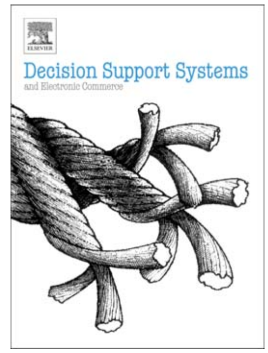
Accepted Manuscript



Business Information Visualization Intellectual Contributions: An Integrative Framework of Visualization Capabilities and Dimensions of Visual Intelligence

Dinko Bačić, Adam Fadlalla

PII:	S0167-9236(16)30103-8
DOI:	doi: 10.1016/j.dss.2016.06.011
Reference:	DECSUP 12735

To appear in: *Decision Support Systems*

Received date:	7 September 2015
Revised date:	8 May 2016
Accepted date:	14 June 2016

Please cite this article as: Dinko Bačić, Adam Fadlalla, Business Information Visualization Intellectual Contributions: An Integrative Framework of Visualization Capabilities and Dimensions of Visual Intelligence, *Decision Support Systems* (2016), doi: 10.1016/j.dss.2016.06.011

Business Information Visualization Intellectual Contributions: An Integrative Framework of Visualization Capabilities and Dimensions of Visual Intelligence

Dinko Bačić[1]
Department of Management and Information Sciences
Romain College of Business
University of Southern Indiana
dbacic@usi.edu

Adam Fadlalla
Department of Accounting and Information Systems
College of Business and Economics
Qatar University

[1] Corresponding Author

Business Information Visualization Intellectual Contributions: An Integrative Framework of Visualization Capabilities and Dimensions of Visual Intelligence

ABSTRACT

Modern organizations treat data as an IT infrastructure based upon which business processes and strategy can not only be informed but shaped. One important step in this process deals with the way users consume data through visual display and how those visualization-reliant technologies could impact decision making. Motivated by business information visualization's (BIV) practical relevance and disjointed nature of academic literature, this research summarizes relevant BIV research landscape; by explicating and clarifying visualization terminology and definitions, and condensing relevant literature using a framework that describes and links essential visual elements of Business Intelligence (BI) platforms to the dimensions of the well-known visual intelligence quotient (IQ) dimensions. The paper identifies gaps and suggests future research opportunities.

Keywords: Business Information Visualization, Information Visualization, Business Intelligence, Visual Intelligence, IQ

1. INTRODUCTION

The use of information systems and data to drive business decision making has been one of the defining quests of IS discipline. Ever since organizations began wider adoption of technology for data collection to support business decision making and strategy, a large body of academic research tackled relevant issues of business decision support technologies. These issues ranged from technology, to strategy, optimization, and human-computer interaction perspectives. In the process, many terms have been used, with Business Intelligence (BI) emerging as an umbrella term for various activities aiming at collecting, storing, processing and analyzing relevant data to support decision making. Due to, among other developments, advances in technical capabilities, such as storage and processing power, BI's traditional focus on Data Warehousing is being gradually replaced with research and practice focusing more on the 'consumption' of collected data. A closer look at business and IT strategy literatures reveals that, from a business impact perspective, our ability to 'consume data' is as important, if not more, as efficiency of its collection, processing and storage. Modern organizations treat data as an IT infrastructure that not only informs, but also shapes business processes and strategy. One important and necessary step in this process deals with the way users consume data visually and how visualization-reliant technologies could align with human abilities to support business judgement and decision making.

After decades of investments in IT, many companies feel that achieving business insight and competitiveness through those investments is not nearly as easy as originally hoped [1]. On the other hand, success stories have been documented in research [2] and practice [3]. Not surprisingly, according to a new Gartner survey of more than 2,800 CIOs, and for the fourth consecutive year, BI and analytics remain the number one investment priority for CIOs [4] . Proliferation of BI vendors offering and heavily marketing their visual display capabilities through reporting, ad-hoc analysis, dashboarding, and visual data discovery, provides evidence of the practical importance of BI's data display to today's modern organizations. Similarly, the academic community over the past few decades identified a number of important aspects and factors of visual data display and its impact on the quality of decision making at, mostly, the user (individual) level. As a result of these efforts, both Business Information Visualization (BIV) practice and research have achieved significant progress, where improvements in system ability to enable conversion of data into actionable insights can be traced to improvements in our understanding and implementation of visual technologies and techniques. At the same time we are witnessing a cross-disciplinary field with, at times, fragmented knowledge, numerous and sometimes conflicting 'best practice principles', and volumes of academic articles that seems to have limited impact on the proliferation of 'chartjunk' when designing reports and dashboards in practice. Although BIV garnered great attention in recent times and could be considered one of the most relevant BI topics and 'fashions' in the last decade, there has been a dearth of research summarizing disparate literature and contextualizing it into the decision making lens. While researchers have widely argued the value of BI [5] and its visual capabilities [6] for improved decision making, they have not equally addressed the possibility that it is through better BI support of users themselves and their human intelligence abilities that better decisions are achieved. Furthermore, little has been done to combine disintegrated literature into a cohesive framework that can provide a more rounded and nuanced understanding of visualization capabilities and help both research and practice in further investigating and deploying those capabilities.

The goal of this research is to bridge these gaps by offering four key contributions. First, consolidation of often overlapping and sometimes disconnected visualization terminologies is provided. Second, in our quest to systematically organize the extensive visualization literature, we adopt and build upon a novel human visual intelligence-based framework [7] for assessing BIV effectiveness. Third, we leverage this framework to identify and internally-connect IS literature on data visualization and graphical presentation, as well as externally-connect relevant literature from Accounting, Marketing, Human-Computer Interaction, Psychology, Cognition, and Perception. Lastly, BIV research gaps and opportunities are identified.

