

MOBILE WAY OR THE HIGHWAY!
THE ROLE OF DEPLOYMENT AND DESIGN IN
PROBLEM SOLVING USING INFORMATION DASHBOARDS

by

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ABSTRACT

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Information dashboards are becoming very popular in the areas of decision making and problem solving. Decision makers use heuristics when facing challenging environmental situations. These could result in systematic errors called biases. How do mobile information dashboards impact these biases? We propose that decision makers are more prone to biases associated with certain heuristics when using information dashboards deployed on mobile devices. Data visualizations displayed on dashboards could be distorted. We also propose that employment of heuristics could increase the negative effect of distortions.

There is a distinct bias in favor of deploying these dashboards on mobile devices versus static desktops. Is this justified by key performance and perceptual outcomes? Borrowing from the reference disciplines of cognitive psychology, instructional and educational psychology, vision search and advertising we arrive at a conceptual model that relates deployment, design and problem task type to performance and perceptual outcomes. The results of our controlled laboratory experiment indicate that use of dashboards with active control deployed on mobile devices will result in lesser task accuracy than the dashboards deployed on static desktops. Also users of highly interactive dashboards deployed on mobile devices experience lesser satisfaction than users of the same dashboards on static desktops. Further research areas including the role of cognitive fit between problem representation and problem type were identified. These could potentially uncover situations when the mobile information dashboards outperform static desktop dashboards.

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CHAPTER 1

1.1 Introduction

The last decade has been witness to a tremendous upsurge in the popularity of mobile devices. Information dashboards that display the key performance indicators on a single screen are increasingly being used at personal and organizational levels. There is a distinct bias towards pushing different kinds of dashboards to mobile devices. Is this bias justified by key performance and perceptual measures? Information dashboard is the star of this research and the phenomenon is characterized by certain content and contextual facets. Information dashboards are often used by decision makers. When faced with uncertainty, decision makers use heuristics to make decisions. These cognitive simplification strategies often result in systematic biases. Dashboards often have presentations that have subtle distortions which are employed to manage the impression of the viewer. In the first essay, “When there is bias in the mind and distortion in the dashboard – A conceptual study”, we look at the distortion as a content factor and bias in the minds of the user as a contextual factor. We arrive at several propositions, including one which ties the bias and distortion.

Deployment of a dashboard on a device and the amount of control a user enjoys are two key content factors that influence key outcomes. Graphs, tables, text and many other forms of visualization objects are seen on a dashboard. A user may work on a problem task that deals with only one object on a screen. Alternatively, the user may have to accumulate or integrate information from multiple objects on the screen. We identify the singular and integrative problem type as a third context factor. How do they work together? We look at the dynamics of the three factors in the second essay “Appearance and Reality – Dashboards on Mobile Devices

– An experimental study” We develop a conceptual model based on theories from several reference disciplines including instructional and educational psychology, cognitive psychology, advertising and vision search. We validate the conceptual model by conducting an experiment with student subjects. The experiment highlights several interesting results that we hope will debias the readers, albeit modestly.

As we analyzed the data from the experiment, we realized that the phenomenon has more intricate nuances than envisaged. The results show the key role played by cognitive fit in the dynamics of the three factors of content and context. In the third essay “A tale of two misfits – mobile dashboards - directions for research and practice”, we delve into the results and arrive at certain promising directions for research and practice.

CHAPTER 2

WHEN THERE IS BIAS IN THE MIND AND DISTORTION IN THE DASHBOARD -

A CONCEPTUAL STUDY

2.1 Abstract

Dashboards are key decision making tools used in personal and organizational contexts. Mobile devices are becoming very popular. There is an increasing trend towards deployment of dashboards on mobile devices. Due to the uncertainty in the environment, decision makers often use heuristics as an aid, which causes bias. In addition, a visual presentation could be distorted in several ways. We conduct an extensive literature review in reference disciplines such as cognitive psychology and perception in order to understand the many different kinds of biases and distortions. We relate biases and distortions to the key aspect of the cognitive load due to the limited screen real estate of mobile devices. In addition to the propositions regarding the biases and distortions, we also propose that certain cognitive biases in the mind of the decision maker may prevent the detection of the subtle distortions on the information dashboard. These propositions may be converted to hypotheses and validated empirically.

2.2 Introduction

An information dashboard can be defined as a “visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance” (Few 2006). They are often replete with texts, tables, graphs, signals, heat maps and other forms of visualizations. Dashboards can be used to plan, communicate, collaborate and control in an organization. Mobile devices have become quite popular in the modern times. There is a large bias among individuals and organizations towards deploying all types of visualizations on mobile devices. In this research article, we study the extent to which users using dashboards use different heuristics and are prone to associated biases.

Decision makers select from various alternatives in an uncertain environment, limited by the shortcomings of their information processing capabilities. Faced with such a situation, they use short cut methods or heuristics in order to make a decision. Employment of these cognitive simplification strategies called heuristics helps the decision maker cope with uncertainty in the environment. However these could result in severe systematic errors called biases (Tversky and Kahneman 1974). The extant literature in cognitive psychology has identified at least forty different types of biases that arise out of the many different heuristics employed by the decision maker. These heuristics often involve using human memory to learn from similar situations and stereotypes encountered in the past. Although key performance data can be presented on dashboards, the decision maker may still not be able to deal objectively with the decision making situation. The user may attempt to use cognitive simplification strategies which are subjective in nature.

In spite of the increasing usage of mobile devices in decision making and problem solving, these devices still have a limited screen real estate. We are greatly intrigued by the following question: - Does the limited screen real estate of mobile devices impact the usage of heuristics leading to biases? Our extensive literature review in the information systems, accounting and cognitive psychology disciplines have not revealed any exploratory research to address the above research question. We are therefore motivated to fill this gap.

Data visualizations are often characterized by various kinds of distortions that could be introduced purposefully to influence the decision maker. They could also be introduced in visualization by the designer due to lack of knowledge or experience. One of the most common forms of distortion is the violation of sound graphical guidelines in order to persuade the decision maker to an action that is favorable to the designer (Tractinsky and Meyer 1999).

Companies disseminate financial information using different vehicles of communication, such as annual reports. These annual reports are available online in many ways. This enables widespread availability of information to the different stakeholders of the company. In the process, companies indulge in a practice called impression management. Impression management at an organizational level deals with the practice of managing the audiences' impressions of the organization. Dashboards can be used for communication, monitoring and persuasion. Companies can motivate key stakeholders to invest via the medium of impression management on dashboards. These dashboards are available over the web. Examples of such websites are www.ml.com, www.Shareholder.com, and www.thomson.com.

Pennington and Tuttle (2009) empirically validate a conceptual model that explicates the relationship between distortions and performance outcomes on hard copy output. While

distortions may have a certain impact on accuracy when displayed on hard copies and static desktop devices, we seek to focus on how these distortions will impact decision making on mobile devices. We are motivated by the following exploratory research question: - Will the distorted representation of key indicators on a dashboard deployed on a mobile device impact the performance of a decision maker adversely? In addition to the propositions regarding biases and distortions, we also propose that certain cognitive biases in the mind of the decision maker may prevent the detection of subtle distortions on the information dashboard.

2.3 Literature Review

2.3.1 Theory of Cognitive Biases

Humans, when confronted with a choice situation are decidedly satisficing rather than optimizing (Simon 1956). They do not use the utility functions to determine which path to choose. This has been attributed partly to the limited capacity of humans to process the information from the stimuli in the environment. In short, humans adapt well to the complex changing environment by a process that has a lesser goal than “maximizing” as deemed by economists (Simon 1955; Simon 1956). In addition, the modern decision maker is further plagued by uncertainty. How does the decision maker respond to this uncertainty? How does he or she evaluate the subjective probabilities in his or her utility function? The decision maker uses certain shortcuts or heuristics in order to arrive at a satisficing decision. These heuristic principles reduce the work to a few judgmental operations (Tversky and Kahneman 1974). However, there is a side effect of using such heuristics; that effect is given the broad term called bias. These biases, or systematic errors, could result in irrational decision making. This research relies, to a large extent, on the various aspects of the cognitive bias theory. The cognitive bias theory does not look at biases only from a negative angle. It also postulates that some of these biases have positive connotations as well.

The extant literature in cognitive psychology is replete with different taxonomies of biases. The earliest taxonomy of biases was provided by Tversky and Kahneman based upon the theory of general judgmental heuristics. The three different categories of heuristics used and the biases associated with each are enumerated in the next section.

2.3.2 Heuristics and associated biases

Cognitive simplification strategies such as heuristics help a decision maker cope with a decision making situation in an uncertain environment. *Representativeness heuristic* is the short cut method where people judge whether an event is likely to occur by its resemblance to a stereotype of a similar set of events. If a decision maker were to be given a description of a person in terms of certain traits and asked to identify his profession, he is most likely to identify the person with the profession which is representative of the description. For example, if the person is an extrovert, orator, has charisma, and is a leader, that person is most likely to be a politician.

Decision makers estimate the probability of an event subjectively in a manner that is not governed by any axioms. The subjective probability may also be discerned from their behavior. Using the laws of probability calculus and looking at the stated assumptions, a decision maker can calculate the objective probability. The laws of probability dealing with uncertain events are not intuitively apparent to most decision makers (Kahneman and Tversky 1972). They are also not easy to apply. It is hardly surprising that most people find it difficult to understand the concept of posterior probability and its application even after rigorous study. Given the above limitations, the decision maker often uses the representativeness heuristic.

When a decision maker uses the representativeness heuristic in order to arrive at the probability of an uncertain event, the parent population's similarities with respect to its properties and the process by which the event is generated are used as guidance mechanisms. If the decision maker has to choose between two alternative events, the choice may be made by looking at the degree of representativeness of the events (Kahneman and Tversky 1972).

The representativeness heuristic is based on similarity or connotative distance (Tversky and Kahneman 1973) and is likely to lead to different biases. The prior probability or the base rate frequency of outcomes should affect the subjective probability of a decision maker. It has been found in experiments that the base rate does not seem to factor in when representativeness is used as a heuristic (Tversky and Kahneman 1974). The subjective probability of a sample statistic is assumed to be representative of the population parameter, irrespective of whether the sample size is small or large. Decision makers often have an incorrect perception of chance events. They may misunderstand the efficacy of the random sampling process when they are dealing with a short sequence. So they think that the local or small part would be representative of the whole process (Tversky and Kahneman 1971). Also decision makers do not appreciate regression towards the mean and assume that extreme events would repeat on subsequent trials. Table 2.1 presents the various biases that occur when the decision maker uses the representativeness heuristic.

The decision maker uses an *availability heuristic* when the person speculates on the probability of an event by looking at how easy it is to bring to mind the various examples or instances. Availability heuristic is based upon the availability or the associative distance. For example, a person decides to bet on his favorite team by looking at its recent performance in terms of victories and defeats. If the team has been playing frequently in the recent past, then it is easier to access its record than if it had been playing seldom. The frequency of an event is judged by the relative ease with which the decision maker can recall instances from memory that are specific to the task (Hogarth 1980). In addition, these cues may be available in the environment. Events that are vivid in memory often dominate over other events. These events have more

visibility in the mind of the decision maker. Several biases result because of the use of the above heuristic. Table 2.2 lists these important biases.

Table 2.1 Biases Due to Adoption of the Representativeness Heuristic

S.No	Bias	Explanation	Example	Impact on decision making using information dashboards on mobile devices
1.	Disregarding Prior Probability	People tend to disregard base rate information in the presence of other information.	Aspiring entrepreneurs often imagine their heady success, but disregard the data regarding failures.	Base rate information provided on dashboard could be ignored due to crowding and inconvenient operations.
2.	Insensitivity to sample size	Our intuition does not inform us about sample size. Understanding that the subjective probability of a sample statistic is representative of the population parameter, regardless of the sample size.	People often indulge in gross over generalizations based upon a few data points.	Typically sample sizes are accorded the least importance on a dashboard where emphasis is placed more on measures. Danger of being ignored.
3.	Incorrect perceptions of chance events	Success\failure on prior attempts need not be indicative of success\failure on future attempts.	Performance below expectations on five different games cannot be used to predict that superlative performance is waiting to happen on the sixth game.	
4.	Inadequate appreciation of regression towards the mean	Decision makers assume that future outcomes can be predicted from past outcomes due to assumption of perfect correlation, especially when the future outcome is less extreme.	“Sophomore Jinx” – Great rookies perform below par in their second year.	
5.	Conjunction Fallacy	The joint probability of two or more than two events appears to be more than the probability of any of the single events. This happens because the conjunctive event is more representative than the individual events.	Decisions regarding response to natural disasters and medical treatments.	

Source :- Bazerman 2006; Tversky and Kahneman 1974

Table 2.2 Biases Due to Adoption of the Availability Heuristic

S.No	Bias	Explanation	Example	Impact on decision making using information dashboards on mobile devices (Explained in detail later)
1.	Ease of Recall due to vividness	An event or situation that resembles the problem situation is very vivid in the memory of the decision maker and is therefore highly available for recall.	Choosing a vivid performance of an employee on a specific instance as an indicator of the overall performance throughout a larger period.	Working memory limitations
2.	Ease of recall due to closer temporal proximity	An event or situation that resembles the problem situation has happened quite recently and is therefore highly available for recall.	Giving more attention to the performance of an employee over the past month rather than the performance over the eleven months before.	Working memory limitations
3.	Retrievability	Some structures in memory are more available for retrieval than others	Words that end in “ing” are more available than words that have “n” as the sixth letter	Working memory limitations
4.	Inadequate consideration of all possible combinations	When several events that are characterized by dichotomous variables occur together, the decision maker may not consider all possible combinations. Instead the combination that is most available in the mind of the decision maker will be used.	Two events that have two levels each account for four possible combinations. Decision maker may use only one of the combinations due to it being predominant in the memory.	Working memory limitations

Source :- Bazerman 2006; Tversky and Kahneman 1974

Decision makers use the anchor and adjustment heuristic when they start with an initial value or anchor and adjust it to arrive at the final solution. The problem itself may suggest the initial value or the decision maker may arrive at it by preliminary computation. Often the adjustment made is seen to be close to the anchor and the original estimate is not adjusted sufficiently keeping in mind the true reality (Tversky and Kahneman 1974).

Bias occurs when the anchor or original adjustment is given to a person or as a basis of partial computation. The final estimate is often misaligned to reality as the decision maker does not adjust it sufficiently and therefore causes *inadequate adjustment*. Depending upon whether the anchor is high or low, the final estimate could grossly overestimate or underestimate the true value. First impression bias is a classic case of inadequate adjustment of the anchor point. Decision makers often depend too much on the first impression a situation or person makes and do not make sufficient adjustment.

In the case of *conjunctive or disjunctive* events, the anchor is often the probability of the original elementary event. Due to the anchoring effect, there is insufficient adjustment. Since the probability of a conjunctive event is often less than that of each elementary event and the probability of a disjunctive event is more than that of each elementary event, the probability may be overestimated or underestimated (Tversky and Kahneman 1974). A decision maker's best estimate does not anchor the *subjective probability distribution* that is useful in such a situation. This could potentially cause a bias.

2.3.3 Affect Heuristic

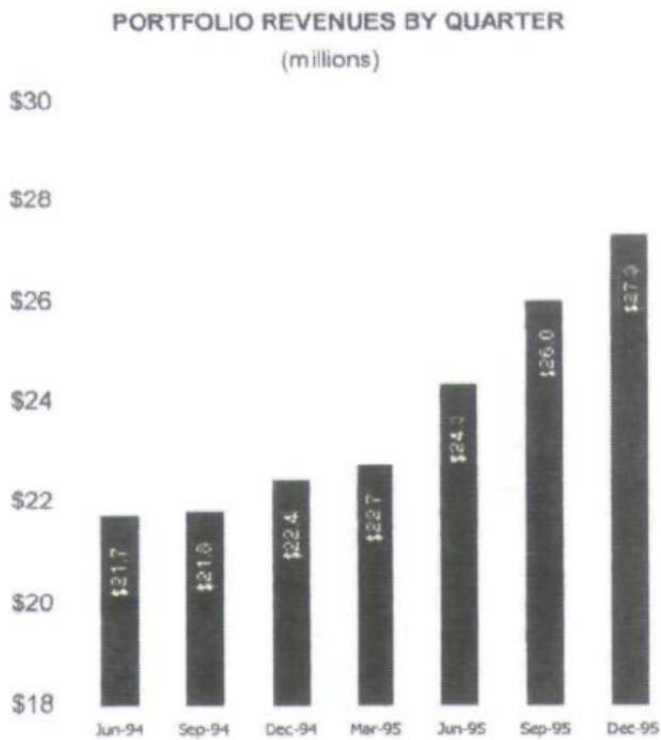
Though there are many rationalistic paradigms of decision making, many academicians have attempted to look at decision making from the perspective of the feeling of the decision maker. We no longer see a person, place or thing as a noun alone. Similarly no action is seen in itself. We qualify nouns and verbs by supplying adjectives and adverbs. Affective heuristic involves looking at any decision making stimulus from a “goodness” or “badness” perspective (Slovic et al. 2007). The decision maker either consciously or unconsciously accesses certain feeling states and clearly identifies a stimulus as being positive or negative. Zajonc (1980) posited that when an individual perceives a stimulus, affective reactions happen almost instantaneously. These guide subsequent judgment and decision making. Affect has been given an important role in the dual process theory of thinking and knowing (Chaiken and Trope 1999). Affect is central to the experiential system as is reasoning to the rational system. The central tenet of the affect heuristic is the concept of representation of objects and events as images in the human memory. These images are tagged with affect markers which either have positive or negative values. A decision maker employing the affect heuristic will search through the affect warehouse and use the affect markers to make a choice. Such a choice would deviate from objectivity and be prone to biases.

2.3.4 Distortions in Graphical Visualization

In the extant literature, there is plenty of evidence that well defined graphs improve the performance of the task by an individual (Benbasat and Dexter 1986; Blocher et al. 1986; Vessey 1991). However graphs can be drawn violating key guidelines and hence used to persuade a decision maker to focus on an exaggerated aspect of the data (Meyer 1997). Several researchers

clearly elucidate the proper design of graphs (Tufté 1997; Wainer 1997). The key principle outlines the idea that a decision maker using a graphical representation should be able to reach the same conclusion if he\she analyzes the numerical data that forms the basis for the graphical representation. Some of the principles identified by Tufté in 1983 include: - magnitude of the change represented by the graphical data should be proportional to the change in the underlying numerical data and, importance of clear labels and proper context that aids in the interpretation of the data. Some of the most common types of distortions that occur with graphical data include proportionality distortion, reversal of year, masking and absence of negative values in the graph (Arunachalam et al. 2002).

Proportionality distortion occurs when the graph designer violates the principle of depicting the trend in graph that is proportional to the trend in the underlying numerical data. Examples of this include the practice of not scaling the vertical axis properly which is achieved either by starting the vertical axis at a value other than the origin or by displaying a break in the scale. The sizes of the vertical axis intervals are rendered unequal and hence it distorts the trend.



(Franchise Financial Corp., 1995 Annual Report)

Figure 2.1:- Proportionality Distortion (source: - Arunachalam et al. 2002)

Figure 2.1 shows the vertical axis starting at \$18 instead of zero. Figure 2.2 shows a 100 percent proportionality distortion.

Accurately Drawn Graph



100 Percent Proportionality Distortion

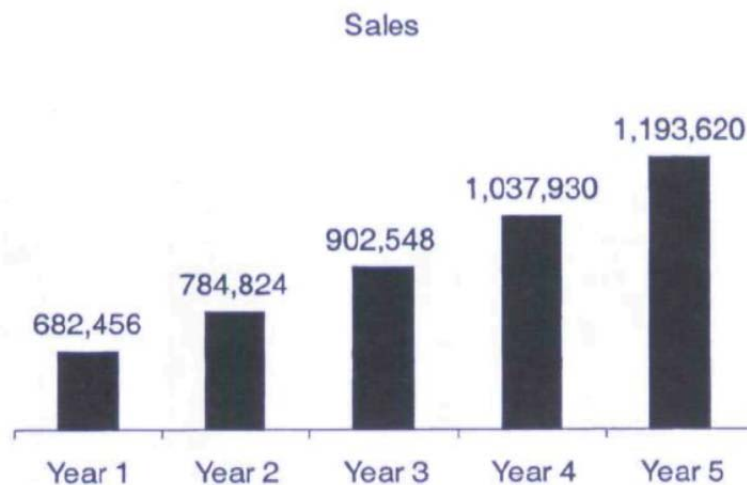
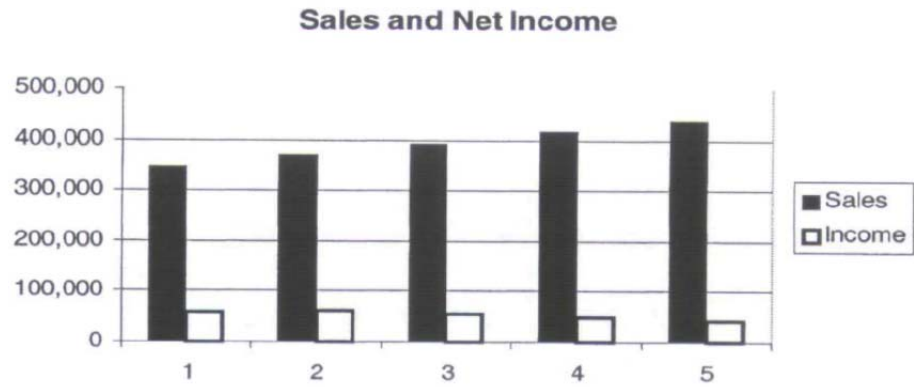


Figure 2.2:- Example of 100% Proportionality Distortion (source: - Arunachalam et al. 2002).

