Business Information Visualization: A Visual Intelligence-Based Framework

Research-in-Progress

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ABSTRACT

Business Intelligence aims to improve decision quality. Research on BI achieving this goal is inconclusive, yet BI is still one of the top priorities among CIOs and is an active IS research area. A better understanding of the relationship between human intelligence and BI capabilities may lead to more fruitful BI endeavors. This paper proposes a conceptual framework that links capabilities of Business Information Visualization, a key modern BI enabler, to non-verbal (visual) intelligence abilities, and suggests propositional guidelines of how BI could improve decision making by impacting these intelligence abilities. The paper demonstrates that there is strong research support to suggest such linkages. Better understanding of what human abilities are important for better decisions, and what specific BI capabilities are needed to support these abilities will help improve the design, deployment, and utilization of BI tools, and, hopefully ultimately, achieve more efficient and effective business decisions.

Keywords

Business Information Visualization, Visual Intelligence, Business Intelligence, Decision Performance

INTRODUCTION

Business Information Visualization (BIV), a BI technology capability of displaying business information visually (Tegarden 1999) is gaining increasing attention with practitioners and researchers (Zhang 2001). In a quest to respond to recent 'visualization fashion', vendors are providing rich visualization capabilities fast, yet the users of BI systems often lack proper training in appropriate use of available graphical solutions and options (such as color, shape, formatting, labeling, etc)(Few 2004). As a result, many BI reporting solutions are enabling deployment of 'chartjunk' – "visual elements in charts and graphs that are not necessary to comprehend the information represented on the graph, or that distract the viewer from this information" (Tufte 1983). Instead of aiding and leveraging human cognitive and nonverbal abilities to reduce information complexity and uncertainty (Zack 2007), BI systems often deploy reporting solution that, at best, increase effort and cognitive load, and at worst, unnecessary increase complexity and uncertainty or even mislead decision makers (Few 2004; Tufte 1983; Tufte 1990; Tufte 1997; Ware 2000).

Our research suggests that in order improve the support and effectiveness of decision making, BI and its BIV capabilities need to assist human abilities and visual intelligence potential as a way of reducing information complexity and uncertainty. By enhancing and enabling human visual intelligence abilities and processes, BI will more effectively achieve its supreme goal of assisting in decision making. More specifically, the paper provides a formal framework that links BI visualization capabilities to human visual intelligence abilities and outlines propositions for future research.

The paper offers three key contributions. First, a novel intelligence-based framework for assessing Business Information Visualization effectiveness is introduced. Second, key Information Visualization and BIV literature is identified and aligned with the proposed framework. Based on DeLone and McLean's (1992) and Clark et al's (2007) recommendation, the paper delivers a framework that allows one to asses prior research about the framework components and allows one to provide a logic about the relationships among the components. Third, the paper suggests propositional guidelines to assess how visual capabilities of BI tools contribute to the goal of "intelligent business".

FRAMEWORK

The main tasks of a BI system include *intelligent* exploration, integration, aggregation of data (Olszak et al. 2007). BI is constructed on the identification and modeling of focused business information. Asking the right questions is the precursor to *making intelligent decisions* (Ranjan 2008). These and many other studies point at *decision making* support as the central desired outcome and goal of BI systems. Decision support should focus on the cognitive processes (Svenson 1979). This requires software that seamlessly interacts with the brain to support and extend its cognitive abilities and enable full and effortless use human intelligence abilities. Unfortunately, BI software too often gets in the way, interrupting and undermining the thinking process rather than complementing and extending it (Few 2006). Our research is suggesting that BIV is a key enabler of BI's role of turning business into 'intelligent business' (Gartner 2010) which, in turn, can lead to improved support for decision making.

Given the link, based on the above literature, between BI capabilities and human abilities and intelligence, this article proposes the adoption of human visual ability and intelligence measurement as a framework to systematically assess, and better leverage supporting capabilities of BIV. The best known human intelligence measurement test is Stanford-Binet IQ (Intelligence Quotient) test. IQ testing, first introduced by French psychologist Alfred Binet in 1904, is a method used by psychologists to measure what is generally considered intelligence. The latest is the fifth edition that is simply referred to as the Stanford-Binet 5(SB5) (Roid 2003). SB5 includes the first published testing of nonverbal content which is of special interest to this paper. The Nonverbal IQ (NVIQ) of SB5 measures the general ability to reason, solve problems, visualize and recall information presented, in pictorial, figural and symbolic form (Becker 2003) which are essential for information-based decision making. NVIQ is thus used as the foundation for the proposed framework and it consists of five nonverbal mental abilities (Becker 2003): Fluid Intelligence/Reasoning (*Gf*), Domain specific Knowledge (*Gkn*), Quantitative Reasoning (*Gq*), Visual-Spatial Processing (*Gv*) and Working and Short Memory (Figure 1).