The rest of the paper is organized as follows. Section 2 provides a summary of relevant terms. Section 3 introduces and discusses the adopted visual intelligence framework. Section 4 provides validation of our adopted framework by aligning relevant literature with the proposed framework. Gaps and future research avenues are identified in section 5. The paper ends with conclusions and implications.

2. VISUALIZATION TERMINOLOGY

A number of terms related to visualization of data are available in the literature, such as Visualization (in general), Data Visualization, Information Visualization (often called InfoViz by practitioners), Scientific Visualization, Visual Analytics, and Business Visualization (often called BizViz by practitioners). Data Visualization emerged in the 1950s with the advent of computer graphics [8] and is defined as the science of visual representation of data. Scientific Visualization was used initially to refer to visualization as a part of a process of scientific computing [8] and focuses on processes for steering the data set and seeing the unseen, thereby enriching existing scientific methods [9]. Other variants and sub-types of data and scientific visualization were coined as well and are based on the type of representation they embody (Cartographic Visualization) or knowledge domain (Statistical Visualization).

Information Visualization has been coined in 1999 as the use of computer-supported interactive visual representations of abstract data to amplify cognition [10]. Typical examples of abstract data that has no inherent mapping to space are employee turnover statistics, bank branch deposit growth data or sales goals figures. Others suggested that "Information visualization utilizes computer graphics and interaction to assist humans in solving problems [11 p.58]" or define it as "…visual representations of the semantics, or meaning, of information. In contrast to scientific visualization, information visualization typically deals with nonnumeric, nonspatial, and high-dimensional data [12 p.12]" or as communication of abstract data through the use of interactive visual interfaces [13].

Visual Analytics is the science of analytical reasoning facilitated by interactive visual interface [14]. The initial domain driving the development of this discipline was homeland security but is currently being applied in security, health, commerce, transportation, energy, and personal applications. It is often described as dealing with complex data that enables detection of the expected and discovery of the unexpected [15].

BIV is an incarnation of visualization and is increasingly gaining researchers' and practitioners' attention [9]. While data visualization has been associated to BI from early static charting to interactive charting and dashboarding, BIV has been primarily presented through a representation and interaction lens or a decision making and task-orientation lens. A number of definitions exist for BIV. Tegarden defines it as "simply the use of visualization technologies to visualize business data or information (p.8)". He also recognizes that "…business information has been visualized in the form of tables, outlines, pie charts, line graphs, and bar charts for a very long time. However, today business information visualization means the use of multidimensional graphics to represent business-related data or information[16 p.8]." Zhang offers a more detailed definition of BIV as "a process of creating appropriate computer-generated visual representations of large amounts of non-geometric managerial data for human problem-solving and decision-making support[9 p.4]." Card, Mackinlay and Shneiderman [10] definition could be applied to business context by defining BIV as the use of computer-supported interactive visual representations of abstract *business* data to amplify cognition.

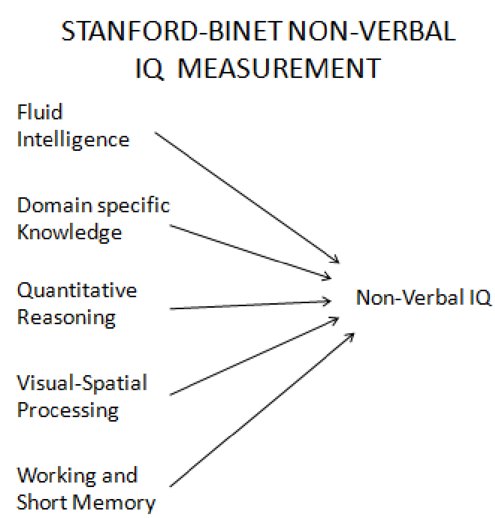
One could discern many similarities and differences among these various definitions. A clear thread among all of the definitions is the computer-supported interactive visualization of data. A temporal dimension can be observed, in that whereas earlier definitions focused on the development of visualization techniques and on the data understanding, the latter definitions focused more on the use of visualization, its impact, and, even, its role in behavioral understanding (for example, in security and business applications). We could offer a more comprehensive definition of BIV as the use of computer-supported interactive visual representations of business data to amplify cognition, achieve better data, business, and behavior understanding to improve decision making and business impact. The advantage of this definition is that it integrates the main features of previous definitions and brings forth the importance of understanding behavior, improving decision making and business impact, and explicitly highlights the importance of linking visualization to human cognition.

3. ORGANIZING FRAMEWORK

In order to organize the substantial business visualization literature we look at the aim of the underlying technology or phenomenon, in this case BI, as a basis for a literature-organizing framework. A goal of BI is to create "intelligent businesses" by delivering "the right information to the right people" [17] where asking the right questions is the precursor to making intelligent decisions. BI is designed to help individual users wrestle with vast quantities of data as they make decisions about organizational operations and processes. The objective is to improve the timeliness, meaningfulness and quality of inputs to the decision process [5] . In short, an effective business decision benefits from an effective BI system that enhances users' *abilities* to make better decisions. In this role, visualization is viewed as key by many [18-21]. More specifically, BIV, to effectively assist human intelligence, needs to manifest intelligence in its own design and deployment by supporting and accentuating relevant human intelligence dimensions. This requires software that seamlessly interacts with the brain to support and extend its cognitive abilities.