The graph on the top in Figure 2.2 has been drawn accurately with the origin beginning at zero. The sales have increased by approximately 75% over a five year period. The height of the bar representing the sales in the fifth year is 1.75 times the height of the bar of sales in the first year. The second graph shown at the bottom in Figure 2.2 has been drawn with the scale starting at a value other than zero and the height of the bar of sales of year 5 is approximately 3.5 times

the height of the bar of sales of the first year. Thus the dramatic growth of the sales deceives the decision maker. Steinbart 1989 indicates that this is often the most common form of distortions in financial reports.

Masking is the method by which changes in two variables are depicted on the same graph. This often detracts the viewer from noticing the changes on both the variables.



Correct Approach: Separate Graphs for Sales and Income Masking

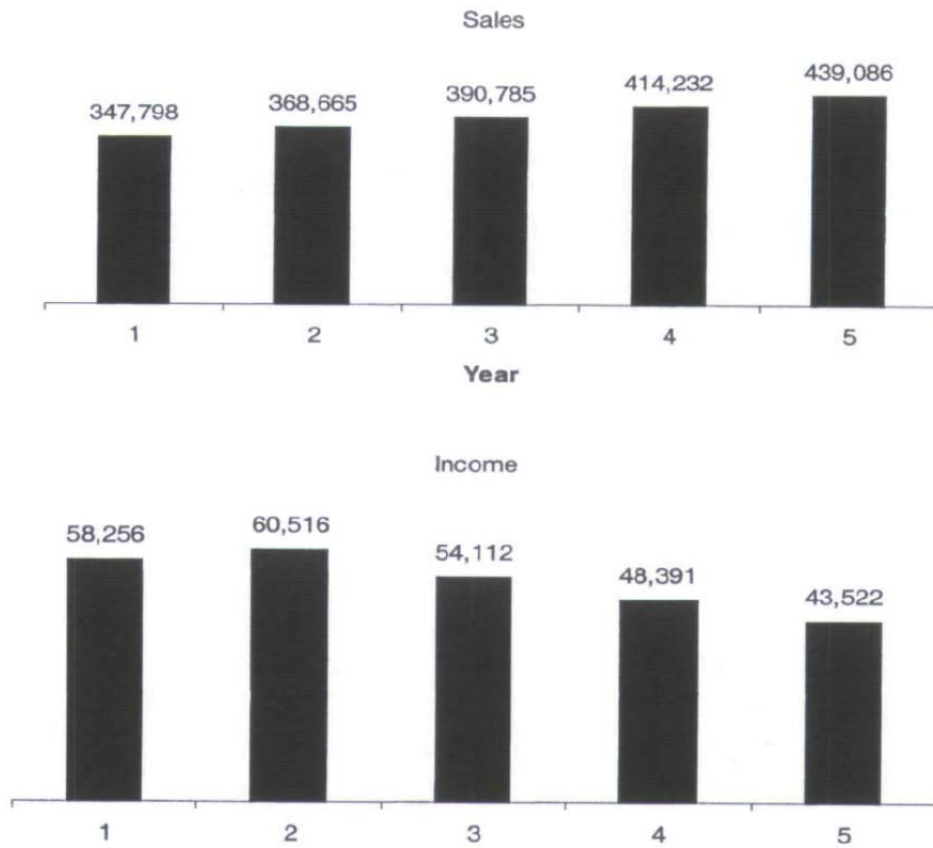


Figure 2.3 Example of Masking (Arunachalam et al. 2002)

Figure 2.3 shows that the declining changes in income is almost invisible when the changes in sales and income are depicted together thereby misleading the decision maker. The change in income over the years is clearly visible when graphed separately.

Year reversal is accomplished by reversing the sequence of years in the horizontal axis. Most people read from left to right and reversing the years often results in the misinterpretation of the trend in data.

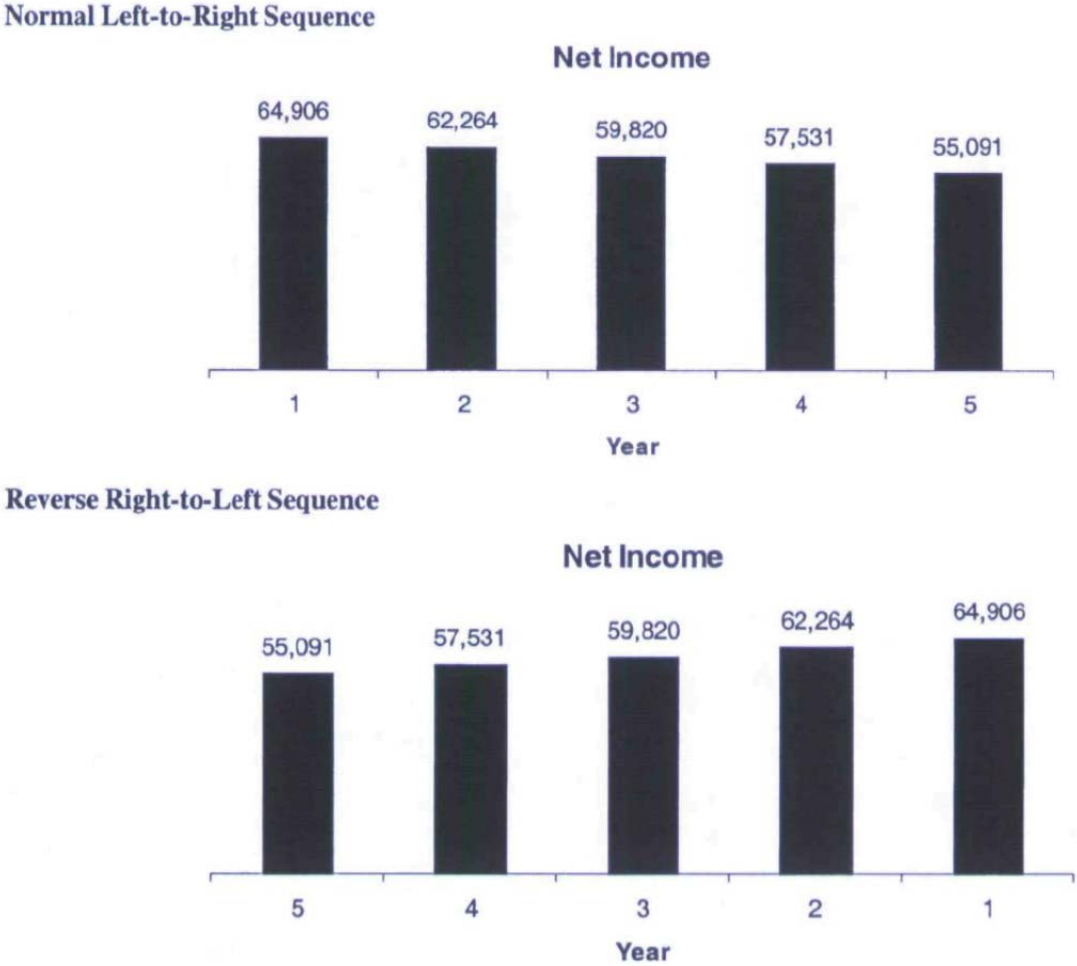


Figure 2.4:- Example of Year Reversal (Arunachalam et al. 2002)

Figure 2.4 is an example of year reversal, where the bar chart seems to indicate that the Net Income is increasing, when in reality it is not.

Omission of negative numbers is often done to erroneously portray a smooth change when in reality the graph variable has taken a dip. Our study examines the most common forms of distortion i.e. proportionality distortion and year reversal.

2.3.5 Impression Management

Many decision makers use financial information displayed on webpages, dashboards, and podcasts to choose among alternative course of actions. The financial information thus displayed often has many graphs such as bar charts, pie charts, line graphs etc. When these graphs violate the principles of effective graph design, they can mislead the decision maker and lead them to incorrect conclusions. The underlying data may suggest poor performance with respect to a financial metric. The decision maker could however be deceived into believing that the performance is good.

Impression management that was originally proposed by Goffman in 1959, was addressed at an individual level. It deals with how an individual acts in order to influence the perception of the audience (Beard 1996; Goffman 1959; Schneider 1981). Impression management at an organizational level emphasizes the actions taken by stakeholders in order to create or change the impression of the organization by a given audience (Elsbach 1998). They often use annual financial reports showing graphs of different financial metrics such as income, earnings per share and dividends per share to name a few. Prior research has been able to discern impression management being carried out via the medium of graphs (Beattie and Jones 1992; Frownfelter-Lohrke and Fulkerson 2001; Steinbart 1989). They are likely to display graphs

which have positive trends and not show them when they have a negative trend (Beattie and Jones 2000).

Many companies are increasingly turning towards online delivery methods in order to communicate financial information to their stake holders (Rapport 2005). The Regulation FD (SEC, 2000) requires that companies make public non-public information that is disclosed to certain stakeholders such as professionals in the security markets and individual shareholders.

Graphs that contained year reversal and proportionality distortion had the strongest effect on investor choices. The experimental subjects were deceived into making erroneous choices (Arunachalam et al. 2002; Pennington and Tuttle 2009). Academicians have explored warnings and prior training as methods to mitigate the sub optimal decision making due to impression management. However they have not been able to conclusively prove the success of both methods (Raschke and Steinbart 2008).

2.4 Biases and Distortions - Propositions

We have explained earlier the biases associated when the individual uses certain heuristics as a cognitive simplification strategy. Based upon our understanding of the inherent features of mobile devices, dashboards, cognitive biases and perceptual distortions, we arrive at certain propositions that tie them together. A mobile device is feature rich in terms of interaction. However it is characterized by small screen real estate. When a user faces a choice making scenario based upon key performance indicators presented on a dashboard, the cognitive load of the decision maker due to the uncertainties in the environmental context is further affected adversely. There is constant swapping of the contents of the working memory. The load on the associative memory is also quite high due to a need to establish a relationship between elements of the dashboard that are now distributed over the visual field of a mobile device which is not visible on a single view. The decision maker has to scroll or swipe and thereby go back and forth. Now we look at how the facets of mobile devices used by a decision maker is associated with certain biases and distortions.

2.4.1 Bias due to recall

When decision makers are faced with a situation where they have to judge the probability or frequency of an event, they could use the associative distance to a similar event that is stored in memory. Decision makers could be affected by vividness and temporal proximity of a similar situation and are biased towards unlikely events due to over estimation of their likelihood. The estimation of the likelihood of an event is based upon several mental operations that include retrieval, construction and association (Tversky and Kahneman 1973). Upon seeing a dashboard deployed on a mobile device, the user experiences an increase in the cognitive load due to

limitations in the working memory. Due to greater usage of the working memory in order to associate contents on the dashboard that are now distributed on the visual field, the decision maker has relatively only a limited space to accommodate the operations inherent in accessing the availability heuristic. Even though a similar event may be vivid and recent in the memory, the recall may be difficult for the user. Therefore the decision maker will be less susceptible to the biases associated with the ease of recall.

If the decision making situation is characterized by large amount of uncertainty, the user could face a dilemma where he has to choose between solving the problem using objective information displayed on the dashboard and using the availability heuristic. Faced with such a predicament, the user may use the affect heuristic which relies more on the quick and easily available experiential process that comprises the emotions and feelings towards a decision making situation. Hence we propose that:-

Proposition No 1. – Decision makers using a dashboard deployed on a mobile device facing a situation that has large uncertainty, may use emotions and feelings to decide and thereby will be more prone to bias associated with usage of affect heuristic and less prone to bias associated with ease of recall associated with the usage of the availability heuristic.

2.4.2 Bias due to retrievability

Certain memory structures are more retrievable than others (Table 2.2). However the working storage memory must be available to store the retrieved information from those complex memory structures. As explained earlier, decision makers using dashboards deployed on mobile devices already face a higher load on their working memory. Therefore the remaining

working memory may not be enough to facilitate the retrieval operations. Hence we propose that:-

Proposition No 2. Decision makers using information dashboards deployed on mobile devices are prone to bias associated with retrievability.

2.4.3 Bias due to preference accorded to certain associations

Decision making scenarios often involve two or more than two events that occur simultaneously. When two dichotomous events occur at the same time, there are four possible combinations. Decision makers may not take into account all the possible combinations and instead give preference to only a few due to employment of the availability heuristic. The information dashboard may provide for all the particular combinations. However the limitations imposed by the small screen size may force the decision maker to disregard the available pool of alternatives and instead consider the alternative provided by using the availability heuristic. So we propose that:-

Proposition No 3. Decision makers using information dashboards deployed on mobile devices are prone to bias associated with preferred associations.

2.4.4 Bias due to inadequate consideration of base rates

A dashboard presents information regarding key performance indicators related to the context of decision making. People often ask certain questions regarding the problem that they intend to solve. Often the question addresses how representative the variable is with respect to a stereotype stored in memory due to prior experience. As explained earlier, their disregarding the base rate information provided in the dashboard may result in a bias towards the stereotype. The

user may not be able to take into account the base rate information provide in the dashboard due to the limited screen size of the mobile device and subsequent distribution of that information across the visual field. So we propose that:-

Proposition 4. Decision makers using a dashboard deployed on mobile devices are more prone to bias due to ignorance of the base rate information on the dashboard.

2.4.5 Bias due to inadequate adjustment after initial anchor

Dashboards display information regarding the health of a situation that is of particular interest to the decision maker. The information helps establish an anchor which the decision maker uses to estimate. However decision makers do not adjust the anchors sufficiently and thus the result is often biased by the anchor. Also the decision maker is motivated to look for more information that is biased towards the anchor. Due to the small screen in a dashboard deployed on a mobile device these anchors may not be clearly visible to the individual. Or their presence may be neglected due to crowding of information. This could result in the decision maker searching for more appropriate anchors elsewhere. Since the decision maker deliberately looks for an anchor, we propose that the decision maker may make proper adjustments in order to arrive at the appropriate alternative.

Proposition 5 – Decision makers using information dashboards on mobile devices are less prone to bias due to inadequate adjustment of the anchoring position.

2.4.6 Distortions on dashboards deployed on mobile devices

Dashboards displayed on mobile devices are not visible with great clarity. The mobile user has to perform many operations such as scrolling, pinching and zooming in order to view the information presented. Only then, the individual can understand the message conveyed by the data visualization. The addition to the cognitive load has been clearly elucidated previously. Due to the increased cognitive load, the decision maker can miss certain important details. The decision maker perceives increased task complexity which could result in inadequate processing of cues present in the dashboard displayed. The scale of the y axis may not start from zero and the user may become oblivious to that manipulation. In a similar manner, the decision maker may not be able to discern that the years have been reversed in order to manage the impression. Therefore increased distortion could be caused. Hence we propose that:-

Proposition 6:- A decision maker using a dashboard displayed on a mobile device will be more adversely affected by proportionality distortion and year reversal distortion.

2.4.7 Heuristics and distortions on mobile devices

Employment of the representativeness heuristic by the decision maker could deceive him. A straight line that has an upward trend is often assumed to be representative of an increasing trend in the variable. However the dashboard itself may have been designed with the purpose of creating such an impression. The viewer may not be able to see the finer details on the dashboard deployed on a mobile device. Use of the representativeness heuristic in this situation could lead to greater deception.

Therefore we propose that:-

Proposition No 7. : - Dashboards that have proportionality or year reversal distortions, when deployed on mobile devices could make the decision maker susceptible to the impression management motives of the dashboard designer.

2.5 Conclusion

The popularity of mobile devices in the current technology landscape has created an inherent bias towards them when individuals and organizations choose to deploy data visualizations. In addition, the decision maker carries many different cognitive biases. We have conducted an extensive literature review and identified the various forms of biases. We also identify certain distortions which may affect the perception of the decision maker. After considering the different aspects of the phenomenon, we propose the impact of biases and distortions on mobile decision making. More research needs to be carried out to understand how dashboards can be designed better in order to reduce the susceptibility of the user to cognitive biases and distortions. External regulatory mechanisms may also help mitigate the deleterious effects of cognitive biases and distortions.

CHAPTER 3

APPEARANCE AND REALITY – DASHBOARDS ON MOBILE DEVICES– AN EXPERIMENTAL STUDY

3.1 Abstract

Can users solve problems accurately using dashboards deployed on mobile devices? Dashboards are displays of key performance indicators on a single screen that aid a decision maker in problem solving and decision making. The use of mobile devices has seen a tremendous surge in the last decade. Dashboards are now increasingly available on mobile devices. We look at the two crucial aspects of content i.e. deployment and design of these dashboards and context i.e. integration of the elements of a problem solving task. We borrow from the extant literature in several reference disciplines such as educational and instructional psychology, cognitive psychology, advertising and vision search in order to arrive at the hypotheses. We conduct a laboratory experiment to validate the conceptual model. The results of the experiment indicate that on problem solving tasks, high active control influences the task accuracy and task satisfaction less favorably on dashboards deployed on mobile devices than dashboards deployed on static devices. Thus we inform the academia with some interesting results and offer directions for future research. Based upon our findings we would like to recommend certain design and deployment combinations under different conditions, which will be of value to the practitioner community.

3.2 Introduction

Since the advent of computers nearly six decades ago, the world has seen enormous changes along the length and breadth of the technology landscape. Clearly, by all accounts the use of mobile devices is pervasive today. According to Gartner 2015, worldwide mobile phones sales are forecast to reach almost 2.06 billion out of the total sales of 2.6 billion computing devices (including PC's and tablets) in 2017 (Gartner 2015). Today the world can be described as FMWC (Fully Mobile Wirelessly Connected) world (Gorlenko and Merrick, 2003). In organizations, one can witness the arrival and sustenance of a group of decision makers called the "mobile elite", a group which makes use of the latest in technology related to mobile devices. This group is empowered to conduct business in a manner that is distinctly different from the employees of yesteryears. Using the communication and visualization technologies in order to make effective and efficient decisions, they are able to contribute to the success of the business enterprise (White, 2012). Interest in Mobile Business Intelligence is growing rapidly as indicated by the keen interest of today's workforce in information that is available real time, anytime and anywhere. BYOD (Bring Your Own Device) is a new paradigm that is increasingly becoming popular and is in the forefront of the rapid consumerization of information technology.

Our search for the text "Business Intelligence" in the quite ubiquitous Google search engine showed 80 million hits in 2016. Among the various elements of Business Intelligence, our search for the text "Data Visualization" alone showed 6.7 million hits in 2016, an increase of more than 100%, from 1.2 million in 2007 (Malik 2007). This points to a surge in the popularity of data visualization. In a study conducted by IDC 2011 for Unisys, it was seen that the percentage of personal devices (such as mobile phone, iPhone and iPad) used to access business applications has increased by 30%, from 30.47% to 40.47% in just one year. The CEO of Unisys

commented that employees in an organization want to use the device that they prefer instead of being guided by the organization.

Managers in an organization are involved in problem solving and decision making. Problem solving involves identifying issues to attend, setting goals and determining alternative courses of action. Decision makers then evaluate the alternative courses of action and choose a particular action (Simon et al. 1987). We cover decision making in detail in the literature review section of the report. Decision makers are able to access crucial company data at any time and from any location. The key constituent in this burgeoning phenomenon is the one screen display of various key performance indicators of the unit that decision maker is associated with. We refer to such display of data as dashboards. Many vendors including Tableau, Qlikview, and Dundas now offer different kinds of dashboards. It has even caught the imagination of academia, where courses are being taught using dashboards.

We look at the history and purpose of dashboards in detail in the literature review section. Dashboards are increasingly used for performance management using KPI's (Key Performance Indicators) displayed in various visual forms such as tables, charts, graphs and maps. Our research pertains to the problem solving context in the area of performance management.

Dashboards are being deployed on various kinds of devices such as mobile and static computing devices. A user can view the dashboard on a desktop and on his iPhone or Android. Mobility and screen size are two key attributes that differentiate desktops from mobile devices. Academicians have begun investigating the impact of screen size on decision making performance. Hancock et al (2015) look at how the screen size in combination with various viewing conditions such as viewing distance and subtended angle is related to the response speed

and accuracy. Jakobsen and Hornbaek (2013) did an empirical investigation on the scalability of interactive visualizations on small and large displays (desktops and large information displays). While these are notable contributions to the field, we are greatly intrigued by the following research question: -

Q1. Are mobile dashboards different from static dashboards with reference to their impact on task accuracy and task satisfaction?

Dashboards are used for different purposes such as to ensure consistency, communication, performance monitoring and planning. Dashboards use many different visual representations such as tables, charts, graphs and maps. KPI's are monitored with the primary motivation to answer the question: - Is there an exception situation? The answer to this question results in identification of various alternatives to take care of the exception condition. The decision making phase then identifies the optimizing or satisficing alternative for implementation. Identification of the exception situation often involves a series of intellectual or problem solving tasks that have a correct answer. The tasks with respect to dashboards could be based on either a single source of information or multiple sources of information (tables, charts, graphs or maps) that need integration. We identify the former as representing the singular problem type and the later as the integrative problem type. Therefore the research question:-

Q2. Do dashboards deployed on mobile devices differ from dashboards deployed on static devices in task accuracy and task satisfaction, when they are used to solve singular and integrative problems?