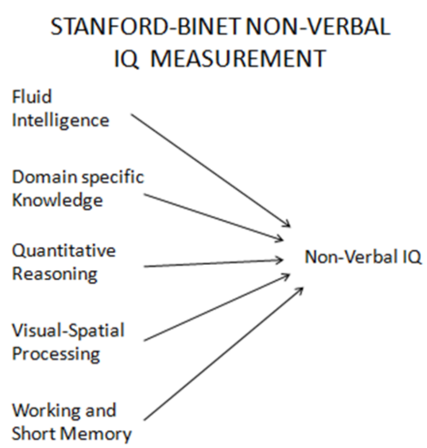

Figure 1: The Nonverbal IQ (NVIQ) of SB5

Given the impact of visualization on decision making support, and the link of the NVIQ abilities to human abilities already identified in extant BIV literature, this research propositions of BIV capabilities that support these abilities and results in a research framework.

PROPOSITIONS

The following propositions, logically aligned based on adopted framework are rooted in extensive literature review and theories of human cognition, perception and memory, are an attempt to shed light and better understand these unique characteristics and challenges.

Business Information Visualization and Fluid Reasoning

Fluid Reasoning has been defined as the use of deliberate and controlled mental operations to solve novel 'on the spot' problems (McGrew 2004). A number of mental operations have been listed as part of this ability: drawing inferences, concept formation, classification, generating and testing hypothesis, identifying relations, comprehending implications, problem solving, extrapolating, and transforming information(McGrew 2004; McGrew 2009). Most, if not all, of these mental operations are often required in the analysis of the business information. The proposed framework argues a useful BIV needs to facilitate these mental operations in a user to support effective decisions with less effort. In a business decision making context, high levels of Fluid Reasoning may be difficult to achieve without a BIV system providing the ability to visually explore, interact with and readily access information.

The topic of data exploration has been researched by many (Baker et al. 2009; Keim 2002; Tufte 1997). Tukey is being credited for separating exploration from statistics in the 1970s. Edward Tufte discussed the subject in the context of visualization by emphasizing the need for exploring data is to "find out what is going on"(1997). Exploration is also defined as examination of data without having an a priori understanding of what patterns, information, or knowledge it might contain (Baker et al. 2009; Tukey 1977). Some of the common exploratory tasks include: observing specific data point, patterns or outliers, making inferences, comparing to one's own prior knowledge, generating hypotheses and drawing analogies (Baker et al. 2009). Automation of graphical presentation format has been discussed in the context of more effective exploration as well (Ahmed et al. 1994; Mackinlay et al. 2007; Stolte et al. 2008), hence:

> *Proposition 1a: Business Information Visualization through effective exploration capability positively influences decision-maker's Fluid Reasoning ability.*

Related to exploration and often serving as its enabler are the interaction capabilities of BIV tools. Interaction, however, can serve goals other than exploration and can be used in confirmatory and presentation tasks as well. The goal of interaction is to enable a user to understand information better by allowing the user to interact with the information. Calls have been made to create a new science of interaction to support visual analytics (Thomas et al. 2005). Classic Information Visualization interaction taxonomy often talks about seven interaction tasks: Overview, Zoom, Filter, Details-on-Demand, Relate, History, and Extract (Kosara et al. 2003) or techniques organized around a user's intent: Select, Explore, Reconfigure, Encode, Abstract/Elaborate, Filter, and Connect (Ji Soo et al. 2007). From the perspective of model-based reasoning, interaction was assessed through the purposes of external anchoring, information forging and cognitive offloading (Liu et al. 2010), hence:

> *Proposition 1b: Business Information Visualization through its effective interaction capability positively influences decision-maker's Fluid Reasoning ability.*

Business Information Visualization and General (Domain specific) Knowledge (Gkn)

General (Domain specific) Knowledge has been defined as an individual's breadth and depth of acquired knowledge in specialized (demarcated) domains that typically do not represent general universal experiences of individuals in a culture (*Gc). Gkn* reflects deep specialized knowledge domains developed through intensive systematic practice and training and the maintenance of the knowledge base through regular practice and motivated effort (McGrew 2004; McGrew 2009). Gkn represents familiarity with particular subject area (Ju 2007; Wildemuth 2004)

While domain knowledge has been extensively researched in psychology and cognition-related literature (Chi et al. 1988; Devine et al. 1995; Hambrick et al. 2002; Ju 2007; Wildemuth 2004), IS discipline is yet to approach this topic in similar depth. An argument has been made that the use of domain knowledge is important in all stages of the knowledge discovery (Fayyad et al. 1996). The importance of expertise was noted in identification of important problem features (Mackay et al. 1992) and better information organization and rationalization (Mao et al. 2000). Moreover, expert systems, through domain knowledge, have been found to impact data mining classification methods performance (Sinha et al. 2008). More recently, the link between domain knowledge and presentation format has been recognized in Accounting Information Systems as well (Cardinaels 2008).

