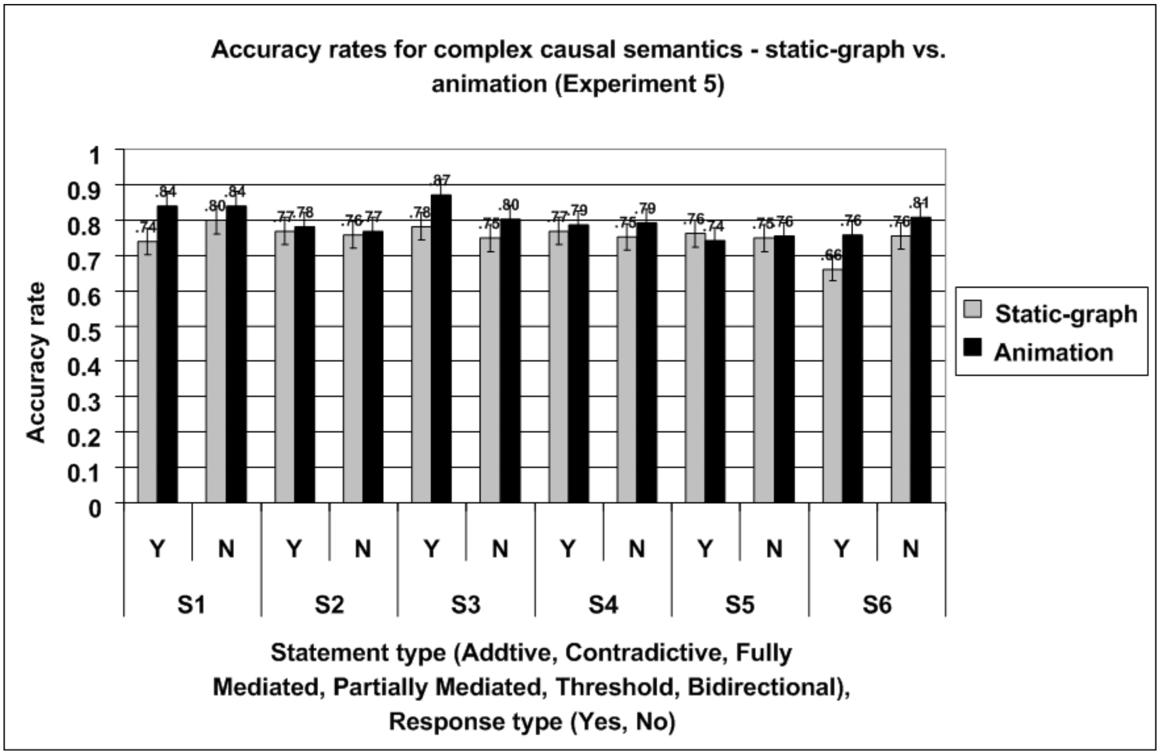

Figure 7.5: Accuracy rates for static-graph and animated representations of statement types: S1(additive causality), S2(contradictive causality), S3(fully-mediated causality), S4(partially-mediated causality), S5(threshold causality), S6(bidirectional causality) and response types: Y(yes), N(no) (±5% error bars depict 95% confidence intervals for the means).

(additive vs. contradictive vs. fully-mediated vs. partially-mediated vs. threshold vs. bidirectional), and response type (yes vs. no) as within-subject factors. Table 7.5 summarizes the overall analysis of the results, along with a summarization of the mean values for the factors showing significance in Table 7.6.

Factor		**Accuracy rate** (↓ = % less accuracy than highest accuracy value for factor(in bold)	**Response time** (↑ = % more time than lowest response time value for factor(in bold)
Representation type (F1)	**Static-graph**	.753 (~5% ↓)	8.115 seconds (~8% ↑)
	Animation	**.795**	**7.441 seconds**
Semantic type (F2)	**Additive causality (Q1)**	**.804**	7.054 seconds (~5% ↑)
	Contradictive causality (Q2)	.770 (~4% ↓)	7.623 seconds (~12% ↑)
	Fully-mediated causality (Q3)	**.801**	**6.670 seconds**
	Partially-mediated causality (Q4)	.775 (~3% ↓)	8.847 seconds (~25% ↑)
	Threshold causality (Q5)	.752 (~6% ↓)	8.257 seconds (~19% ↑)
	Bidirectional causality (Q6)	.745 (~7% ↓)	8.217 seconds (~18% ↑)

Response type (F3)	**Yes**	-	8.102 seconds (∼8% ↑)
	No	-	**7.454 seconds**

Table 7.6: Summary of accuracy rates and response times for factors showing significance in the analysis of Experiment 5 results. *NOTE: Highest accuracy rate and lowest response time for each factor are highlighted in bold. The ↓ arrow shows reduction in accuracy rate when compared to the highest accuracy rate for the factor and the ↑ arrow shows increase in response time when compared to the lowest response time for the factor.*

An analysis of the accuracy points showed a main effect of representation type $F(1, 48) = 20.339, MSe = .025, p < 0.001$. A comparison of the means showed that participants were ∼5% more accurate when causal relations were presented using animations. The results suggest that participants were able to comprehend and recall the causal information more accurately with the animations, compared to the static-graph representation.

The analysis also showed a main effect of semantic type $F(5, 240) = 4.267, MSe = .028, p < 0.005$ and a comparison of the means showed that participants were most accurate with fully-mediated causality and least accurate in recognizing bidirectional causality (Figure 7.5).Finally, the analysis showed significant interaction between semantic and response types, $F(5, 240) = 2.656, MSe = .032, p < .05$. Detailed analysis revealed a main effect of semantic type for the 'Yes' responses, $F(5, 240) = 4.559, MSe = .033, p < .001$, as shown in Figure 7.5. These results are expected

Factor	**Accuracy rate**	**Response time**
Representation type (F1)	**Significance**	**Significance**
Semantic type (F2)	**Significance**	**Significance**
Response type (F3)	No significance	**Significance**
F1 × F2 interaction	No significance	**Significance**
F1 × F3 interaction	No significance	No significance
F2 × F3 interaction	**Significance**	**Significance**
F1 × F2 × F3 interaction	No significance	**Significance**

Table 7.5: Summary of analysis showing significant results (in bold), for Experiment 5: Complex causal semantics, DG1 & DG2, Representation type(F1): *Static-graph vs. Animation*, Semantic type(F2): *Additive causality vs. Contradictive causality vs. Fully-mediated causality vs. Partially-mediated causality vs. Threshold causality vs. Bidirectional causality*, Response type(F3): *Yes vs. No*, Intuitiveness Evaluation Experiment.

because fully-mediated causality contains the least amount of causal information as the mediator is not active, and bidirectional causality contains the most amount of causal information as it is a two way relationship between the factor and the target.

An analysis of the response times showed a main effect of representation type $F(1, 43) = 12.118, MSe = 9.906, p < 0.005$. The basis for this main effect was that participants responded faster when the causal relations were visualized using anima-

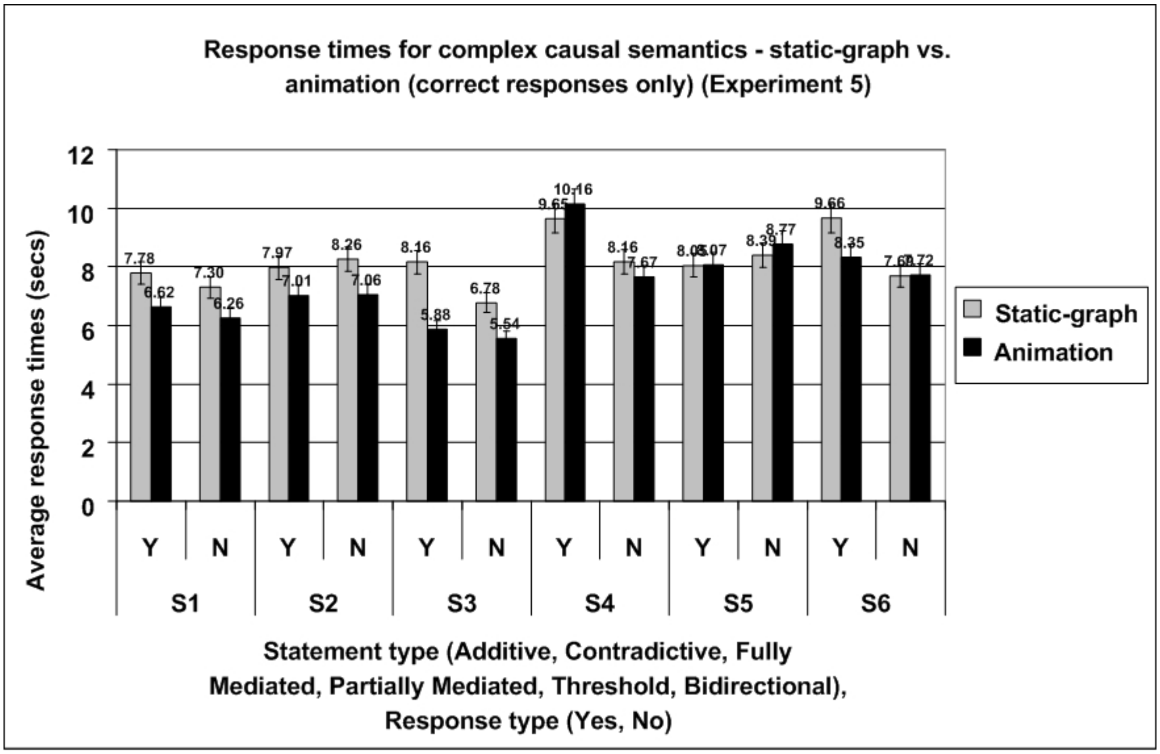

Figure 7.6: Response times for static-graph and animated representations of statement types: S1(additive causality), S2(contradictive causality), S3(fully-mediated causality), S4(partially-mediated causality), S5(threshold causality), S6(bidirectional causality) and response types: Y(yes), N(no) (±5% error bars depict 95% confidence intervals for the means).

tions. Specifically, participants were ∼8% faster with animations than static graphs (7.441 seconds vs. 8.115 seconds), which suggests that the animations were more intuitive and could be comprehended faster. The analysis also showed a main effect of semantic type $F(5, 215) = 15.266$, $MSe = 7.705$, $p < 0.001$, which suggests that participant performance was dependent upon the type of semantic that was displayed. Specifically, participants took the longest to respond to partially-mediated causality statements (mean = 8.847 seconds), while they were ∼6% faster in responding to threshold causality statements, ∼7% faster in responding to bidirectional causality statements, ∼14% faster in responding to contradictive causality statements, ∼20% faster in responding to additive causality statements, and ∼25% in responding to fully-mediated causality statements (Figure 13). Again, the results suggest that participants responded to fully-mediated causality statements fastest as it contained the least amount of information to memorize and recall.

The analysis also showed a main effect of response type $F(1, 43) = 10.564, MSe = 10.500, p < 0.005$. Surprisingly, a comparison of the means showed that participants were ∼8% faster in recognizing a mismatch between the displayed relation and the given statement than in recognizing a match. This is in contrast to the previous experiments and suggests that as the participants had fewer relations to remember, they were quickly able to recognize the mismatch, but in cases where the relations and statement matched, feedback from the participants suggested that they took longer to double-check in order to ensure that they were providing the correct response.

The analysis of the response times also showed significant interaction between representation type and semantic type $F(5, 215) = 5.495, MSe = 4.850, p < 0.001$, between semantic type and response type $F(5, 215) = 9.182, MSe = 5.159, p < 0.001$, and between all three variable groups; representation type, semantic type, and response type $F(5, 215) = 2.469, MSe = 4.363, p < 0.05$. These interactions suggest that participant response times were significantly influenced by the condition (representation type vs. semantic type vs. response type) that was presented. The analysis was broken down into simpler 2×2 and one-way ANOVA's to examine individual effects. Results of these analysis showed that for semantic type Q1 (additive causality), although there was no significant difference in recognizing correct matches ('Y' response type), for both representation types, participants had significantly lower response times (∼17%) with animations, $F(1, 43) = 9.431, MSe = 3.727, p < 0.005$, when asked to recognize a mismatch between the given statement and visualization ('N' response type). The analysis of participant performance for semantic type Q2 showed significant reduction in response times with the animated representation when compared to the static representation, both for response type 'Y': ∼11% faster, $F(1, 43) = 4.398, MSe = 3.546, p < 0.05$, and response type 'N': ∼17% faster, $F(1, 43) = 8.096, MSe = 5.749, p < 0.01$. With semantic type Q3 participants were again significantly faster with animations than static representations for both response type 'Y': ∼37.6% faster, $F(1, 43) = 29.920, MSe = 3.717, p < 0.001$ and response type 'N': ∼16.8% faster, $F(1, 43) = 9.095, MSe = 3.161, p < 0.005$.

Summary of Experiment 5

Summarizing the results of this analysis:

- Overall, participants were ∼5% more accurate and ∼8% faster when the causal relations were represented using animations.
- Participants were ∼8% faster in recognizing a mismatch between relation and statement as they took longer to verify that they were providing the correct answer when they recognized a match.
- Participant performance depended upon the combination of representation type, semantic type, and response type that was presented during each trial of the

experiment. Animations in general had higher accuracy rates and lower response times than the static-graph representation. This difference in performance was significant with the simple causal notations such as additive, contradictive, and fully-mediated causalities. However, as the complexity of the causal information increased, the difference between the representations reduced; although this can be attributed to the inexperience of the participants and the limited training that was provided to them before the start of the experiment.

The analysis of my experimental results concurs with *Hypothesis 1* as the participant accuracy improved when animations were employed to depict the causal information. The results also concurred with *Hypothesis 2* as response times significantly reduced with animations when compared to the static-graph representation. The results also suggest that the combination of representation, semantic, and response types uniquely influence participant performance and that the representation should be chosen based on the type of causal information presented to the viewer.

A point to note in the above studies is the difference between the methods of displaying the relations using the two representations. In the static-graph representation, all the causal relations in a scenario were presented simultaneously (using unique colors), while in the animated representation the relations were shown sequentially. It would be interesting to determine if the improvement in participants' performance was seen because of the animation of the bullets and the nodes or because of the isolation of information when the relations were displayed in sequence. Therefore, in order to establish the effectiveness and intuitiveness of the animations, I also tested a comparable and dynamic version of the static graphs to the animated representation. Two types of static representations were therefore identified in the course of this study; static-graph and static-sequence. The next chapter describes experiments that were designed to compare the intuitiveness of the animations to their corresponding static-sequence representations.

Chapter 8

Component IV: Isolating the efficiency of the animated visualizations: animation vs. static-sequence representations - Experiments 6, 7, 8, and 9

Previous research [Tversky et al., 2000] states that animations are costly and should be used only when necessary. Such studies have also concluded that where static representations can convey the same information as that of animation, the former are preferable to the latter.

The results of Chapter 7 determined that participants performed more accurately when causal descriptions were enhanced with animations rather than with static rep-

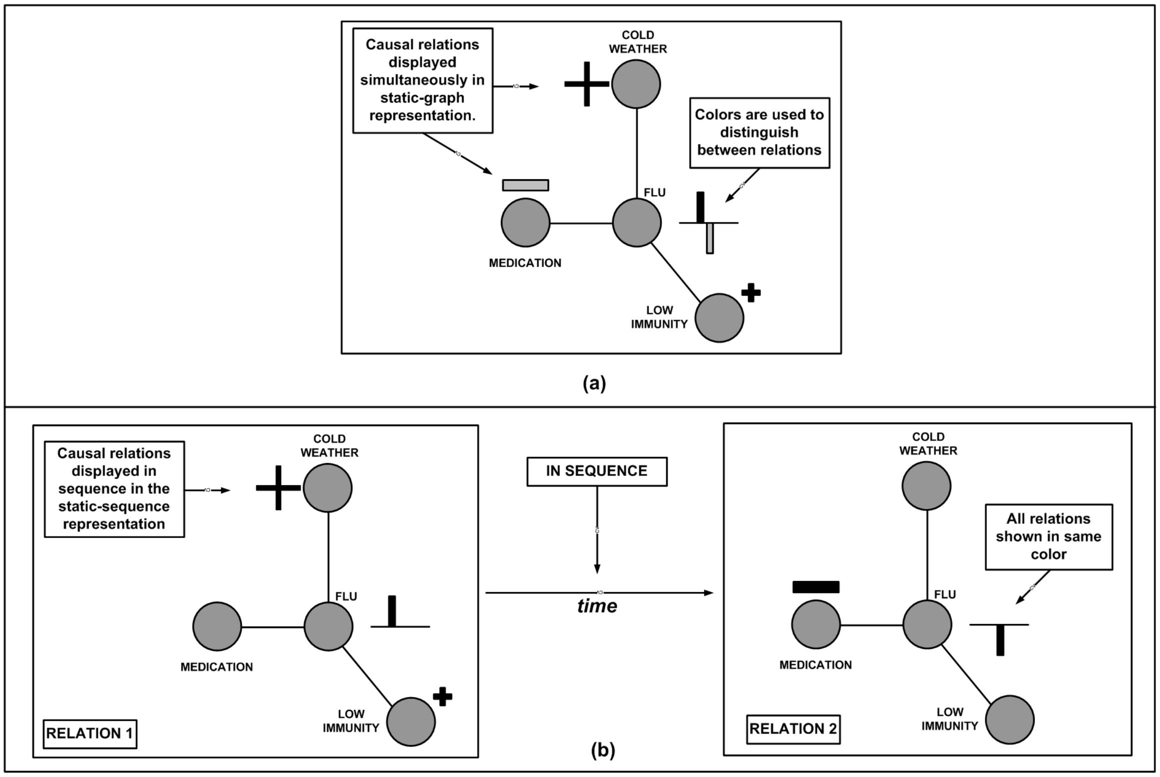

Figure 8.1: (a) Static-graph representation of a Flu scenario showing simultaneous presentation of causal relations, which are distinguished from one another using unique colors, and (b) static-sequence representation of the Flu scenario showing the isolation and sequential presentation of causal information, eliminating the need for color coding.

resentations. However, it can be argued that the main reason for this improved performance can be attributed to the reduction in clutter, when the causal relations were animated in sequence, and not to the animation itself. Therefore, this experiment focuses on determining which component of the animation causes the improvement in performance over the static-graph representations. For purposes of analysis the animation can be divided into two major components:

- **Smooth animation of the graph:** The animation of the graph includes movement of the bullets between the factors and the targets, describing influence, and the smooth deformation of the target, describing effect (Figure 8.1.(a)).

- **Sequential animation of the causal relations:** The second component of the animated visualization is the method of displaying the causal relations in sequence. By separating and clearly identifying one causal relation from another, the animated representation reduces clutter and removes the participant's dependency on color, which was a main characteristic of the static-graph representation (Figure 8.1.(b)).

The experiments conducted in Chapters 6 and 7 visualized the causal semantics using the static-graph representation. The main differences of this representation (from the animations) were (a) representation of information using static glyphs, (b) simultaneous presentation of causal relations, and (c) color coding to distinguish between the relations. As I was trying to determine the effectiveness of the *smooth animation of the graph* in the animated representation, the static-graph was enhanced with the *sequential animation of the causal relations* (vs. feature (c) of the static-graph representation) and renamed as the *static-sequence* representation:

- **Static-graph representation:** In the older static-graph representation, all the causal relations in the scenario were displayed simultaneously and the participants were asked to use color codes to group glyphs into their respective causal relations.

- **Static-sequence representation:** In the static-sequence version, the causal relations were isolated and shown one at a time, in sequence, thus reducing clutter and also removing the participants' dependence upon color codes.

The goal of the experiments in this chapter was to compare the effectiveness of static-sequence representations to animated representations of the causal semantics.

8.1 Experiment 6 - Comparing static-sequence to smooth animation of simple causal relations

This experiment focused on testing static-sequence, and animated representations of the simple causal semantics and comparing the static-sequence results to the performance of the static-graph representation in Experiment 2 (section 6.2).