Struggling with similar issues, prior research [7] initiated a suggestion of formal human intelligence-based lens to BIV-focused BI capabilities. Even though the importance of linking decision support technologies and human intelligence was recognized quite early [22] [23] [24] [25], a large body of BI and BIV literature has ignored this link. Yet, anchoring our perspective on the link between technology and human intelligence, and evaluating existing and prospective research through this lens offers a new way to assess the literature. Therefore, this research adopts and expands the human intelligence based framework as originally suggested in Bacic and Fadlalla [7]. This framework is based on the best known human intelligence measurement test - Stanford-Binet IQ (Intelligence Quotient) test and its latest fifth edition (SB5) [26]. SB5 includes the first published testing of nonverbal content which is of special interest to this paper. The Nonverbal IQ (NVIQ) or Visual IQ of SB5 (Figure 1) measures the general ability to reason, solve problems, visualize and recall information presented, in pictorial, figural and symbolic form as opposed to information presented in the form of words and sentences. Skills in solving abstract, picture-oriented problems; solving quantitative problems shown in picture form; assembling designs and recalling tapping sequences, are examined in NVIQ [27]. SB5 consists of five nonverbal mental abilities [27]: Fluid Intelligence, Domain specific Knowledge, Quantitative Reasoning, Visual-Spatial Processing and Working and Short Memory.

Figure 1: Visual Intelligence Dimensions [16]



In this research we present a literature-supported framework that links BIV elements to human visual mental abilities outlined by NVIQ: (i) Exploration and Interaction with Fluid Intelligence, (ii) Business Acumen and Relevant Data with Domain Specific Knowledge, (iii) Analytics and Statistics with Quantitative Reasoning, (iv) Representation, Perception, Cognition, and Cognitive Effort with Visual-Spatial Processing, and (v) Memory and Storytelling with Working and Short Memory. As a result, the linkage of Visual IQ dimensions and eminent BIV elements emerges (Table 1).

Table 1: Visual IQ-based BIV elements

Visual IQ Dimensions	BIV Elements
Fluid Intelligence	Exploration
	Interaction
Domain Specific Knowledge	Business Acumen
	Relevant Data
Quantitative Reasoning	Analytics
	Statistics
Visual-Spatial Processing	Representation
	Perception
	Cognition
	Cognitive effort
Working and Short Memory	Memory
	Storytelling

Just as it would be inappropriate to use non-verbal (visual) IQ alone as a predictor of success in personal and professional life, isolated focus on BIV elements would be inappropriate for assessment of their effect on decision performance. It is reasonable to expect a more complex approach to understanding the influence of BIV elements on decision performance. Our visual IQ-based framework suggests not only the list of important elements but also requires understanding of relationships between those elements in and with their decision making context. Linkages and alignment between BIV literature and BIV elements, decision making context and their interactions is presented next.

4. MAPPING OF VISUAL IQ DIMENSIONS AND BIV ELEMENTS[2]

4.1. Fluid Intelligence - Exploration and Interaction Capabilities

Fluid intelligence (or Fluid Reasoning) has been defined as "the use of deliberate and controlled mental operations to solve novel 'on the spot' problems (i.e., tasks that cannot be performed automatically)"

[2] The literature search process consisted of a number of steps. First, initial search was conducted by using 'Information Visualization' and 'Visualization' as keywords using Business Source Complete database. Resulting articles and articles based on their references were analyzed until common larger themes emerged. In some instances, non-verbal IQ framework was suggestive enough to provide larger themes (for example, domain knowledge or memory) and; therefore, the same articles were analyzed for those themes as well. Second, once larger themes emerged, they were used as keywords themselves to expand the search. The process was stopped once larger themes were saturated with enough article count or research contribution significance. Third, resulting themes (BIV elements) were aligned with non-verbal IQ dimensions. This method resulted in a significant list of relevant BIV literature; however, it was not designed to be all-encompassing (due the maturity of the field) but rather impactful and parsimonious.

[28 p.6]. It includes mental operations such as drawing inferences, concept formation, classification, generating and testing hypothesis, identifying relations, comprehending implications, problem solving, extrapolating, and transforming information[28, 29]. Fluid reasoning is often described as the ability to recognize patterns [30]. Faced with business problems, users are often dealing with informational complexity and uncertainty. In the process they look for patterns, identify relations between data, extrapolate and, in general, transform data. In other words, in order to problem solve, BI users are often solving novel problems and performing mental operations that are known to be the elements of fluid intelligence. However, instead of relying solely on human brain ability to perform these operations, BI's visual technology components are now offering capabilities to support Fluid Intelligence, namely exploration and interaction. More specifically, in a business decision making context, high levels of Fluid Reasoning may be difficult to achieve without a BI system providing the ability to visually explore and interact with information [7] .

In information visualization literature, BI capabilities of exploration and interaction with data emerged and are well positioned to support users' fluid reasoning. Origins of exploration, as we know it, date back to 1970s when Tukey separated exploration from statistics [31]. In another seminal work, Edward Tufte discussed the subject in the context of visualization by emphasizing the need for exploring data [32]. In this stream of research, exploration has been defined as examination of data without having an apriori understanding of what patterns, information, or knowledge it might contain [7, 31, 33]. 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 [33]. The benefits of automated selection of data representation format (table, map, line graph, etc.) have been approached in the context of more effective exploration [34] and have resulted in vendors like Tableau and SAS (SAS Visual Analytics) deploying default format selection of display based on data type selected. With the advent of multi-dimensional reporting technologies, visualization techniques are moving away from static reporting to new exploration paradigm. Multi-dimensional information visualization literature focuses on how visualization techniques provide benefits to users interested in exploratory tasks that require fluid analysis of data [35, 36]. These and other exploration and interaction enabling developments greatly simplified the process of visual discovery as user effort is being shifted from information formatting to activities such as inferences, hypotheses generating and testing, identifying relations, and extrapolating; i.e., supporting fluid reasoning.