Since it is widely accepted that large level of domain knowledge is needed to achieve expertise (Chi et al. 1988), BIV deployed by a user that already possess a level of expertise/business acumen is suggested to positively influence a decision-maker's domain specific knowledge intelligence. Without business acumen, a user/designer of BI will face difficulty in basic interactions with the system such as encoding, filtering, connecting and relating. Similarly, the effectiveness of the BIV, even if deployed effectively in every other aspect, will be greatly diminished if deployed using inappropriate data/data source in terms of issues of latency (Hackathorn 2004), content and granularity. Hence, the following propositions are offered:

> *Proposition 2a: Business acumen impacts the influence of Business Information Visualization on decision-maker's General (Domain) Knowledge Intelligence*

> *Proposition 2b: Business data and source appropriateness impacts the influence of Business Information Visualization on decision-maker's General (Domain) Knowledge Intelligence*

Business Information Visualization and Quantitative Reasoning (Gq)

Quantitative Reasoning has been defined as a person's wealth (breadth and depth) of acquired store of declarative and procedural quantitative knowledge. *Gq* represents an individual's store of acquired mathematical knowledge, not reasoning with this knowledge (McGrew 2004; McGrew 2009). In BIV, a system can enhance decision making through Quantitative

Reasoning by offering ready-to-use, statistical functions and capabilities especially useful in modeling and predicting. Examples include, on the fly summary statistics such as averages, medians, standard deviations, percentiles as well as more complicated algorithms, calculations, and data mining techniques such as regressions, clustering, and association analysis. BI Vendors are starting to recognize the significance of statistical and quantitative capabilities of their BI offerings. Leading BI tools are starting to incorporate these capabilities, for example, IBM Cognos integrated SPSS statistical engine with core BI offering**.** Spotfire and Tableau**,** two leaders in business data visualization, also incorporate significant on-the-fly statistical capabilities. For further details see for example Davenport and Harris (2007).

Proposition 3: Business Information Visualization through its statistical capabilities positively influences decision-maker's Quantitative Reasoning ability.

Business Information Visualization and Visual-Spatial Processing (Gv)

Visual Spatial Processing abilities are defined as the ability to generate, retain, retrieve, and transform well-structured visual images (Lohman 1994). The *Gv* domain represents a collection of different abilities each emphasizing a different process involved in the generation, storage, retrieval and transformation of information. These abilities need the perception and transformation of visual shapes, forms, or images and/or tasks which in turn require the maintenance of spatial orientation with regard to objects that may change or move through space (McGrew 2009). Representation can be viewed through the prism of representation methods (histograms, tables, bar charts, bullet graphs, etc…) and representation elements (color, text, symbols, size, etc…). Effective representation is primarily built on understanding of the human visual perception principles as well as the human cognition science.

Information representation (spatial representations that are derived from symbolic data (Card et al. 1999)) has been researched extensively and a large part of it centered on understanding the significance of representation method. The representation method research largely focused on understanding the impact of display choice between tabular and graphical. It has been noted (Baker et al. 2009) that this body of research resulted in formulation of Cognitive Fit Theory, that suggests the importance of fit between the problem representation and the problem-solving task in achieving effective performance

In addition to representation methods, researchers created a significant body of knowledge around representation elements such as color (Benbasat et al. 1986a; Benbasat et al. 1986b; Cleveland 1985; Davis et al. 1986; Tufte 1990; Ware 2000), object depth and dimensionality (Kumar et al. 2004; Tractinsky et al. 1999; Watson et al. 1983) and organization, symbols, labels, text, icons, lines, grids, and axes (Bertin 1983; Cleveland 1985; Ives 1982), suggesting the significance of representation on BIV effectiveness, hence:

Proposition 4a: Business Information Visualization through its effective use of representation (methods and elements) positively influences decision-maker's Visual-Spatial Processing ability.