My hypotheses for this experiment were as follows:

- **Hypothesis 1:** Participants will perform the recall tasks with higher accuracy rates when the causal relations are enhanced with animations, when compared to a textual description of the information.

- **Hypothesis 2:** Participants will be able to perform the recall tasks with faster response times when the causal relations are enhanced with animations.

- **Hypothesis 3:** Sequential presentation of information will not improve performance (accuracy rates and response times) of the static representation.

8.1.1 Method

Participants

41 undergraduate psychology students of a local university participated in this experiment. The participants satisfied the same selection criteria as in Experiment 2 (age, normal to corrected vision, no prior experience with causal graphs). Color blindness tests were not conducted in this experiment, as color codes were unnecessary due to the sequential (vs. simultaneous) representation of the relations.

Materials

The experiment consisted of two major conditions for representing the relations; static-sequence and animations. The experiment was generated as a .NET program with the embedded static-sequence and animated Macromedia Flash™ files. Individual copies of the program were executed on a Windows XP computer and displayed on a 17" Dell monitor with a 1024 × 768 pixel screen resolution.

Design

The experiment was based on a 2 × 4 within-subject design, similar to Experiment 2 (section 6.2.1). The two independent variables were: Representation Type and Statement Type.

Representation type

Two types of representations were shown to the participants: Static-sequence and Animation.

- **Static-sequence:** The static-sequence representation was similar to the static-graph representation in Experiment 2, with the only difference that in the static-sequence representation the relations were isolated and shown sequentially using monochromatic glyphs.

- **Animation:** This representation type was the same as that tested in Experiment 2. The participants were shown an animation, which contained about 1 - 2 causal relations, repeated 3 times.

Statement type

At the completion of each trial, the participants were shown a statement based on the relation(s) they viewed. The statement types were similar to the ones used in Experiment 2:

- **Type of outcome (S1):** tested the ability of the participant to distinguish between positive and negative outcomes in the causal relation.

- **Strength of influence (S2):** tested the ability of the participant to comprehend the amount of influence a factor had on the target.

- **Magnitude of the outcome (S3):** tested the ability of the participant to comprehend the magnitude of the outcome.

- **Combination of components (S4):** tested the ability of the participant to identify all the constituent elements of a causal relation, such as the type and magnitude of outcome and strength of the influence.

Tasks

As in Experiment 2, the experiment consisted of two tasks; memorization and recall. In the *memorization* task the participants were shown the causal relations for a pre-determined length of time (9 seconds per causal relation) and asked to carefully view all the possible relationships that existed in the scenario. In the *recall* task, the participants were shown a statement and asked to determine if it matched one of the displayed relations (B = 'Yes' or N = 'No'). Participants were instructed to respond as accurately and quickly as possible.

The trials were fully counterbalanced using a Latin square design and each trial was based on a random selection of 1 of 12 topics, with one statement per trial. The experiment consisted of 96 trials in total, divided into 6 sessions. Overall, with 41 participants, 6 sessions, 2 representation types (static-sequence and animations) per session, 4 statement types per representation (S1, S2, S3, and S4), and 2 response types (Yes and No) per statement, a total of 3936 responses were collected for analysis.

Procedure

The experiment was conducted in two phases. In the *training* phase, the participants practiced on a sample version of the experiment, without help from the experimenter. In the *experiment* phase, each trial recorded the participants' response accuracy and time. At the end of each session, timers were paused and the participants were allowed to take a break if desired.

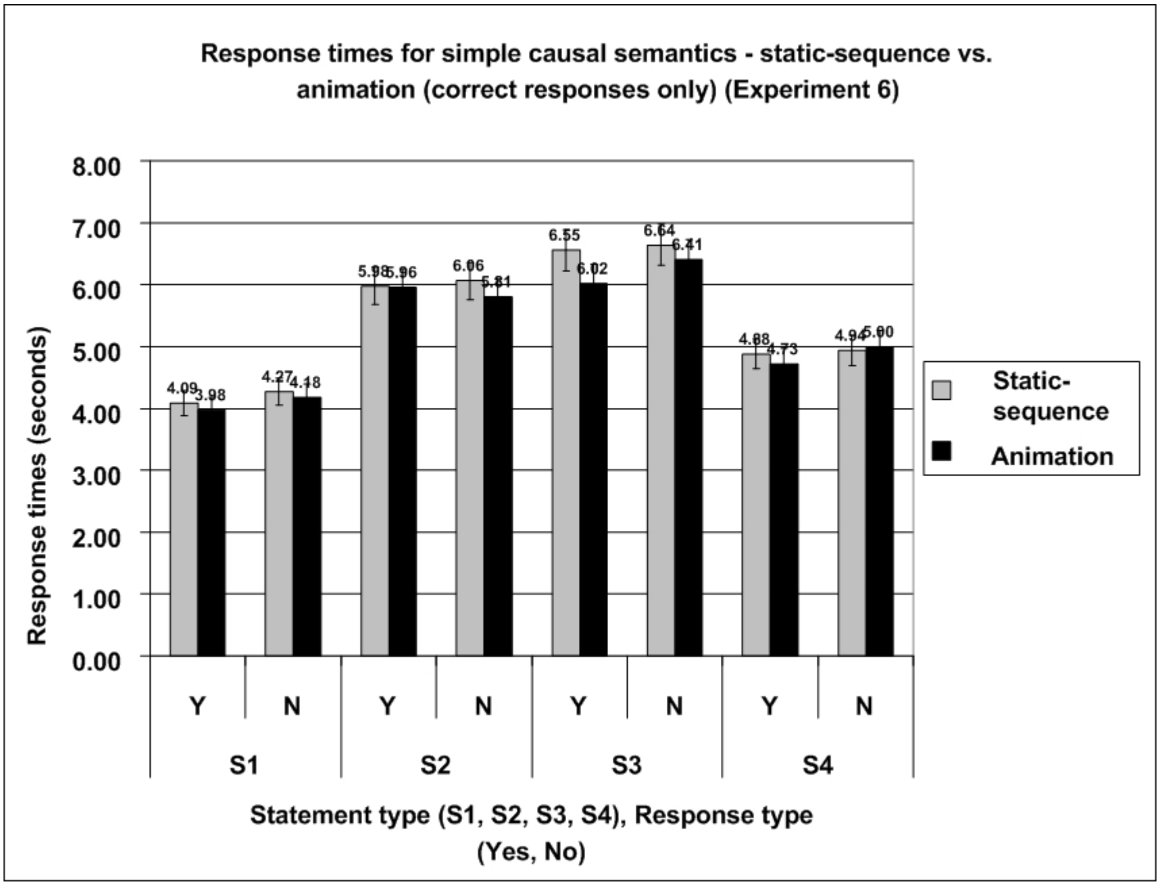

Figure 8.2: Response times for static-sequence and animated representations of statement types: S1(type of outcome), S2(strength of influence), S3(magnitude of outcome), S4(combination of components) and response types: Y(yes), N(no) (±5% error bars depict 95% confidence intervals for the means).

8.1.2 Results and Discussion

Following the description provided in the Method section, two values were recorded for each answer provided by the participant: accuracy and response time. These values were then submitted to a 2 × 4 × 2 repeated-measures Analysis of Variance (ANOVA) treating representation type (static-sequence vs. animation), semantic type

(S1 vs. S2 vs. S3 vs. S4), and response type ('Y' vs. 'N') as within subject factors. Table 8.1 summarizes the overall analysis of the results, along with a summarization of the mean values for the factors showing significance in Table 8.2.

Factor	**Accuracy rate**	**Response time**
Representation type (F1)	No significance	**Significance**
Semantic type (F2)	**Significance**	**Significance**
Response type (F3)	**Significance**	No significance
F1 × F2 interaction	No significance	No significance
F1 × F3 interaction	No significance	No significance
F2 × F3 interaction	**Significance**	No significance
F1 × F2 × F3 interaction	No significance	No significance

Table 8.1: Summary of analysis showing significant results (in bold), for Experiment 6: Simple causal semantics, Representation type(F1): *Static-sequence vs. Animation*, Semantic type(F2): *Type of effect (S1) vs. Strength of influence (S2) vs. Magnitude of outcome (S3) vs. Combination of components (S4)*, Response type(F3): *Yes vs. No*, Intuitiveness Evaluation Experiment.

Factor		**Accuracy rate** (↓ = % less accuracy than highest accuracy value for factor(in bold)	**Response time** (↑ = % more time than lowest response time value for factor(in bold)
Representation type (F1)	**Static-sequence**	-	5.4 seconds (~3% ↑)
	Animation	-	**5.2 seconds**
Semantic type (F2)	**Type of effect (S1)**	**.902**	**4.042 seconds**
	Strength of influence (S2)	.825 (~8% ↓)	5.988 seconds (~32% ↑)
	Magnitude of outcome (S3)	.818 (~9% ↓)	6.379 seconds (~36% ↑)
	Combination of components (S4)	.835 (~7% ↓)	4.791 seconds (~15% ↑)
Response type (F3)	**Yes**	**.874**	-
	No	.816 (~7% ↓)	-

Table 8.2: Summary of accuracy rates and response times for factors showing significance in the analysis of Experiment 6 results. *NOTE: Highest accuracy rate and lowest response time for each factor are highlighted in bold. The ↓ arrow shows reduction in accuracy rate when compared to the highest accuracy rate for the factor and the ↑ arrow shows increase in response time when compared to the lowest response time for the factor.*

An analysis of the response times showed a reliable main effect of representation type $F(1, 40) = 4.577, MSe = 1.425, p < .05$. Specifically, participants were ~4% faster in responding to questions when the causal relations was visualized using the animations, than the static-sequence graphs. This could be credited to the intuitiveness of the animations which allows for transitioning from the beginning to the end. The results also showed a main effect of semantic type $F(3, 120) = 69.245, MSe = 2.748, p < 0.005$. A comparison of the means showed that participants were fastest in responding to questions about the type of outcome (S1), and took about ~19%, ~48%, ~58% more time in responding to statement types S4, S2, and S3 respectively. Figure 8.2 compares the response times for 'Yes' and 'No' responses, for statement types S1 – S4.

An analysis of the accuracy rates did not show a main effect of representation type $F(1, 40) = .106, MSe = .022, p > 0.5$. Specifically, a comparison of the means for the static and animated representations (.847 vs. .843 respectively) showed that participants were equally efficient with both modes of visualization. These results concur with the results in Experiment 2 and can be attributed to the simplicity of the semantics being illustrated. However, the analysis showed a main effect of semantic type $F(3, 120) = 11.364, MSe = 0.22, p < 0.005$ and a comparison of the means showed that participants were most efficient in comprehending the type of outcome (S1, mean = .902) as the glyphs (static-sequence) and the changes to the target (animation) were highly intuitive. Although accuracy rates were quite high, participants had most difficulty in determining the strength of the influence (S2, mean = .825) and magnitude of the outcome (S3, mean = .818). The deterioration

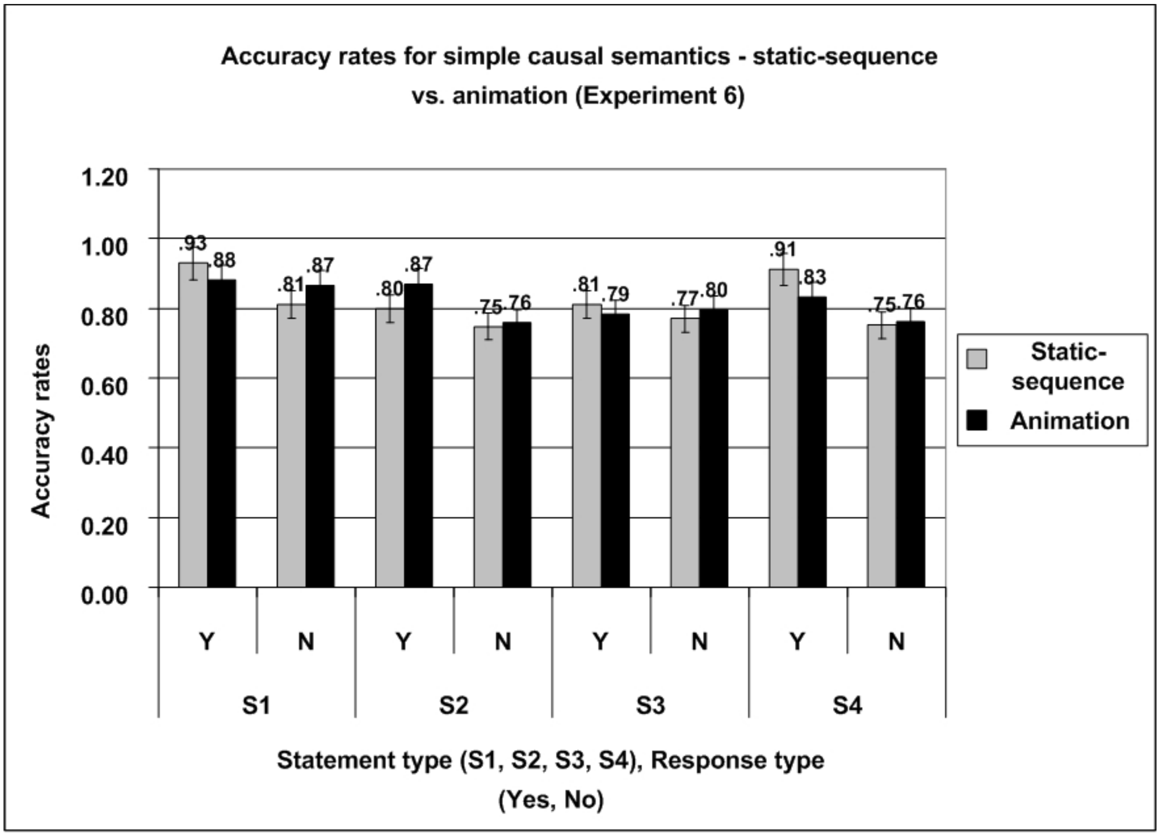

Figure 8.3: Accuracy rates for static-sequence and animated representations of statement types: S1(type of outcome), S2(strength of influence), S3(magnitude of outcome), S4(combination of components) and response types: Y(yes), N(no) ($\pm 5\%$ error bars depict 95% confidence intervals for the means).

in performance can be attributed to the lack of legends for comparison, which would have helped in determining the size of the influences and outcomes (small or large). This issue has been addressed in the remaining experiments.

The analysis also showed a main effect of response type, $F(1,40) = 19.732, MSe = .028, p < 0.001$, which suggest that participants were $\sim$7% more accurate in recognizing correct matches than incorrect matches between visual representation and statement. With respect to recognizing mismatches, participants were most effective with statement type S1 and least effective with statement type S2, mostly due to lack of legends (Figure 8.3). The analysis also showed interaction between semantic and response type, $F(3,120) = 2.926, MSe = .024, p < .05$. Detailed analysis of the 'Yes' responses also showed interaction between representation and statement type, $F(3,120) = 5.033, MSe = .014, p < .005$, and a breakdown comparison of representation types for each semantic type suggests that the static-sequence representation performed with ∼6% higher accuracy rates, $F(1,40) = 7.234, MSe = .008, p < .05$, in comprehending the type of outcome and ∼8% higher accuracy rates, $F(1,40) = 10.730, MSe = .009, p < .005$, in understanding the overall causal statement, than animations. Animations, however, performed with ∼8% higher accuracy rates, $F(1,40) = 6.359, MSe = .012, p < .05$, than static-sequence in comprehending the strength of the factor's influence, which suggests that response times using static-sequence were comparable when the relation matched the given statement attributing it again to the simplicity of the causal information being represented.

As this experiment replicated the design of Experiment 2, the lack of legends again showed to be a major concern here as participants were significantly delayed because they are not able to distinguish between small and large amounts of influences and outcomes. However, this problem has been addressed in the remaining experiments.

Comparison of static-graph (Experiment 1) and static-sequence (Experiment 6) representation of simple causal semantics

In order to compare the efficiencies of the static-graph and static-sequence representations, I also conducted a between-subjects ANOVA on the accuracy rates and response times collected in Experiments 2 (section 6.2) and 6 (current), using Type III sum of squares, due to the vast difference in sample sizes between the factors (static-sequence: $N = 42$, static-graph: $N = 108$). ANOVA analysis on the accuracy rates suggest that there is no significant difference in static-sequence and static-graph representations except in statement type S4 (combination of components) 'Y' responses, where the static-sequence representation performed ∼22%, $F(1, 148) = 31.363, MSe = .026, p < .01$, more accurately than the static-graph representation. Similarly, ANOVA analysis on the response times did not show any significant difference between the two factors, except for statement type S3 (magnitude of outcome) 'N' responses, where participants were ∼13%, $F(1, 148) = 4.587, MSe = 6.791, p < .05$, faster with the static-sequence representation than with the static-graph representation. These results suggest that static-sequence might improve performance in some conditions, however as this difference was not seen in the individual components of the causal relation (i.e. S1, S2, and S3), we can infer that the improvement in performance could be due to the participants' comprehension capability. Therefore this analysis cannot confirm that sequential isolation of the causal relations has significant impact on participant performance and concludes that both the static-graph and static-sequence representations can be used as alternatives while using glyphs to describe the causal information. These results are encouraging as it supports my hypothesis that animations are intuitive and also that the sequential presentation of information in the animated representation does not have an influence on the lower response times of the participants, when compared to the static-sequence or static-graph representations (concurrence with *Hypothesis 3*).

	Experiment 2	**Experiment 6**
Accuracy rate	.843	.843
Response time	5.373 seconds	5.2 seconds

Table 8.3: Comparison of accuracy rates and response times in the animated condition for Experiment 2 and Experiment 6.

Another interesting comparison can be conducted here between the results for the animated representation between Experiments 2 and 6, since the experiment designs were exactly the same (with the exception of the type of static representation) to determine if the intuitiveness of the animated representation was carried across a larger population of subjects. As seen in Table 8.3, the accuracy rates and response times in both experiments are very similar which suggests that the performance of participants with the animated representation was independent of the type of participants and could be replicated over larger populations of subjects. These results are very encouraging and further support my hypothesis that my animations are more intuitive than the corresponding static representations.

Summary of Experiment 6

The following inferences were made from the results of this experiment:

Statement type	**Accuracy rate** ($\downarrow$ = % less accuracy than highest accuracy value for factor(in bold)	**Response time** ($\uparrow$ = % more time than lowest response time value for factor(in bold)
Type of outcome (S1)	.902	4.402
Strength of influence (S2)	$\sim 8\% \downarrow$	$\sim 48\% \uparrow$
Magnitude of outcome (S3)	$\sim 9\% \downarrow$	$\sim 58\% \uparrow$
Combination of components (S4)	$\sim 7\% \downarrow$	$\sim 19\% \uparrow$

Table 8.4: Comparison of accuracy rates and response times for Experiment 6 statement types S1, S2, S3, and S4.

- An analysis of response times showed that participants were significantly ($p < .05$, $\sim$4%) faster with animations than with the static-sequence representation. Participant accuracy rate did not differ significantly ($p > 0.5$) between the static-sequence and animated representation.

- Participant performance depended significantly ($p < .005$) upon the type of semantic that was presented. Participants were most accurate and fastest in comprehending the type of outcome (S1), and were least accurate and slowest in comprehending the magnitude of the outcome (S3). Figure 8.4 compares the accuracy rates and response times for the four statement types.

- Participants were ~7% ($p < .001$) more accurate in recognizing a matched visualization – statement pair, than in recognizing a mismatch. This could be attributed to the ability of the participant to translate the given visualization into a textual statement.

- Results also suggested that participant performance was dependant upon the combination of semantic type – response type presented. Participants performed with higher accuracy rates using static-sequence in statement types S1 and S4, for 'Yes' responses only, and with higher accuracy rates with the animations in statement type S2.

- Comparison of the static-sequence to the static-graph representation did not show significant difference in accuracy rates or response times, except in some in statement types where static-sequence showed higher accuracy rates; ~22% in S4 ('Y' response, Accuracy rate) and ~13% in S3 ('N' response, Response time). However, this significance is not supported by the other conditions and therefore cannot claim the superiority of the static-sequence representation.