Academicians have studied website interactivity and its impact on certain outcome variables such as buying intention (Jiang et al. 2010). Dashboards can be designed to offer little

choice to the user with respect to the control of the form and content. On the other hand they may be highly interactive and provide control through filters and drill down facilities. Our in-depth literature review did not yield any empirically tested findings regarding the active control of dashboards. Hence we ask the following the research question: -

Q3. Do dashboards deployed on mobile devices differ from dashboards deployed on static devices in task accuracy and task satisfaction, when they have low and high control features?

We note that our research questions in the performance management context neatly fit into framework given in appendix A (Yigitbasioglu et al. 2012). Our study looks at problem solving using dashboards deployed on various devices. We conduct an extensive literature survey in information systems with specific reference to information presentation and visualization, and look at several reference disciplines such as decision making, instructional psychology, cognitive psychology, vision research and advertising to provide us deeper and richer insights. We develop a model and validate the model using an experiment.

We hope to contribute to the academic research by looking in detail at this popular phenomenon and to practitioners by coming up with certain interventions regarding the design and deployment of the dashboards that can help decision makers. We would like to understand the impact of using mobile devices to solve problems and make decisions and make recommendations on designing effective data visualization aids.

Ariely (2000) in a seminal experiment has looked at the impact of controlling the information flow on decision making. Our study looks at the impact of controlling the content of information presented to the user on problem solving.

3.3 Literature Review

The information technology landscape is changing rapidly. The impact of this wave after wave of technological improvements is felt by organizations as they are overwhelmed by enormous amount of data. Key decision makers in organizations are faced by the triumvirate of complexity, change and diversity (Jackson, 2008). The data that becomes the backbone of decision making reflects these aspects. We did have many different information presentation formats before, like text based, graph based, video and audio based. The most recent development is that of the information dashboard. The key phenomenon of interest in this dissertation is decision making using information dashboards deployed on static and dynamic computing devices.

What is a dashboard? “A dashboard is a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance” (Few, 2006) . “Dashboards have not been invented to be mere data displays; their mission should be to help users make better decisions and achieve their goals” (Fronza, 2013). Dashboards allow decision makers to make immediate sense of dense information enabled by the effective presentation on a single screen. Indeed, one can say that dashboards are a type of decision support system (Arnott and Pervan, 2005). The modern day dashboards are designed using principles from such diverse disciplines as information systems, accounting and cognitive psychology. One of the key differentiators of the modern day dashboard and the myriad information presentation formats of yesteryears is the way the complex data is communicated to the decision maker through a process called visualization. The focus of visualization is on the amplification of cognition (Card et al. 1999).

Dashboards trace their origin to the EIS (Executive Information System) of the 1980's. Though these visionary systems provided information to the senior executives, they could not effectively integrate all the different data sources. Towards the end of the 1990's, many BPM (Business Performance Management) tools such as balanced score card emerged. The Enron scandal in 2001 was one of the chief instigators that beckoned companies to look closely at performance management (Few, 2006). The dashboards of today have the capability to access data from a variety of sources including legacy flat files, modern databases, ERP sources, Hadoop repositories and others and show a concise picture to the decision maker. This picture usually represents the KPI's (Key Performance Indicator) of the past and present and the metrics relevant to the future. The user can use various features such as drill down and what-if analysis in order to monitor performance. Indeed dashboards can be designed in order to fulfill different roles such as strategic, analytical or operational. While operational personnel such as service advisors at a car dealership can use them to monitor servicing of cars arriving for maintenance, middle level managers can use them in an analytical mode to understand deviant measures and top level executives can use them to see how the company is performing relative to strategic objectives. The modern dashboard, in addition to being a key tool for performance management, is also used for advanced analytical purposes enabled by tools such as scenario analysis and drill down capabilities.

The early predecessors of dashboards were the many different display and presentation formats. In the 1980's and 90's several articles appeared in leading information systems and management journals that studied the impact of different types of display format and information presentation on decision making. Benbasat and Dexter (1985) conducted an experiment to understand the impact of graphical information presentation on decision quality, decision time

and user perceptions of information system attributes. The theory of cost-benefit of information presentation (Beach and Mitchell, 1978) posits that decision makers work to strike a balance between the effort required to make a decision and the accuracy of the outcome. The two key elements of any problem in a decision making scenario are the problem representation and the task. When the information type inherent in the problem representation matches the information type in the task, the problem solver uses similar processes to process the information, which aids in decision making (Vessey and Galetta, 1991). Vessey (1994) used the theory of cognitive cost-benefit and cognitive fit to look at the impact of information presentation on decision making, and theorized that decision makers were bound to sacrifice some accuracy in order to reduce cognitive effort. While these and many others made stellar contribution to research, dashboards have received scant attention in both academic and industry journals, with a few noteworthy exceptions.

A survey of top journals including MIS Quarterly, Journal of Management Information Systems, Information Systems Research, Decision Sciences and Decision Support Systems revealed that there was only one article with dashboards as the main topic. Negash and Gray (2008) have identified dashboards as one of the key BI (Business Intelligence) tools. Many accounts of the successes and failures of dashboards have appeared in journals. Edward Hospital used the IBM Business Objects Dashboard manager in order to manage account receivables and hence improve cash flow (Yigitbasioglu et al. 2012). Continental Airlines implemented the flight management dashboard as a part of its real time business intelligence initiative. This helped the airlines improve its profitability by enabling the operations staff identify flight network issues that affected customers before the flight management dashboard was implemented (Watson et al. 2006; Wixom et al. 2008). Pauwels et al in 2009 looked at dashboards with specific reference to

the motivations of using them, implementation stages, and selection of metrics. They attributed the motivation of using dashboards to poor organization of relevant data, biases of decision makers, accountability and integration of practices dealing with reporting of the performance.

Dashboards are related to information presentation format and our literature survey revealed many articles in leading journals that have delved deep into this aspect. However, there is perceptible disagreement over the key determinants of what contributes to effective and efficient decision making using these prevalent information presentation formats (O'Donnell and David, 2000). While Vessey in 1991 laid emphasis on the type of tasks, others have brought to the fore various determinants such as knowledge (Cardinaels, 2008), cognitive style of the user (Huber, 1983), and personality of the user (Boon and Tak, 1991).

A review article on information dashboards by Yigitbasioglu and Velcu (2012) captures the key details succinctly in a table which is presented in appendix B. The above literature review and the literature review done by us have highlighted one particular aspect of the research on dashboards i.e. while there is a plethora of articles that have looked at presentation formats in great detail, only a handful have looked at dashboards in particular. This report has highlighted the difference between the two earlier. Our research addresses a key issue which is missing from the current discourse. The overarching research question that we seek to address in this research is: - How do the dashboard deployment media type, problem type and active control relate to task accuracy and task satisfaction when dashboards are used for problem solving tasks?

3.3.1 Decision Making

Decision making by decision makers is quite ubiquitous, both inside and outside organizations. It has received considerable attention of researchers from diverse disciplines such

as management, economics, psychology, cognitive science and operations research. A decision is quite important because it is irrevocable. A decision is made by the decision maker who invests in certain amount of thought and effort. Each decision has consequences that are relevant to the values of the decision maker (Edwards and Fasolo, 2001).

There are various theories of decision making. They are broadly classified under normative and descriptive categories. Normative theories seek to elucidate how decisions should be made, whereas descriptive theories elaborate on how decisions are actually made. The human decision maker, under the normative theory, was thought to be an economic man who is completely informed, infinitely sensitive and deeply rational (Edwards, 1954). A rational decision maker should be able to choose an option that maximizes his utility when the choices are riskless. When dealing with risky choices, the decision maker would maximize the expected utility. Examples of normative theory include the subjective expected utility theory, and the different models that deal with multiple objectives and/or multiple attributes. In reality, however, the human decision maker is often seen to indulge in irrational and below optimal decision making due to limited cognitive capacity and environmental complexity (Simon, 1956). Simon questioned the normative approaches, highlighting the importance of perceptual, cognitive and learning factors that influence decision making. The behavioral decision making paradigm which forms a part of the descriptive decision theory, dealt with the imperfect decision maker and allowed for the constructive nature of preferences and beliefs (Payne and Bettman, 1992). This study was one among the many to challenge the assumption of invariant preference structure of normative theories. They argued that preferences may shift as new knowledge becomes available. Decision makers may start with very vague and fuzzy goals that seem to become clearer as they take part in the decision making process (Slovic, 1995).

Decision making can be understood as a three stage process (Beach and Connolly, 2005). In the first stage, anomalous events trigger the diagnosis stage. These events could be internal or external changes. The decision maker could also realize that decisions made in the past did not result in the desired results. For the current scenario, the decision maker may draw upon a set of frames or lenses that have been conditioned by past experiences, beliefs and values. The decision maker often diagnoses the situation by looking at the most salient features. The decision maker selects an appropriate action in the next stage. Many economic and rationality based theories propound that the decision maker has knowledge of a set of options to choose and maximizes the expected utility by choosing the best possible option. However there has been a growing realization, that decision making often is characterized by a sense of “feeling along” (Beach and Connolly, 2005) where the decision maker does not know all the alternatives at a given point of time. Rather, he or she learns along the way by some form of feedback. This view accommodates the phenomenon of dynamic decision making. The process of decision making culminates in the implementation stage. In this stage the decision maker acts upon the chosen option and verifies that the anomalous conditions are ameliorated. We wish to highlight the fact that in decision making, there is a fair amount of feedback in the process involved which enables the decision maker learn on the go and dynamically construct his preferences.

3.3.2 Decision Support Systems on Mobile Devices

The data communication technology has evolved significantly over the past two decades enabling users to transmit data rapidly through hand held devices. By all accounts, the dawn of the internet age has been accompanied by the swift rise of mobile devices. There is tremendous variety in hardware, software and network options available for mobile devices. They are being used extensively by people in decision making, at various levels of the organization. When one

goes to a car dealer to show the car to a mechanic, the service advisor comes to greet you with an iPad and notes down your service request. Later on he works on the service request on a desktop device. Mobile devices are lightweight, can be carried on person and often reflect the convergence of many technologies with different functionality. We are in an age of nomadic computing, and these devices offer tremendous possibilities in terms of accessibility and sharing of information (Lyytinen and Yoo, 2002).

Decision Support Systems evolved at the confluence of two major concepts, Anthony's categorization of management activities (Anthony, 1965) and Simon's demarcation of decision types (Simon, 1960). Anthony divided management activities into three levels of strategic planning, management control and operational control. Simon described the management decision making problems along a continuum, from programmed at one end to the ill structured, non-programmed at the other end. Gorry and Scott Morton in 1970 combined both and created a new classification of decisions, with the three classes of structured, semi-structured and unstructured decisions. They also brought in Simon's phases of decision making such as intelligence, design and choice. Intelligence refers to the search for problems, design to the extraction of alternatives and choice to the process where one of the alternatives is chosen for decision making. A DSS (Decision Support System) is primarily a human-machine problem solving system dealing with at least a stage which is semi-structured in nature using the judgment of the decision maker (Gorry and Scott Morton, 1970). With the advent of the Internet, web based decision support systems became more and more popular. Web based decision support systems were different from the earlier generation of decision support systems. They focused on customers in addition to employees, addressed different problem domains and had a different architecture using a thin client (Bharathi and Chaudhary 2004). Shim et al (2002)

have looked at the evolution of decision support systems as new paradigms of technology, structure and systems. They have highlighted the emergence of the mobile decision support systems as mobile devices become more and more popular. This has been attributed to the increasing role played by the e-services, and wireless access protocols.

Mobile devices are characterized by mobile interaction whereas stationary devices are associated with stationary interaction. Gorlenko and Merrick (2003) have captured the key differences between the two types of interactions in the following table.

Interaction Parameters	Stationary Interaction	Mobile Interaction	
		Mobile Office Context	Field Context
Environment	Largely indoors, few fluctuations in the environment	Indoors and outdoors, with frequent fluctuations	Indoors and outdoors, with frequent fluctuations
Device Size	Medium to large	Small	Small
Time of Interaction	Medium to long	Short to medium	Short to medium
User Mobility	Fixed, mainly sitting position, restricted body maneuver	Any position, various degrees of free body movement allowed	Any position, various degrees of free body movement allowed
Competition for Attention	Little	Some	Significant
Task Hierarchy	As a rule, interaction-related tasks are the primary activity	Interaction-related tasks may be a secondary activity	Interaction-related tasks are mainly a secondary activity
Parallel Manipulation of Physical Objects outside Interaction	Rare	Occasional	Frequent
Interaction Styles	High dependence on direct manipulation; other styles are complementary	Greater reliance on forms and menu selection, supported by direct manipulation and natural language	Natural language is of prime importance, supplemented by menu selection and forms

Table 3.1:- Stationary versus Mobile Interaction

The research on mobile decision support systems is quite scarce, with certain exceptions. Heijden and Sorenson (2002) look at mobile decision aids and their impact on decision making effectiveness with respect to one decision making strategy i.e. the additive compensatory strategy. Heijden 2006 has looked at a consumer based mobile decision support system and

found attractiveness of the product to be a key determinant of its effectiveness. However, there are no articles in leading information system journals that deals with decision making using information dashboards.

3.3.3 Cognitive Load

Based upon Simon's bounded rationality theory, one can understand that decision making in an organization at any level involves a certain amount of cognition and hence there is a load on the cognitive system of the decision maker. A key tenet of the theory that has been widely used in the design of instructional materials and e-learning pertains to the notion of a limited working memory capacity and a large long term memory capacity (Baddeley 1976; Miller 1956). Each sensory channel is related to the processors that are partially independent which comprise the working memory. While the processor for the visual information is the "visuo-spatial sketchpad", the phonological loop takes care of the audio information. In the field of instructional design, the stipulation of the cognitive load theory with respect to the limitations of the working memory has been widely used (Hollender et al. 2010).

Cognitive load theory clearly divides the load on the working memory into the three different types (Sweller et al. 2011). Intrinsic load is the load on the working memory due to the complexity of the domain of the pertinent information. One of the key determinants of intrinsic load is the interactivity of elements. Extrinsic load is the load imposed on the cognitive memory by the presentation format. Several factors may influence extrinsic load, including the need to integrate elements on different areas or screens of the presentation format. Since working memory is limited, if there are more disparate pieces of information to be integrated, then there is

a need for swapping of the contents of the working memory. Germane cognitive load is the load imposed on the memory due to construction of schemas dynamically (Sweller et al. 1998).

Intrinsic, extrinsic and germane cognitive loads are additive in nature. Since it is not possible to control the intrinsic load associated with the decision making domain, one can reduce the extrinsic load. The working memory space freed up by reducing the extrinsic load can be allocated to germane load (Paas et al. 2003). The increased germane load capacity has the potential to increase active schema preparation and hence enhance learning.

3.3.4 Interactivity

Academicians in many reference disciplines such as learning, child development, communication, marketing and advertising have looked at interactivity. Steuer (1992) defined interactivity as the ability of the user to change the form or content of a web-site operating under real time conditions. Liu and Shrum (2002, 2009) have explicated the construct as a multi-faceted one addressing the three aspects of user-machine, user-user and user-message interaction. Interactivity has been defined as “The degree to which two or more communication parties can act on each other, on the communication medium, and on the messages and the degree to which such influences are synchronized” (Liu and Shrum 2002). Interactivity of websites comprises two components – mechanical and social (Hoffman and Novak 1996).

The three dimensions of interactivity are active control, two-way communication and synchronicity. Active control is the voluntary control exercised by the user of the machine. This is also referred to as mechanical interactivity (Jiang et al. 2010). Using active control the user is able to make a choice about the information to be displayed. In a dashboard, active control is provided by the sliders, filters and drill down facilities that guide the interaction of the user. The

user actively makes a conscious choice regarding the information. Reciprocal communication is the two way communication and involves feedback. Synchronicity is concerned with the immediacy of the feedback from the other communicating party.

When an information system provides active control, it enables the user to act with a greater degree of autonomy and flexibility (Kettanurak et al. 2001; Teo 2003). Liu and Shrum (2002) propose that active control facilitates a greater sense of controllability, which in turn fosters self-efficacy (Gist and Mitchell 1992). Liu and Shrum then, propose self-efficacy as a partial mediator leading to greater user satisfaction.

Information control, which is the essence of the mechanical aspect of interactivity, has associated benefits and costs. Researchers identified benefits in probabilistic learning environments where the emphasis is on identifying probabilistic linkages among attributes (Hammond et al. 1980; Hammond et al. 1975). Klayman (1988) empirically validated that when subjects are allowed to design their own learning environments, they not only exhibit greater learning but also greater command over the structural foundation of system environment. Children, with control over the games used for learning, exhibited greater anticipatory schemas with respect to their actions' outcomes (Kuhn and Ho 1980). While the above studies focused on the benefits, several others looked at the costs of providing information control.

Users working in highly interactive environments feel that the information control itself becomes a secondary task (Posner 1986; Treisman and Davies 1973). Understanding the information is the primary task. Users when faced with limited processing capacity can be handicapped by this additional task. The users have even lesser resources available for the primary task (Anderson 1983; Bongard 1995). This increased demand on the cognitive resources

led to decreased comprehension. In the case of interactive information systems, the primary task of understanding the information is often dependent upon how the secondary task of information control is executed. Ariely (2000) experimentally validated that information control positively impacted performance outcomes under conditions of low cognitive load. However, under high cognitive load conditions, providing information control led to poor performance. Jiang et al (2010) have posited and empirically validated cognitive and affective involvement as mediators to the impact of active control on the dependent variable of purchase intention in the context of online shopping using interactive websites.

3.3.5 Competition for Attention Theory

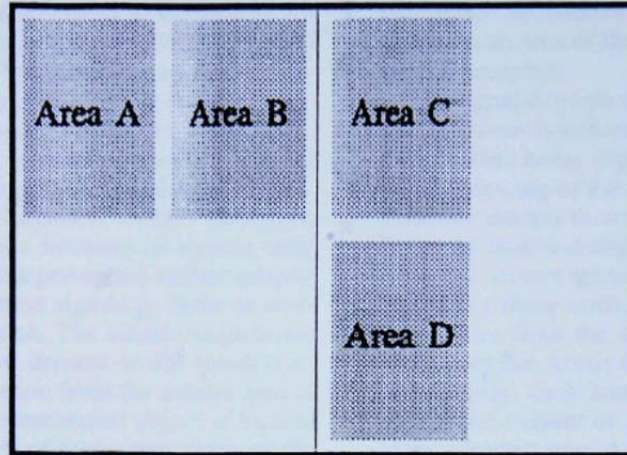
A user sees certain objects in the visual field. The human attention is capable of seeing only certain objects due to processing limitations (Kahneman 1973; Pashler 1998; Shaw and Shaw 1977). The focal and non-focal objects compete for attention of the user within the same visual field (Janiszewski 1998). The human visual processing system is made of certain receptors in the retina and influences the attention gathering of focal and non-focal objects. The two determinants of the demand on attention, i.e. salience, and the distance between the object and the area of focal attention have been studied in advertising. Salience is often changed by manipulating the size and contrast of the object in the viewing field (Janiszewski 1998). Contrast is determined by the uniqueness of certain features of the object. This enables the focal object to stand out among non-focal objects.

The demand on the attention of the viewer by the surrounding non-focal objects is calculated by dividing the square root of the area of the non-focal object by the distance between the centers of the focal and non-focal objects (Janiszewski 1998). Hong et al 2004 have

compared the demand on attention by matrix and list displays of online websites and proved that the demand of competing objects of attention of a list display is more than that of a matrix display.

FIGURE 2

THE COMPETITION FOR ATTENTION EXPERIENCED DURING THE VIEWING OF EACH AREA OF A DISPLAY



COMPETITION FOR ATTENTION WHILE VIEWING AREA A			
Area _a	Size _b	Dist _c	Demand _d
B	7cm	7cm	1.00
C	7cm	14cm	0.50
D	7cm	16cm	0.44

COMPETITION FOR ATTENTION WHILE VIEWING AREA C			
Area	Size	Dist.	Demand
A	7cm	14cm	0.50
B	7cm	7cm	1.00
D	7cm	8cm	0.88

COMPETITION FOR ATTENTION WHILE VIEWING AREA B			
Area	Size	Dist	Demand
A	7cm	7cm	1.00
C	7cm	7cm	1.00
D	7cm	10cm	0.70

COMPETITION FOR ATTENTION WHILE VIEWING AREA D			
Area	Size	Dist	Demand
A	7cm	16cm	0.44
B	7cm	10cm	0.70
C	7cm	8cm	0.88

Figure 3.1 Demand on Attention by Various Non-focal Objects on the Focal Object (Janiszewski 1998)

3.3.6 Scanpath Theory

The human eyes perceive various objects in the external environment. Noton and Stark's (1971) seminal scanpath theory in the area of vision research explains the function of eye movements in an object field. The reference discipline of marketing and advertising has used it to explain the effect of various aspects of product communication. Eye movements are typically made up of saccades and fixations. When the human eye moves from one location to another in a visual field, the vision is suppressed. Saccades represent these quick movements. When the eyes rest on an object, their mobility is suppressed. Fixation is the gap between two saccades. Design of advertisements has to focus on the content and pattern of these fixations (Pieters et al. 1999).