Perception is "the process of interpreting and recognizing sensory information" (Ashcraft 1998), p. 428). Regardless of the choice of information, the encoding of information, and impressiveness of the presentation, a graph is a failure if the visual decoding fails (Cleveland 1985). This decoding process occurs in part due to visual perception abilities. Miller (1956) reports human perceptual ability in terms of making judgment about unidimensional and multidimensional stimuli and explains the ability to distinguish line maker locations, levels of direction, line length, size and color. Studies like this suggest that we could exploit our visual channel inputs to a degree, without creating an overload. Others focus on the promise of visual imagery (Shepard et al. 1982) leading to improve business decision making (Kosslyn 1980; Tegarden 1999). Psychologists (Koffka 1935; Wertheimer 1938) have also presented a series of Gestalt principles (e.g., Proximity, Similarity, Common Fate, Objective Set, Direction, and Good Form) to be used to effectively leverage human perception. Researchers have discussed these principles in the context of business graphical display and comprehension (Ives 1982; Kosslyn 1989; Kumar et al. 2004). Gestalt principles and related preattentive attributes (high speed visual perception occurring below consciousness) have been utilized (Tufte 1983; Tufte 1990; Baker, Jones et al. 2009) in improving representations.

Studies of human perceptional ability including visual imagery, cognitive fit, gestalt principles and preattentive attributes, have led to a number of design principles (Cleveland et al. 1984; Ives 1982; Jarvenpaa et al. 1988; Kosslyn 1994; Tufte 1983; Tufte 1990), and motivate the following proposition:

Proposition 4b: Business Information Visualization through its effective support of human visual perception abilities positively influences decision-maker's Visual-Spatial Processing ability.

Cognitive science suggests that users have internal representation of visualizations they see (Liu et al. 2010) and as such external representation should leverage the available research on internal visualization. Within Decision Support Systems (DSS), there has been a recognition of a need for systems to support a decision maker's general thinking processes to reduce cognitive biases in decision making (Chen et al. 2003). Zmud argues that IS support should focus on executives' thought support in problem and opportunity recognition and diagnosis instead of providing support for the evaluation and choice phase of the decision-making process (1986). Additional contributions of interest to the intersection of BIV and cognition includes work on recall (Kosslyn 1980; Schmell et al. 1988; Watson et al. 1983), and mental imagery (Kosslyn 1980). This significant and cross-disciplinary body of research and its findings suggests the following proposition:

Proposition 4c: Business Information Visualization through its effective support of human cognition abilities positively influences decision-maker's Visual-Spatial Processing ability.

Business Information Visualization and Working and Short Memory

The importance of memory and effective use of memory when presenting and processing information visually is widely acknowledged (Bin et al. 2010; Kosslyn 1989; Lohse 1997; Miller 1956; Schmell et al. 1988). Within representation capability, the use of design principles leveraging memory is well documented (Kosslyn 1989; Miller 1956; Tegarden 1999; Tufte 1983; Tufte 1990). The issue of limited amount of information storable in short term memory is central to many design constraints. An effective way to increase the amount of information in short-term memory called "chunking" was proposed (Kosslyn 1994; Tufte 1990) and often indirectly adopted when deciding to use line graph to plot measures of interest across sequential months of data vs. tabular presentation of the same data. In terms of visualization methods, the choice of colors (Benbasat et al. 1986a) and symbols (Bertin 1983) is often done in consultation with memory and cognition literature.

Verbal working memory was suggested to impact the effectiveness of visual interfaces (Bin et al. 2010; Lohse 1997). In the context of domain knowledge, the superior performance of experts appears to be related to various cognitive tasks such as improvements and impacts to memory, such as long term memory (Ericsson et al. 1995), working memory capacity (Ricks et al. 2009) and comprehension that leads to impacts in problem solving performance. Responding faster on perceptual tasks was explained via the theory of Long Term Working Memory (Ericsson et al. 1995), in which skilled activities (domain knowledge related) allow the sequence of stable states (retrieval structures) to be stored in long-term memory and to be directly accessible through the retrieval cues in short-term memory. This research suggests the following proposition:

Proposition 5: BIV through its effective support of human memory positively influences decision maker's working and short memory ability.

RESEARCH MODEL AND METHODOLOGY

The above propositions posit that BI-enabled decision making is a result of technology and human interactions where technology capabilities enable more effective leverage of human abilities. Our definition of technology capability includes not only the systems but also resources and the way resources deploy those systems. Hence, capabilities could be grouped as functional capabilities (system), competencies (resources), and ability aware principles (deployment). We also suggest, based on Zack (2007) that technology capabilities and human abilities do not directly impact decision performance but rather help decision makers with organizational challenges by reducing information complexity and uncertainty that has the potential to aid in decision making. In other words, the value of technology capabilities and their enablement of human abilities is limited in decision performance if the goal of information complexity and information uncertainty reduction is not achieved (Figure 2).