The results of this experiment did not satisfy *Hypothesis 1* as no significant difference was seen in accuracy rates between the two representations. However, response time data satisfies *Hypothesis 2* as participants were significantly faster with animations than with the static-sequence representation. Finally, comparison of the static-sequence to the static-graph representation did not show any difference, which conformed with *Hypothesis 3*.

As the results of this experiment suggests that participant performance was not influenced by isolating the relations and presenting them sequentially, it would be interesting to see how the static-sequence representation influences the comprehension of the complex causal semantics, as described in the next set of experiments.

8.2 Experiment 7 - Comparing text, static-sequence, and animated representations of Design-group 1 causal semantics

The main focus of this experiment was to compare text, static-sequence, and animated representations of DG1 group of complex causal semantics, which comprised of additive causality, contradictive causality, and fully-mediated causality. In addition, this experiment replicated the methodology of Experiment 3 (section 7.1) in an effort to compare the efficiency of the static-sequence representations to their static-graph counterparts.

My hypotheses for this experiment were as follows:

- **Hypothesis 1:** Participants will perform the recall tasks with higher accuracy rates and faster response times when the causal relations are enhanced with visualizations, when compared to a textual description of the information.

- **Hypothesis 2:** Participants will perform more accurately and with faster response times when the causal relations are enhanced with animated (vs. static-sequence) visualizations.

- **Hypothesis 3:** Participant performance (accuracy rates and response times) will not be influenced by the sequential animation of the static representation.

8.2.1 Method

Participants

41 undergraduate psychology students of a local university, between the ages of 20 to 30 years, participated in this experiment. As in the previous experiments, none of the students had any formal computer training, had good English language skills, and had normal to corrected vision. Color coding was not used in this experiment as the relations were shown in isolation.

Materials

As in Experiment 3 (section 7.1), the visualizations were embedded as Flash movies in a .NET program and run in a Windows XP environment. The display consisted of a 17" monitor with a 1024 × 768 pixel screen resolution.

Design

This experiment comprised of a 3 × 2 within subject design with two independent variables: Representation Type and Statement Type.

Representation type

Three types of representations were shown to the participants; Text, Static-sequence, and Animation.

- **Text:** The text representation consisted of a list of single-line descriptions of the causal relations.

- **Static-sequence:** The static-sequence representation was similar to the static-graph representation of Experiment 3; the only difference being the sequential animation of the causal relations, in the case of the static-sequence representation. Other features such as the design and function of the nodes, connections, $+$ and $-$ signs, and upright and inverted bars were retained.

- **Animation:** The animated representation consisted of animated nodes, bullets, and targets, describing the causal relations.

Statement type

As in the previous experiments, two types of statements were presented to the participant:

- **Correct:** A correct statement was one where all the components of the given statement matched one of the relations provided during the trial, and would require a "True" response from the participant.

- **Incorrect:** An incorrect statement was one that only partially matched a relation presented during to the trial and would require a "False" response, along with corrections, from the participant.

Tasks

As before, the experiment consisted of three conditions (text-only, text + static-sequence, and text + animated) and the participants were given two tasks to perform: memorization and recall.

- **Memorization task:** This task consisted of two steps. In the first step, the participant was asked to read and memorize the passage for 1½ minutes. In the second step, they were asked to either connect a sequence of dots (text-only condition) or view the static-sequence visualization (text + static-sequence condition) or the animation for the next 1½ minutes (text + animation condition). As the length of the animated visualization was 30 seconds, it was repeated 3 times to fill the 1½ minute timeslot.

- **Recall task:** In this task the participants were asked to answer a set of 6 questions based on the relations they just viewed.

The representation types were fully counterbalanced using a Latin square design. Overall, with 41 participants, 3 visual conditions (text-only, text + static-sequence, text + animation), 3 semantic types per condition (additive, contradictive, fully-mediated), and 2 statement types per semantic (correct, incorrect), a total of 738 responses were collected for analysis.

Procedure

The experiment was conducted in three phases. In the first phase, a *training* session was conducted to describe the causal relations and their representations to the participants, which was followed by a *self-training* phase wherein the participants interacted with a demo version of the experiment until they were comfortable start the third, and final, *experimental* phase. As in the other experiments, experimental conditions were randomly assigned and time constraints were strictly enforced. At the end of each condition, the participants were given 8 minutes to answer the corresponding questionnaire. The experiment captured the number of correct responses that the participant gave in each of the phases along with their response times. Participants were given a maximum score of 1 for each correct answer, a corresponding fraction of the maximum score for each partially correct answer, and a minimum score of 0 for each incorrect answer they provided.

8.2.2 Results and Discussion

Following the procedure described in the Method section and in the non-sequence experiments, two values were recorded for each answer provided by the participant: accuracy and response time. These data were then submitted to a $3 \times 2 \times 3$ repeated-measures Analysis Of Variance (ANOVA) treating semantic type (fully-mediated vs. additive vs. contradictive), statement type (yes vs. no-with-corrections), and representation type (text-only vs. text + static-sequence vs. text + animation) as within-subject factors. Table 8.5 summarizes the overall analysis of the results, along with a summarization of the mean values for the factors showing significance in Table 8.6.

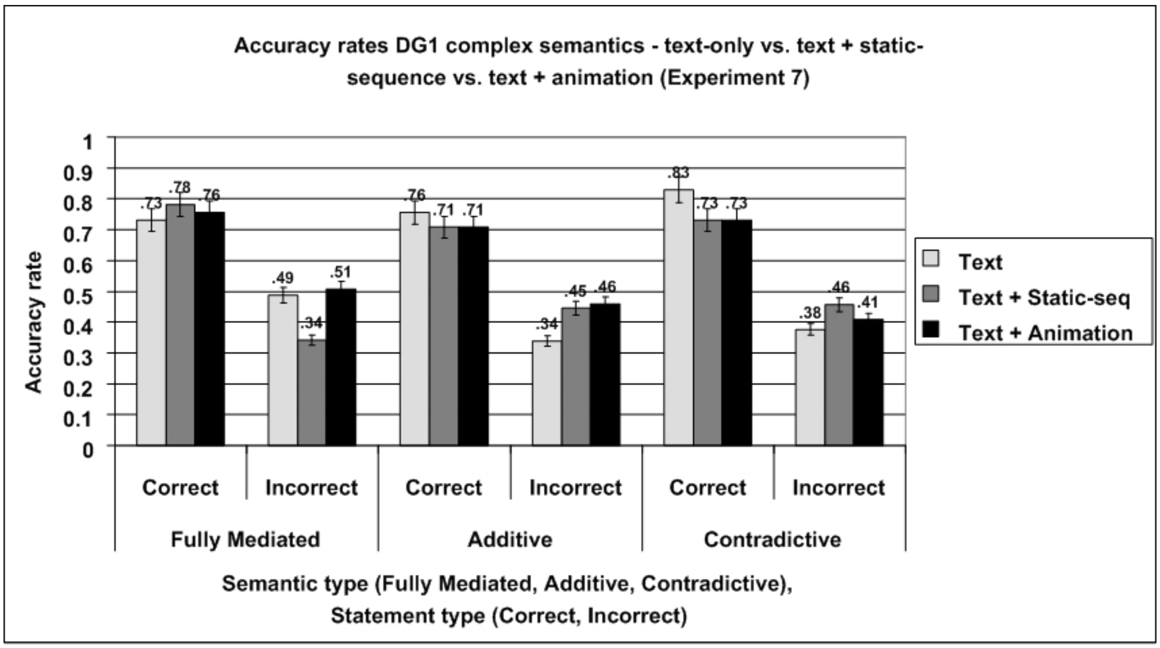

Figure 8.4: Accuracy rates for text-only, text + static-sequence, and text + animated representations of DG1 complex semantics: partially-mediated causality, threshold causality, bidirectional causality and statement types: correct, incorrect (±5% error bars depict 95% confidence intervals for the means).

Factor	**Accuracy rate**	**Response time**
Representation type (F1)	No significance	No significance
Semantic type (F2)	No significance	**Significance**
Response type (F3)	**Significance**	**Significance**
F1 $\times$ F2 interaction	No significance	No significance
F1 $\times$ F3 interaction	No significance	**Significance**
F2 $\times$ F3 interaction	No significance	No significance
F1 $\times$ F2 $\times$ F3 interaction	No significance	**Significance**

Table 8.5: Summary of analysis showing significant results (in bold), for Experiment 7: Complex causal semantics, DG1, Representation type(F1): *Text-only vs. Text+Static-sequence vs. Text+Animation*, Semantic type(F2): *Additive causality vs. Contradictive causality vs. Fully-mediated causality*, Response type(F3): *Correct vs. Incorrect-with-corrections*, Memory Recall Experiment.

Factor		**Accuracy rate** (↓ = % less accuracy than highest accuracy value for factor(in bold)	**Response time** (↑ = % more time than lowest response time value for factor(in bold)
Semantic type (F2)	**Additive causality**	-	11.725 seconds (∼19% ↑)
	Contradictive causality	-	11.062 seconds (∼14% ↑)
	Fully-mediated causality	-	**9.429 seconds**
Response type (F3)	**Correct**	**.748**	**9.198 seconds**
	Incorrect-with-corrections	.425 (∼43% ↓)	12.279 seconds (∼25% ↑)

Table 8.6: Summary of accuracy rates and response times for factors showing significance in the analysis of Experiment 7 results. *NOTE: Highest accuracy rate and lowest response time for each factor are highlighted in bold. The ↓ arrow shows reduction in accuracy rate when compared to the highest accuracy rate for the factor and the ↑ arrow shows increase in response time when compared to the lowest response time for the factor.*

An analysis of the accuracy points showed a main effect of statement type $F(1, 40) = 51.403, MSe = .375, p < 0.001$, which showed that participants were ~43% more accurate in recognizing matches between given statements and displayed relations than in recognizing mismatches. The analysis did not show significance between semantic types ($p > 0.5$), in keeping with the results of Experiment 3. The analysis also did not show a main effect of representation type ($p > 0.5$) (Figure 8.4). This suggests that sequencing of the relations is most likely fitted for animations and not for static representations. The main reason for this preference is that sequencing eliminated a strong of feature of the static representation, the simultaneous presentation of information, which was flexible and did not constrain the participant to follow a preset order while viewing the information.

Response times (seconds) were also recorded for each accurate response provided by the participant and a similar 3 × 2 × 3 repeated-measures ANOVA analysis was conducted on this data. Results of the analysis revealed a main effect of semantic type $F(2, 80) = 6.966, MSe = 49.298, p < 0.005$, which showed that participants were fastest in comprehending fully-mediated causality relations when compared to additive and contradictive causality relations. Specifically participants comprehended fully-mediated relations ~17% faster than contradictive relations and ~24% faster than additive relations (Figure 8.5). Results of the analysis also showed a main effect of statement type $F(1, 40) = 50.042, MSe = 35.008, p < 0.001$, which showed that as in the other experiments, participants were able to accurately recognize a match between the statement and the relations ~33% faster than a mismatch. The analysis did not show a main effect of representation type, from which I can infer that

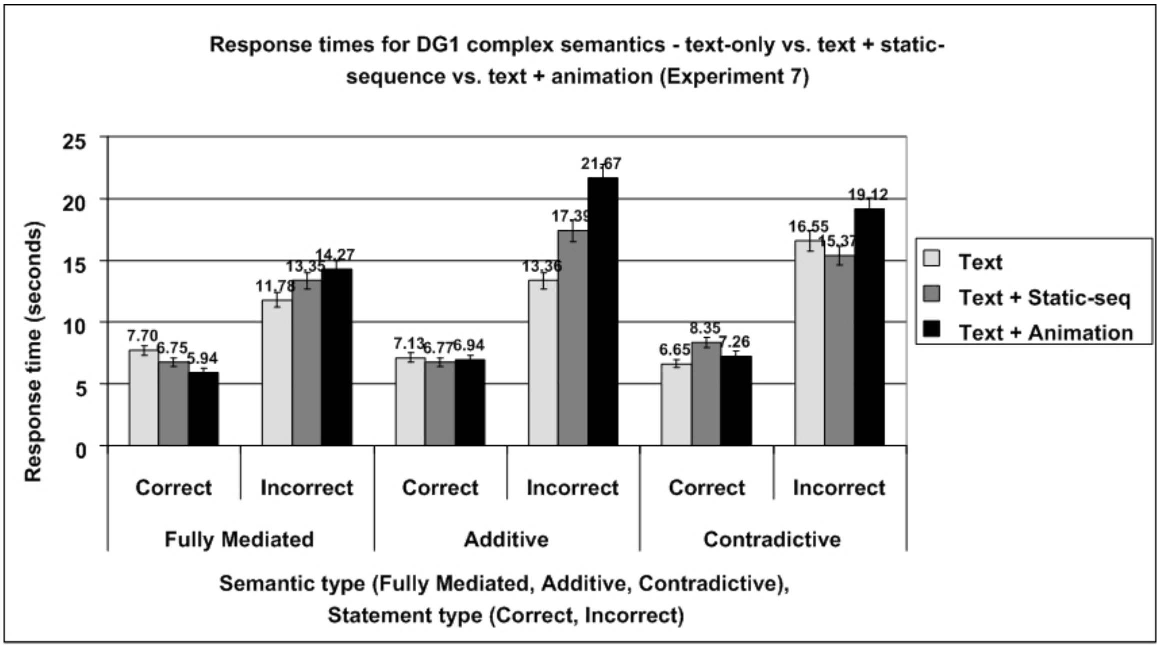

Figure 8.5: Response times for text-only, text + static-sequence, and text + animated representations of DG1 complex semantics: partially-mediated causality, threshold causality, bidirectional causality and statement types: correct, incorrect (±5% error bars depict 95% confidence intervals for the means).

participants were able to comprehend the relations more-or-less equally using the three representation types. Finally, the analysis showed a main effect of interaction between all three dependent variables (semantic type, statement type, and representation type) $F(4, 160) = 2.763, MSe = 62.022, p < 0.05$. Specifically, participants were significantly faster with the text representation than with the static-sequence (∼34%) and the animated (∼70%) representations in representing additive causality statements, $F(2, 80) = 7.861, MSe = 80.181, p < 0.01$, when asked to recognize incorrect matches between the displayed relation and given statement. No significance was seen in the other combinations of the within-subject factors.

Comparison of static-graph (Experiment 3) and static-sequence (Experiment 7) representation of DG1 semantics

An additional analysis of the accuracy and response times was conducted in order to compare the efficiency of the static-sequence representation (data collected from the current experiment) to the static-graph representation (data collected from Experiment 3) of the same set of semantics. As this analysis compared the two versions of the static representation, it did not include data concerning the text or animated representations. Due to differing sample sizes, a between-subjects ANOVA was conducted using Sum of Squares type III analysis. The analysis did not show significant differences in participant performance between the static-graph and static-sequence in any of the combinations of semantic vs. statement, except in the case of contradictive causality, where participants were ~26% faster with the static-sequence representation, $F(1,66) = 5.013, MSe = 54.519, p < .05$, in recognizing incorrect matches between statement and relation. Therefore, this analysis satisfies *Hypothesis 3* and suggests that sequential animation of the relations does not have significant influence on the efficiency of the representation.

Since the experiment designs for Experiments 3 and 7 were identical, with the exception of the static representation, we can compare the accuracy rates and response times for the text-only and text+animated condition between the two experiments to determine if the results can be applied to a larger population (Table 8.7). The accuracy rates for the text-only representation are very similar which suggests that the participants performance was consistent between the two groups. However, the response times for the text-only condition are quite lower in Experiment 7. Since,

		Experiment 3	**Experiment 7**
Accuracy rate	**Text-only**	.562	.587
	Text+animation	.626	.595
Response time	**Text-only**	11.349 seconds	9.850 seconds
	Text+animation	11.779 seconds	11.630 seconds

Table 8.7: Comparison of accuracy rates and response times in the text-only and text+animation conditions for Experiment 3 and Experiment 7.

the design of the experiments were identical, I can only infer from this difference in response times that the participants were either recalling the information faster or they were overwhelmed with the amount of information shown to them and guessed the answers. However, the accuracy rates and response times for the text+animated condition were very similar, which suggests that the performance was consistent over the different groups.

Summary of Experiment 7

The following inferences can be made from this experiment:

- The analysis showed that participants were ∼43% more accurate and responded ∼33% faster when asked to recognize a correct match, than an incorrect one, between a given causal relation and statement.
- The analysis did not show a main effect of representation type, which can be attributed to the complexity of the information, the number of causal relations that had to be memorized, and need to convert visual information into text

before matching it to the given statement (which was not required in the text-only condition).

- Participants responded fastest to fully-mediated causality relations, which shows that this relation is the simplest of the three, as the participant was required only to focus on the factor and the target while ignoring the inactive mediator.

- Comparison of the static-sequence results from this experiment to the static-graph results from Experiment 3 did no show significant change in participant accuracy rates and response times. The results suggest that sequential presentation of information did not improve the static representation, and also does not bias the performance of the animated representation.

The overall analysis of the data collected in this experiment did not concur with *Hypothesis 1* or *Hypothesis 2* as no significant improvement was seen in accuracy rates or response times with the textual representation was enhanced using my visualizations, which could be attributed to the complexity and amount of information presented during the experiments. Finally, comparison of performances in Experiment 4 and 7 did not show any improvement in accuracy rates or response times when the static-graph was enhanced by sequential animation of the relations, which shows concurrence with *Hypothesis 3*.

The next step is to check whether the static-sequence representation shows higher accuracy rates or lower response times while visualizing DG2 group of semantics (Experiment 8), and finally to directly compare the static-sequence to the animated representation, without the aid of a textual representation (Experiment 9).

8.3 Experiment 8 - Comparing text, static-sequence, and animated representations of Design-Group 2 causal semantics

As in the previous static-sequence experiments, the main aim of this experiment was to compare the improvement in performance when textual representations of causal information are enhanced by static-sequence and animated representations. The experiment mainly focussed on DG2 group of complex semantics comprising of partially-mediated causality, threshold causality, and bidirectional causality. The second aim of this experiment was to compare the static-sequence representation to the static-graph representation of Experiment 4 (section 7.2). Therefore, for purposes of analysis the animation was divided into two major components; *smooth animation of the graph* and *sequential animation of the causal relations*.

My hypotheses for this experiment were as follows:

- **Hypothesis 1:** Participants will perform the recall tasks with higher accuracy rates and faster response times when the causal relations are enhanced with visualizations, when compared to a textual description of the information.

- **Hypothesis 2:** Participants will perform more accurately and with faster response times when the causal relations are enhanced with animated (vs. static-sequence) visualizations.

- **Hypothesis 3:** Participant performance (accuracy rates and response times) will not improve with *sequential animation of the causal relations* in the static-sequence representation.

8.3.1 Method

Participants

18 undergraduate psychology students of a local university, between 20 to 30 years of age, with no formal computer training, good English language skills, and normal to corrected vision participated in this experiment.

Materials

The visualizations were embedded as Flash movies in a .NET program and run in a Windows XP environment. The display consisted of a 17" monitor with a 1024 $\times$ 768 pixel screen resolution.

Design

This experiment consisted of a 3 $\times$ 2 within-subject design, with two independent variables: Representation Type and Statement Type.

- **Representation type:** Three types of representations were shown to the participants; text (passage with relations described in English), static-sequence (sequential animation of a static representation), and animation (smooth animation of nodes and sequential animation of relations).
- **Statement type:** Two types of statements were shown to the participant at the end of each trial; Correct (all components of the given statement matched one of

the previously viewed causal relations) and Incorrect (some of the components of the given statement matched one of the previously viewed causal relations). Participants responded True (statement was Correct) or False-with-corrections (statement was Incorrect).

Tasks

As before, the experiment consisted of three conditions (text-only, text + static-sequence, and text + animated) and the participants were given two tasks to perform: Memorization and Recall per condition.

- **Memorization task:** In this task the participants were asked to read a passage for 1½ minutes and view a visualization (or perform filler tasks such as connect-the-dots in the text-only condition) for the next 1½ minutes.
- **Recall task:** In the recall task, the participants were asked to answer questions based on the relations they just viewed, within an 8 minute timeframe.