Scanpaths refer to how the fixations follow in quick succession. There are two types of scanpaths – Local and Global (Groner et al. 1984; Groner and Menz 1985). Local scanpaths indicate fixations that rapidly follow each other quickly over the visual area. The stimuli represented by the objects in the visual field regulate the eye movements in a bottom-up mode. Global scanpaths, on the other hand, involve greater duration on each fixation over a longer time frame and are guided by the top-down processes that originate in the user. The user, in such situations is motivated by certain search strategies.

3.3.7 Memory

Memory of the decision maker is a key factor in decision making. Associative memory and working memory are the two distinct parts of memory. Procedural tasks involving small screen devices are often hampered by memory overload due to the demands made on associative and working memory (Byrd and Caldwell 2011). A dashboard may have many graphs and tables. Associative memory explains how the knowledge ingrained in one element is related to the

knowledge inherent in other elements of the screen. It is also related to how various objects are situated on a display device and the conceptual glue that one can apply to them. Working memory refers to the short term retentive capacity of the brain involved in a decision making task using cognitive resources (Byrd and Caldwell 2011). The decision maker may look at a portion of a dashboard, look away and make a decision. The working memory has a role to play during this transition period.

When viewing a dashboard on a mobile device with small screen real estate, the information may be distributed over multiple screens. Then the user has partial view of information at any given time. Therefore, the user requires a mental visual image in order to understand the situation holistically (Kosslyn and Thompson 2003). The small screen real estate user with low spatial ability finds it difficult to construct a visual mental model of the system which has been found to impact performance (Stanney and Salvendy 1995). Such a user increases the demand on his associative memory due to the need for cognitively arranging the whole piece of the puzzle while creating the visual mental model.

3.3.8 Dependent Variables

The dependent variables of this study are task accuracy and task satisfaction. Task accuracy is defined as the proximity of the task solution of an individual to a known, correct answer. Kintsch (1988) captures it succinctly in the following :- “Discourse comprehension, from the viewpoint of a computational theory, involves constructing a representation of a discourse upon which various computations can be performed, the outcomes of which are commonly taken as evidence for comprehension” (p. 164). User comprehension has been identified with three outcomes, namely, task accuracy, task timeliness and mental workload

(Baddeley 2003; Kintsch 1988). In the field of human-computer interaction, it has been identified as a part of the task performance measure (Kim et al. 2009). Task accuracy has been measured by the percentage of correct answers in a given task (Romano-Bergstrom et al. 2013) or across many sub-tasks (Biros et al. 2002). Decision accuracy with respect to a decision making task is measured by the distance of the solution obtained by the user from the correct solution (Benbasat et al. 1986; Dickson et al. 1986)

A dashboard is an instance of an information system. Academicians have looked at user satisfaction from the perspective of various theories such as Expectancy, Utility and Needs theories. A product aims to fulfill the need of a consumer to some extent. Oliver (1997) gave a definition to product satisfaction that used the level of pleasure gained by consumer. The marketing discipline explains consumer satisfaction by understanding the extent to which expectations have been disconfirmed (Yi 1990). Bhattacharjee (2001) and Ryker (1997) have used the expectation confirmation theory to explain information system satisfaction.

Academicians in the consumer behavior arena have used equity theory (Adams 1965) to explain product satisfaction. Equity theory posits that if the individual's inputs are greater than the benefits received, then there is dis-satisfaction. This does not depend upon the benefit-input ratio of the other individuals. Similar concepts have been used in IS research (Boddy 2002; Goodhue and Thompson 1995; Joshi 1989). Satisfaction has also been defined as the extent to which a product satisfies the innate needs of an individual. Needs theory has several proponents including Alderfer (1969), Herzberg et al (1959), Maslow (1943), and McClelland (1965). Bailey and Pearson (1983) and Goodhue (1998) have used this approach in the Information Systems area. Au et al (2008) have combined the above theories in an equitable needs fulfillment model to explain end user satisfaction.

Balijepalli et al (2009) and Mangalraj et al (2014) have investigated task satisfaction in the context of programming and software design tasks respectively. Task satisfaction is the affective response of an individual to the overall task. Balijepalli et al (2009) empirically validated that during a programming task, pairs were more satisfied with the task than individuals. Mangalraj et al (2014) found that during a software design task, the task satisfaction of pairs were higher than that of individuals.

The satisfaction of the user performing a task is related to the three components of interactivity namely active control, two-way communication and synchronicity (Liu and Shrum 2002). Active control increases the controllability of individuals and has pleasurable effects. When individuals have greater control, their self-efficacy belief increases (Gist and Mitchell 1992). Liu and Shrum propose that the relationship of active control with user satisfaction is partially mediated by self-efficacy.

3.4 Model and Hypotheses Development

We now discuss the conceptual model (Figure 3.2) and the various hypotheses regarding the relationship between the constructs of interest in this study.

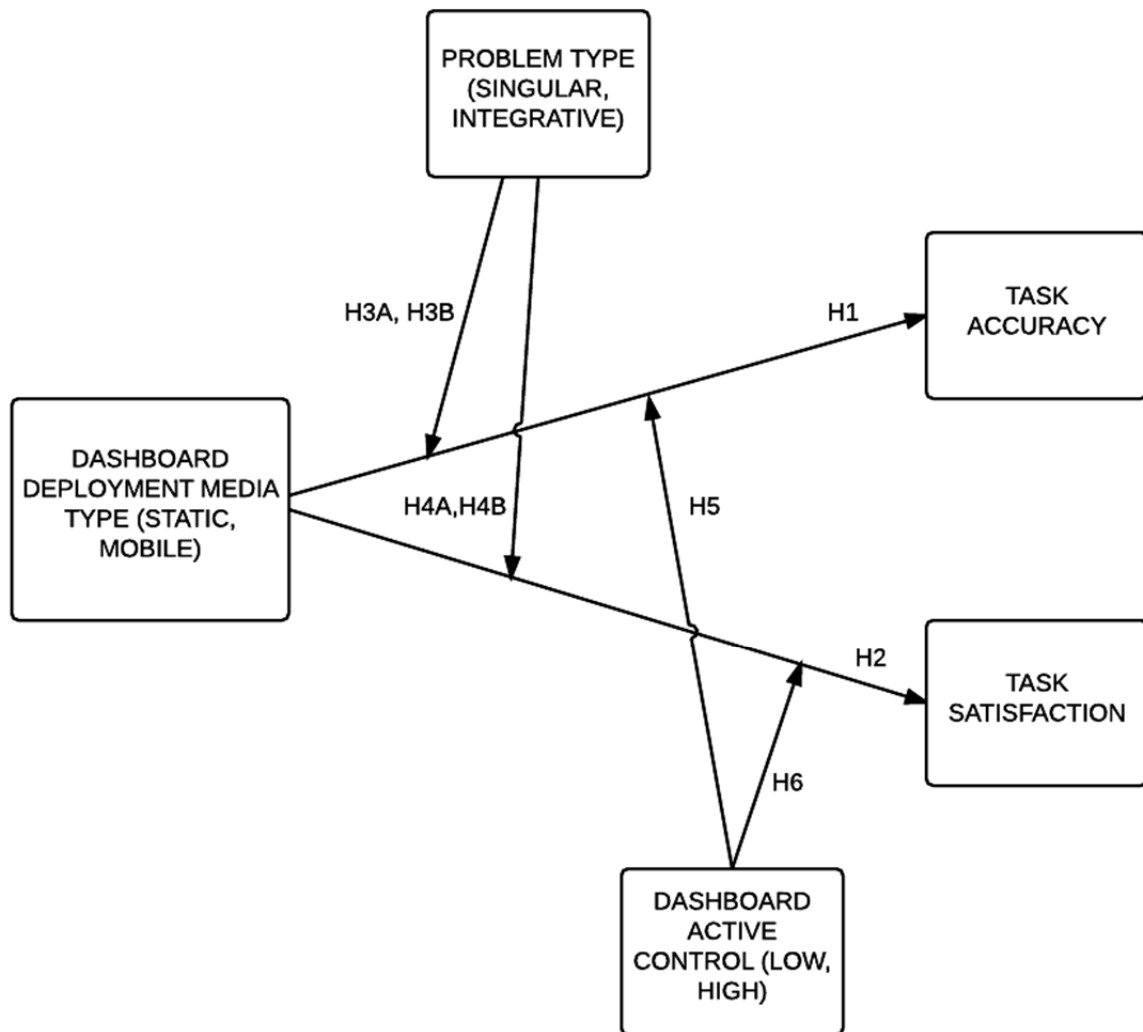


Figure 3.2 Conceptual Model

For the purposes of this study we clearly identify the static device level of the dashboard deployment media type to the desktop devices that are not movable. Keyboards and mouse alone are used to operate them. They do not have touch screen facility. The mobile device level is the smart phone that has touch facility and can be operated without the use of a keyboard and mouse. All reference hereafter to static device and mobile device are made keeping the above characteristics in mind. We first discuss in the above model, the hypotheses relating the main effects of dashboard deployment media type to the dependent variables, task accuracy and task satisfaction. Then we hypothesize about the interaction effects of problem type and dashboard active control with dashboard deployment media type on task accuracy and task satisfaction.

3.4.1 Main Effect Hypothesis

Dashboards are responsively designed and appear smaller on screens with low real estate. A user using a dashboard on a mobile device is not able to see the contents of the whole dashboard with great clarity. The mobile dashboard user, therefore, has to scroll, pinch and zoom in order to locate the portion of the dashboard that contains task relevant information. Also the task may involve looking at data from two or more objects in the dashboard. So the user has to use his working memory to store the data values and swap the contents when he moves to a different screen. This increases the extraneous load component of the total cognitive load on the working memory. The total cognitive load comprises the intrinsic, extraneous and germane load (Sweller 1988). The total cognitive load of a mobile dashboard user could surpass the working memory capacity and hence impact accuracy in a negative manner.

The user viewing the information visualization on a dashboard displayed on a small screen requires greater associative memory resources because he/she has to organize the

information present on many screens cognitively and create a visual mental model. The user also may need to perform several operations and thereby feel lost in the process. Such a user can feel disoriented (Buyukkokten et al. 2001). On the other hand static devices have larger displays and many objects can fit into the same visual area with clarity. Hence, the static dashboard user can solve problems with greater accuracy. Therefore we hypothesize that:-

Hypothesis 1:- When used for a problem solving task, use of dashboards deployed on mobile devices will result in lower task accuracy than the use of dashboards deployed on static devices.

Due to the overloading of the working memory and greater use of the associative memory, the user of mobile dashboards is likely to be frustrated when solving problems. This may impact the satisfaction adversely. Hence we state that:-

Hypothesis 2:- While working on a problem solving task, users of dashboards deployed on mobile devices experience lower task satisfaction than users of dashboards deployed on static devices.

3.4.2 Moderation Hypothesis

Problems that are of the singular type depend upon one source of visualization (table, chart, graph or map). That source becomes the focal object. The focal object of a dashboard displayed on a larger static device often has to compete for attention with other non-focal objects within the same dashboard. When the dashboard is displayed on a device with small screen real estate, the user often pinches and zooms in order to increase the size of the object, so that it accommodates the whole screen and hence gets more clarity. In the process we argue that the number of non-focal objects is often reduced than when the same dashboard is displayed on a

larger desktop. The competition for attention associated with the dashboard deployed on smaller mobile devices could be lesser than that of the same dashboard deployed on a larger desktop. This could be a factor resulting in greater task accuracy for the dashboard displayed on a smaller device.

Unlike online shopping which is more akin to a browsing task, dashboards are often used for performance management which is more search oriented task. When the competition for attention is rather high (i.e. the desktop dashboard), the many competing non-focal objects implies divided attention and hence a local scanpath. Search tasks are top down tasks that are directed by a pre-determined cognitive strategy. They are associated with global scanpaths that are characterized by longer fixation of the eye. The scanpath of the task and the scanpath inherent in the larger screen devices may not match and hence cause cognitive strain. This could impact the task accuracy of the user. This increased cognitive strain could adversely affect the task satisfaction of the user who uses the dashboard in larger screen devices. Competition for attention and scan path theory have been successfully used in the information systems area to explain the effects of information format and shopping task on how consumers shop online (Hong et al. 2004).

An integrative problem is based upon multiple sources of information. The information cues reside on different objects within the same dashboard. On a larger screen display device all the objects are visible to the user on a single view. On mobile devices with smaller screen real estate, the user has to perform many operations including scrolling, pinching and zooming. These operations could result in cognitive load that is greater than the working memory capacity. The user has to integrate information from multiple objects that are available only after many

operations. There is therefore greater demand on the associative memory. Both factors lead to problem solving with lesser accuracy on mobile devices.

Hence we state the moderating relationship in the following pair of hypotheses:-

Hypothesis 3A:- When used for solving singular problems, use of dashboards deployed on mobile devices will result in greater task accuracy than use of dashboards deployed on static devices.

Hypothesis 3B:- When used for solving integrative problems, use of dashboards deployed on mobile devices will result in lower task accuracy than use of dashboards deployed on static devices.

While solving problems of the singular type that require information from a single source, the large screen static devices are associated with greater competition for attention and associated distraction and mismatch in the scanpaths. The user can become frustrated in executing the task. While solving integrative problems that need integration of information from multiple sources, the small screen real estate of mobile devices results in greater cognitive load and demand on associative memory. The user experiences greater cognitive strain and is less satisfied.

Hence we state that:-

Hypothesis 4A:- While working on a singular problem solving task, users of dashboards deployed on mobile devices experience greater task satisfaction than users of dashboards deployed on static devices.

Hypothesis 4B:- While working on an integrative problem solving task, users of dashboards deployed on mobile devices experience lower task satisfaction than users of dashboards deployed on static devices.

Active control in dashboards is provided by incorporating sliders, filters, highlighting and drill down mechanisms. In dashboards deployed on static devices, high active control engages and motivates the user to solve problems better. The user may be prompted to use the control elements to get more clarity when the presentation is crowded with many data points.

Understanding the information in the ecosystem of the dashboards is the primary task. When the dashboards provide greater active control, the user is faced with the addition of a secondary information control task (Posner 1986, Treisman and Davies 1973). The user now has to figure out how to look for information. The given memory resources of the user now have to be allocated to both the primary and secondary task (Anderson 1983; Bongard 1995). Ariely (2000) empirically validated that under low cognitive load, controlling the information flow is beneficial. However under higher cognitive load, information flow control led to decreased performance for new users and improved as they gained more experience.

As with interactive systems, in dashboards the primary task of information comprehension is dependent upon the secondary task of information control. Ariely (2000) demonstrated that under conditions of high cognitive load, information control negatively impacted performance outcomes. In dashboards deployed on mobile devices, cognitive load is already high due to greater extraneous load and demand on the associative memory. The information control operations on the small screen of a dashboard on a mobile device are quite cumbersome to operate. It is, therefore, evident that greater active control magnifies the load imposed by the smaller screen real estate of the mobile device. We therefore state that:-

Hypothesis 5:- When used to solve problems, use of dashboards with active control will result in less favorable task accuracy when they are deployed on mobile devices than when they are deployed on static devices.

Active control facilitates a greater sense of controllability which is positively related to self-efficacy (Gist and Mitchell 1992). The user experiences increased autonomy and flexibility (Kettanurak et al. 2001; Teo, 2003). Liu and Shrum (2009, 2001) proposed that active control is associated with greater user satisfaction, partially mediated by self-efficacy. The users exhibit greater command over the structural environment (Klayman 1988). They also are able to form and use anticipatory schemas with respect to the action outcome. Active control is therefore positively associated with task satisfaction.

The smaller real screen estate on mobile dashboards increases the difficulty of operating the active control. Whereas, on dashboards deployed on static devices the display area is larger and it is much easier to operate the controls. So we argue that the difference in task satisfaction of the user using a dashboard on the static vis-à-vis the mobile device is amplified more when the active control increases.

Hypothesis 6:- While working on a problem solving task, users of dashboards with active control experience less favorable task satisfaction when they are deployed on mobile devices than when they are deployed on static devices.

3.5 Research Methodology

We validated the conceptual model by conducting a laboratory experiment. We chose to conduct an experiment in order that we may exercise good control over factors that may affect the outcomes and yet be of no interest as far as this research is concerned.

3.5.1 Experimental Design

We were interested in understanding the impact of the following independent variables in the experiment: - dashboard deployment media type (mobile or static), problem type (singular or integrative) and dashboard active control (low or high). We conducted a 2 X 2 X 2 factorial experiment where all the independent variables were manipulated between treatments. The various combinations of treatment conditions are presented in Table 3.2.

Table 3.2 Treatment Combinations of the Independent Variables			
Treatment	Dashboard Deployment Media Type	Problem Type	Dashboard Active Control
A	Static Device	Singular	Low
B	Static Device	Singular	High
C	Static Device	Integrative	Low
D	Static Device	Integrative	High
E	Mobile Device	Singular	Low
F	Mobile Device	Singular	High
G	Mobile Device	Integrative	Low
H	Mobile Device	Integrative	High

Each participant was assigned a problem solving task that comprised 20 problems. We identified job seeking as the domain of the experiment. We chose a general domain for the experiment in order to attract participants from a large subject pool. Each problem related to one

or more of the four objects on the dashboard. An object on the dashboard could be a table or a graph. We asked two types of questions, symbolic and spatial. A symbolic question required the subject to identify discrete or concrete values. A spatial question required the subject to identify associations or perceive relationships among data points (Umanath et al. 1990). The experimental dashboards had two types of objects, graphs and tables. Graphs display spatially related information showing the relationship among pieces of data. Tables are symbolic in nature and show discrete values (Larkin and Simon 1987). The task comprised 5 questions each on the four possible combinations indicated in table 3.3.

Table 3.3 Combinations of Task Questions and Objects on Dashboard	
Question	Object on Dashboard
Symbolic	Table (Symbolic)
Symbolic	Graph (Spatial)
Spatial	Table (Symbolic)
Spatial	Graph (Spatial)

3.5.2 Participants

We recruited the students of a large public university in the United States to take part in the experiment. We were able to attract a large subject pool due to the general nature of the experiment. The experiment was conducted over two successive weekends in a semester. There were a total of ten sessions in each weekend. Students used an online website developed using Qualtrics to self-enroll in the various sessions of the experiment. We paid the participants \$15 for taking part in the experiment. 257 students participated in the experiment. We discarded the

responses of 8 participants due to large amount of missing data on the dependent variables. We discarded one observation as it was an extreme outlier. Seven participants responded partially to some items of the task satisfaction scale. We imputed the missing items from the responses of the other completed items. However these 7 respondents did reply to each question of the main experimental task that was used to measure task accuracy. Table 3.4 below shows the distribution of the demography of the 248 participants whose responses were used for statistical analysis. The average age of the participants was 23.9 years. Each treatment combination had 31 participants.

Table 3.4 Distribution of Demographic Data of Participants

Demographic Variable	Value	Number	Percentage
Gender	Female	74	29.8
	Male	173	69.8
Age	18-21	37	15
	22-25	162	65
	26-29	39	16
	>29	10	4
Degree	Undergraduate	45	18
	Graduate	201	81
	PhD	2	1
Major	Engineering	70	28.2
	Computer Science	91	36.7
	Management	81	32.7
	Others	6	2.4

3.5.3 Experimental Setting and Procedures

The computer labs in the large public university in the United States were used to conduct the experiments. Prior to the actual experiment, we identified 24 seats in the lab with

sufficient spacing between them. Each seat was assigned a number. Each seat had a pre-assigned experimental packet that contained detailed instructions and the task problems. After the participant signed the sign-up sheet upon arrival, we allocated a location to participant by drawing a random number. Each random number was associated with one of the 8 experimental treatment conditions. The same randomization procedure was repeated in every session for all the subjects. We gave the participant a mobile device if the random number was associated with the treatment involving mobile devices. The participant assigned the desktop device used the desktop at his location. The participants were then instructed to go to the particular location. All treatment conditions were represented in each session. We seated the students in such a way that enabled the students to see and work only on their experimental artefact, without seeing the work of other subjects. We instructed the students to work individually and not look at what their colleagues are working on.

After signing the informed consent document, the participants were instructed to open the experimental packet. At the beginning, they were asked to answer the survey questions pertaining to the need for cognition control which was used as a covariate. Then they read a document that familiarized them with the purpose and features of a dashboard. The participants were then instructed to complete the warm up task. The warm up task involved launching the assigned warmup dashboard on the device assigned to them and answering 5 questions. The warm-up task was expected to take 10 minutes. The participants were then instructed to proceed with the main experimental task. Each participant launched the main experimental dashboard assigned to them on their device and then worked on the 20 problems. They wrote their answers to the questions of the warm-up and main experiment tasks beneath the questions. The participants then answered questions regarding the manipulation check of the independent

variables, dependent variables, possible covariates and demographic data that included age and GPA. Upon return of the completed experimental packet to the investigator, they completed their experimental follow up procedure and received reimbursement for participation. Overall, the task completion time varied from 30 minutes to 90 minutes.

3.5.4 Manipulation of independent variables

We used job seeking as the domain of the experiment. We presented yearly trend details for five years about the different parameters of the jobs located in five different fictitious cities. The parameters were salary, bonus, cost of living index and median price of homes. The actual numerical quantities involved were chosen randomly not keeping in mind the different hypotheses of the study.

We manipulated the dashboard deployment media type by deploying the dashboards on either a hand-held mobile device or a static desk-top. The dashboards were designed using responsive design so that the visualization was reduced proportionately in size for the smaller mobile device.