Exploration capabilities are often facilitated through interaction capabilities. Interaction, however, can aid not only in exploration tasks but can assist in confirmatory and presentation tasks as well [7]. 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 [14]. Classic Information Visualization interaction taxonomy often talks about seven interaction tasks: Overview, Zoom, Filter, Details-on-Demand, Relate, History, and Extract [37]. A more recent framework of interaction that departs from these classical low-level interaction techniques has been proposed and is organized around a user's intent (Select, Explore, Reconfigure, Encode, Abstract/Elaborate, Filter, and Connect) while interacting with a system [38]. From the perspective of model based reasoning, interaction was assessed through the purposes of external anchoring, information forging and cognitive offloading [39]. Taxonomy based on the user intention, visual effects, and the possibility of selection and interaction with data was proposed with focus on user's purpose and benefits of visual analysis[35].

The discussion about visualization and interaction benefits, concerns and designs continues to be robust and cross-disciplinary [6, 39]. Dilla, Janvrin et al. [40] identified a series of cross-discipline research articles focused on interactive data visualization building the evidence of interactivity, information navigation and selection impact on decision-making process and outcome. They also identified a series of mostly marketing research suggesting benefits of interactive visualization: allow decision makers to navigate through complex data sets and decision accuracy through considerations of multiple factors, increase control over the data flow, enable the restructuring of the information environment, and lower the cognitive cost. The impact of interactivity on processes and outcomes has been proposed by combining it with information context of vividness, evaluability and framing [6].

4.2 Domain specific Knowledge Intelligence - Business Acumen and the Use of Relevant Data

Domain specific knowledge has been defined as individual's breadth and depth of acquired knowledge in specialized (demarcated) domains that typically do not represent the general universal experiences of individuals in a culture [28, 29]. General (Domain Specific) Knowledge 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 [28, 29]. It represents familiarity with particular subject area [41] and is modifiable "software" aspect of the cognitive system [42]. In BIV literature and practice, business acumen (or business domain knowledge) along with the ability to eliminate noise and focus on using relevant data emerged as aligned with Domain Specific Knowledge dimension of adopted framework. As such, these abilities are needed to use visual systems more effectively.

Although functional/domain knowledge was identified as important for report designers [43] early on in IS discipline, IS literature focused on visualization is yet to approach this topic in similar depth as in the fields of psychology and cognition. The emergence of visualization-requiring Knowledge Discovery in Databases (KDD); however, elevated the importance of domain knowledge and expertise [44] for identification of key problem features [45] and better information organization and rationalization [46]. Moreover, domain knowledge has been found to impact performance of data mining classification methods [47]. More recently, the link between domain knowledge and presentation format in Accounting Information Systems [48] and presentation format choice [49] has been recognized.

Big Data created a fertile environment for BIV to assist in reduction of information complexity, while at the same time possess the power to generate new hypothesis, ask for new and relevant information and, therefore, reduce uncertainty. The new breed of analysts in this Big Data environment require a number of skills, including business acumen. Without business acumen, a user/designer of BI will face difficulty in basic interactions with the system such as encoding, filtering, connecting and relating. Furthermore, business acumen is essential to knowing when to use ending balance versus average balance (crucial in banking), when to use median compensation figures versus average compensation versus a range from 25th to 75th percentile (important in HR related analysis), or that body mass index (BMI) is a function of height and weight (relevant in healthcare). 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 [50], content, and granularity, to name a few.

4.3 Quantitative Reasoning Intelligence - Statistical and Analytics Capabilities

Quantitative Reasoning represents both individual's store of acquired mathematical knowledge (perform mathematical calculations correctly or, for example, knowing the meaning of slope of the curve or p-value), as well as reasoning with numbers (recognizing relationships and patterns) [28, 29]. Practice and research have elevated statistical and analytics capabilities of BIV solutions as important; we are witnessing a number of visual discovery tools including those capabilities as product features, allowing for users' to experience higher levels of quantitative reasoning abilities. In BIV, a system can enhance decision making through Quantitative Reasoning by offering ready-to-use, statistical functions and advanced analytics capabilities. Recognizing the significance of statistical and quantitative capabilities, leading BI vendors are starting to incorporate these capabilities. For example, data displays using regression lines, box plot, percentiles, and reference lines for median, mode and mean values were once reserved for strictly statistical visualizations but in todays' new breed of BI tools are becoming both accepted and expected capability.

With the advent of more advanced analytics and its popularity in the context of Big Data, BI users are starting to expect higher integration of analytics capabilities and visual technologies as well. Gartner is noting that advanced analytics platforms are increasingly being directed at business analysts, and designating leading status to Tibco Spotfire visualization tool for advanced analytics in part due to customers liking the all-in-one nature of its solution, and its range — from data visualization to predictive analytics [51]. Tableau recently added advanced analytics features like forecasting and continued integration with providers of advanced algorithm libraries and data mining solutions[52].