The trials were fully counterbalanced using a Latin square design. Overall, with 18 participants, 3 visual conditions (text-only, text + static-sequence, text + animation), 3 semantic types per condition (partially-mediated, threshold, bidirectional), and 2 statement types per semantic (correct, incorrect), a total of 324 responses were collected for analysis.

Procedure

The experiment was conducted in three phases; training, self-training, and experiment. In the *training* phase the participants were given brief descriptions of the

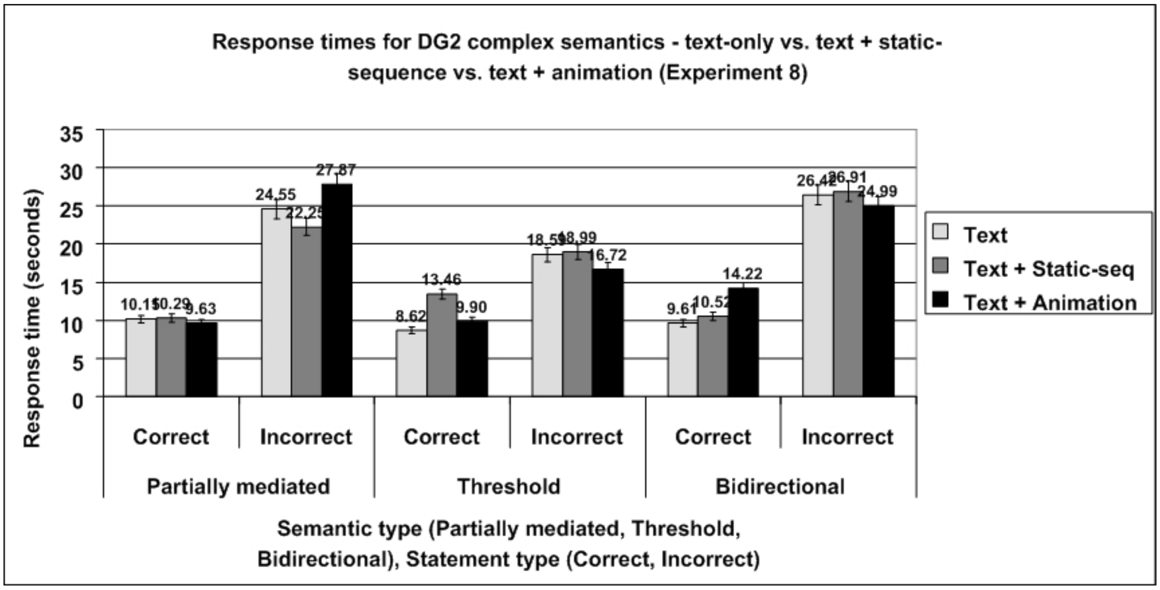

Figure 8.6: Response times text-only, text + static-sequence, and text + animated representations of DG2 complex semantics: partially-mediated causality, threshold causality, bidirectional causality, and response types: correct, incorrect (±5% error bars depict 95% confidence intervals for the means).

semantics, representations, and experimental layout. In the *self-training* phase the participants were asked to practice on a sample version of the experiment, until they felt comfortable with its tasks. The *experiment* phase captured participant responses and response times. Scoring was the same as in the other experiments with a score of 1 for a correct answer, a score of 0 for an incorrect answer, and a fractional score for partially correct answers.

8.3.2 Results and Discussion

Following the procedure described in the methods section, two values were recorded for every response provided by the participant; accuracy and response time. The collected data were then submitted to a 3 × 2 × 3 repeated measures Analysis Of Variance (ANOVA) treating semantic type (partially-mediated vs. threshold vs. bidirectional), statement type (correct vs. incorrect), and representation type (text vs. text + static-sequence vs. text + animation) as within-subject factors. Table 8.8 summarizes the overall analysis of the results, along with a summarization of the mean values for the factors showing significance in Table 8.9.

Factor	**Accuracy rate**	**Response time**
Representation type (F1)	No significance	No significance
Semantic type (F2)	No significance	**Significance**
Response type (F3)	No significance	**Significance**
F1 × F2 interaction	No significance	**Significance**
F1 × F3 interaction	No significance	No significance
F2 × F3 interaction	No significance	No significance
F1 × F2 × F3 interaction	No significance	No significance

Table 8.8: Summary of analysis showing significant results (in bold), for Experiment 8: Complex causal semantics, DG2, Representation type(F1): *Text-only vs. Text+Static-sequence vs. Text+Animation*, Semantic type(F2): *Partially-mediated causality vs. Threshold causality vs. Bidirectional causality*, Response type(F3): *Correct vs. Incorrect-with-corrections*, Memory Recall Experiment.

An analysis of the response times showed a main effect of semantic type, $F(2,34) =$

Factor		**Accuracy rate** (↓ = % less accuracy than highest accuracy value for factor(in bold)	**Response time** (↑ = % more time than lowest response time value for factor(in bold)
Semantic type (F2)	**Partially-mediated causality**	-	17.267 seconds (∼8% ↑)
	Threshold causality	-	**15.815 seconds**
	Bidirectional causality	-	18.970 seconds (∼16% ↑)
Response type (F3)	**Correct**	-	**13.683 seconds**
	Incorrect-with-corrections	-	21.018 seconds (∼35% ↑)

Table 8.9: Summary of accuracy rates and response times for factors showing significance in the analysis of Experiment 8 results. *NOTE: Highest accuracy rate and lowest response time for each factor are highlighted in bold. The ↓ arrow shows reduction in accuracy rate when compared to the highest accuracy rate for the factor and the ↑ arrow shows increase in response time when compared to the lowest response time for the factor.*

$5.258, MSe = 51.214, p < 0.5$. Specifically, participants responded fastest to questions about threshold causality (mean = 15.82 seconds), were ~9% slower in responding to questions about partially-mediated causality and ~20% slower in responding to questions on bidirectional causality (Figure 8.6), which is expected since threshold causality contains the least amount of causal information when compared to the other two semantics. The analysis also showed a main effect of statement type $F(1, 17) = 47.416, MSe = 91.892, p < 0.005$, which suggests that participants were ~35% faster in recognizing correct matches, than in recognizing mismatches, between the displayed relations and given statements, which again is expected as the participants found it more difficult to recall and provide the correct causal information, compared to identifying matches between given relations and statements. The analysis also showed a main effect of interaction between semantic and statement type $F(2, 34) = 5.619, MSe = 53.167, p < 0.05$, which suggests that participants' response time was dependent upon the combination of semantic and statement type that was presented to them. Further analysis of this interaction reveals that a main effect of semantic type was seen for the 'Incorrect' statements, $F(2, 34) = 13.461, MSe = 38.793, p < .001$, which suggests that the significant influence of semantic, as suggested in the main analysis, was seen mostly when the participants were asked to recognize mismatches between statement and relation.

An analysis of the accuracy points did not show a main effect of semantic ($p > 0.5$) or statement type ($p > 0.5$), which shows that all three semantics were similarly comprehended and that there was little difference in recognizing matched or mismatched statements. The analysis also did not show a main effect of representation type

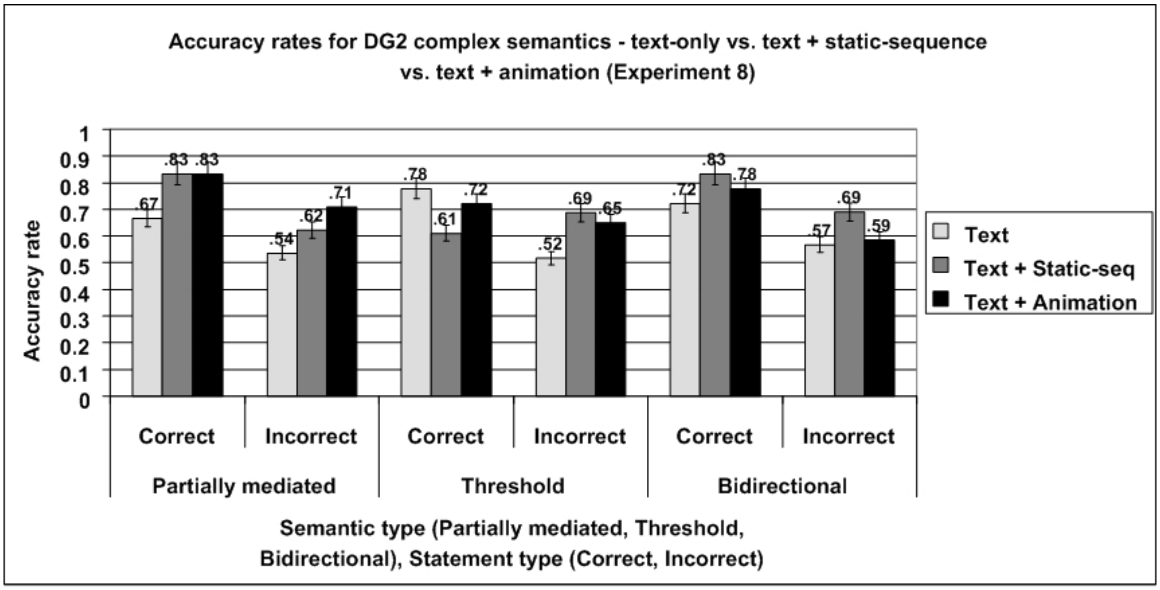

Figure 8.7: Accuracy rates text-only, text + static-sequence, and text + animated representations of DG2 complex semantics: partially-mediated causality, threshold causality, bidirectional causality, and response types: correct, incorrect (±5% error bars depict 95% confidence intervals for the means).

($p > 0.5$), which suggests that there was negligible difference in comprehension when the semantics were presented using static-sequence graphs or animations. This could be attributed to the complexity of the causal semantic being represented and the difficulty in comprehending the information provided to the participants (Figure 8.7).

Comparison of static-graph (Experiment 4) and static-sequence (Experiment 8) representation of DG2 semantics

The final step of this analysis focused on comparing the data collected from the static-graph representation to the data collected from the static-sequence representation of partially-mediated, threshold, and bidirectional causalities. Due to difference in sample sizes and participants, a between-subjects ANOVA was conducted using Sum of Squares type III analysis. The analysis did not show significant difference between the two versions of the static representation for partially-mediated or bidirectional causalities. However, response times for threshold causality suggested that participants were significantly faster with the traditional static-graph representation rather than the enhanced static-sequence representation. Specifically, participants were ~30% faster, $F(1, 56) = 4.315, MSe = 63.664, p < .05$, in recognizing 'Correct' statements, and ~33% faster, $F(1, 56) = 7.846, MSe = 64.666, p < .01$, in recognizing 'Incorrect' statements, with the static-graph visualization. This analysis suggests that sequential animation of the relation does not help, and sometimes deters, information acquisition using the static representation.

Due to the similar design of Experiment 4 and 8, I compared the accuracy rates and response times for the text-only and text+animated conditions to determine if the results can be expanded over a larger population of subjects. However, the comparisons(Table 8.10) showed differences between the accuracy rates and response times for the two conditions. Comparing the accuracy rates for text-only with static in Experiment 4 (difference = .08) and for Experiment 8 (difference = .08) we see very similar differences between the two representations, suggesting the difference in accuracy rates for this condition between the experiments was due to the capacity of the participants to memorize more of the information in Experiment 8. Similarly the differences between the accuracy rates for text+static and text+animation conditions for Experiment 4 (difference = .006) and Experiment 8 (difference = 0) and the differences between response times for Experiment 4 (difference = .267 sec-

		Experiment 4	**Experiment 8**
Accuracy rate	**Text+static**	.643	.713
	Text-only	.563 (difference = .08)	.631 (difference = .082)
	Text+animation	.637 (difference = .006)	.713 (difference = 0)
Response time	**Text+static**	14.053 seconds	17.609 seconds
	Text-only	14.811 seconds (difference = .758 seconds)	16.592 seconds (difference = 1.017 seconds)
	Text+animation	14.320 seconds (difference = .267 seconds)	17.851 seconds (difference = .242 seconds)

Table 8.10: Comparison of accuracy rates and response times in the text-only and text+animated conditions for Experiment 4 and Experiment 8. *NOTE: "difference" denotes the difference in value between the representation type and the static representation that was tested in each experiment.*

onds) and Experiment 8 (difference = .242 seconds) are very similar. Overall, this suggests that the performance for the text-only and text+animated conditions were similarly different from the static-sequence representation, but different between the two experiments, which can be attributed to the memory and recall capabilities of the participants between the two experimental groups.

Summary of Experiment 8

The following inferences can be made based on the results of this experiment:

- Analysis of response times showed main effect of statement type and suggested that participants were ∼35% faster in recognizing matches, than mismatches, between statement and relation pairs.

- Analysis of the response times also showed a main effect of semantic type and main interaction between semantic and statement type, which suggests that participant responses were significantly different for the 'Incorrect' responses. Specifically, participants were fastest in providing responses regarding threshold causality (mean = 15.82 seconds), ∼9% slower responding to partially-mediated causality, and ∼20% slower with bidirectional causality statements. These response times suggest the general order of complexity of these three semantics.

- Analysis of the accuracy rates did not show a main effect of representation type ($p > .05$), which suggests that participants were able to comprehend the information with similar accuracy with all three representation types.

- Comparison of static-graph and static-sequence results from experiments 4 and 8 respectively did not show major significance in the results for partially-mediated and bidirectional causality. However, the results suggested that response times for threshold causality drastically increased, when the causal relations were presented sequentially (static-sequence).

The results of this experiment did not concur with *Hypothesis 1* as no significance was seen in the accuracy rates between the representation types. The results also do not satisfy *Hypothesis 2* as no significant difference was seen between the performances of the static-sequence and the animated representations. Finally, a comparison of static-sequence to the static-graph representation suggests concurrence with *Hypothesis 3*, as either an insignificant change or a decline in performance was seen when the relations were sequentially presented.

Therefore, this study infers that information using the static representation is best represented simultaneously and also determines that sequential presentation of information does not create an unfair bias in the animated representation. However, in order to round off the analysis and generate a strong support for the animated representation, a final experiment was conducted that repeated the procedure of Experiment 5, but replaced the static-graph representation with the static-sequence and compared it to the animated representation, in order to test their efficiency as stand-alone modes of presenting causal information.

8.4 Experiment 9 - Comparing static-sequence and animated representations of complex causal semantics

As in the other static-sequence experiments, the main aim of this experiment was to determine whether the improvement in performance in Experiment 5 (section 7.3) was due to the smooth animation of the causal relations or due to sequential animation of the causal relations.

My hypotheses for this experiment were as follows:

- **Hypothesis 1:** Participants will perform the recall tasks more accurately when the causal relations are described using animations, when compared to a textual description of the information.

- **Hypothesis 2:** Participants will be able to respond faster when the causal relations are depicted as animations.

- **Hypothesis 3:** Participant performance will not be influenced by the sequential animation of the causal relation in the static-graph representation.

8.4.1 Method

Participants

35 undergraduate psychology students of a local university participated in this experiment. The participants satisfied the same selection criteria as in the previous experiments (age, normal to corrected vision, no prior experience with causal graphs). Color blindness tests were deemed unnecessary as color coding was not used in the static-sequence representation.

Materials

The experiment was executed as a .NET program with embedded static and animated Macromedia Flash™ files. Individual copies of the program were executed on a Windows XP computer and displayed on a 17" Dell monitor with a 1024 × 768 pixel screen resolution.

Design

As in Experiment 5, the experiment comprised of a 2×6 within subject design. The two independent variables were: Representation Type and Statement Type.

Representation type

Two types of representations were shown to the participants: Static-sequence and Animation.

- **Static-sequence:** In this representation type, the participants were shown a static graph with 1 – 2 causal relations. In the case where 2 causal relations were shown, the casual relations were shown one after the other in sequence. All other features such as $+$ and $-$ glyphs to depict influences, and upright and inverted bars to depict effects remained the same as in the static-graph representation.

- **Animation:** As in the animated representations of the previous experiments, the causal relations were visualized using animated factors, bullets, and targets.

Statement type

At the completion of each trial, the participants were shown a statement based on the relation(s) they viewed. As in Experiment 5, each statement represented one of the 6 complex causal semantics being tested; additive causality (S1), contradictive causality (S2), fully-mediated causality (S3), partially-mediated causality (S4), threshold causality (S5), and bidirectional causality (S6).

Tasks

The experiment consisted of two tasks:

- **Memorization:** In this task the participant was shown either a static or an animated causal relation for 9 seconds (one relation) or 18 seconds (two relations). The participant was asked to view the visualization and memorize the causal relation(s) being depicted.

- **Recall:** In this task the participant was asked to match a given statement to the relation(s) viewed in the memorization task. Participant was required to respond "Yes" ('B' key on the keyboard) for an exact match and "No" ('N' key on the keyboard) for a mismatch between statement and relation, in order to score 1 point. Incorrect answers were given a score of 0.

The trials were fully counterbalanced using a Latin square design. Each trial was based on a random selection of 1 of 12 topics, with one statement per trial. The experiment consisted of 120 trials in total, divided into 5 sessions. Overall, with 35 participants, 5 sessions, 2 representation types (static-sequence, animations) per session, 6 statement types per representation (additive, contradictive, fully-mediated, partially-mediated, threshold, bidirectional), and 2 response types (yes, no) per statement type, a total of 4200 responses were collected for analysis.

Procedure

The experiment was divided into two phases. In the *self-training* phase, the participant was asked to run a sample version of the program until they were comfortable

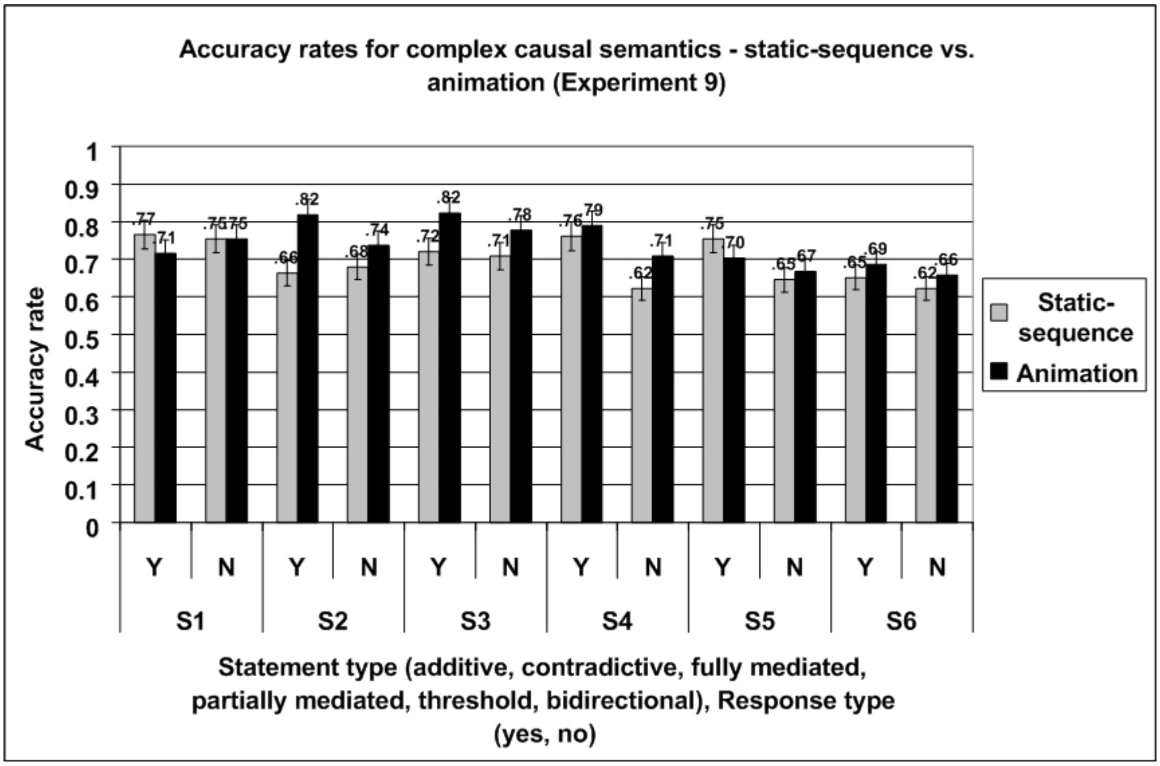

Figure 8.8: Accuracy rates for static-sequence and animated representations of statement types: S1 (additive causality), S2 (contradictive causality), S3 (fully-mediated causality), S4 (partially-mediated causality), S5 (threshold causality), S6 (bidirectional causality), and response types: Y (yes), N (no) (±5% error bars depict 95% confidence intervals for the means).

with the experimental tasks. In the *experiment* phase, the trials in the experiment were divided into 5 sessions, with 24 trials per session. At the end of each session, the timers were paused and the participant was allowed to take a break if required.