We manipulated problem type variable by designing the task questions. The questions for the singular problem type referred to the information contained in one table or graph. The questions for the integrative problem type referred to more than one object in the dashboard. All the questions had a single correct answer. Appendices C and D show the singular and integrative task questions respectively. We designed the dashboards using Tableau software (Version 9). We created two different dashboards each for the warm up and main experimental task. Each dashboard displayed two tables and two graphs (line and bar chart). In order to manipulate the high active control treatment condition, we included scroll bars, sliders and check boxes which

could be used to select the data to be displayed. The dashboard corresponding to the low active control treatment condition had only the scroll bar. The dashboards were deployed on the mobile and static desktop devices. We used 12 LG mobile devices (Tribute 5 Model mobile phone) and 12 desktops in each session. We ensured that all the mobile devices were identical in all respects. The participants could launch the dashboard by touching an icon on the mobile device. The participants could launch the dashboard on the desktop device by entering the website address on the browser. Appendices E and F show the dashboards with low and high active control respectively. Appendix G shows the same dashboards on a smart phone.

3.5.5 Response Variable Measurements

We measured two dependent variables in this experiment. They are task accuracy and task satisfaction. Task satisfaction was measured using Likert scale items borrowed from previous studies.

We used task accuracy as an objective measure. We looked at each of the twenty problems in the singular and integrative tasks and assigned a numeric weight to each by understanding the nature of search, accumulation, comparison and integration. An object on the dashboard could be a table or a graph. Search involved looking for a particular point on the target object\objects on the dashboard. Accumulation involved searching for more than one point on the dashboard object\objects. Comparison required the subjects to compare two numerical quantities after the completion of the search and accumulation process. Some problems required the subjects to integrate information retrieved from many data points on the displayed objects. We adopted this method in order to be fair to all the 20 questions of the dashboard, such that

questions with greater severity received more weights than questions with lesser severity. Task accuracy was then calculated as the weighted average.

We adapted the task satisfaction measure from extant literature (Bhattacharjee, 2001). The subjects were asked to respond to the statement “Please indicate how you feel about your overall experience of your working on the dashboard task today”. They used Likert scales that ranged from (1) very dissatisfied to (7) very satisfied, (1) very displeased to (7) very pleased, (1) very frustrated to (7) very contented and (1) absolutely terrible to (7) absolutely delighted. Task satisfaction of each subject was measured by the average score of the four items (Cronbach’s $\alpha = .934$).

3.5.6 Control Variables

The literature review revealed that certain covariates may indeed affect the outcomes. Users who may have used mobile devices frequently will develop a certain degree of familiarity with the screen operations like scrolling, pinching and zooming that are predominantly features on mobile devices. Similarly the users of static devices would be very familiar with scrolling and double clicking on static desktop devices. They may be able to search for the target object with relative ease and hence could arrive at accurate results. They may also be more satisfied with the task. Hence we used frequency of use as a covariate. Need for cognition is the tendency of people to engage and enjoy thinking (Cacioppo et al. 1984). Need for cognition has been empirically validated to affect graphical comprehension (Greenberg 2014). We therefore included need for cognition as a covariate. We administered the need for cognition scale (Appendix H) at the beginning of the experiment. We also measured the frequency of use and

familiarity with the devices and Tableau software, which was used to design and display the dashboards.

3.5.7 Pilot Testing

We conducted a pilot test with twelve graduate students in order to test the different dashboards, the problem type manipulation and the deployment of the dashboards on mobile and static devices. The artefacts and the problem task questions were modified based feedback from the pilot test.

3.5.8. Preliminary Analysis

3.5.8.1 Random Assignment of subjects to treatments

We confirmed the random assignment of subjects to treatments by conducting statistical tests on the demographic data and the eight treatment combinations. Chi-square tests revealed no significant association ($\alpha = .05$) for categorical variables in the demographic data table 3.4. Three way ANOVA between the treatment variables and the continuous demographic variables showed no significant difference in means ($\alpha = .05$).

3.5.8.2 Verification of Independent Variable Manipulations

Each packet kept at the location of the participant had a marker that indicated the problem type and the active control of the dashboard. In addition we noted the dashboard deployment media of each subject (cell phone or desktop). The participants answered three questions with respect to each independent variable (Appendix I). Based upon responses to the manipulation check questions, we verified that the independent variables were manipulated as intended.

3.6 Analysis and Results

All the three dependent measures were measured at the individual level. We identified MANOVA\MANCOVA as a possible statistical method for validation of the significance of the experimental manipulations. SPSS Version 24 was used for the statistical analysis.

We had identified need for cognition and GPA as possible covariates; frequency of use of device, familiarity with the device and the dashboard software as possible blocking factors. The scatter plot matrices and the linear regression of those co-variates with the three dependent variables did not return any trace of linearity in the relationship. The scatter plot matrices clearly showed a cloud pattern. Based upon the above findings, the covariates were not considered for further analysis. When we used the frequency of use of the device, familiarity with the device and familiarity with the dashboard software as blocking factor, they did not change the significance of the different effects in the model. So they were not considered in the final analysis.

On examination of the correlation between the two dependent variables, it was seen that task satisfaction and task accuracy were not significantly correlated (Pearson Correlation =.053, p value = .403). We ran a preliminary MANOVA on the experimental data. Box's M test indicated that the null hypothesis of equality of covariance matrices was rejected (F=2.118, p value = .000). Since this key assumption was violated we chose not to interpret the MANOVA results any further. Given the low value of the correlation, we decided to use univariate ANOVA for further analysis. We used t-test's with Bonferroni correction to validate individual hypotheses after confirming significant effects of the ANOVA procedure.

Table 3.5 shows the values of the means and standard deviations of the task accuracy and task satisfaction for the different treatment combinations.

Table 3.5 Means and Standard Deviations for Task Accuracy and Task Satisfaction

	Static						Mobile					
Measures	Low Active Control			High Active Control			Low Active Control			High Active Control		
	Singular	Integrative	Mean	Singular	Integrative	Mean	Singular	Integrative	Mean	Singular	Integrative	Mean
Task Accuracy (Range 0-100)												
Mean	65.13	47.68	56.40	82.02	66.23	74.13	66.89	50.73	58.81	68.50	52.54	60.52
SD	14.43	18.14	18.48	15.50	20.32	19.61	11.66	17.60	16.90	19.06	20.32	21.13
n	31	31	62	31	31	62	31	31	62	31	31	62
Task Satisfaction (Range 1-7)												
Mean	5.91	5.86	5.89	6.46	5.98	6.22	5.65	4.83	5.24	5.21	4.88	5.05
SD	1.00	.97	0.98	.67	.84	0.79	1.02	1.56	1.37	1.37	1.53	1.45
n	31	31	62	31	31	62	31	31	62	31	31	62

3.6.1 Task Accuracy

First we tested the various assumptions of ANOVA. The data in five out of the eight treatment groups conformed to the normal distribution as validated by the Kolmogorov-Smirnov and Shapiro-Wilk tests. The Levenne's test indicated that the assumption of equality of variance was marginally rejected (Levenne statistic 2.108, p value .043) at an α of .05. However Hartley's test on the ratio of the largest variance (413) to the smallest variance (136) indicated that the assumption of equality of variance could not be rejected (Test statistic = 3.03, critical value = 3.12). Neter et al (1996) indicate that the F tests in ANOVA are fairly robust against violations of normality. Also since the sample sizes for our analysis are equal in all the treatment cells (31), the impact of the inequality in variance on the inferences based on the F test is expected to be minimal (Hair et al. 1998; Neter et al. 1996). The third assumption of independence of error terms also could not be rejected because we incorporated randomization procedures while allocating the subjects to the treatments. Randomization offers a certain degree of protection with respect to the violation of this assumption (Hair et al. 1998). Also the distribution of the error terms did not show any discernible patterns.

In addition to using the General Linear Model (GLM) Univariate procedure of SPSS ANOVA we also tested using the Generalized Linear Model procedure of SPSS ANOVA with robust estimation which reduces the impact of unequal variance. We have reported the results of the General Linear Model (GLM) Univariate ANOVA analysis here.

Using the flowchart in Neter et al (1996, p. 848), the interaction effects are examined first. The full model was run including the three way interaction between the three independent variables. The three way interaction was not significant ($F(1,240) = .028$, p value = .868, $\alpha =$

.05). The lack of fit tests on the reduced model without the three way interaction showed that we fail to reject the null hypothesis of lack of linear fit ($F(2, 240) = .036, p = .965$).

Table 3.6 GLM Univariate ANOVA Results for the Dependent Variable Task Accuracy

	Sum of Squares	Degrees of Freedom	Mean Square	F statistic	p-value
Dashboard Deployment Media (DEVCODE)	1944.447	1	1944.447	6.498	0.011*
Dashboard Active Control (CTRCODE)	5858.014	1	5858.014	19.576	0.000*
Problem Type (PROBTYPE)	16561.687	1	16561.687	55.344	0.000*
DEVCODE X CTRCODE	3975.905	1	3975.905	13.286	0.000*
DEVCODE X PROBTYPE	4.702	1	4.702	.016	0.900
ERROR	72418.010	242	299.248		
TOTAL	100762.766	248			

R Squared = .281 (Adjusted R Squared = .266)

* Significant at $\alpha = .05$

Table 3.6 above shows that the relationship of dashboard deployment media type and task accuracy is not contingent upon the type of problem solving task ($F(1, 242) = .016, p \text{ value} = .900$). So hypotheses H3A and H3B are not supported.

The interaction of the dashboard device media type and dashboard active control was found significant ($F(1, 242) = 13.286, p \text{ value} = .0003$). The profile plot of the estimated marginal means is shown in figure 3.3 -

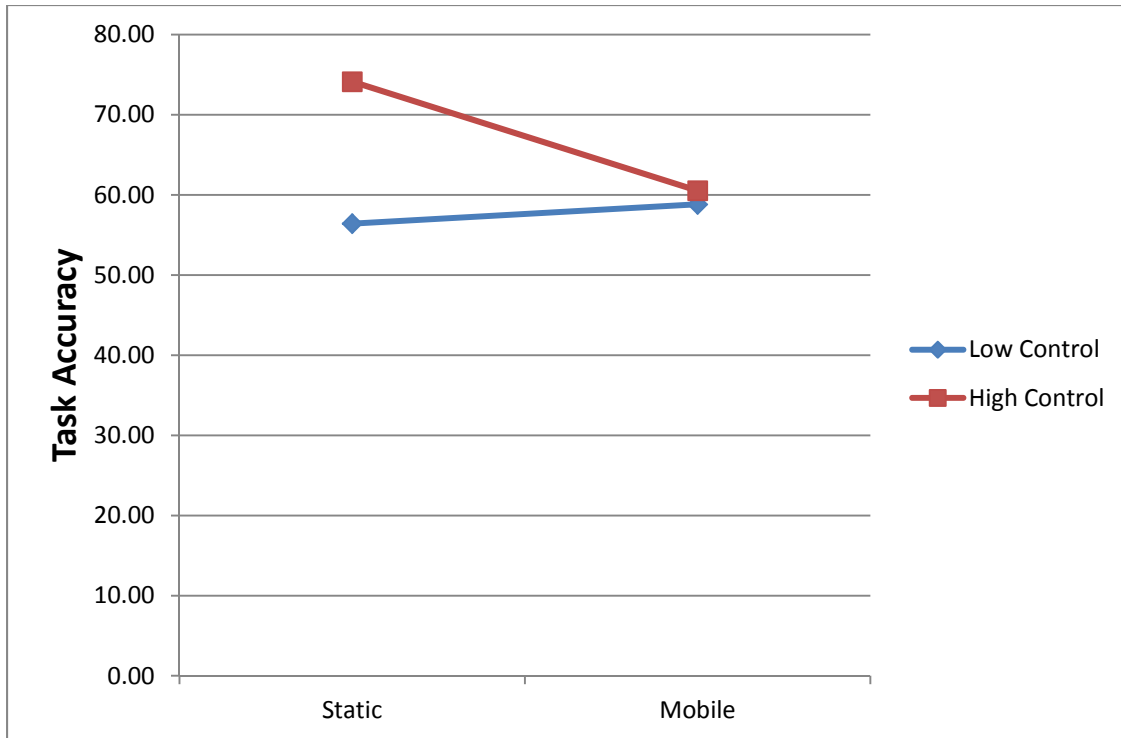


Figure 3.3 Profile Plot of the Estimated Marginal Means of Task Accuracy Showing the Interaction Between Dashboard Deployment Media Type and Dashboard Active Control.

The figure 3.3 indicates an ordinal interaction (the two lines are not parallel, but do not intersect). We use linear contrasts to analyze the interaction further. Bonferroni's test was utilized. We report the results of the Bonferroni test. The difference in the means of task accuracy of mobile and static dashboards that have high control was lower than the difference of means of task accuracy of mobile and static dashboards that have low active control by 11.26 units. The mean task accuracy was 62.47 units and therefore this interaction is important. The spread vs level plot indicates no transformation needs to be used. However when Kirk's method (1995) is employed a square transformation is suggested. Upon trying a simple transformation (square of the dependent variable) and testing once again using univariate ANOVA it was seen

that the interactions were still significant. So it is very clear that the two way interaction is indeed important. We examine the interaction further.

The difference in the means of task accuracy of mobile and static dashboards that have high control was lower than the difference in the means of task accuracy of mobile and static dashboards that have low active control ($L = -11.20$, $SE = 4.412$, $df = 242$, $p = .0002$, $\alpha_{FW} = .05$, $\alpha_{PC} = .01$). H5 therefore was supported. We have reported the result of Bonferroni's test. We used a family of five contrasts, one for the planned comparison and the other four for post hoc tests.

3.6.2 Task Satisfaction

Normality tests (Kolmogorov-Smirnov and Shapiro-Wilk) on this dependent variable reveal that the distribution of task satisfaction for only one treatment combination resembles a normal distribution. The Levene's test for equality of variances shows strong evidence to indicate that the variances are not equal ($F = 6.154$, $p \text{ value} = .000$). Comparing all the treatment combinations, largest variance is more than 5 times the smallest variance. Hartley's Fmax test confirms the same findings (Test statistic = 5.46 and critical value = 3.12). Based upon the spread and level plot and Kirk's method (1995), we compared the square and cube transformation. The square transformation on the original data still fails both Levene's test and Hartley's Fmax test. The cube transformation on the original data showed that the assumption of equality of variances could not be rejected marginally ($F = 2.140$, $p \text{ value} = .088$). The application of Hartley's Fmax test shows that the assumption of equality of variances cannot be rejected (Test statistic = 2.22, critical value = 3.12). The application of the cube transformation on the original data was more reasonable with respect to the assumption of equality of variances

and was chosen for task satisfaction. Shapiro-Wilk and Kolmogorov-Smirnov tests for normality also indicate that the transformed values resemble the normal distribution in five of the eight treatment combinations.

As explained earlier for task accuracy, all treatment combinations have the same number of participants (31). So the impact of unequal variance on the inferences based upon the F distribution is minimal (Hare et al. 1998; Neter et al. 1996). The error variance distribution shows no patterns and hence assumption of independence of error terms is not violated. We conducted the statistical analysis using both GLM (General Linear Model) and Generalized Linear Model ANOVA's in SPSS. The robust estimation option also protects against the violation of unequal variance assumption and we report those results here.

The full model was run including the three way interaction between the three independent variables. The three way interaction was not significant ($F(1, 240) = 2.486, p \text{ value} = .116$). The lack of fit tests on the reduced model without the three way interaction showed that we fail to reject the null hypothesis of lack of linear fit ($F(2, 240) = 1.283, p = .279$).

Table 3.7 GLM Univariate ANOVA Results for the Dependent Variable Task Satisfaction

	Sum of Squares	Degrees of Freedom	Mean Square	F statistic	p-value
Dashboard Deployment Media (DEVCODE)	314273.908	1	314273.908	34.749	.000*
Dashboard Active Control (CTRCODE)	5406.967	1	5406.967	.598	.440
Problem Type (PROBTYPE)	67433.979	1	67433.979	7.456	.007*
DEVCODE X CTRCODE	30941.556	1	30941.556	3.421	.066**
DEVCODE X PROBTYPE	565.478	1	565.478	.063	.803
ERROR	2188678.507	242	9044.126		
TOTAL	2607300.395	248			

R Squared = .161 (Adjusted R Squared = .143)

*significant at $\alpha = .05$, **significant at $\alpha = .1$

Table 3.7 shows that the relationship of dashboard deployment media type and task satisfaction is not contingent upon the type of problem solving task ($F(1,242) = .063$, p value = .803). So hypotheses H4A and H4B are not supported.

The interaction of the dashboard device media type and dashboard active control was found insignificant ($F(1, 242) = 3.421$, p value = .066). While research is beginning to look at the differences between mobile devices and desktop devices, our extensive literature review has indicated that little empirical research has been conducted in the specific context of dashboards. While this interaction may be marginally significant at an α of .05, it becomes significant at a less conservative α of .1. As we show later this could have practical relevance and be a subject for further research. We therefore analyze this interaction further.

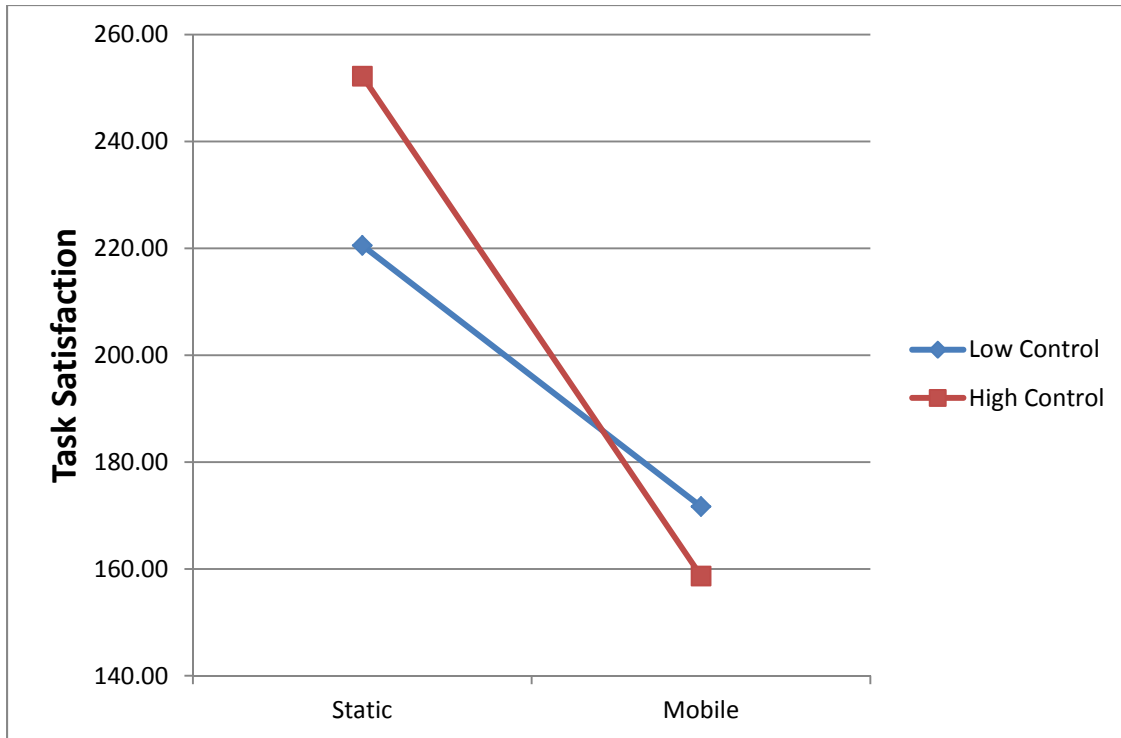


Figure 3.4 Profile Plot of the Estimated Marginal Means of Transformed Task Satisfaction Showing the Interaction Between Dashboard Deployment Media Type and Dashboard Active Control.

The difference in the means of task satisfaction of mobile and static dashboards that have high control was lower than the difference in the means of task satisfaction of mobile and static dashboards that have low active control ($L = -44.60$, $SE = 24.13$, $df = 242$, $p = .0326$, $\alpha_{FW} = .05$, $\alpha_{PC} = .05$). Therefore H6 was supported. We have reported the result of Bonferroni's test.

Table 3.8 summarizes the validation of the various hypotheses.