This trend indicates that what once was strictly used by individuals strong in declarative, procedural quantitative knowledge, and acquired mathematical knowledge (i.e Quantitative Reasoning/Intelligence), such as statisticians, modelers and data-scientists, is now being consumed by business analysts via visual BI tools. These new capabilities appear to have the ability to act as non-verbal IQ dimension equalizer.

4.4 Visual-Spatial Processing Intelligence - Representation and informed design based on Visual Perception, Cognition, and Cognitive Effort

Visual Spatial Processing abilities (intelligence) are defined as having the ability to generate, retain, retrieve, and transform well-structured visual images [53]. Significant amount of IS literature is focused on enablement of those visual-spatial processing abilities through research focused on data representation (formats and features), and how visualization impacts human perception, cognition, and cognitive effort..

Visual Spatial Processing 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 [29]. In BIV, representation of graphics and tabular reports, if implemented properly, enhances the Visual–Spatial Processing ability of the user and therefore positively influences decision making. 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.

4.4.1 Representation

Most of the existing Information Visualization and Business Information research was viewed through the lens of information representation. Information representation (spatial representations that are derived from symbolic data [10]) has been researched extensively and a large part of it centered on understanding the significance of representation format (method). What we call representation method others have called metaphor [16] techniques [54], display format [55], visualization components [56], views [34], presentation format [57, 58] and presentation mode [59]. Although the list of available representation methods is growing [60], the research traditionally focused on understanding the impact of display choice between tabular and graphical categories [18, 55, 57, 59, 61, 62].

It has been noted [33] that this body of research resulted in formulation of Cognitive Fit Theory [63-65], that suggests the importance of fit between the problem representation and the problem-solving task in achieving effective performance [33, 40, 54, 66-69]. Cognitive Fit Theory is a native IS theory that came about as a reaction to the inability to rationalize the findings from previous empirical research [66] that compared decision performance in simple tasks across tabular and graphical presentation formats. In CFT-based literature, there is a prevalence of studies considering the effect of matching spatial or symbolic tasks using tables, graphs and maps as external representation formats [48, 65, 70-75]. Recently, the nature of visual displays used in this research evolved to external representation formats beyond tables and graphs. New external representation formats include modeling tools types [76], maps [71], competing programming languages [77], product nature [78], gaming tools [79], online interface design formats [69], circle vs. force interface [68], history and negotiation dance graphs[80], high vs. low oriented text [81], plan vs. elevation view vs. 3D Display [82], parallel coordinate–plots [83], and heatmaps [83-85]. Similarly, data representations have been evaluated in cross-disciplinary contexts, and tested in more varied and complex tasks. Some of those contexts include personal and firm level finance [70, 72, 75], accounting [48], human resources [86], modeling [76, 87], software and programming [63, 70], and geographic systems [71, 88]

In addition to representation methods, researchers created a significant body of knowledge around representation elements such as color [18, 21, 58, 59, 61, 89], object depth and dimensionality [67, 90-92] and organization, symbols, labels, text, icons, lines, grids, and axes [18, 57, 93, 94].

4.4.2 Visual Perception

Studies of human perceptual ability including visual imagery, cognitive fit, Gestalt principles and preattentive attributes, have led to a number of design principles [20, 21, 57, 62, 95-97]. Perception is “the process of interpreting and recognizing sensory information [98], 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 [18]. This decoding process occurs in part due to visual perception abilities. Miller [99] 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 [100] leading to improve business decision making [16, 101]. Psychologists [102] 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 [19, 57, 92]. Consequently, Gestalt principles and related preattentive attributes (high speed visual perception occurring below consciousness) have been leveraged [20, 21, 33]) in representations.

The existence of decoding process, the management of visual channel overload, and insights stemming from designs based on Gestalt principles and preattentive attributes represent human perception element of BIV that is closely aligned with abilities captured by Visual-Spatial Intelligence.

4.4.3 Cognition

Although in cognition science, cognition includes visual perception, we adopt the view in which cognition incorporates only post-perceptual processing of information[33]. This separation is needed to more effectively separate the distinct impacts of perceptual and post perceptual processing on BIV [7].

Cognitive science suggests that users have internal representation of visualizations they see [39] and as such external representation should leverage the research on internal visualization. Relationship between mental models (special form of internal representation) and external representation has been suggested [39]. Within DSS, there has been recognition for systems to support a decision maker's general thinking processes to reduce cognitive biases in decision making [103]. 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 [104]. In other words, "an effective cognitive decision support system should do more than passively present information to executives. It should actively engage in the executive's thinking process and provide both flexibility and guidance in decision support [103] p. 149". Additional contributions of interest to the intersection of BIV and cognition include work on recall [91, 101, 105] and mental imagery [101].

4.4.4 Cognitive Effort

Within greater discussion of cognition, a robust IS literature stream emerged with focus on the role of cognitive effort. CFT [64], introduced in section 4 has been used to suggest a significant role of cognitive effort in user efficiency and effectiveness when dealing with data representations. According to the original CFT, if both the problem representation and the problem-solving task involve the same cognitive style, then there is said to be a "cognitive fit" between them which reduces cognitive effort. As a result, the impact on user's cognitive effort and ultimate decision performance depends upon the fit between information presentation, task, and decision processes used by the decision maker. The original theory was expanded a number of times [63, 65, 106] to attempt to further explain problem solving performance but the underlying role of cognitive effort remained.

In summary, CFT-based research suggests that user's cognitive effort can be impacted by visual displays of data and other factors that constitute cognitive fit. This effort is experienced by users in their attempt to generate, retain, retrieve, and transform well-structured visual images, i.e. it is aligned with the visual-spatial processing ability/intelligence dimension of visual IQ.