8.4.2 Results and Discussion

Following the procedure described in the Method section and in the static-graph experiments, two values were recorded for each answer provided by the participant: accuracy rate and response time. These data where then submitted to a 2 × 6 × 2 repeated-measures Analysis of Variance (ANOVA) treating representation type (static-sequence vs. animation), statement type (additive vs. contradictive vs. fully-mediated vs. partially-mediated vs. threshold vs. bidirectional), and response type (yes vs. no) as within-subject factors. Table 8.11 summarizes the overall analysis of the results, along with a summarization of the mean values for the factors showing significance in Table 8.12.

Factor		**Accuracy rate** (↓ = % less accuracy than highest accuracy value for factor(in bold)	**Response time** (↑ = % more time than lowest response time value for factor(in bold)
Representation type (F1)	**Static-graph**	.696 (∼5% ↓)	8.029 seconds (∼6% ↑)
	Animation	**.736**	**7.527 seconds**
Semantic type (F2)	**Additive causality (Q1)**	.747 (∼1% ↓)	**6.763 seconds**
	Contradictive causality (Q2)	.724 (∼4% ↓)	7.666 seconds (∼12% ↑)

	Fully-mediated causality (Q3)	**.757**	6.876 (∼2% ↑)
	Partially-mediated causality (Q4)	.720 (∼5% ↓)	8.796 seconds (∼22% ↑)
	Threshold causality (Q5)	.693 (∼8% ↓)	8.407 seconds (∼20% ↑)
	Bidirectional causality (Q6)	.654 (∼13% ↓)	8.160 seconds (∼17% ↑)

Table 8.12: Summary of accuracy rates and response times for factors showing significance in the analysis of Experiment 9 results. *NOTE: Highest accuracy rate and lowest response time for each factor are highlighted in bold. The ↓ arrow shows reduction in accuracy rate when compared to the highest accuracy rate for the factor and the ↑ arrow shows increase in response time when compared to the lowest response time for the factor.*

An analysis of the accuracy rates showed a main effect of representation type $F(1, 34) = 20.730, MSe = .017, p < 0.001$. Specifically, participants were ∼6% more accurate when the casual relations were visualized using animations. The analysis also showed a main effect of statement type, $F(5, 170) = 4.069, MSe = .049, p < .01$, which suggests that participants were most accurate in comprehending fully-mediated causality and least accurate with bidirectional causality (Figure 8.8), similar to Experiment 5. However, the analysis also showed significant interaction between the

Factor	**Accuracy rate**	**Response time**
Representation type (F1)	**Significance**	**Significance**
Semantic type (F2)	**Significance**	**Significance**
Response type (F3)	No significance	No significance
F1 × F2 interaction	**Significance**	**Significance**
F1 × F3 interaction	No significance	No significance
F2 × F3 interaction	No significance	**Significance**
F1 × F2 × F3 interaction	No significance	No significance

Table 8.11: Summary of analysis showing significant results (in bold), for Experiment 9: Complex causal semantics, DG1 & DG2, Representation type(F1): *Static-sequence vs. Animation*, Semantic type(F2): *Additive causality vs. Contradictive causality vs. Fully-mediated causality vs. Partially-mediated causality vs. Threshold causality vs. Bidirectional causality*, Response type(F3): *Yes vs. No*, Intuitiveness Evaluation Experiment.

representation type and the type of statement that was presented to the participant $F(5, 170) = 2.866, MSe = .034, p < 0.05$. Analysis of this interaction suggests that, with animations, participants performed with ∼16% higher accuracy rates, $F(1, 34) = 11.093, MSe = .035, p < .01$, in comprehending contradictive causality (S2) statements, with ∼12% higher accuracy rates, $F(1, 34) = 7.391, MSe = .035, p < .05$, in comprehending fully-mediated causality (S3) statements, and with ∼8% higher

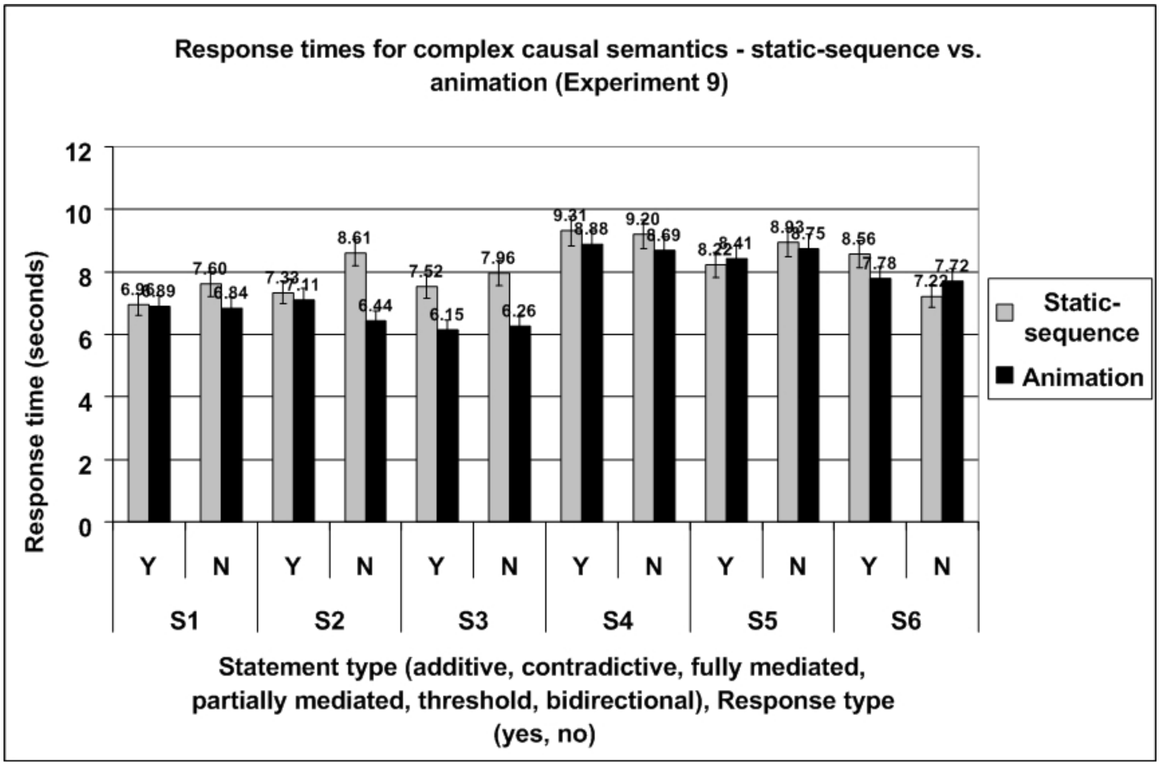

Figure 8.9: Accuracy rates for static-sequence and animated representations of statement types: S1(additive causality), S2(contradictive causality), S3(fully-mediated causality), S4(partially-mediated causality), S5(threshold causality), S6(bidirectional causality), and response types: Y(yes), N(no) ($\pm5\%$ error bars depict 95% confidence intervals for the means).

accuracy rates, $F(1,34) = 8.718, MSe = .013, p < .01$, in comprehending partially-mediated causality statements. Finally, the analysis also showed a significance in response type, $F(1,34) = 8.413, MSe = .049, p < .01$, for partially-mediated causality ($\sim$16% more accurate with response type 'Y'), which suggests that, for most statement types, participants were able to recognize matches and mismatches between given statement and displayed causal relation, with comparable effectiveness.

An ANOVA analysis of the response times also suggests similar effects. The results showed a main effect of representation type $F(1, 34) = 11.288, MSe = 4.701, p < 0.001$ and a comparison of the means showed that participants responded ∼7% faster when the causal relations where represented using animations (Figure 8.9). The analysis also showed a main effect of statement type $F(5, 170) = 17.659, MSe = 5.443, p < 0.001$, which suggests that participant response times were dependent upon the type of statement that was presented. A comparison of the means shows that participants took the least amount of time to match additive causality statements and the most amount of time to match partially-mediated causality statements. The analysis also showed significant interaction between the type of representation and statement $F(5, 170) = 2.313, MSe = 3.826, p < 0.05$. Analysis of this interaction suggests that, with animations, participants were ∼15% faster, $F(1, 34) = 16.759, MSe = 3.742, p < .001$, in responding to contradictive causality statements (S2), and ∼13% faster, $F(1, 34) = 7.224, MSe = 4.579, p < .05$, in responding to fully-mediated causality statements. Finally, the analysis also showed significant interaction between statement and response types, $F(5, 170) = 2.292, MSe = 3.139, p < .05$. Analysis of this interaction suggests that, with the 'Y' response type, participants were ∼5% faster, $F(5, 170) = 11.529, MSe = 4.230, p < .001$, with animations than the static-sequence representation. Analysis of the 'N' response types showed that, with animations, participants responded ∼21% faster, $F(1, 34) = 14.750, MSe = 3.998, p < .01$, to contradictive causality statements and ∼11% faster, $F(1, 34) = 4.637, MSe = 2.412, p < .05$, to fully-mediated causality statements, compared to their static-sequence counterparts. These results suggest that animations generally performed with faster response times than the static-sequence representation and this difference was more prominent with contradictive and fully-mediated causality statements.

Comparison of static-graph (Experiment 6) and static-sequence (Experiment 9) representation of the complex causal semantics

The last step of this analysis focused on comparing the data collected from the static-graph representation to the data collected from the static-sequence representation of complex causal semantics. The experiment design of Experiment 9 was similar to Experiment 5, however due to difference in sample sizes and participants, a between-subjects ANOVA was conducted using Sum of Squares type III analysis. The analysis did not show significant difference between the two representation types for any of the semantics (all $p's > .05$), which suggests that participant performance was not influenced by the simultaneously or sequential representation of the causal relations. Thereby, the analysis also infers that participant performance was not enhanced or biased in favor of the sequential presentation of the information in the animated representation.

Comparing the accuracy rates and response times for the animated conditions in experiments 5 and 9 suggests that there are difference between the values for the two experiments(Table 8.13). However, on comparing the difference between the accuracy rates for the animation and static representation in Experiment 5 (difference = .042), it is very similar to the difference in accuracy rate between the animation and static representation in Experiment 9 (difference = .04). Similarly, the difference

		Experiment 5	**Experiment 9**
Accuracy rate	**Static**	.753	.696
	Animation	.795 (difference = .042)	.736 (difference = .04)
Response time	**Static**	8.115 seconds	8.029 seconds
	Animation	7.441 seconds (difference = 0.674 seconds)	7.527 seconds (difference = 0.502seconds)

Table 8.13: Comparison of accuracy rates and response times in animation conditions for Experiment 5 and Experiment 9. *NOTE: "difference" denotes the difference in value between the representation type and the static representation that was tested in each experiment.*

between the response times of animation and static are very similar for both Experiment 5 (difference = .674 seconds) and Experiment 9 (difference = .502 seconds). These difference suggest that the animations results are similar but on a slightly different scale, which could be attributed to the memory and recall capability of the participants within each experimental group.

Summary of Experiment 9

The following inferences were made from this experiment:

- The results of the experiment showed that participants were ~6% more accurate and responded ~7% faster when the complex causal semantics were visualized using animations.

- The results also showed a significant interaction between representation type and statement type, which suggests that participant responses were affected by the type of causal semantic and the type of representation presented to them. Specifically, participants were ~16% more accurate and ~15% faster with contradictive causal statements, ~12% more accurate and ~13% faster with fully-mediated causal statements, and ~8% more accurate with partially-mediated causal statements, with animations rather than the static-sequence representation.

- The results did not show a main effect of response type which suggests that participants were able to recognize matches and mismatches between the given relation and statement with similar efficiency.

- Analysis of the response times showed that participants provided ~5% faster 'Yes' responses while viewing animated, rather than static-sequence, information. Animations also fared with faster response times, than their static-sequence counterparts, when providing 'No' responses for contradictive (~21% faster) and fully-mediated (~11% faster) causal statements.

- Comparison of the static-sequence representation to corresponding static-graph representations did not show any significant change in accuracy rates or response times, which suggests that sequential presentation of information is not a major factor in the superior performance of the animated representation.

The results of this experiment show that participants performed with higher accuracy rates and faster response times with animations, which concurs with both *Hypotheses 1 & 2*. Analysis of the accuracy and response times of static-graph (Experiment 5) and static-sequence representations show that participant performance was not enhanced when the causal information was presented in sequence. The results therefore also fully concur with *Hypothesis 3* and conclude that the sequential animation does not bias participant performance in the animated representation.

Experiments 1 through 9 describe the various studies and analysis that have been conducted to evaluate causal semantics and their visual representations. The overall consensus of these analysis along with a summary of the experiments has been described in the next chapter.

Chapter 9

Experimental Studies Summary

9.1 Design Summary

My main premise in this study is that animations intuitively describe causal semantics. However, research states that animations should be used with care as they can quickly get out of control and overwhelm the user [Tversky et al., 2000]. Therefore, it is also important to test if the causal information can be adequately displayed using equivalent static images and whether animations improve the comprehension of the relations, over their corresponding static versions. Four representation types were therefore tested during the course of my study:

- **Text-only representation:** The text-only representation is used as the control condition in the Memory Recall experiments to analyze the improvement in comprehension when the causal semantics are visualized using the static and animated representations.

- **Static representation:** The static representation visualizes the causal semantics using nodes (to depict the factor and targets), connecting lines (to depict the relation between factor and target), and glyphs (to depict the influences and effects). The static representation is divided into two categories depending on the method of displaying the relations:

  - **Static-graph:** In the static-graph representation, the entire set of causal relations is shown simultaneously, so that the participants can view the information in their orders of preference. Colors are used abundantly in order to differentiate between relations.

  - **Static-sequence:** In the static-sequence representation, the causal relations are isolated and shown in sequence. Order is pre-determined and colors are not employed.

- **Animated representation:** In this representation, factors and targets are depicted as nodes, the relation between them is depicted by a connecting line, influences are depicted by animated bullets that move from the factor(s) to the target, and final effects are depicted by change in target size. Relations are shown one at a time and follow a storyboard pattern.

In my research, I hypothesized four main outcomes, one or more of which were assumed in each of the experiments:

- **Hypothesis 1 (H1):** Participants will perform the recall tasks with higher accuracy rates and faster response times when the causal relations are enhanced with visualizations, when compared to a textual description of the information (i.e. text vs. static/animation).

- **Hypothesis 2 (H2):** Participants will perform the recall tasks with higher accuracy rates when the causal relations are enhanced with animations.
- **Hypothesis 3 (H3):** Participants will perform the recall tasks with faster response times when the causal relations are enhanced with animations.
- **Hypothesis 4 (H4):** Participant performance (accuracy rates and response times) will not improve with the sequential presentation of the causal relations in the static representation (static-graph vs. static-sequence).

Finally, two experiment designs were created to test the effectiveness of the visual representations:

- **Memory Recall:** This experiment compared the visual representations to a control condition, namely a text-only description of the causal relations. The experiment tested 3 conditions; text-only, text + static (static-graph or static-sequence), and text + animation. In the text-only condition, the participants were initially shown a set of causal relations described using English statements for half the time, and then were asked to fill the rest of the time performing non-essential tasks such as connect-the-dots. In the text + static condition, the participants first viewed a textual description of the relations and then viewed a static (static-graph or static-sequence) representation of the same relations for the rest of the time. Similarly, in the text + animation condition, the participant viewed the textual description followed by the animated representation. The experiment consisted of 3 conditions with a questionnaire proceeding each condition. In each questionnaire session the participant was asked to recall and recognize matches ('Correct' response) or mismatches ('Incorrect' response with corrections) between the given statements and the set of memorized relations. Participants could take breaks between conditions and the experiment concluded after all three conditions were completed. Experiments 1, 3, 4, 7, and 8 were based on this design.

- **Intuitiveness:** This experiment compared only the static (static-graph or static-sequence) and animations, without the aid of the textual descriptions. The experiment was divided into 5 – 6 sessions with 16 – 24 visualization-statement pairs per session. Each pair consisted of 1 – 2 static or animated representations and one statement corresponding to the visualization. Participants viewed the visualization for a given period of time and then responded to the statement. Participants were limited to only 'Yes' ('B' key) and 'No' ('N' key) responses, for a match or a mismatch respectively. Participants were allowed to take breaks at the end of each session and the experiment ended after all the sessions were completed. Experiment 2, 5, 6, and 9 were based on this design.

My entire research is divided into four main components, and chapters 6, 7, 8, and 9 describe the experiments conducted in analyzing simple visualizations of causal information, which form components II, III, and IV of my research:

- **Component I:** focuses on recognizing the causal semantics inherent in the world around us, and has been detailed in Chapter 5.

- **Component II:** compares the efficiency of static-graph and animated visualizations in representing simple causal semantics.

- **Component III:** compares the efficiency of static-graph and animated visualizations in representing complex causal semantics.

- **Component IV:** repeats the experiments of Components II and III by comparing the animations to the enhanced version, static-sequence, of the static representation.

The following are summaries of the three components of experimental analysis in my research:

9.1.1 Component II

The main focus of this component was to compare the efficiency of the static-graph and animated representations in depicting the simple causal semantics. Two experiments were conducted here:

- **Experiment 1:** This experiment tested the improvement in comprehension when static-graph and animated visualizations were employed to enhance a text-only representation of the simple causal semantics. Hypotheses **H1** and **H2** were tested in this experiment. This study was paper-based (answers were recorded on paper) and did not calculate response times. Therefore, **H3** was not assumed.

- **Experiment 2:** This experiment compared the efficiency of the static-graph and animated representations in representing the simple causal semantics. Hypotheses **H2** and **H3** were tested in this experiment.

9.1.2 Component III

The main focus of this component was to extend the experiments designed in Component II to test the efficiency of the static and animated representations in enhancing text-only representations and in visualizing the set of complex causal semantics. Three experiments were conducted in this phase:

- **Experiment 3:** This experiment tested the improvement in comprehension when static-graph and animated visualizations were employed to enhance a text-only representation of DG1 of the complex causal semantics. Hypotheses **H1** and a combination of **H2** & **H3** were tested in this experiment.

- **Experiment 4:** This experiment tested the improvement in comprehension when static-graph and animated visualizations were employed to enhance a text-only representation of DG2 of the complex causal semantics. Hypotheses **H1** and a combination of **H2** & **H3** were tested in this experiment.

- **Experiment 5:** This experiment compared the efficiency of the static-graph and animated representations in representing DG1 and DG2 of the complex causal semantics. Hypotheses **H2** & **H3** were tested in this experiment.

9.1.3 Component IV

The main focus of this component was to compare the static-sequence to the animated representations of the causal semantics, in order to determine if sequential presentation of information had any significant influence on the superior performance of the animations in the previous experiments. Four experiments were conducted in this component, one testing the simple causal semantics and the other three testing the representations of the complex causal semantics:

- **Experiment 6:** This experiment replaced the static-graph representation by the static-sequence representation and compared it to the animated representation of the simple causal semantics. Hypotheses **H2**, **H3**, and **H4** were tested in this experiment.