Table 3.8 Hypotheses Validation Table				
S.No	Hypothesis Statement	pvalue of the F Test	pvalue of the t-test with Bonferroni Correction	Remarks
H1	<i>When used for a problem solving task, use of dashboards deployed on mobile devices will result in lower task accuracy than the use of dashboards deployed on static devices.</i>	.011*	.006	Supported
H2	<i>While working on a problem solving task, users of dashboards deployed on mobile devices experience lower task satisfaction than users of dashboards deployed on static devices.</i>	0.000*	0.000	Supported
H3A	<i>When used for solving singular problems, use of dashboards deployed on mobile devices will result in greater task accuracy than use of dashboards deployed on static devices.</i>	0.9		Not supported
H3B	<i>When used for solving integrative problems, use of dashboards deployed on mobile devices will result in lower task accuracy than use of dashboards deployed on static devices.</i>	0.9		Not supported
H4A	<i>While working on a singular problem solving task, users of dashboards deployed on mobile devices experience greater task satisfaction than users of dashboards deployed on static devices.</i>	0.803		Not supported
H4B	<i>While working on an integrative problem solving task, users of dashboards deployed on mobile devices experience lower task satisfaction than users of dashboards deployed on static devices.</i>	0.803		Not supported
H5	<i>When used to solve problems, use of dashboards with active control will result in less favorable task accuracy when they are deployed on mobile devices than when they are deployed on static devices.</i>	0.000*	.000	Supported
H6	<i>While working on a problem solving task, users of dashboards with active control experience less favorable task satisfaction when they are deployed on mobile devices than when they are deployed on static devices.</i>	0.066**	0.0326	Supported

*significant at p = 0.05, ** significant at p = 0.1

3.6.3 Post Hoc Analysis

We used a family of five linear contrasts with Bonferroni correction for one priori hypothesis testing and four post hoc tests. The mean of task accuracy of dashboards deployed on static devices that have low active control was lower than those dashboards that have high active control ($L = -17.73$, $SE = 3.09$, $df = 242$, $p < .001$, $\alpha_{FW} = .05$, $\alpha_{PC} = .01$). There was insufficient evidence to support that the mean of task accuracy of dashboards deployed on mobile devices that have low active control was lower than the mean of task accuracy of those dashboards that have high active control ($L = -1.712$, $SE = 3.140$, $df = 242$, $p = 0.293$, $\alpha_{FW} = .05$, $\alpha_{PC} = .01$). Figure 3.3 shows that the mean of task accuracy of dashboards that have low active control is higher on mobile devices than static devices. We found insufficient evidence to support this rather interesting difference ($L = -2.40$, $SE = 2.82$, $df = 242$, $p = 0.197$, $\alpha_{FW} = .05$, $\alpha_{PC} = .01$). The mean of task accuracy of dashboards that have higher active controls deployed on mobile devices was lower than the mean of task accuracy of the same dashboards deployed on static devices ($L = -13.608$, $SE = 3.395$, $df = 242$, $p < 0.001$, $\alpha_{FW} = .05$, $\alpha_{PC} = .01$).

3.7 Discussion

We have examined the impact of two content variables i.e. deployment (dashboard deployment media type) and design (active control), and one context variable i.e. problem type (singular versus integrative) in the phenomenon of problem solving using information dashboards.

The results indicated that while using the dashboard to solve problems, the relationship of the dashboard deployment media type and user performance measured as task accuracy is not contingent upon the type of problem task (singular or integrative). On mobile devices, there is greater cognitive load due to increase in use of associative memory. This increase was not amplified sufficiently by inherent integration necessary in the integrative task to put the integrative problem task solver on the mobile device at a much higher disadvantage. Looking at the interaction from the perspective of competition for attention and scanpath of the users, the focused attention of the mobile user on a single object on the screen did not translate sufficiently into greater differential benefits. Therefore the association of device deployment media type and task accuracy was not found to be contingent on the type of problem solving task.

The relationship between dashboard deployment media type and task accuracy was found to be contingent upon the level of active control. The effect size is moderate as indicated by the partial eta squared (.052). As expected, the users of dashboards deployed on static devices with high active control exhibited higher task accuracy over the users of dashboards deployed on static devices with low active control. We attribute it to the greater clarity that the user has on being able to use the active control elements to choose the particular data points needed in order to solve the problem. The information control did not seem to impose too high a secondary load

over and above information comprehension. Our expectations regarding the lower task accuracy of mobile dashboards with low active control with respect to the dashboards with high active control were not met. Post hoc tests revealed that when dashboards with higher active control were deployed on static devices, they outperformed the same dashboards deployed on mobile devices, with respect to task accuracy. We attribute it to the amplification of the extraneous load by the secondary load of information control due to active control.

The results of our study indicate that the relationship between dashboard deployment media type and task satisfaction is different for the low and high levels of active control. Contrary to popular belief, the active control features favorably affect task satisfaction of users of mobile devices less than that of the users of static devices. The cognitive load due to the higher extraneous component may have been amplified by the greater need for information control secondary control task.

3.7.1 Limitations

Can the results of this experiment be generalized to problem solving situations in organizations? The information dashboards used in the experiment addressed the job seeking domain. Though we used student subjects in the experiment, they were quite aware of the domain of the experimental dashboards. Therefore, they did not face any unfamiliar situation. We argue that the cognitive and perceptual processes found in the situation faced by the subjects in the laboratory setting of our experiment are quite similar to those faced by problem solvers in organizations.

The mobile devices used in the experiment were smart phones. The results with other mobile devices such as iPads could be different and could be part of future research.

3.7.2 Implications for Research and Practice

We have brought together seminal perspectives from several reference disciplines including, instructional and educational psychology, advertising cognitive psychology and visual perception in order to understand a very intriguing phenomenon. Through a rigorous academic research that included an experiment, we have sought to de-bias the quite ubiquitous bias towards pushing a wide spectrum of data visualizations to mobile devices. Data visualizations on the bigger screens do have some distinct advantages, especially in the realm of task accuracy and task satisfaction. While this research included three independent variables in the conceptual model, our findings are indicative of the immense promise of cognitive fit as a fourth independent variable. Cognitive fit is an important factor to consider when there are different categories of problem task and problem representation.

The results of the empirical validation of the conceptual model can be used to set certain guidelines for practitioners. We would like to emphasize that the results of our study will have practical significance only after the findings have been replicated across several such studies. When task accuracy and task satisfaction are of paramount importance to the problem solver, dashboards that have many active controls perform better when they are deployed on static desktop devices rather than mobile devices. The difference in task accuracy between dashboards deployed on mobile and static desktop devices when they have very little active control is quite small and attributable to chance. The study found little evidence of systematic differences in task accuracy and task satisfaction between dashboards deployed on mobile and static devices, when they are used to solve singular and integrative problems.

3.7.3 Future Research Directions

The study revealed that the key relationship of dashboard deployment media type and task accuracy was not contingent upon the two different problem types (singular and integrative). However this does not preclude a more nuanced three factor moderating relationship with a third factor. We speculate that the third factor could be the two types of symbolic and spatial problem task and/or problem representation.

Tables are the primary form of symbolic representation. Similarly graphs such as line graphs and bar charts are examples of spatial representation. The problem task can also be either symbolic or spatial. Symbolic tasks pertain to a single data point whereas spatial tasks consider the relationships among two or more than two data points. Cognitive fit is enhanced when the problem task matches the problem representation i.e. symbolic with symbolic and spatial with spatial. When the problem task and representation do not match, then the user bears an increased cognitive load because either the task or the problem representation needs to be transformed cognitively before solving the problem (Vessey and Galetta, 1991). Our study incorporated the four different combinations of problem task and representation in the experiment. Preliminary results suggest that there are different patterns for each combination. Future research can examine this interesting angle, examine various theories and perform hypotheses validation. This effort will further the cause of academic research in this area and offer more nuanced recommendations for practitioners.

Future studies can examine the role of mediating variables such as cognitive strain, perceived task complexity and subjective mental workload in the conceptual model. This can help provide a richer tapestry for the current research.

Our research has examined the phenomenon of problem solving using information dashboards by looking at it from the perspective of cognition and visual perception. It will be worthwhile to use the emotional lens also and thereby build a holistic understanding of the phenomenon.

Post hoc tests showed that there was no sufficient evidence to support the better performance of the low active control dashboards deployed on mobile devices over the same dashboards deployed on static devices. A bigger sample size could perhaps have found better results.

3.8 Conclusions

This research paper makes a significant contribution in the area of data visualization on mobile devices. While deploying information dashboards on mobile devices appears attractive, the reality as shown by our experiment is somewhat different. Our research indicates that the dynamics of the two content factors, design and deployment together should be considered when pushing information dashboards to mobile devices. Dashboards deployed on the static desktop devices do have value in terms of accuracy and satisfaction in certain context. We arrive at some informed directions for future research in academia and managerial action in organizations.

APPENDIX

Appendix A FLOWCHART OF RESEARCH ON DASHBOARDS

(Yigitbasioglu et al. 2012)

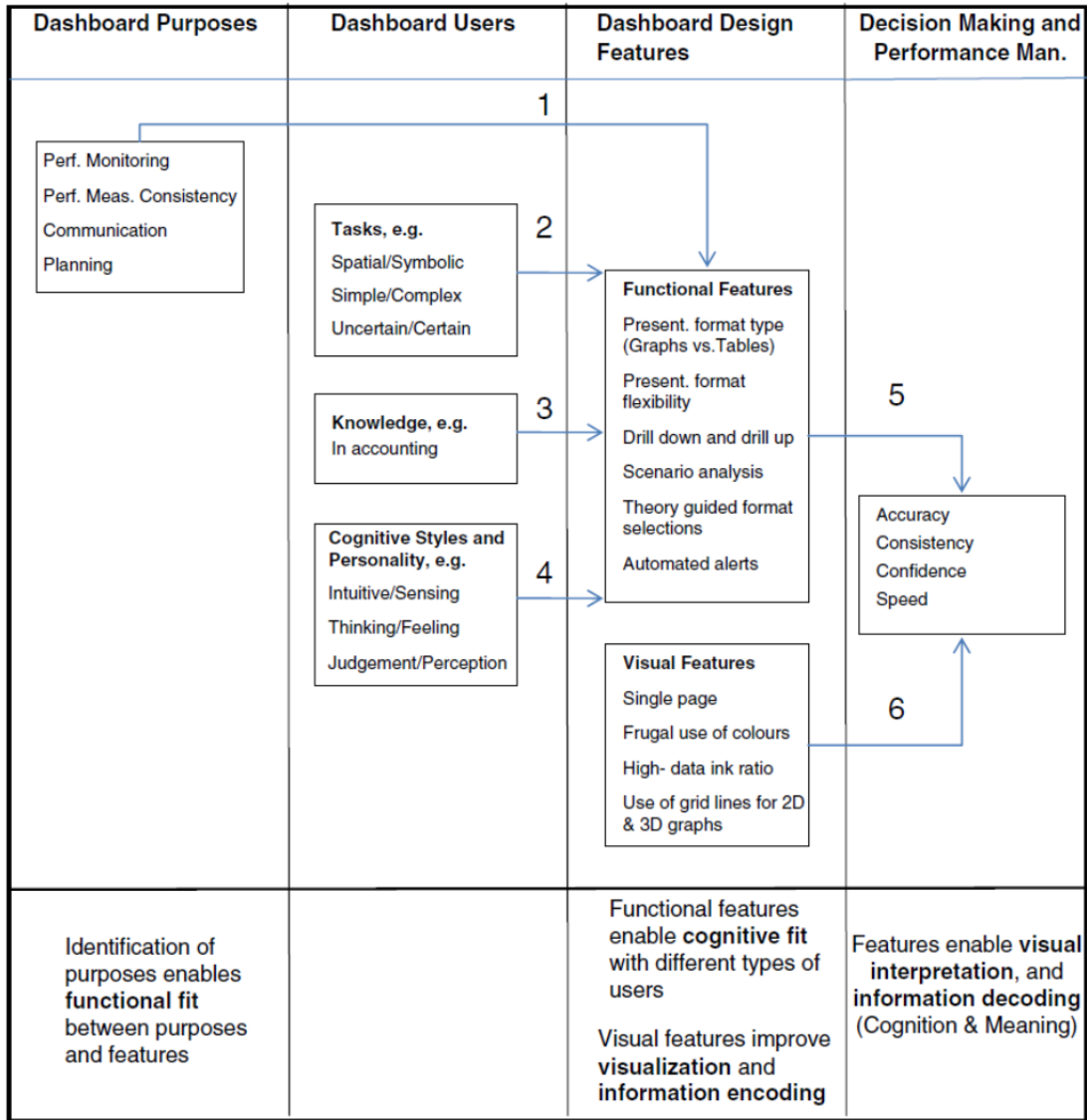


Fig. 1. A summary of dashboard research paths with implications on design.

Appendix B - Summary of reviews on dashboards (Yigitbasioglu et al. 2012)

Table 1
Summary of key findings regarding presentation formats and dashboards.

Dashboard definition and purposes (1), visual feat., information load → Decision Performance (6)	Study
Dashboard definition	Few (2006)
Dashboard purposes	Pauwels et al. (2009)
A dashboard should fit on a single screen but allow data to be drilled down	Few (2006)
The use of Gestalt principles to improve perception	Moore and Fitz (1993)
Use of colours to enhance perception	Goldstein (2007)
High data to ink ratio to maximize attention paid to important information	Tufte (2006)
The introduction of grid lines into 2D and 3D graphs prevents decision bias	Amer and Ravindran (2010)
There is a U relationship between information load and decision accuracy	Shields (1983), Iselin (1988)
Increasing the number of information cues can lead to less consistent decisions	Chewning and Harrell (1990), Stocks and Harrell (1995)
Altering the display format can help focus on more relevant information	Dilla and Steinbart (2005)
Supplementing BSC's with strategy maps increased attention paid to KPI's	Banker et al. (2004)
Performance markers (e.g. +/-) can help eliminate bias in connection to BSC presentation format	Cardinaels and van Veen-Dirks (2010)
User tasks, knowledge and presentation format → decision Performance (2 + 5) (3 + 5)	Study
Tabular information was superior to graphs with respect to consensus among decision makers. Task difficulty not affected by supplementary BSC information	Dilla and Steinbart (2005)
Tabular information more suitable for symbolic tasks; e.g. for extracting specific values and combining them to an overall judgement	Vessey (1991), Umanath and Vessey (1994)
Tabular information led to better decisions involving selective tasks (monitoring specific values)	Amer (1991)
Tabular information was found to be more superior when tasks became more complex and information cues became less consistent	Davis (1989a, 1989b), Liberatore et al. (1989), Blocker et al. (1986), So and Smith (2004)
Tabular information led to more accurate decisions for accumulation tasks	Hard and Vanecek (1991)
Presentation format did not affect value judgements of auditors	Kaplan (1988), Bricker and Nehmer (1995), Frownfelter-Lohrke (1998)
Sales forecasts based on tabular format were more accurate than graphical animations	Hasbun (2009)
No one form of presentation is best in all situations. Graphs are more suitable for spatial tasks; e.g. for comparing a set of values.	Davis (1989a, 1989b) Vessey (1991) Umanath and Vessey (1994), Vessey and Galletta (1991)
Graphs reduced the negative influence of information overload	Diamond and Lerch (1992), Umanath and Vessey (1994)
Graphs led to more accurate financial predictions	Hard and Vanecek (1991)
Graphs were found to be superior for correlation and sales forecasting tasks but value added decreased with auditing experience	Anderson and Mueller (2005)
Broad scope information (less aggregate) appeared to be more beneficial in marketing, where marketing was assumed to have a higher level of uncertainty than production	Mia and Chenhall (1994)
Graphs produced better correlation estimates and decreased time on task	Schulz and Booth (1995)
Graphs improved accuracy of bankruptcy, earnings, and sales forecasts	MacKay and Villarreal (1987), DeSanctis and Jarvenpaa (1989), Anderson et al. (1992), Anderson and Reckers (1992)
Graphs led to higher accuracy for complex auditing tasks	Wright (1995)
Graphs produced better performance evaluations that required holistic decision strategies	Tuttle and Kershaw (1998)

(continued on next page)

Table 1 (continued)

Users who chose preferred presentation format made more accurate decisions for symbolic tasks	Wilson and Zigurs (1999)
Self organizing maps and multidimensional scaling did not significantly outperform tabular representations.	Huang et al. (2006)
Schematic faces and bar chart graphs produced superior performance to financial ration and trend diagrams	So and Smith (2003)
Geographical information systems do not ensure superior performance over tabular information	Dennis and Carte (1998)
Higher task uncertainty requires more disaggregate data	Benbasat and Dexter (1979)
Users with low level of accounting knowledge made better decisions with graphs. Users with high level of accounting knowledge made better decisions with tables	Cardinaels (2008)
Personality type and presentation format → decision performance (4 + 5)	Study
Personality type did not affect the value perceived from different presentation formats	Liberatore et al. (1989) and Carpenter et al. (1993)
Customization of user interfaces to match personality type may lead to success	Boon and Tak (1991)
Users performed better when they handled an interface that matched their personality type	Kostov and Fukuda (2001)
Cognitive styles (MBTI) and field independence had no impact on decision quality with varying presentation formats	So and Smith (2003)
Decision support systems should not be designed according to the desires of individual managers	Vessey and Galletta (1991)
Low analytics with disaggregate data performed better than low analytics with structured and aggregate data	Benbasat and Dexter (1979) Bariff and Lusk (1977)
Analytic planners performed more confidently with less aggregate data. Heuristic planners performed equally well with aggregate and less aggregate data	Lederer and Smith (1988)

Appendix C Main Task A (Singular)

Get-a-job-Quick is a new web site being designed to help students find jobs. To help design an awesome website, please look at the dashboard on the display device and answer the following questions.

1. What was the median house price in Bechian in 2012?
2. What was the cost of living index in Sikam in 2011?
3. In which year was the median house price in Yaku \$130,000?
4. In which year was the Cost of living index in Conten 8.50?
5. What was the median house price in Dundew in 2012?
6. What was the salary of the employee in Bechian in 2012?
7. What was the bonus given out to an employee in Sikam in 2011?
8. In which year was the salary in Yaku \$64,000?
9. In which year was the bonus in Conten \$2300?
10. What was the salary in Dundew in 2012?
11. Was the median home price of homes in Bechian more than that of Yaku in 2013?
12. Was the cost of living index in Sikam more in 2011 than in 2013?
13. Between which two consecutive years did the median price increase in Dundew?
14. Between which two consecutive years did the cost of living index decrease in Conten?

15. Which year witnessed the greatest cost of living index in Bechian?
16. Was the salary of employees in Bechian more than that of Yaku in 2013?
17. Was the bonus paid to employees in Sikam more in 2011 than in 2013?
18. Between which two consecutive years did the salary of employees increase in Dundew?
19. Between which two consecutive years did the bonus of employees decrease in Conten?
20. Which year witnessed the greatest salary paid to employees in Bechian?

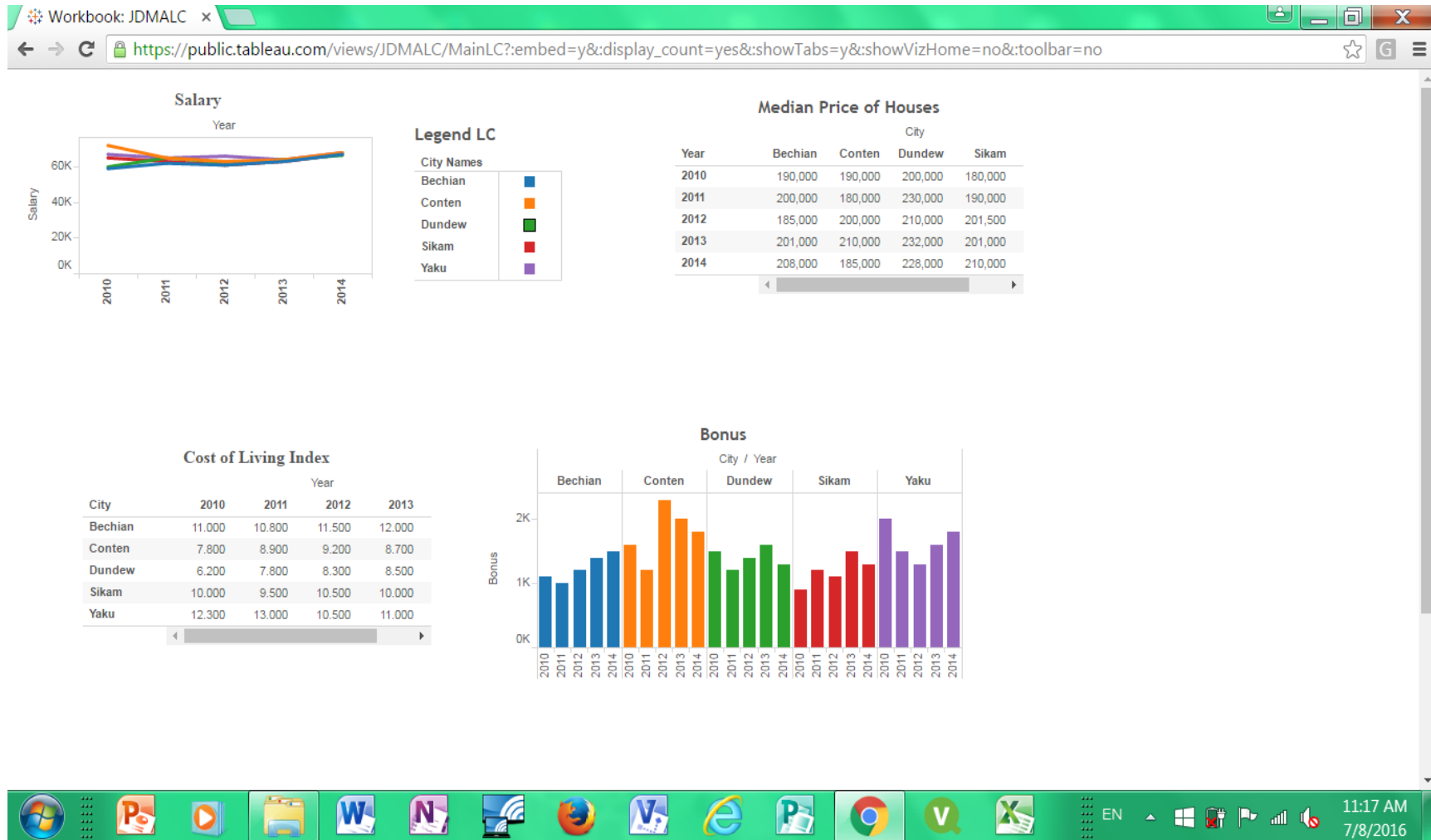
Appendix D Main Task B (Integrative)

Get-a-job-Quick is a new web site being designed to help students find jobs. To help design an awesome website, please look at the dashboard on the display device and answer the following questions.