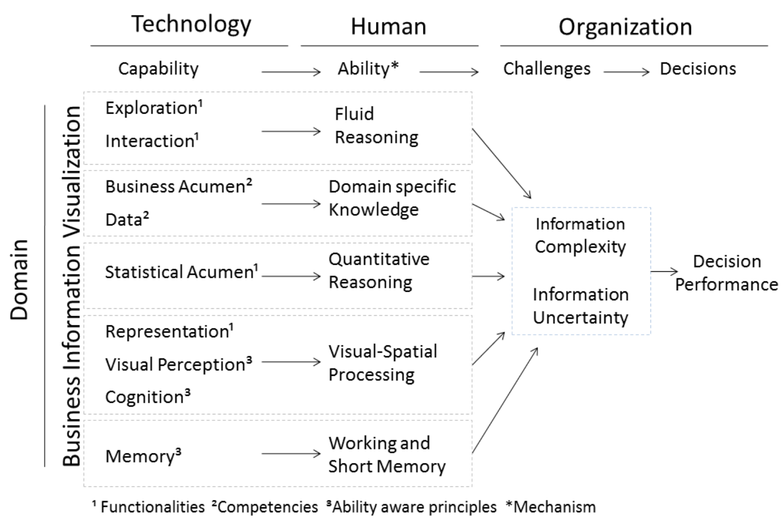

Figure 2: BIV Research Framework

In order to validate the framework and the resulting model we propose the operationalization of functionalities (Exploration, Interaction, Statistical, and Representation) as the level of existence of those capabilities in BIV technology. Business acumen competency is to be measured as the level of user's domain knowledge (survey), while Data competency is to be measured as the level of appropriateness of data source. Ability aware principles (Visual Perception, Cognition and Memory) are to be operationalized as the level of existence of literature supported perceptual, cognitive, and memory amplifiers and shortcuts (gestalt principles, preattentive attributes, seven +/- two, memory chunking, etc.) in BIV solution/deployment. The use of eye-tracking and brain-scanning technologies is suggested for further validation. Human abilities are to be measured by adapting the Nonverbal IQ (NVIQ) questions to experimental context. Information Complexity and Information Uncertainty are suggested to be measured as perceptual survey items. Decision Performance is to be measured through efficiency (time) and effectiveness (quality and the number of insights).

SUMMARY AND IMPLICATIONS

As suggested by Svenson (1979) in Mackay and Elam (1992):

> "*. . . it is gradually becoming clear that human decision making cannot be understood by simply studying final decisions. The perceptual, emotional and cognitive processes which ultimately lead to the choice of a decision alternative must also be studied if we want to gain an adequate understanding of human decision making*" (p. 86).

In line with above quote, this paper focused on antecedent processes that lead to BI-enabled decision making. First, we proposed a novel framework using Stanford-Binet's (5^{th} edition) measurement of Non-verbal IQ as a foundational framework. Second, we linked BIV capabilities to decision makers' abilities by drawing on over 30 years of visualization, graphical presentation, and cross disciplinary literature, and suggesting a series of propositional research guidelines. Third, technology capabilities were linked to existing framework (Zack 2007) of organizational challenges where technology can play important role as aids in decision making.

The newly proposed intelligence based framework offers a new way of understanding how visualization impacts BI systems and vice versa. To the best of our knowledge, no publication has organized such a large body of business-context related visualization research into a single unifying framework up to this point.

Our framework provides a new perspective and offers a number of research implications. First**,** initial categorization of significant research work is now available for structured knowledge building in the arena of intelligence seeking decision making through BI. Second, our approach can be used to assess the value and requirements of visualization across BI tools. The use of BIV capabilities should not be solely housed in traditional visualization-rich systems such as data mining and dashboarding. Even standard mass and tabular reports could and should use the capabilities proposed in our model. However, the right amount and the level of each BIV capability across different reporting platforms deserve further exploration. Third, we identified five groupings of capabilities that BIV should possess in order to improve BI's support of decision making. BI departments and vendors should be able to assess their current state relative to identified BIV capabilities and identify their strengths and weaknesses.

Lastly, despite relative comprehensiveness, our framework and resulting propositions invite additional research. A number of potential extensions are possible including the implication of user characteristics, cognitive fit, interactions between identified capabilities and/or abilities, as well as the need to understand the interactions between BIV capabilities and visual abilities in various organizational and decision making contexts and tasks.

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