- **Experiment 7:** This experiment replaced the static-graph representation by the static-sequence representation and tested the improvement in comprehension when static-sequence and animated visualizations were employed to enhance a text-only representation of DG1 of the complex causal semantics. Hypotheses **H1**, a combination of **H2** & **H3**, and **H4** were tested in this experiment.

- **Experiment 8:** This experiment replaced the static-graph representation by the static-sequence representation and tested the improvement in comprehension when static-sequence and animated visualizations were employed to enhance a text-only representation of DG2 of the complex causal semantics. Hypotheses **H1**, a combination of **H2** & **H3**, and **H4** were tested in this experiment.

- **Experiment 9:** This experiment compared the efficiency of the static-sequence and animated representations in representing DG1 and DG2 of the complex causal semantics. Hypotheses **H2**, **H3**, and **H4** were tested in this experiment.

9.2 Results Summary

The experiment tested the efficacy of my static and animated representations as an enhancement to the text-only representation and as stand-alone modes of visualizing simple and complex causal semantics that were identified in my taxonomy. The results of the experiments were analyzed using SPSS® mathematical analysis software. Each set of data was analyzed using repeated-measures Analysis of Variance (ANOVA). The following conclusions can be made from these experiments:

The first step of the research was to analyze the simple causal semantics, using a Memory Recall test, in order to determine the easiness of comprehending and recalling the visual information presented to the participants. **Experiment 1** therefore, compared the effectiveness of the static-graph and animated representations in enhancing a text-only representation of the simple causal semantics. The results of the experiment showed that the participants showed ~8% higher accuracy rates in the text + animated condition, when compared to the text-only condition and ~10% higher accuracy rates when compared to the text + static-graph condition. These results suggested that the animations enhanced the textual description and were easily comprehended and recalled by the participants. As this experiment was a paper-based study, response times were not calculated or analyzed. The results partially concurred with **H1** as only the text + animated condition showed higher accuracy rates than the text-only representation. The results also concurred with **H2** as participants were more accurate in the text + animated condition than in the text + static-graph condition.

The next step now was to isolate and compare the Intuitiveness of my static-graph and animated representations, without the aid of the text-only representation, as was done in **Experiment 2**. Results of the experiments did not show significance in accuracy rates between animations and static-graph representations, which suggests that participants were able to understand the information similarly with both representations. The results also showed that participants were ~9% faster with the animated representation than with the static-graph representation, which suggests that the animations were intuitive and faster to recall when matching the statement to the given relation. These results suggests non-concurrence with **H2**, as significance was not seen between the accuracy rates for the two representation types, and full concurrence with **H3** due to the significantly faster response times with the animated representation.

The results of the simple causal semantics experiments were encouraging and showed that animations showed faster response times than the corresponding static-graph representations. The next set of experiments extended these designs to test the effectiveness of the representations in visualizing complex causal semantics. Firstly, **Experiment 3** conducted a Memory Recall test on DG1 of the complex causal semantics and results of this experiment did not show a reliable main effect of representation types, as the semantics were still simple and could be adequately represented by all three representations (non-concurrence with **H1**). The analysis of the response times also did not show a reliable main effect of representation type, which suggests that participants took similar time to respond to statements represented by each of the three conditions (non-concurrence with **H2/H3**). Overall the results of this experiment were not significant and this could be attributed to the number of causal relations (6 relations) that the participant was asked to memorize and to the difficulty in sorting through and recalling this information when asked to match the relations to the given statement.

Experiment 4 conducted a Memory Recall experiment on DG2 of the complex causal semantics and, again, the results of this experiment did not show a reliable main effect of representation type for both accuracy rates and response times, showing non-concurrence with **H1** and **H2/H3**. The lack of significance in this experiment can be attributed to the complexity and volume of information provided to the participants, and their difficulty in recalling the accurate information when asked to match the relations to the given statements.

From the results of Experiment 3 and 4, I was unable to conclude which of the two visualizations (static-graph or animated) were more effective in describing the complex causal semantics. Therefore, **Experiment 5** tested the Intuitiveness of the static-graph and animated representations. The results of this experiment showed a reliable main effect of representation type in that participants were $\sim$5% more accurate when the causal semantics were visualized using animations, when compared to the static-graph representations (concurrence with **H2**). An analysis of the response times also favored animations, as participants were $\sim$8% faster with animations than with static-graphs (concurrence with **H3**). This suggested that animations were intutitive, comprehended easily, and recalled faster when compared to the static-graph representations of the causal semantics. However, the results also showed a main effect of interaction between representation type and statement type as performance using the preferred representation type was dependent upon the type of semantic being represented. Participants were faster with animations in responding to additive causality ('N' response: ~17%), contradictive causality ('Y' response: ~11%, 'N' response: ~17%) and fully mediated causality ('Y' response: ~37.6%, 'N' response: ~16.8%). The static-graph representation displayed faster response times for partially mediated causality (~9%), which could be attributed to the time taken to mentally replay the animation before providing a response.

One concern that arose during the course of these experiments was whether the sequential presentation of the relations had any influence on the superior performance of the animated representation. In order to address this concern, **Experiment 6** conducted an Intuitiveness test to compare the efficacy of an enhanced version of the static-graph representation (called static-sequence) to the animated representation of the simple causal semantics. The results of this experiment showed that participants were equally efficient with both types of visualizations (non-concurrence with **H2**) but responded ~4% faster when the relations were depicted using animations (concurrence with **H3**), which were similar to the results from Experiment 2 suggesting the ability of the participants in quickly recalling the causal information when it was represented using animations. A comparison of the static-sequence results from this experiment to the static-graph results from Experiment 2 did not show any significant improvement in performance when the relations in the static representation was shown in sequence. Also, the static-sequence representation showed a significant deterioration in performance when participants were asked to recognize correct matches for the overall combination of components (S4, ~22% deterioration). However, when asked to recognize incorrect matches for magnitude of outcome (S3), participants were

~13% faster with the static-sequence than the static-graph representation. Therefore, the results showed that in general the sequential presentation does not influence participant performance, except in isolated conditions which also could be attributed to the comprehending ability of the participant (concurrence with **H4**). In addition, it can be inferred from these results that the sequential presentation of information does not influence or promote the effectiveness of the animated representation. Another observation from this experiment was that the mean accuracies and response times for the animated representation were very similar with Experiments 2 and 6, which showed the consistency of participants performance and the adaptability of the animated representations to larger populations.

The next step was to address the concern about the simultaneous representation of the complex causal semantics, as was done with the simple semantics. Experiment 6 did not show a change in performance when the static-graph was replaced with the static-sequence representation. However, I was concerned if the lack of change in performance could be attributed to the simplicity of the semantics being represented, and if any difference can be seen if the complex causal semantics were visualized using the static-sequence representation. Therefore Experiments 7 (Memory Recall, DG1), 8 (Memory Recall, DG2) and 9 (Intuitiveness, DG1 & DG2 combined) tested the effectiveness of the static-sequence representation. The results of **Experiment 7** did not show a main effect of representation type, showing non-concurrence with **H1**, which can be attributed to the the number of causal relations (6 in total) being presented to the participants. Analysis of response times also did not show a main effect of representation type (non-concurrence with **H2/H3**), suggesting that participant took similar amounts of time to match statements to the given relations in each of the representation types, which again could be attributed to the difficulty in memorizing and recalling the causal information. The results of the static-sequence representation collected in this experiment were compared to the static-graph representation from Experiment 4. Analysis of these results did not show significant difference between the two variations of the static representation, which suggests that the sequential presentation of information does not influence performance (concurrence with **H4**). Comparison of the means for text-only and text-animated conditions between Experiment 3 and Experiment 7 suggested that the accuracy rates and response times were very similar, which in turns shows the consistency of the results and extendability of the results to larger populations.

The results of **Experiment 8** again did not show a main effect of representation type, (non-concurrence with **H1**). The analysis did not show significant difference between the static-sequence and the animated representations (non-concurrence with **H2/H3**) with both accuracy rates and response times, which suggests that the causal information was complex and difficult to memorize and recall. Comparison of the static-sequence results to corresponding static-graph results (from Experiment 5) showed no significant difference between the two representations for partially mediated and bidirectional causal statements. However, participants were significantly faster with the static-graph representation in responding to threshold causality statements (‘Correct’ response: $\sim$30%, ‘Incorrect’ response: $\sim$33%). The overall consensus of this analysis signifies concurrence with **H4** and suggests that sequential presentation of information does not influence participant performance, and in some cases deteriorates the performance of the static representation. Although, comparisons between results of Experiment 4 and Experiment 8 did not show similar accuracy rates and response times for the text-only and text+animated conditions, comparing these values to the accuracy rates and response times for the respective text+static condition showed a consistent change in the values. This suggests that the accuracy rates and response times were similar, but on a slightly different scale, which can be attributed to the memory and recall capacities of the participants between the two experimental groups.

Finally, with **Experiment 9**, I wanted to determine if the static-sequence representation improved performance if it was used as a stand-alone mode of visualization. Here, the analysis showed a main effect of representation type, and as hypothesized, animations proved more effective and performed with $\sim$6% higher accuracy and $\sim$7% faster response times than the static-sequence representation (concurrence with **H2** and **H3**). In addition, a comparison of the static-sequence results to the static-graph results from **Experiment 6** did not show any significant difference between the performances of the two representations, thereby showing full concurrence with **H4**. Also, comparisons between accuracy rates and response times for the animated representations of Experiment 5 and Experiment 9 showed similar differences from the respective static representation, which suggests that the results were similar but on a slightly difference scale due to the difference in comprehension and recall capabilities of the participants between the two experimental groups.

The overall consensus of this research was that comprehension of the simple causal semantics was improved when the textual information was enhanced using the static and animated visualizations (Experiment 1). Specifically, the animations proved to be more effective and induced faster response times than the static representations (Experiment 2). Memory recall studies on the complex causal semantics showed that there was no significance between my animated and static visualizations, due to the complexity of the relations being presented (Experiment 3 & 4). However, as stand-alone representations, animations had higher accuracy rates and lower response times than the static-graph representation (Experiment 5). Alternatively, static-sequence representations did not improve comprehension of the simple (Experiment 3) or the complex causal semantics (Experiments 7 & 9), and in some cases showed a deterioration in performance (Experiment 8). Therefore, I can conclude that the relations should be shown simultaneously and not sequentially in the static representation. Finally, as hypothesized and after the long series of studies, I have determined that my animations are the preferred method of representing the set of causal semantics identified in my taxonomy.

Experiments 1 to 9 comprise the studies I conducted to analyze the effectiveness of my causal visualizations. I will now conclude with a summary of my inferences and suggestions of the impact my visualizations will have on the greater community.

Chapter 10

Conclusion

This research reports on the construction and evaluation of visual semantics that enhance information content in causal diagrams. My representations are based on perceptual structural rules for recognizing causal occurrences, as suggested by Michotte and Thinés [1963]. This study consists of four components to design and analyze the effectiveness of my representations in describing causal semantics.

In the first component I focused on defining a taxonomy of causal semantics that are commonly encountered our environment. This component then aimed at defining the structure of the causal relation and designed a framework for constructing the path of the relation. The final step of this component focused on creating visual representations of the causal semantics using the suggestions of other research in the area [Michotte and Thinés, 1963; Sekuler and Ganz, 1963], and of the structure and path of the causal relation.

The main hypotheses of my research are that visual representations help in improving comprehension and that my animations are more accurate and have lower response times when compared to the static representations in describing the causal semantics. In the second component of my research, I tested the static-graph and animated representations of the simple causal semantics. Two experiments were conducted in this phase. In both experiments animations had higher accuracy rates and lower response times than the corresponding static-graph and textual representations. Animations were ∼8% more accurate when used to complement textual descriptions in the Memory Recall test (Experiment 1) and ∼8% more accurate and ∼9% faster when compared to the static-graph representations for an Intuitiveness Evaluation (Experiment 2).

Encouraged by the results of the second component, the third component of my research aimed at testing static-graph and animated depictions of the complex causal semantics. Although there was no significant difference between the animations and static-graph representations in the Memory Recall experiments (Experiment 3 and 4), the Intuitiveness evaluation (Experiment 5) suggested that animations improved comprehension by ∼5% and response times by ∼8%.

Finally, in the fourth component of my study, I enhanced the static-graph representation, by sequentially animating the relations, and compared it to the animations using both Memory Recall and Intuitiveness evaluations. The goal of these experiments was to determine if the sequential animations of the relations had any influence on the performance of the animations. Results of this study did not show significant differences between the static-graph and static-sequence representations, and also suggested that animations were still the preferred form of visualization of my causal semantics. Overall, the experiments conducted in my research support my hypothesis that visualizations, animations specifically, are effective modes of representing my causal semantics.

In keeping with the main goals of my research, I did not focus some complex, critical aspects of causal relations, such as multiple targets, continuous scales for influence and effect, and time domains. The reason for focusing on the basic representation of my semantics is because I believed that it is essential to build a strong foundation for future research in the area of causal visualization and this can be achieved by first identifying the taxonomy of causal semantics and then using existing theories of perception to build simple visualizations to describe these semantics. Some of the limitations of my research has been discussed in the next section.

10.1 Limitations of my research

My research focused on designing and testing basic visualizations of the causal semantics identified in my study. Therefore, some complex features of causal relations have not been addressed, as mentioned below.

1. My causal semantics only focus on single target scenarios, and do not take into consideration conditions when a factor affects more than one target. The reason for this is that I wanted to focus on the type and magnitude of outcome with respect to a target. I do recognize that multiple targets are common in real-life scenarios, and understand that more semantics might be identified when the focus shifts to multiple targets and outcomes, however, this was currently beyond the scope of my thesis.

2. The influence and effects are deterministic and based on a 0/1 scale, i.e. small/large influences and increase/decrease in effect. This scale was chosen in order to maintain the simplicity of the experiments and to focus on the effectiveness of the visualization in depicting the causal semantic. Also, participants were not given additional interactive aids, such as tooltips, to help them in determining the magnitude of the influences or effects, and so I wanted to show a clear distinction between the magnitudes. However, I do understand that a more continuous scale, along with interactive tools, will need to be adapted when applying my visualizations to applications in the life sciences, which would form future work for this research.

3. The causal graphs used in this research are small, simple, and fit within the participants' screen. The reason for this is again to keep the experiments simple and to focus on each type of causal relation rather than on the whole scenario. However, if my visual designs are applied to more complex scenarios, additional dynamic techniques will need to be investigated and/or incorporated to enable easy viewing and traversal of the causal graphs. Some of these techniques could include zooming, scrolling, node selection, and division of the visualization into small segments using checkpoints.

4. Time domains were not incorporated in my research as I focused on one causal event at a time and each event was isolated and disconnected from the next event within the given scenario. The main reason to this experimental design was because I was testing the individual semantic and components of the causal relation, and was not focused on the scenario or sequence of events within the

scenario. However, I do recognize that in real-life applications, the visualizations will need to incorporate time domains when describing the causal semantics.

5. The current thesis focuses on creating a non-domain specific taxonomy of causal semantics. The reason for this decision was that I wanted to identify the semantics and design simple representations such that they can be applied to several domains. This would require application and testing in different domains, which has been identified as part of my future work and described in the next section.

I recognize that real-life applications are more complex than the simple representations designed in my thesis. However, the main focus of my thesis was to define a set of relations and design simple visualizations for them. The research also focuses on initial experimental studies to test these visualizations, as I believe they have immense potential and future to be incorporated in real-life applications. Therefore, although this study only focused on testing the causal visualizations in a laboratory environment, I am confident that these representations can be applied to different real-time scenarios in order to extract information and make critical decisions. Some example scenarios that display the practical applicability of my visualizations have been explained in the next section.

10.2 Future applications of my research and its impact on the greater community

Newton's third law of motion states that, "every action has an equal and opposite reaction". The causal equivalent of this statement is that, "every cause has a precise effect". Every action performed is the result of a preceding cause and gives rise to a succeeding effect. Hence, causality is so general and abundant in the universe that it can be obtained by simply observing the environment around us and discerning the causal relationships from it. However, when it comes to comprehending these semantics and making future predictions and judgments from them, it can be quite complex to remember the interconnections between different relationships, and also to perceive the overall picture. This is where visualization plays an important role. Visualizations elucidate the complex concepts using simple visual representations, which cause the concepts to be comprehended, remembered, and appreciated. Simple visualizations are employed in many fields, such as medicine, pharmacy, education, computer science, management, physics, and chemistry, to explicate complex semantics.

In the medical and health fields, these representations can be used in radiotherapy to show the actions of radiations on various organs of the body. They can be used in surgery to visualize the outcomes of different surgical methods and can also help to choose the method with least complications and risks. They can be used to show the behavior of the human anatomy and how it reacts to different diseases, medications or circumstances. The visualizations can also be used to show the origin and spread of diseases, their range, the rate at which they spread, timelines, methods that can be employed to stop or reduce this spread, and the effectiveness of these methods (Figure 10.1).

In the pharmaceutical field, my visualizations can be used in drug research. They can be used to simulate the ways in which drugs affect a disease, which combinations of drugs might have a significant effect on destroying or bringing the disease under

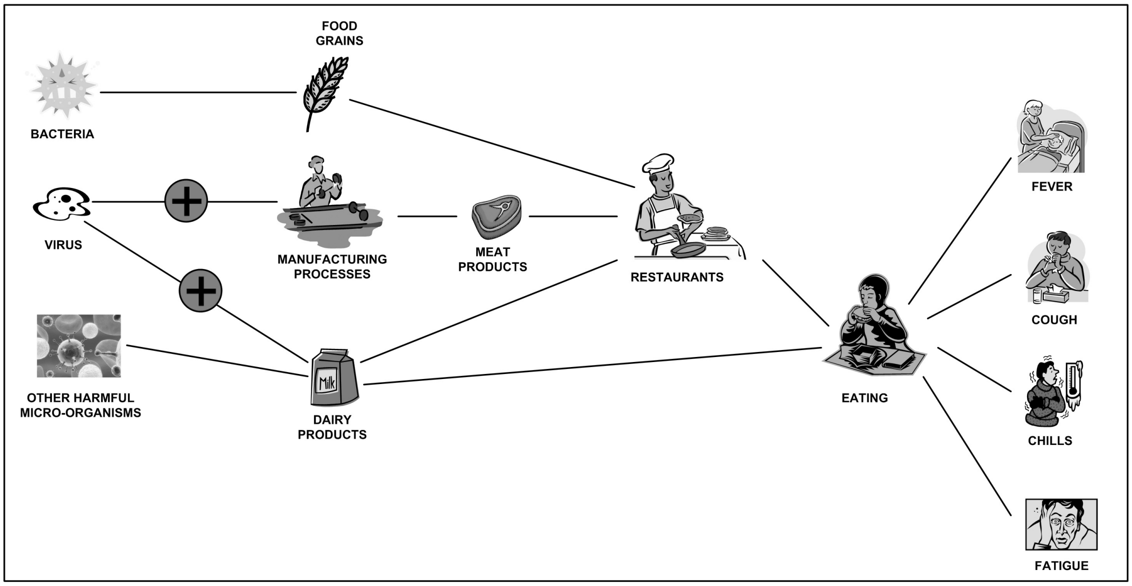

Figure 10.1: Example of a causal graph that can be used by disease surveillance organizations, such as the Public Health Agency of Canada (PHAC), to monitor the source of different diseases and their effect on the health of the Canadian public.

control, which drugs have adverse effects, the side-effects of these drugs, and the amounts that should be administered for best results. The representations can also be used to monitor the administration of the drug in a sick person for testing purposes.