4.5 Working and Short Memory Intelligence - Memory informed design and Storytelling

4.5.1 Memory

Visual designs that minimize memory limitations of human brains have been discussed in IS literature along with more recent research on storytelling and are directly linked to memory dimension of visual IQ. The importance of memory and effective use of memory when presenting and processing information visually is widely acknowledged [19, 68, 99, 105]. Within representation capability, the use of design principles leveraging memory is well documented [16, 19-21, 99]. 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 [21, 96] 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 [59] and symbols [93] is often done in consultation with memory and cognition literature.

Verbal working memory was suggested to impact the effectiveness of visual interfaces [68]. 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 [107], working memory capacity [108] and comprehension that leads to impacts in problem solving performance. In psychology, substantial evidence suggests that skilled individuals (acting in their domain of expertise) perform operations more quickly than less skilled individuals and respond faster on perceptual tasks. [109]. This phenomenon was explained via the theory of Long Term Working Memory [107], in which skilled activities (domain knowledge related), allow the sequence of stable states (retrieval structures) to be stored in long-term memory and are directly accessible through the retrieval cues in short-term memory. This theory was explained through the reasoning that domain-knowledge could have easily accessible retrieval structures in Long Term Memory serving as the expansion of Working Memory capacity [108].

4.5.2 Storytelling

Most recently, literature is beginning to recognize the important role storytelling and narrative play in business information visualization. This development is partially rooted in the realization that report designers are not always decision makers[49], necessitating the need for well-organized and captivating communication [110]. Early research centered on storytelling is starting to transition into business information visualization and is often deployed though dashboards [111, 112]. Vendors like Tableau are creating product features to allow for creation of storyboards within their visualization tool. One significant benefit of effective storytelling includes its impact on decision maker's memory [113].

Convergence of computer technology, art and media is now allowing for various storytelling techniques to be deployed [114] in business context as well. These techniques include: building the picture, using comics metaphor, animating, setting mood and place in time, conflict and ambiguity resolution, intentional omission, continuity, effective redundancy, and increasing attention [114-116]. In the BI context, a set of requirements for enhancing analysis was proposed consisting of fluid transition, integration, narrative aids, interactive visualization, appropriate BI story templates, reuse, and option playback [111].

In the context of visualization framing, other techniques have been proposed using rhetoric: information access rhetoric to limit the amount of information presented, provenance rhetoric to provide background information, mapping rhetoric to map elements of the visualization, procedural rhetoric to constrain interaction over time, and linguistic rhetoric [117]. Other storytelling topics such as the role of sequencing in visual narrative [118], classification of patterns [119], scientific storytelling [120], field history and related research agenda [110] are offering promising new frontiers for storytelling using business data.

4.6 Contextualization of BIV elements for business decision making

Available literature supports our framework's suggestion for the need to contextualize BIV elements in decision making context. This context is often described through interactions and relationships between BIV elements, user, and problem characteristics. In general terms, the literature is strongly rooted in task-technology fit lens [121] and decision optimization [122]. More specifically, it is based on a notion that efficiency and effectiveness of decision performance is influenced by human preference for optimizing between effort and performance (see section 4.4.4).

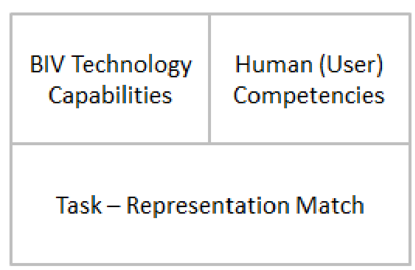
Beyond importance of data representation and cognitive task types [72, 75] (see section 4.4.1), other task types emerged in BIV contextualization for decision making. They include introduction of tasks based on complexity [73, 74], information load level [70], difficulty level [123], and comprehension [124] . The list of task types and characteristics continues to grow, as anticipated when the concept of cognitive fit was introduced [65]. It is important to note that problem task is also addressed though problem solving/domain lens (see section 4.4.1 and CFT context overview). Therefore, the condition in which decision performance is evaluated (often labeled as 'task') is best described through a combination of problem domain and task type.

Contextualization of BIV elements in business decision making is not limited to specifying interactions and relationships between task types, representations and problem domains. A number of research efforts integrated other, mostly user-focused variables. They include mental processing [65], domain knowledge and expertise [54, 87, 125], need for cognition [88], and spatial abilities [73, 74], to name a few. Evaluation of literature suggests that more nuanced research effort attempts to integrate more complex exemplification of decision making context by analyzing relationships amongst all four context elements - task type, problem domain, data representation and user characteristics.

The literature suggests that BIV elements identified through our framework are contextualized in decision performance by either instantiating components (data representation, domain knowledge) or representing dimensions of components (task and user characteristics) that create 'fit' condition. For example, a closer look at various categories of task type reveals that BIV elements of interaction, exploration, cognition, and memory are fundamental dimensions that often define task type categories themselves (elementary vs high mental tasks [62, 92], analyzable vs less analyzable tasks [126], exploratory vs confirmatory tasks [21, 31-33, 127], etc.) or user characteristics (mental processing, spatial ability, expertise, need for cognition, etc.). Similarly, cognitive effort BIV element is the underlying mechanism through which 'fit' impacts performance. Literature is yet to address integration of other BIV elements such as statistical and analytical capabilities and storytelling with other elements and components of 'fit' in a more meaningful way. This seems to be a gap and an opportunity for further BIV research.