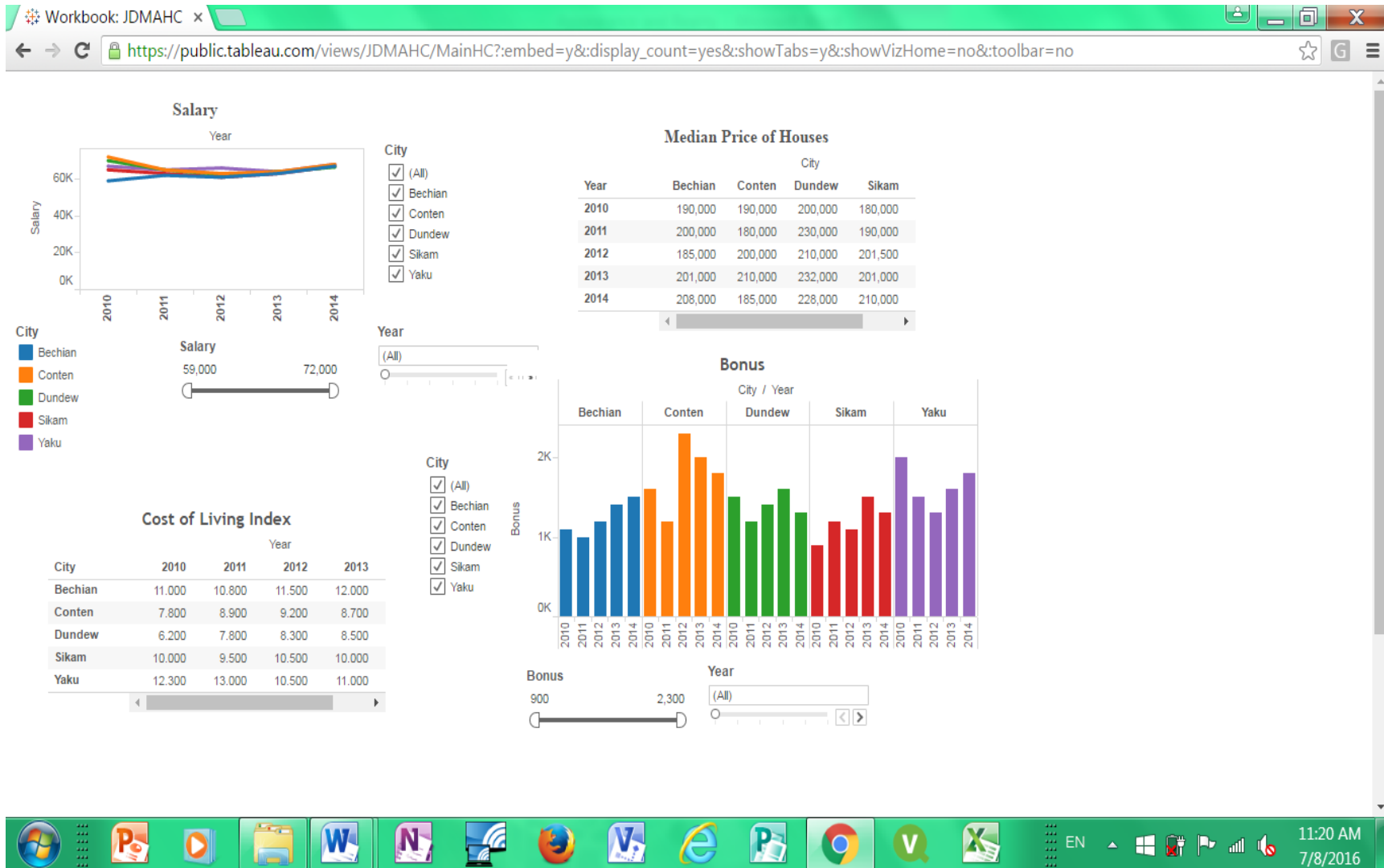
1. What was the median house price and cost of living index in Bechian in 2012?
2. What was the median house price and cost of living index in Sikam in 2011?
3. In which year(s) was\were the cost of living index less than 11.5 and median house price in Yaku less than \$140,000?
4. In which year was the cost of living index more than 8.7 and median house price in Conten more than \$200,000?
5. What was the median house price and cost of living index in Dundew in 2012?
6. What was the salary and bonus of the employees in Bechian in 2012?
7. What was the salary and bonus of the employees in Sikam in 2011?
8. In which years was the salary of the employees in Yaku less than less than \$150,000 and bonus more than \$1500?
9. In which years was the salary of the employees in Conten more than \$150,000 and bonus less than \$1500?
10. What was the salary and bonus of employees in Dundew in 2014?

11. Was the median home price of homes and cost of living index in Bechian more than that of Yaku in 2013?
12. Was the median price of homes and cost of living index in Sikam more in 2011 than in 2013?
13. Between which two consecutive years did the median price of homes and cost of living index increase in Dundew?
14. Between which two consecutive years did the median price of homes and the cost of living index decrease in Conten?
15. Which year(s) witnessed the greatest median price of homes and cost of living index in Bechian?
16. Was the salary and bonus of employees in Bechian more than that of Yaku in 2013?
17. Was the salary and bonus paid to employees in Sikam more in 2011 than in 2013?
18. Between which two consecutive years did the salary and bonus of employees increase in Dundew?
19. Between which two consecutive years did the salary and bonus of employees decrease in Conten?
20. Which year(s) witnessed the greatest salary and bonus paid to employees in Bechian?

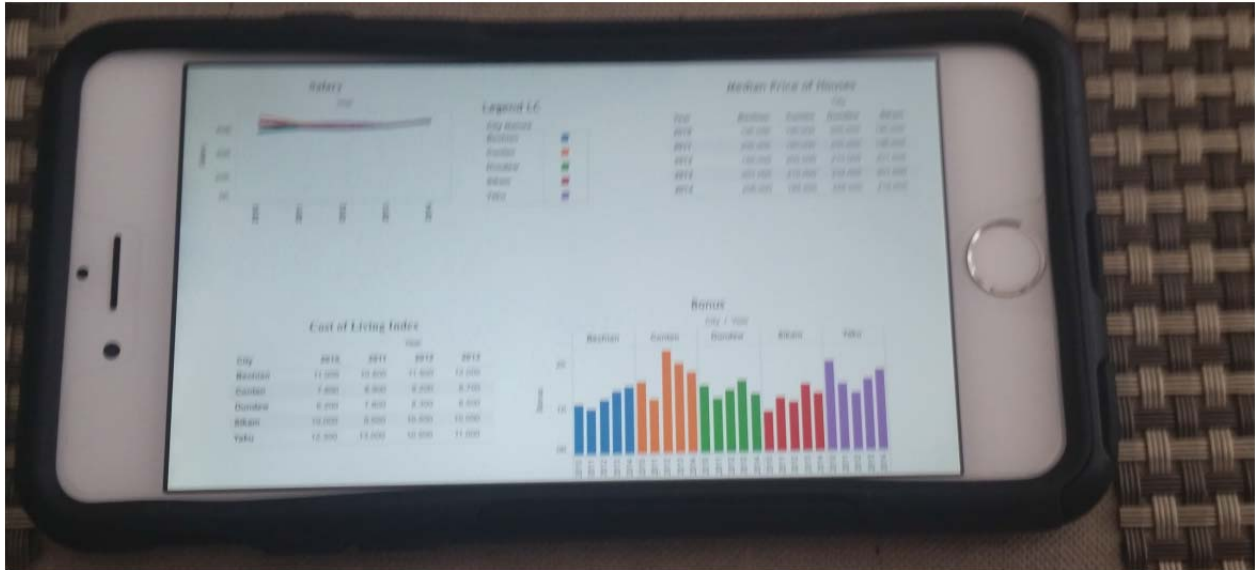
Appendix E - Dashboard With Low Active Control



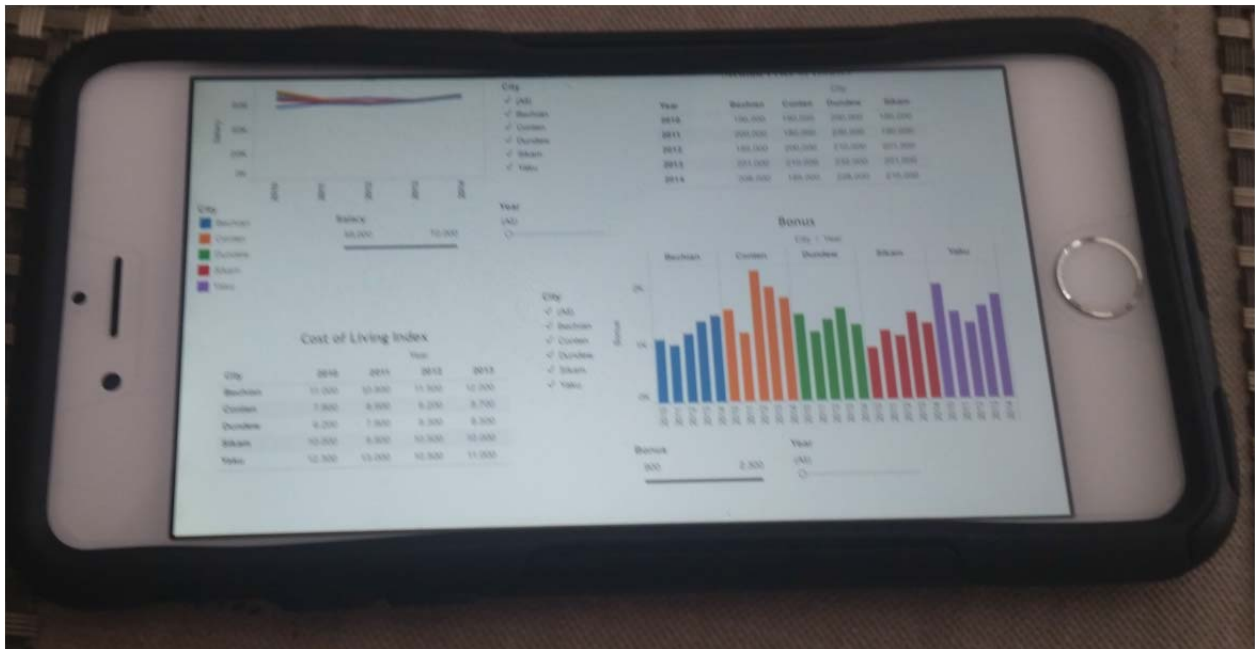
Appendix F - Dashboard With High Active Control



APPENDIX G



Dashboard with low active control on a mobile device



Dashboard with high active control on a mobile device

Appendix H Need for Cognition Questionnaire

Pre Experiment Participant Survey

For each of the statements below, please indicate whether or not the statement is characteristic of you or of what you believe. For example, if the statement is extremely uncharacteristic of you or of what you believe about yourself (not at all like you) please place a "1" on the line to the left of the statement. If the statement is extremely characteristic of you or of what you believe about yourself (very much like you) please place a "5" on the line to the left of the statement. You should use the following scale as you rate each of the statements below.

1 extremely uncharacteristic of me	2 somewhat uncharacteristic of me	3 Uncertain	4 somewhat characteristic of me	5 extremely characteristic of me
---	--	----------------	--	---

1. ____	I prefer complex to simple problems.
2. ____	I like to have the responsibility of handling a situation that requires a lot of thinking.
3. ____	Thinking is not my idea of fun.
4. ____	I would rather do something that requires little thought than something that is sure to challenge my thinking abilities.
5. ____	I try to anticipate and avoid situations where there is a likely chance I will have to think in depth about something.
6. ____	I find satisfaction in deliberating hard and for long hours.
7. ____	I only think as hard as I have to.
8. ____	I prefer to think about small daily projects to long term ones.
9. ____	I like tasks that require little thought once I've learned them.
10. ____	The idea of relying on thought to make my way to the top appeals to me.
11. ____	I really enjoy a task that involves coming up with new solutions to problems.
12. ____	Learning new ways to think doesn't excite me very much.
13. ____	I prefer my life to be filled with puzzles I must solve.
14. ____	The notion of thinking abstractly is appealing to me.

15. ____	I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought.
16. ____	I feel relief rather than satisfaction after completing a task that requires a lot of mental effort.
17. ____	It's enough for me that something gets the job done; I don't care how or why it works.
18. ____	I usually end up deliberating about issues even when they do not affect me personally.

Note: **=reverse scored item.

Source <http://www.psy.ohio-state.edu/petty/documents/ncogscale.pdf> on 04-02-2016

APPENDIX I

Post Experiment Participant Survey

Please indicate your response to the following questions based upon the experiment you performed today.

1. You performed a task based upon a dashboard displayed on a device. What was the type of device? (Please circle one option)

Static (Desktop)

Mobile (Cell Phone)

2. You performed a task based upon a series of questions on the task document.

How many objects (tables, graphs) was each task question based on?

(Please circle one option)

One

Many

3. Did you observe and use the controls (scroll bar, sliders, and checkboxes) on the dashboard to answer the questions on the task document (Please circle one option)

Yes

No

4. Please indicate how you feel about your overall experience of your working on the dashboard task today.

Very Dissatisfied 1 2 3 4 5 6 7 Very Satisfied

Very Displeased 1 2 3 4 5 6 7 Very Pleased

Very Frustrated 1 2 3 4 5 6 7 Very Contended

Absolutely Terrible 1 2 3 4 5 6 7 Absolutely Delighted

Please indicate what you felt about the task.

5. I found this to be a complex task.

Completely Disagree 1 2 3 4 5 6 7 Completely Agree

6. The task was mentally demanding.

Completely Disagree 1 2 3 4 5 6 7 Completely Agree

7. This task required a lot of thought and problem solving.

Completely Disagree 1 2 3 4 5 6 7 Completely Agree

8. I found this to be a challenging task.

Completely Disagree 1 2 3 4 5 6 7 Completely Agree

Other General Questions

9. How often do you use a mobile device (cell phone)? Please circle one option.

Never Rarely Sometimes Often Always

10. How familiar are you with a mobile device (cell phone)? Please circle one option.

Not at all Slightly Somewhat Moderately Extremely

11. How often do you use a desktop computer? Please circle one option.

Never Rarely Sometimes Often Always

12. How familiar are you with a desktop? Please circle one option.

Not at all Slightly Somewhat Moderately Extremely

13. How familiar are you with Tableau? Please circle one option.

Not at all Slightly Somewhat Moderately Extremely

CHAPTER 4

A TALE OF TWO MISFITS? - MOBILE DASHBOARDS – DIRECTIONS FOR RESEARCH AND PRACTICE

4.1 Abstract

Information dashboards, the single screen display of performance indicators are increasingly being deployed on different kinds of devices. In an earlier research paper, academicians have examined the impact of dashboard deployment media type, the design aspect of active control, the problem type and their combinations on the key performance outcome of task accuracy. Borrowing from the results of the experiment, we attempt to identify certain patterns regarding moderation of the relationship between dashboard deployment media type and task accuracy by the active control, across several categories. These categories include the cognitive fit, problem task type and problem representation. It was seen that use of dashboards deployed on mobile devices were associated with greater task accuracy when the user had little control, when the problem type is singular and when there is low cognitive fit. However, use of dashboards deployed on static devices resulted in greater task accuracy when the user had more control and when the problem task dealt with identifying relationships between data points. We also identify certain key areas where further research could be done. These include using theoretical underpinnings to understand how the symbolic and spatial elements of cognitive fit interact with the dashboard deployment media type, active control and problem type to impact task accuracy.

4.2 Introduction

Mobile devices are increasingly becoming popular in the modern world. Dashboards are data visualizations that contain key performance indicators presented in a single screen. Dashboards are used to monitor, communicate and control performance of various aspects of personal and organizational entities. Many companies that produce data visualization software (for example Tableau and Qlikview) enable the dashboards to be deployed on mobile smart phones and on static desktop devices. Raman (2016) investigated this phenomenon and explored the question – Are dashboards deployed on mobile devices associated with greater task accuracy and satisfaction than those deployed on static devices, when these dashboards are used for problem solving? They conducted an experiment with student subjects at a large public university to validate a conceptual model. The current paper is based upon the results of that experiment.

Dashboards often present summary information in graphs of various types. Tables are also included which contain information about the various states of key performance indicators. Academics have looked at the efficacy of graphs versus tables for over three decades. An old saying – “a picture is worth a thousand words” is quite popular. Vessey in 1991 looked at the inconsistent results with respect to graphs versus tables and explicated the theory of cognitive fit. Graphical or tabular representations are used in problem solving and decision making.

Humans solve problems aided by the mental representation held in working memory. These mental representations are derived from the characteristics of the problem representation and the problem solving task. Both the problem representation and the task inherently emphasize certain processes on processing information. The mental representations are easily and more

consistently formed when the information emphasized in the problem representation matches the information emphasized in the problem task. When they do not match, there is a need to transform the mental representation or the data because of the use of different processes to process information in the problem representation and problem solving task.

Graphs and tables are based upon the same set of data and one can be inferred from the other (Simon, 1981). In the psychology literature, data organization has been categorized into images and words (Glass et al. 1979). Graphs portray information in a continuous manner whereas tables convey information in discrete values. Vessey (1991) identifies graphs as being spatial representations, whereas tables can be considered as being symbolic representations. Graphs are used to identify trends and simple and complex comparisons. They are associated with perceptual processes that are used to associate and relate different points to each other. Tables are used for identifying discrete values and exemplify analytical processes.

Tasks can also be identified as spatial or symbolic (Umanath et al. 1990). The problem solver looking at a spatial task is motivated to see associations or relationships between data points. While solving symbolic task problems, the person gleans discrete data values from the presentation. Cognitive fit theory posits that the perceptual processes evoked by the spatial representations match with the associative nature of the spatial problem task. Similarly, the analytical processes that are triggered by symbolic representations match with the discrete nature of the symbolic data. Better performance outcomes are realized when there is a match.

The following is the extended problem solving model:-

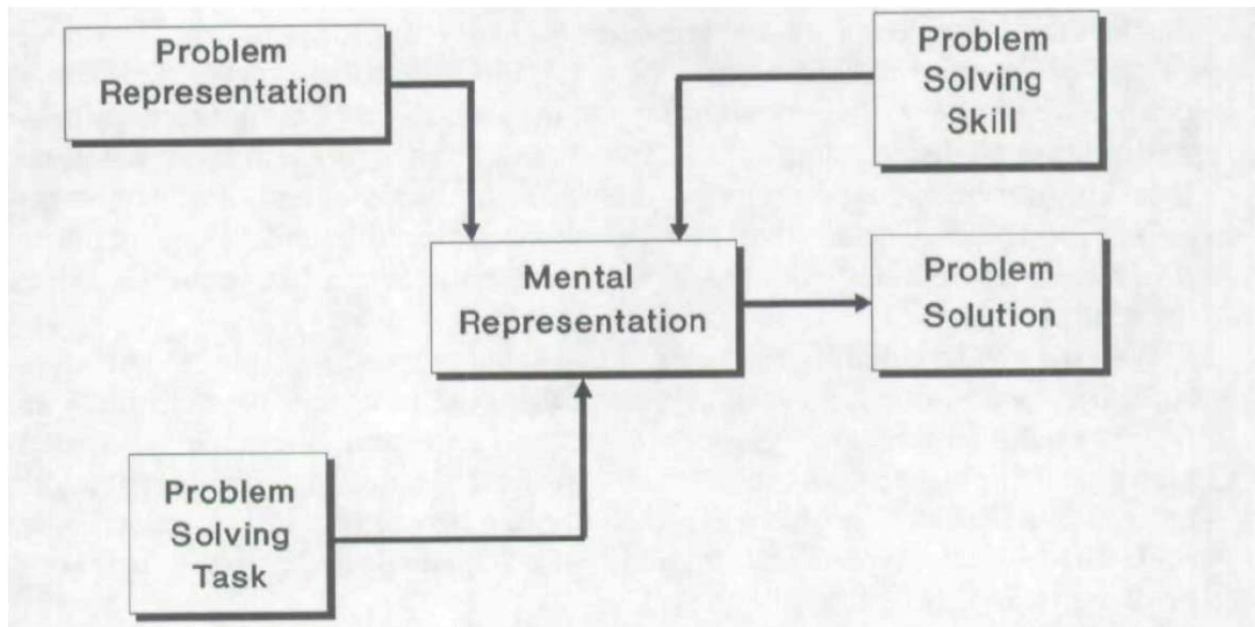


Figure 4.1:- Extended Problem Solving Model (Vessey 1991)

Cognitive fit theory has been used in the information systems arena to understand various phenomena. It has been used to understand the adaptation of web pages during presentation (Adipat et al. 2011), attribute based decision support systems (Kamis et al. 2008) and map based geographical information systems (Mennecke et al. 2000) to name a few instances.