In the educational field, my visualizations can be used in many places effectively. They can be used in hospitals, such as in children's hospitals, as educational tools to educate children on their illness. The tools can be of various forms such as quizzes or video games, which can use these visualizations to teach to teach children the causes of their illness, how their medications help control the disease, what foods or drinks they should avoid, and what other procedures they should take to prevent a relapse. They can also be used in general to show patients the extent of their diseases and

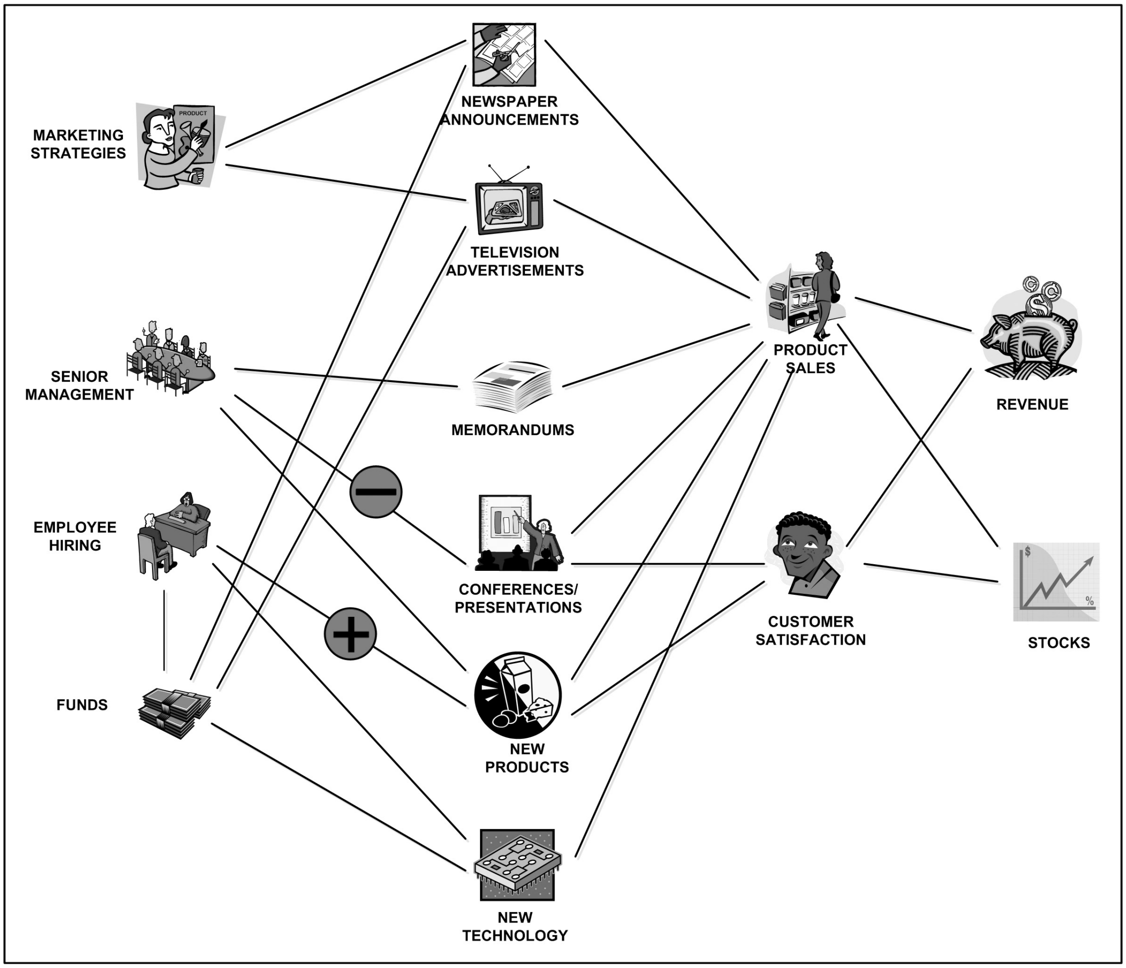

Figure 10.2: Example of a causal graph that can be utilized to analyze the structure of a company, its efforts, and finally its outcomes.

progress of their medication plans. In the universities, my representations can be used for research purposes.

Likewise, some other fields that will benefit from my visualizations include, but are not restricted to, computer science, physics, chemistry, and management. In computer science, my visualizations can be used in the universities and industries to visualize program models, communications between components in a system, project timelines, workload division, input from the team members, side-effects, and by-products of a system. The visualizations can also be used by the students to describe their programs and also test them with different sets of inputs. These visualizations can be used by physicists and chemists to view the effects of light on various substances, heat on elements, combinations of mixtures, and radiation effects on a substance. They can also be used by businesses to review marketing strategies, product lines, profits, and losses (Figure 10.2).

In consensus, causal semantics are abundant in almost every profession and field of research. Hence, I hypothesize that my visualizations are powerful enough to help simplify the complex semantics that are encountered on a regular basis.

Appendix A

Passage Recall Experiment Screenshots

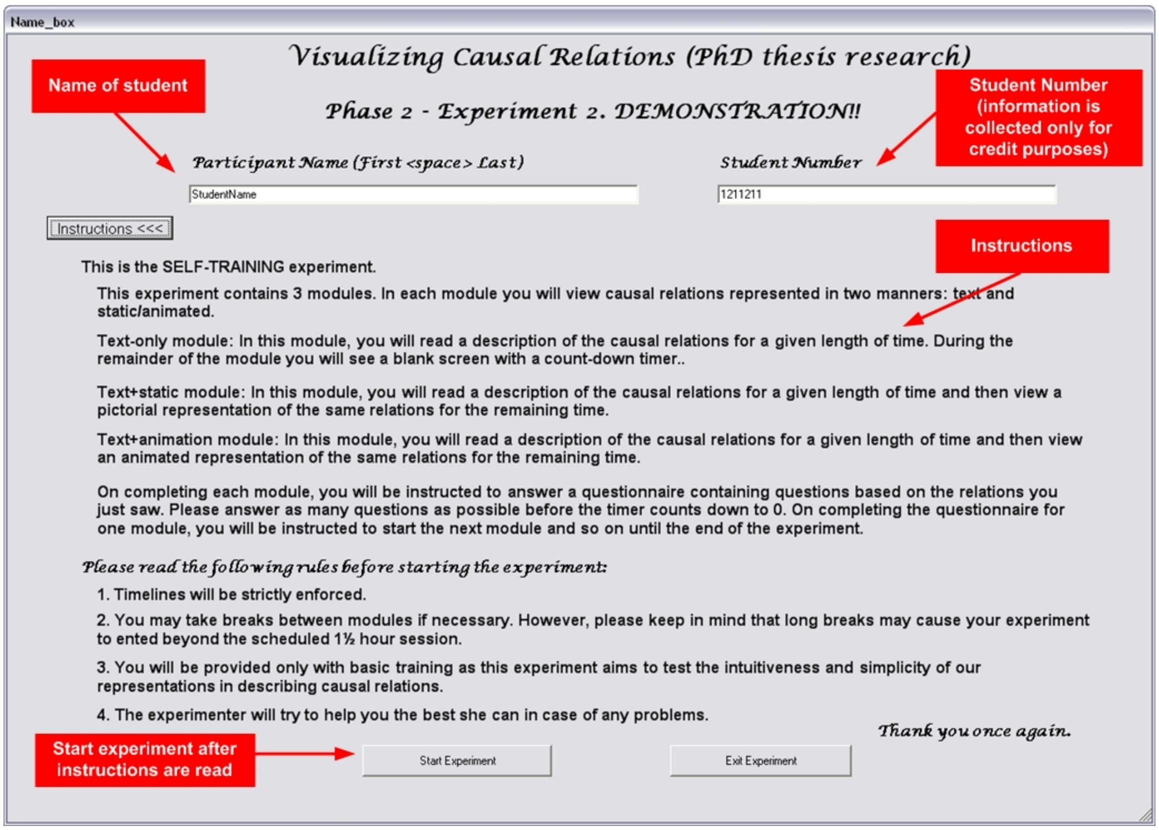

Figure A.1: The main screen for the Passage Recall experiment. This screen recorded participant name, student number, a brief description of the experiment along with any instructions.

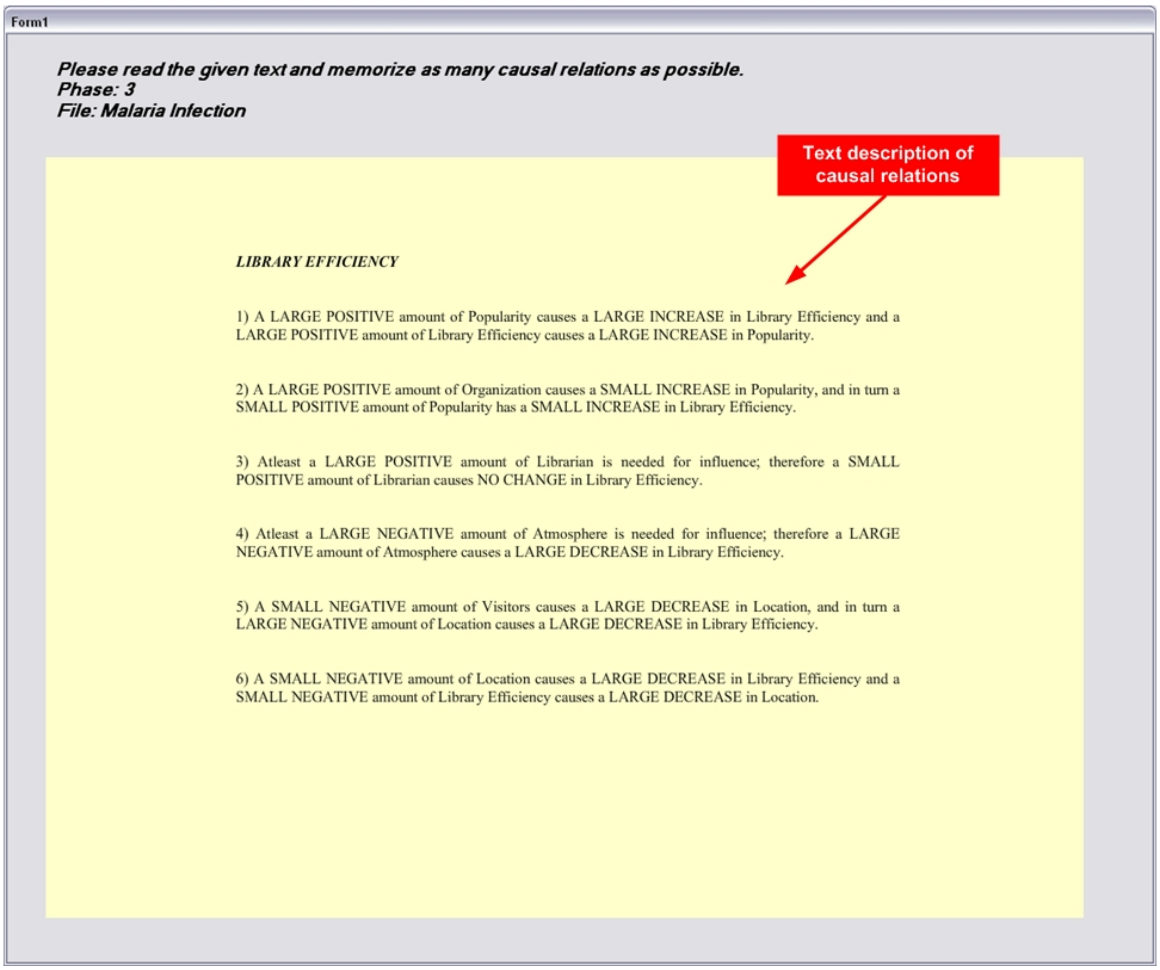

Figure A.2: Text representation was displayed through one line descriptions of the causal relations.

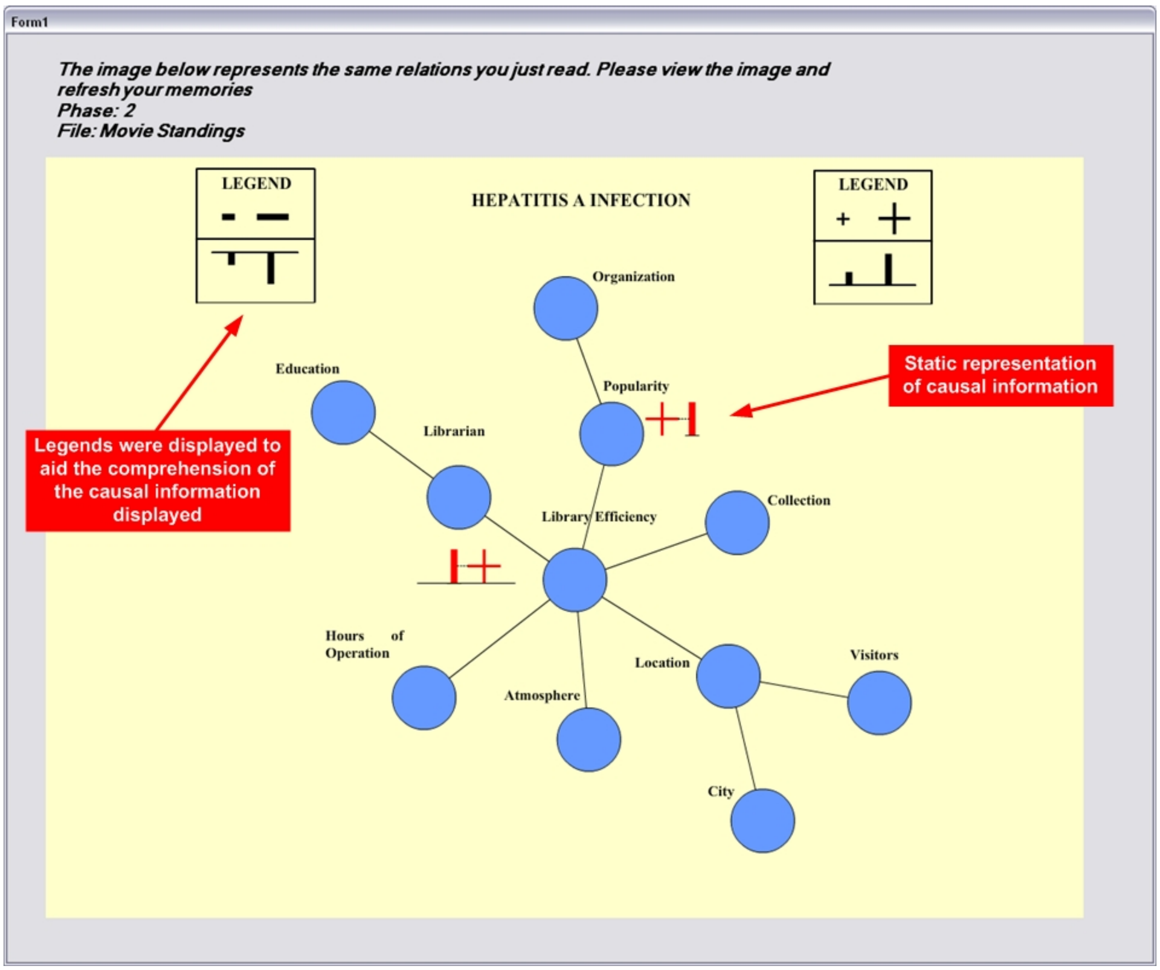

Figure A.3: Static Representation was displayed using +/- glyphs to depict influences and upright/inverted bars to depict effects.

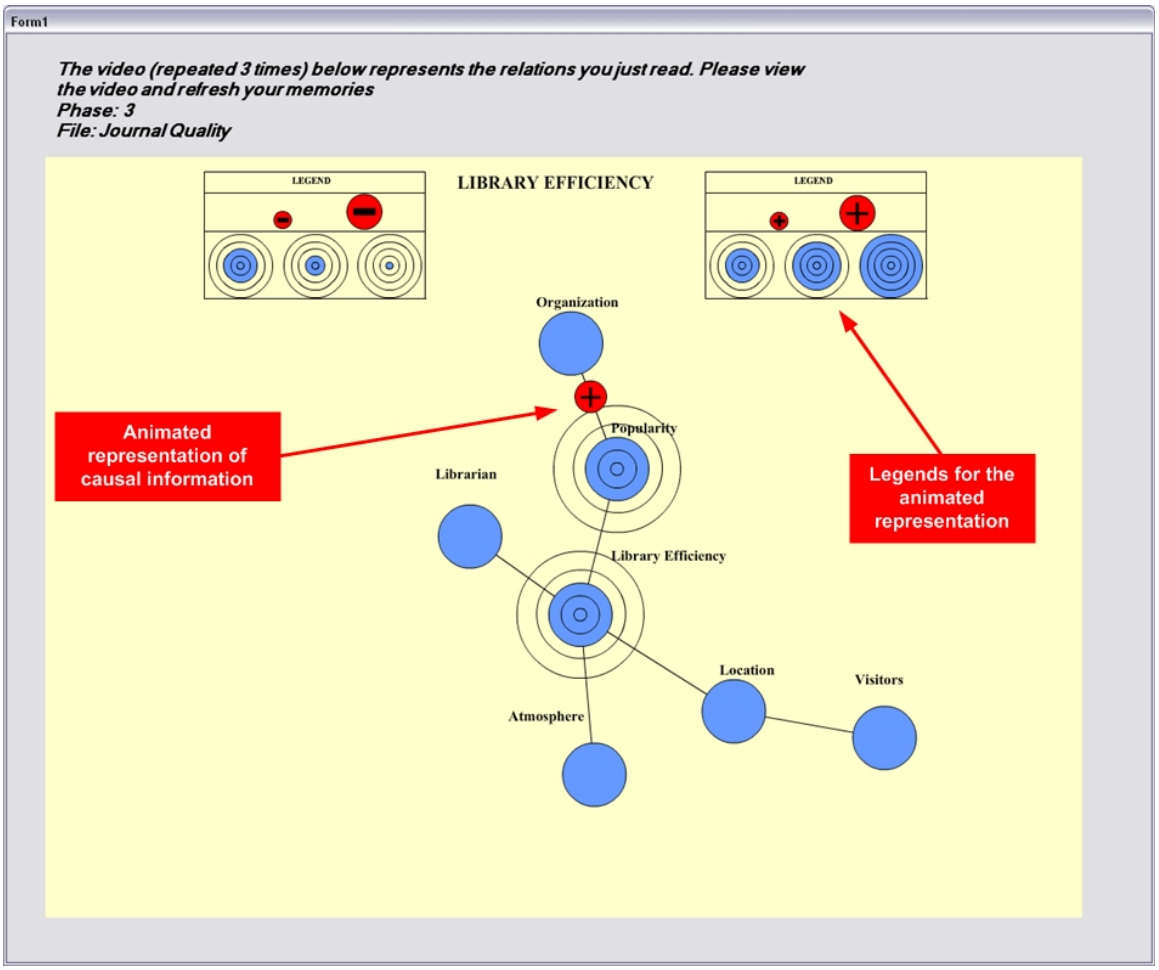

Figure A.4: Animated representation was displayed using moving bullets to show influences and target expansion/contraction to show effects.