Lastly, in light of identified elements and their contextualization in decision making process, BIV elements could be organized in terms of task, technology, and user characteristics (Figure 2). The literature suggests that foundational base of BIV's ability to support decision making is dependent on effectively matching task to data representation. The ability of other BIV elements to positively influence decision making without proper match between task and data representation is greatly limited. On the other hand, the aforementioned match is necessary but often not sufficient. Once matching with problem task is achieved, BIV technologies need to allow for context dependent level of BIV Technology Capabilities (Exploration, Interaction, Statistics and Analytics) that could be then deployed by BIV authors and designers that possess certain user characteristics in terms of business (Business Acumen, Relevant Data) and human visualization (Perception, Cognition, Cognitive Effort, Memory, and Storytelling)

Figure 2: Contextualizing BIV - Task/Technology/User Perspective



competencies. It is important to note that the criticality of BIV Technology Capabilities and Human (User) Competencies is also a function of task at hand as some tasks, for example, will require little in terms of Interaction but significantly more in terms of Business Acumen or design principles (as it relates to knowing the limits of human perception and cognition).

5. FUTURE RESEARCH AVENUES

Our visual IQ-based framework organizes extensive literature and identifies elements to assist in demarcating research gaps and opportunities. While there may be value in discovering new types of representation formats or creating more efficient statistical methods to incorporate into visual display, we suggest that there is also value to business decision making from researching and improving how users integrate BIV elements and translate that integrated knowledge into practical use. Therefore, we structure our discussion of research opportunities through a paradigm that emphasizes processes and outputs that leverage BIV elements. The paradigm allows us to go beyond input-output emphasis as it offers valuable and interesting research directions to demystify "black-box" relationships between BIV framework elements. Within this structure, BIV elements are treated as inputs so that our discussion of research agenda is focused on the use and alignment of those elements (as processes) and their effects (outputs).

5.1 Processes – Integration of BIV elements for increased practical value

While progress has been made in establishing relationships between BIV elements, along with other user or technology characteristics (process) to help with decision performance, we identify three significant categories of importance as future research paths. First, BIV research needs to make sure that context, experimental set-up of studies and scenarios used closely reflect conditions facing decision makers. Abundance of research suggests that sole and isolated focus on BIV elements (representations, exploration, memory, etc.) may be not be sufficient. Instead we need to understand conditions under which each type of BIV element and/or combination of elements is appropriate. More importantly, the analysis of conditions should reflect how decision making is actually conducted within organizations. BIV research instantiates those conditions, in part, trough choice of tasks. Often, task types are 'borrowed' from other disciplines and are too abstract or do not effectively reflect decision making tasks in BIV practice. Similarly, those tasks are often not combined with decision making conditions experienced by practitioners. For example, decision making in practice is executed across many organizational levels; it is frequent and influenced by various forms of disruptions and the multitasking nature of decision making. Decisions are frequently made in teams, and report/visualization authors and consumers are often not the same individuals. Visualizations are expected to work across multiple display sizes, be interactive and allow easy transition from static display to data exploration. Decision makers and users vary in their levels of domain expertise, graphical display or visual techniques mastery. These realities of how practitioners are using BIV to support decision making are often lacking in BIV academic effort. Consequently, the relevance of research findings is greatly minimized causing a widening gap between visualization practitioners and academics. Future research studies should contextualize BIV elements identified by our framework in settings that more accurately capture decision making process in practice. Due to criticality of task in this research stream, research focused on clarifying task characteristics and providing task taxonomy may be particularly useful.

Second, CFT is a dominant theoretical lens through which most empirical efforts identified in this study assess visual display appropriateness. CFT-based literature integrates a number of BIV elements identified in our framework (such as representations, cognition (mental models) and domain knowledge). This theoretical perspective suggests that cognitive effort (sometimes called burden, load, workload) is the underlying mechanism influencing visualization's effectiveness and efficiency. Yet, despite criticality of cognition and inconclusive, and sometimes contradicting, results, BIV literature is very limited in capturing, measuring or discussing cognitive effort directly. Without greater understanding and measurement of the mechanism that determines a user's performance quality, research could be exposed to criticism that challenges fundamental underpinnings of substantial portions of BIV literature. These gaps should be addressed in future by adopting available measures of cognitive effort, both perceptual and more objective, such as those advocated through biometric measurement.

Third, largely driven by emergence of Big Data and our challenges with consuming of that data, the integration and impact of more advanced statistical and storytelling capabilities into BIV technologies along with resurgence in desirability of those skills for data analysts provides fertile ground for practice-grounded research. The integration of statistical capabilities, depth of their features and display with other BIV elements (representation, interaction, exploration, etc.) is scant and could be valuable for practitioners. Similarly, greater understanding is needed to assess the role of storytelling in the context of effort, memory, decision confidence, user and system trust, and overall conversion of data into actionable insights.

5.2 Outputs – Dependent Variable

Research presented in this study assesses the role of visual display of data on decision performance as a dependent variable category. In this context we highlight two future research paths. In each case, our visual intelligence framework identified BIV elements that should be considered as significant factors that influence decision performance directly or indirectly through their interrelationships.