4.3 How the data informs practitioners?

The participants in the experiment conducted by Raman (2016) were assigned to either a dashboard displayed on a mobile device or a dashboard displayed on a static desktop device. Some solved problems that were based upon a single object on the dashboard display; while others solved problems that used information based upon multiple objects on the dashboard. Each dashboard either had minimal user control or had many control elements such as checkboxes and sliders. Each experimental task comprised 20 questions. The 20 questions belonged to four different categories. The categories are displayed in table 4.1.

Table 4.1 Symbolic and Spatial Combinations of Task Questions and Objects on Dashboard	
Question	Object on Dashboard
Symbolic (Identifying point values)	Table (Symbolic)
Symbolic (Identifying point values)	Graph (Spatial)
Spatial (Identifying relationship between data points)	Table (Symbolic)
Spatial (Identifying relationship between data points)	Graph (Spatial)

The participants solved the problems while viewing the dashboard. Task accuracy and satisfaction were measured at the end of the experiment. Tables 4.2 and 4.3 shows the mean value of task accuracy as evaluated from the response of the experiment participants. Various categories have been displayed that look at task accuracy from various perspectives. The overall

summary results have been examined at a more granular level. These include the levels of cognitive fit (low and high), problem task type (symbolic and spatial) and problem representation (symbolic represented by tables and spatial represented by graphs). Table 4.2 shows the task accuracy as measured for the four combinations of two levels each of problem task type and problem representation.

Analysis of the data presented in the two tables reveal certain patterns which can be verified using rigorous statistical methods. Further, in order to establish practical significance, replicative studies need to be carried out, before vouchsafing these recommendations. The users of dashboards solving singular problems on static devices having high active control demonstrated the highest task accuracy in all categories examined.

The user may have control only over the media on which the dashboard is deployed. We give below a sample of a few recommendations. We can use associative rule mining to provide an exhaustive list of recommendations for meeting certain desired objectives. We now look at table 4.2 to arrive at a few directions. If the dashboard displayed has very little active control, and the problem type is singular and there is low cognitive fit between the problem representation and problem task, then the user may solve problems better with the dashboard deployed on a mobile device. The problem task may be spatial dealing with trends, and integrative. The dashboard may have a large number of active controls that help the user achieve more clarity. In such a situation, users of dashboards deployed on static devices will achieve more task accuracy. The problem task could be symbolic and representation spatial thereby causing a certain degree of cognitive misfit. For integrative tasks, dashboards having low active control and displayed on mobile devices have the lowest accuracy.

Table 4.2 Means of Task Accuracy for Different Scenarios

	Static						Mobile					
Measures	Low Active Control			High Active Control			Low Active Control			High Active Control		
	Singular	Integrative	Mean	Singular	Integrative	Mean	Singular	Integrative	Mean	Singular	Integrative	Mean
Regular	65.13	47.68	56.40	82.02	66.23	74.13	66.89	50.73	58.81	68.50	52.54	60.52
Low Cognitive Fit	57.56	32.44	44.99	82.51	60.39	71.45	61.46	39.43	50.44	60.78	43.64	52.21
High Cognitive Fit	71.39	62.51	66.94	81.62	71.92	76.77	71.38	61.73	66.55	74.89	61.20	68.04
Symbolic Task	62.58	23.22	42.90	93.22	38.13	65.68	56.12	21.07	38.60	70.96	25.80	48.39
Spatial Task	65.93	54.12	60.02	78.52	69.31	73.92	70.26	61.21	65.74	67.74	59.42	63.58
Symbolic Representation	75.21	50.00	62.60	82.34	60.39	71.36	77.07	57.89	67.48	68.25	56.54	62.40
Spatial Representation	56.80	45.42	51.11	81.78	71.92	76.84	58.48	43.76	51.12	68.72	48.64	58.68

Table 4.3 Means Task Accuracy for Different Cognitive Fit Scenarios

	Static						Mobile					
Measures	Low Active Control			High Active Control			Low Active Control			High Active Control		
	Singular	Integrative	Mean	Singular	Integrative	Mean	Singular	Integrative	Mean	Singular	Integrative	Mean
LOW COGNITIVE FIT												
Symbolic Task and Spatial Representation	29.03	14.74	21.89	93.54	61.29	77.41	26.45	10.14	18.29	56.77	24.88	40.82
Spatial Task and Symbolic Representation	67.74	43.69	55.71	78.57	59.82	69.19	73.96	58.06	66.01	62.21	55.57	58.89
HIGH COGNITIVE FIT												
Symbolic Task and Symbolic Representation	92.13	59.90	78.02	92.90	61.29	77.09	85.80	57.60	71.70	85.16	58.06	71.61
Spatial Task and Spatial Representation	64.51	64.09	64.30	78.49	78.40	78.44	67.38	64.23	65.80	72.04	63.11	67.58

Table 4.4 Results of UNIVARIATE ANOVA Tests on Task Accuracy (p values)

EFFECTS	CATEGORIES						
	Overall	Low Cognitive Fit	High Cognitive Fit	Symbolic Task	Spatial Task	Symbolic Representation	Spatial Representation
Dashboard Deployment Media Type (DEVCODE)	.012*	.007*	.067	.000*	.379	.444	.000*
Dashboard Active Control (CTRCODE)	.000*	.000*	.023*	.000*	.026*	.492	.000*
Problem Type (PRBTYPE)	.000*	.000*	.000*	.000*	.000*	.000*	.000*
DEVCODE X CTRCODE	.000*	.000*	.094	.000*	.002*	.010*	.000*
DEVCODE X PRBTYPE	.901	.424	.631	.047*	.728	.129	.166
CTRCODE X PRBTYPE	.833	.434	.625	.000*	.752	.315	.697
R Square	.281	.364	.110	.757	.106	.211	.311

*Significant at α of .05, ** Significant at α of .1

Table 4.5 Results of UNIVARIATE ANOVA Tests on Task Accuracy (p values) for Different Cognitive Fit Scenarios

	Symbolic Task and Spatial Representation	Spatial Task and Symbolic Representation	Symbolic Task and Symbolic Representation	Spatial Task and Spatial Representation
Dashboard Deployment Media Type (DEVCODE)	.000*	.999	.042**	.123
Dashboard Active Control (CTRCODE)	.000*	.320	.861	.028
Problem Type (PRBTYPE)	.000*	.000*	.000*	.004*
DEVCODE X CTRCODE	.000*	.001*	.886	.042
DEVCODE X PRBTYPE	.885	.113	.279	.340
CTRCODE X PRBTYPE	.004*	.255	.622	.653
R Square	.588	.147	.331	.061
*Significant at α of .05, ** Significant at α of .1				

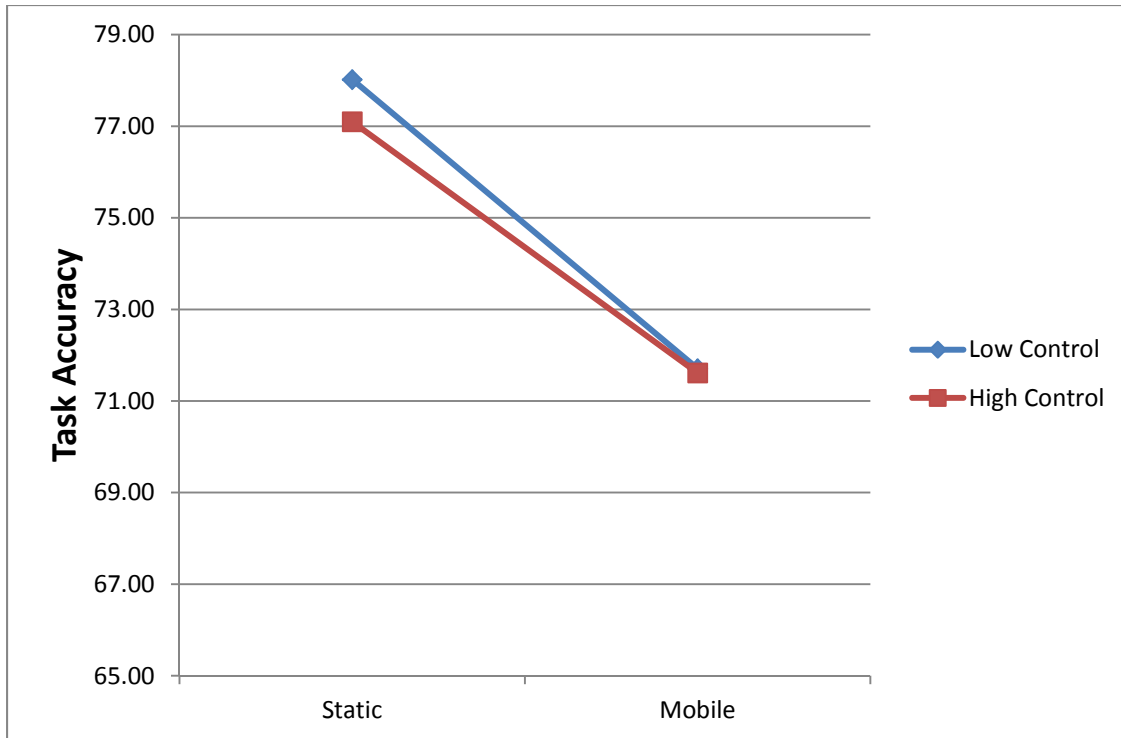


Figure 4.2 Moderation by Active Control of the Relationship between Dashboard Deployment Media Type and Task Accuracy When the Problem Task is Symbolic and Problem Representation is also Symbolic.

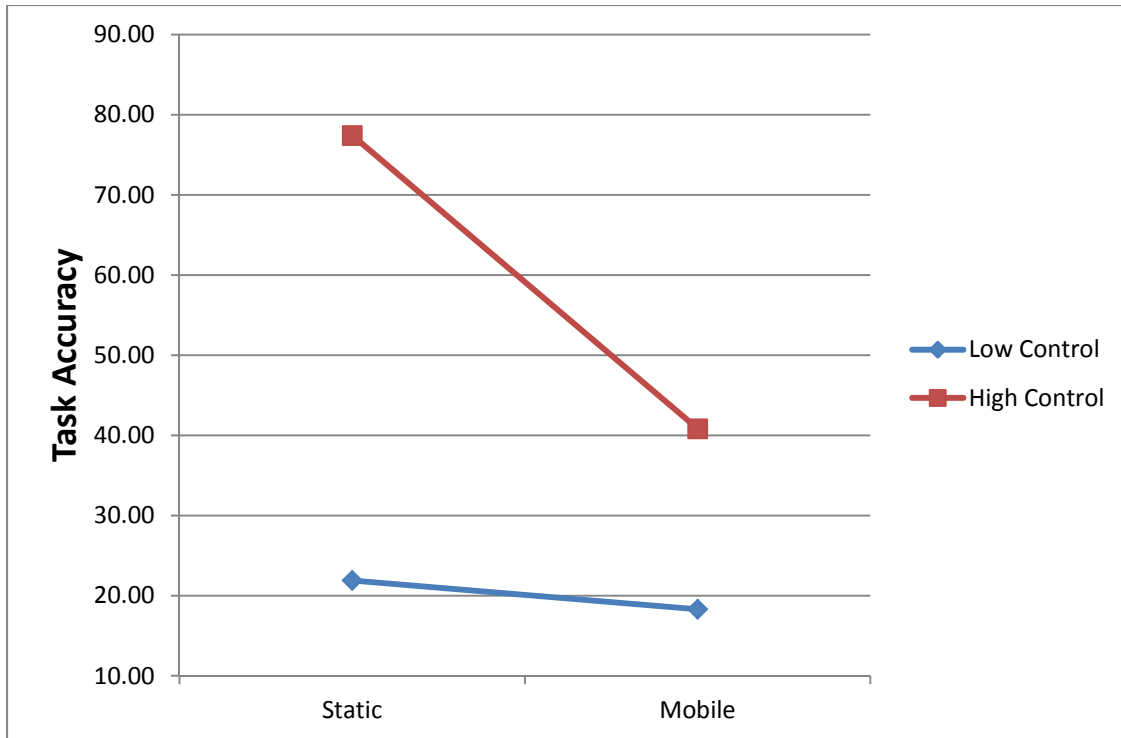


Figure 4.3 Moderation by Active Control of the Relationship between Dashboard Deployment Media Type and Task Accuracy when the Problem Task is Symbolic and Problem Representation is Spatial.

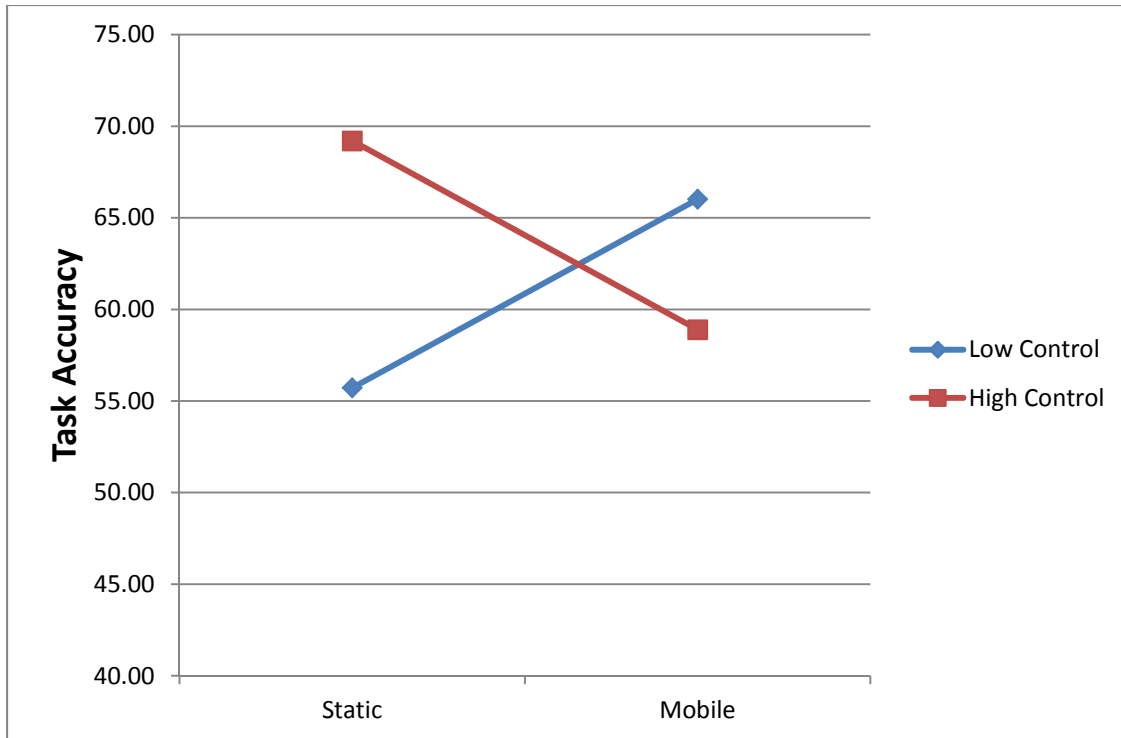


Figure 4.4 Moderation by Active Control of the Relationship between Dashboard Deployment Media Type and Task Accuracy when the Problem Task is Spatial and Problem Representation is Symbolic.

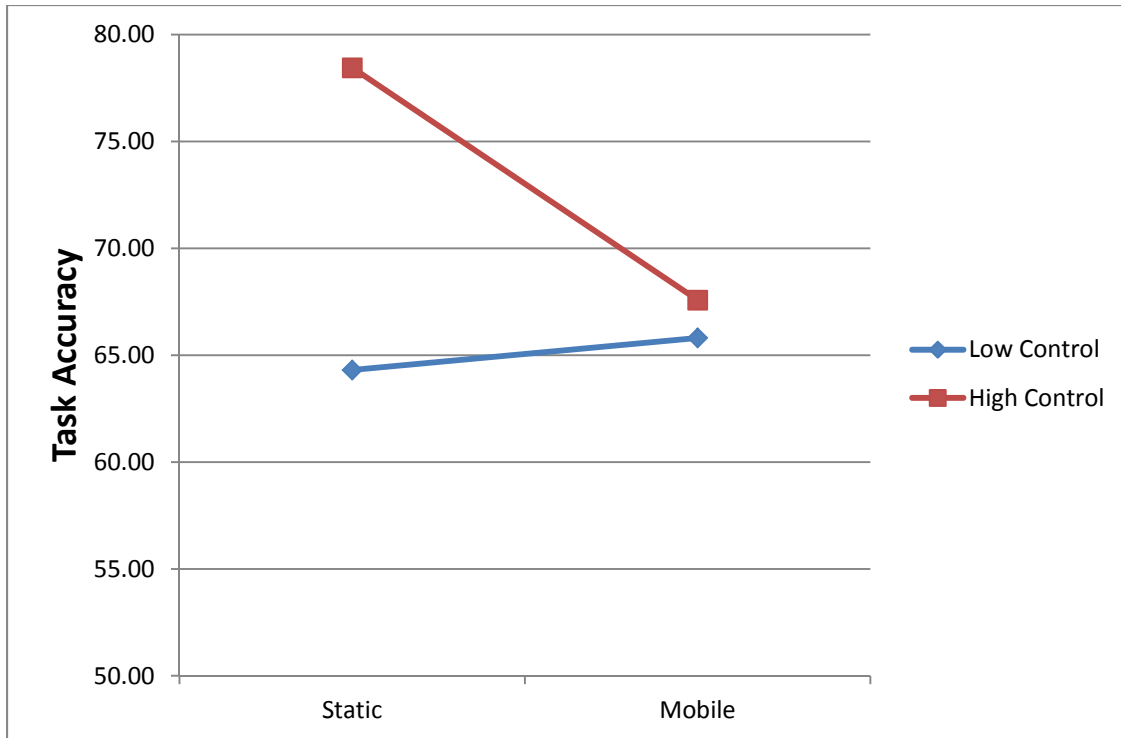


Figure 4.5 Moderation by Active Control of the Relationship between Dashboard Deployment Media Type and Task Accuracy when the Problem Task is Spatial and Problem Representation is also Spatial.

4.4 Future Research Directions

Table 4.4 indicates that the relationship between dashboard deployment media type and task accuracy is weakly moderated by problem type for symbolic tasks. A preliminary linear contrast check confirmed the same result. Table 4.4 also indicates that when the problem task is symbolic, the relationship between active control and task accuracy is moderated by problem type.

Figures 4.2 through 4.5 indicate that the interaction between dashboard deployment media type and active control is different for the two levels of problem task and problem representation. Figure 4.2 indicates that if problem task and problem representation are both symbolic, use of dashboards with active control will result in less adverse task accuracy when they are deployed on mobile devices than when they are deployed on static devices. Figure 4.3 however shows a reverse pattern for the moderating relationship between dashboard deployment media type and task accuracy. If the problem task is symbolic and problem representation is spatial, active control on dashboards is associated with less favorable task accuracy when they are deployed on mobile devices than when they are deployed on static devices. Figure 4.4 shows a very interesting cross over interaction between dashboard deployment media type and active control. The main effects of deployment media type and active control are not significant. The task accuracy of mobile devices seems to be greater than the task accuracy of mobile devices when the problem task is spatial and problem representation is symbolic. Figure 4.5 shows a similar interaction when the problem task and problem representation are both spatial. However there is no cross over interaction. These four different types of interactions may be validated by using statistical methods. Research could also look at the various theoretical underpinnings that

can explain the nature of the phenomena at a more granular level that includes the different elements of cognitive fit.

4.5 Conclusion

Information dashboards are being increasingly deployed on mobile devices. Based upon an experiment to understand this phenomenon, we have examined the measure of accuracy across the different categories of cognitive fit and elements of cognitive fit, the problem task and problem representation. We highlight a few patterns that emerge in the data. We also examine the results of the statistical analysis of the experiment and identify the crucial need to look at the phenomenon at a lower granular level. It may very well be that while dashboards deployed on static devices outperform those on mobile devices on task satisfaction in a majority of situations, there may indeed be a few special scenarios where the latter performs better.

CHAPTER 5

5.1 General Conclusions

Information dashboards are increasingly being deployed on mobile hand held devices. We conduct an in-depth research on this phenomenon by borrowing from many research disciplines including information systems, cognitive psychology, educational and instructional psychology, vision search, human memory and advertising. The information dashboard itself was the key content factor in this research.

Our research analyzed bias in the mind of the decision maker as a contextual factor in this phenomenon. We proposed that when decision makers employ certain heuristics while using information dashboards on mobile devices, they could be more prone to the associated biases. We also looked at the distortion in the data visualization and proposed that decision makers may be susceptible to the negative effects of the distortion on the mobile dashboards, due to the use of the representativeness heuristic.

We conducted an experiment to validate a conceptual model relating the two key content factors of dashboard deployment media, amount of user control and the contextual factor of problem task type to the performance and perceptual outcomes. We found that the relationship between dashboard deployment media type and task accuracy is contingent upon whether the user is provided low or high control over the form and content of the dashboard. Similarly we found that mobile users of interactive dashboards experience lesser satisfaction than static users.

Our research indicated that the ubiquitous bias towards pushing information dashboards to mobile devices is not quite justified, due to the negative impact on accuracy and satisfaction. However we found that there is an area where the mobile information dashboards could

outperform static information dashboards. Future research could look at the fourth factor of cognitive fit between the problem representation and problem task in order to identify the opportunity.

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