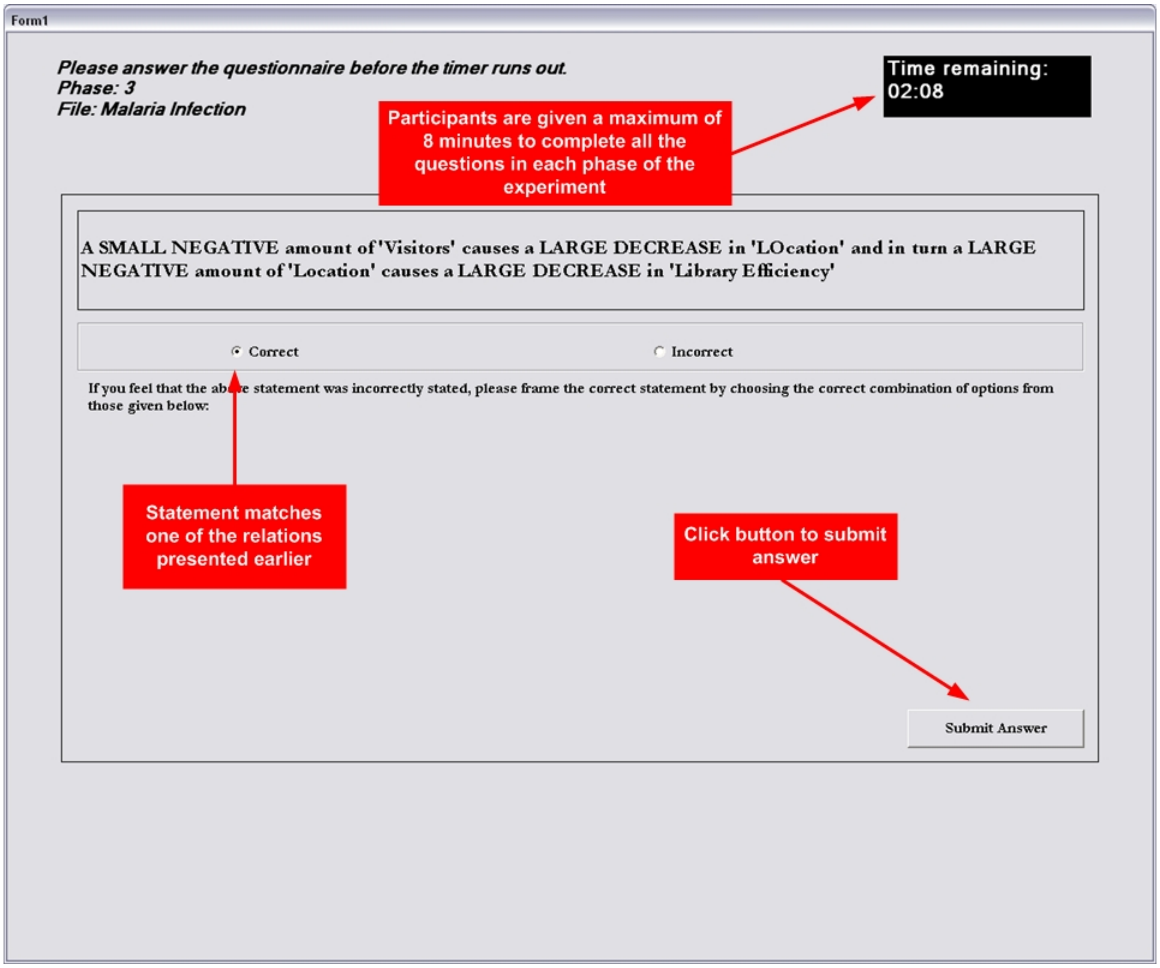

Figure A.5: Each phase of the experiment displayed the text representation followed by a visual representation. At the end of each phase, participants shown a statement and asked to choose 'Correct' if the statement correctly matched one of the relations shown in that phase.

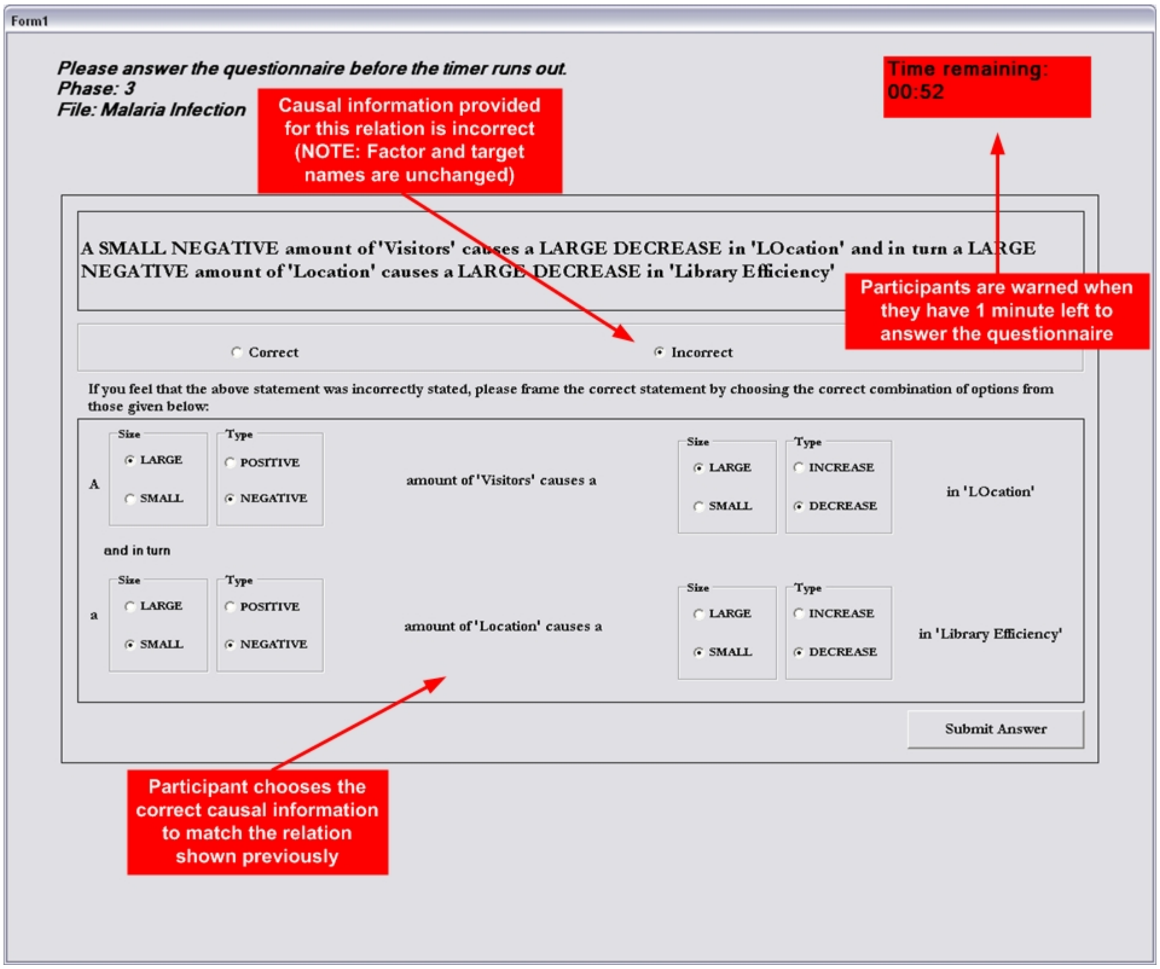

Figure A.6: If the given statement did not match any of the relations shown in that phase, the participant was asked to choose 'Incorrect' and provide the correct causal information.

Appendix B

Intuitiveness Evaluation Experiment Screenshots

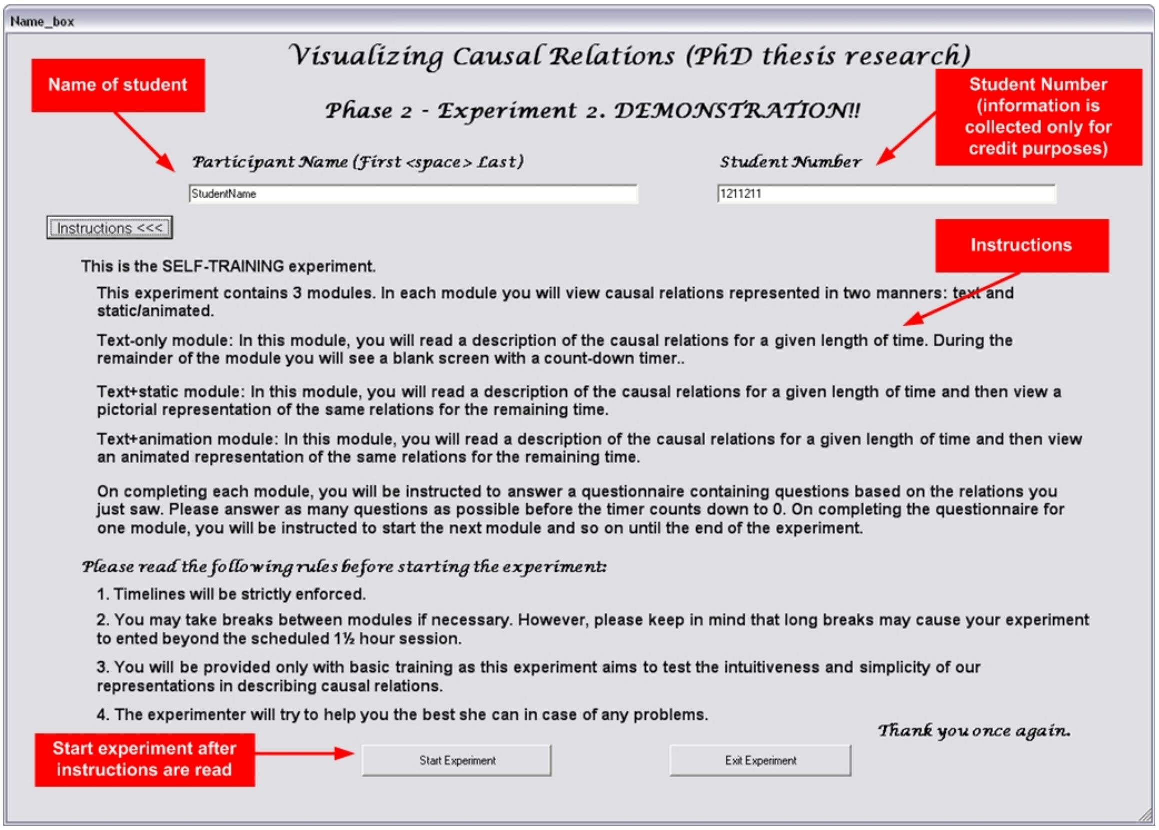

Figure B.1: The main screen for the Intuitiveness Evaluation experiment. This screen recorded participant name, student number, and a brief description of the experiment along with any instructions.

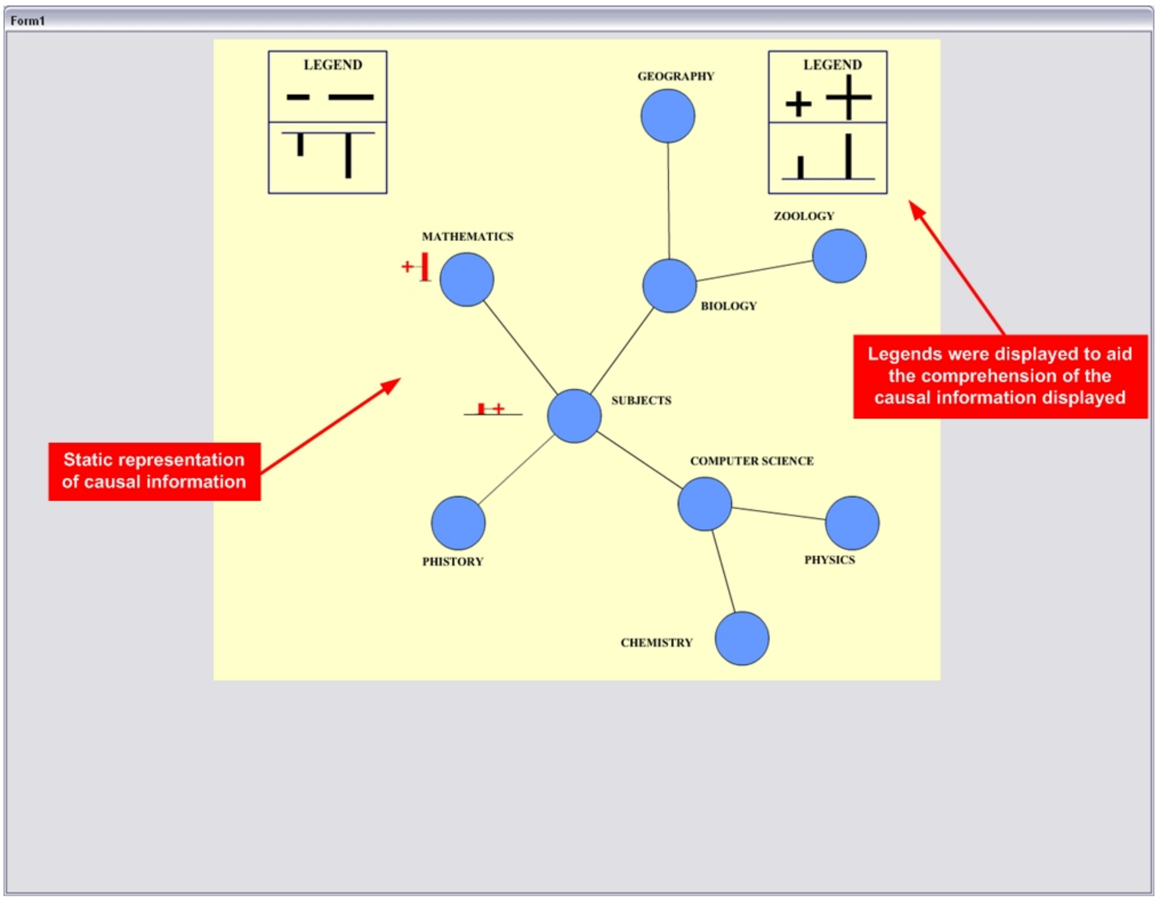

Figure B.2: In the static representation, participants were shown 1–2 relations using static plus/minus glyphs to show influences and upright/inverted bars to show effects.

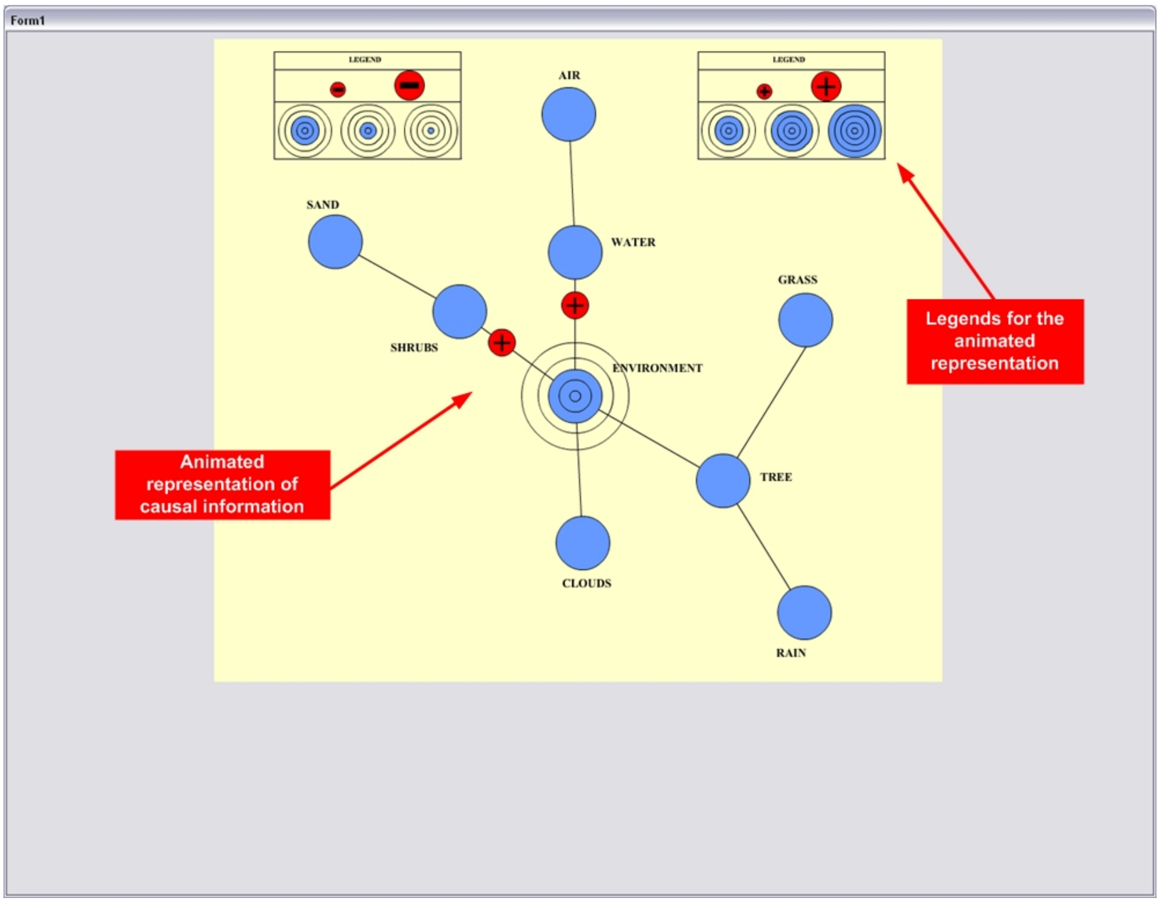

Figure B.3: In the animated representation, participants were shown 1–2 relations using moving bullets to show influences and and target expansion/contraction to show effects.

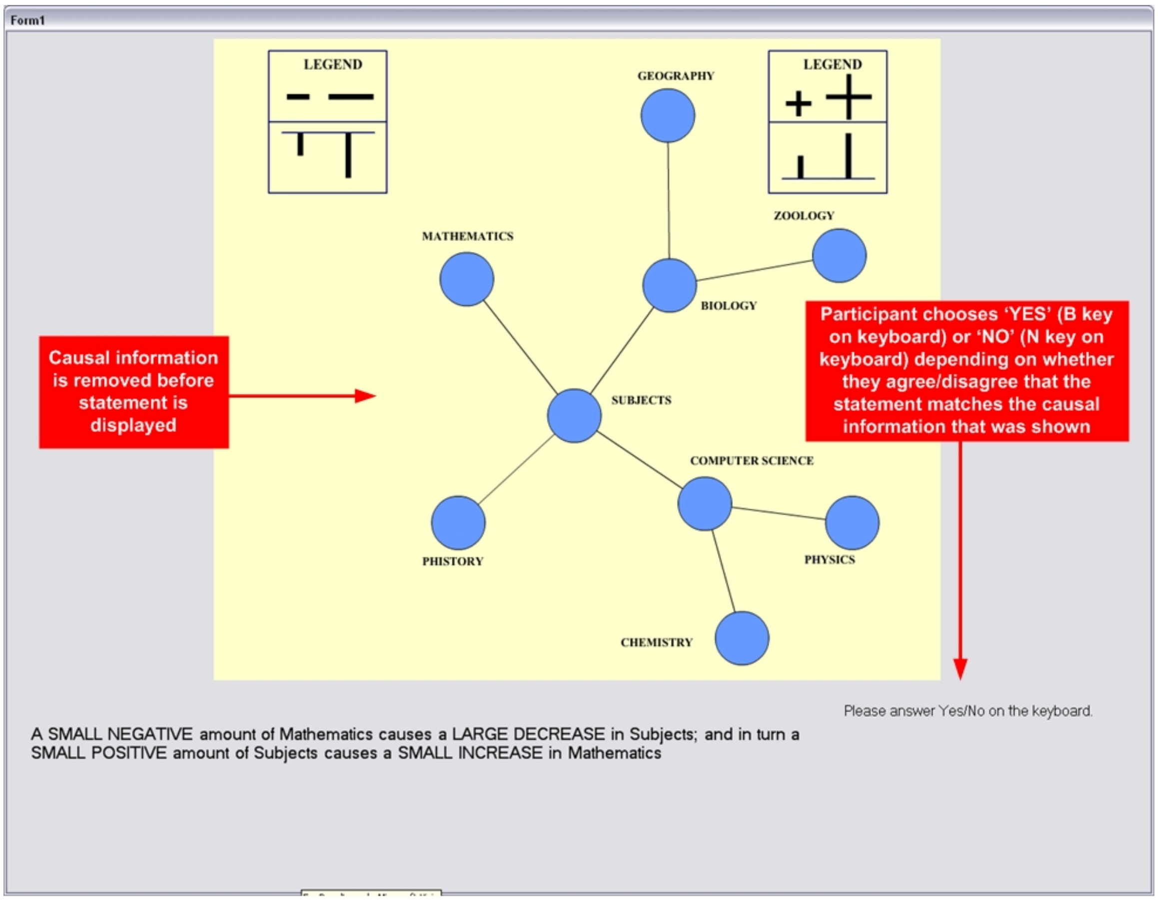

Figure B.4: Each experiment trail consisted of a visualization followed by a statement. Participants were asked to choose 'Yes' or 'No' depending on whether they agreed/disagreed that the statement matched the displayed visualization.

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