First, many studies tend to limit the measurement of decision performance to mostly decision speed, accuracy and recall. This focus can be largely explained by researchers' reliance on theories and early literature that featured decision quality mostly through these metrics. Furthermore, in practical business contexts and decision making arena, those three measures are often thought as fundamental to decision making. While there are studies focusing on other types of performance measures, knowledge of data visualization impact on outputs such as decision confidence, trust and credibility (both in terms of data/information, system itself, or visualization author/communicator) is limited. Even traditional factors that influence technology adoption and use continuance are often overlooked. Furthermore, in some contexts, the role of BIV on decision creativity and mindfulness may be more important than simple focus on decision speed and accuracy. Despite the need for a more rounded understanding of how BIV supports and influences decision performance, research is limited and the quest for more diverse dependent variables requires more attention.

Second, understanding of relationships between the decision performance measures themselves is limited. We live in a complex decision making environment where a number of system outputs are used as inputs in a decision making process (for example speed, recall, accuracy, confidence, trust). At times, one measure/output may have negative implications or have context-dependent impact on another critical measure. For example, we rarely consider that those same conditions (task-representation fit) that lead to decision speed may have sub-optimal decision performance as measured through decision creativity. Current research is mostly silent about those relationships.

6. IMPLICATIONS AND CONCLUSION

6.1 Contribution and Implications

In the process of meeting the research goal, our paper offers four key contributions. First, the paper consolidated often overlapping and sometimes disconnected visualization terminologies. We find that i) a number of terms related to visualization of data are available in the literature, ii) terms are not necessarily mutually exclusive and have been sometimes used inconsistently, and iii) definitions evolve with research interest and progress where early definitions focused on data, representation, and domain type, while newer definitions tend to focus on user impact and purpose.

Second, the paper adopted a novel framework to ground relevant literature for formation and identification of literature-supported BIV critical elements. The choice of a literature-organizing framework was deliberate as to ensure the alignment of literature mapping with the aim of the underlying technology - enhancing the decision making abilities of information consumers. This approach enabled additional contribution of this research. Namely, the focus on underlying technology aim reveals important link between visualization and decision making support through the emphasis on human visual abilities. As a result, the framework suggests the need for BI's visualization components to assist human intelligence. This requires software to seamlessly interact with the brain to support and extend its cognitive and perceptual abilities. While others have suggested similar notions in the past, no prior work approached it in this multi-dimensional, framework-driven and widely-encompassing fashion. More specifically, building on earlier work, we make a case for leveraging best known human intelligence measurement test (IQ) to identify five anchoring dimensions of human visual intelligence: Fluid Intelligence, Domain specific Knowledge, Quantitative Reasoning, Visual-Spatial Processing, and Working and Short Memory. Additionally, we provide further support for framework appropriateness by resurfacing early IS literature that suggested and predicted greater symbiosis between visual capabilities of MIS systems and human intelligence. Lastly, in this research we further enhance earlier work by including literature and practice-supported insightful concepts of cognitive effort, storytelling and advanced analytics as BIV elements that emphasize Visual-Spatial Processing and Quantitative Reasoning Intelligence.

Third, key representative BIV and BIV-related literature is identified and aligned with the proposed framework, thus the mapping of key areas of interest allowed for literature–grounded identification of twelve elements aligned with five intelligence dimensions. This effort resulted in a number of contributions: i) substantial and relevant cross-disciplinary contributions from other research efforts were identified; ii) BI vendors and BI-focused departments are provided with a list of BIV elements that should be considered when building and purchasing BI tools to ensure completeness of their capabilities; and iii) report and dashboard designers are informed of important design considerations embedded in identified BIV to ensure more effective consumption of visual data by enabling full potential of users' visual intelligence abilities.

Fourth, our visual IQ-based framework identifies elements to assist in demarcating research area gaps and opportunities. These opportunities are focused on making sure that research is more practically relevant when it comes to experimental set up, better understanding of cognitive effort as a mechanism through which visualization impacts decision performance, understanding of how storytelling, statistical and advanced analytical capabilities interact with other BIV elements and decision making context, encouraging diversification of decision performance measures, and investigating the relationship between the decision performance measures themselves..

6.2 Limitations

As any other research effort, this research has limitations that should be addressed in subsequent research. First, the selection of the anchoring framework has the potential to influence the list of identified BIV elements. While we suggest the value and importance of human visual intelligence dimensions for this research field, we recognize that frameworks emphasizing other dimensions of human ability could be valuable and should be explored in the future. Although identified literature and its findings support our adopted framework use, other frameworks have the potential to identify further important visual elements.

Second, while we are not aware of any other work in the context of BIV that is as extensive in terms of identifying key literature, literature review-based research is susceptive to subjective interpretation and inadvertent omission of other worthy research effort. This is especially the case when evaluating a cross-disciplinary phenomenon such as visualization and recognizing publication space constraints. By being rooted in BI and its support of human abilities, our guidance through literature-organizing framework, and by seeking peer feedback through early stages of this work[3], we attempted to minimize this limitation. We invite others to build on our effort by expanding significant literature identification.

Lastly, our research is highly conceptual in nature and could be further enhanced by empirical testing of potential relationships using identified BIV elements, visual intelligence dimensions and visualization success factors. While this was not within the scope of our effort, we do recognize its value. The evaluation of these complex relationships has a potential for a worthwhile research effort.

6.3 Concluding Remarks

Motivated by BIV's practical relevance and disjointed nature of academic literature, we set our goal to summarize relevant business information visualization research landscape by clarifying visualization definitions and condensing relevant literature into a framework that describes essential visual elements of BI platforms. Our research highlights the need for continued cross-disciplinary understanding of business information visualization. This approach highlights that visual components of BI systems need to manifest intelligence in their own design and deployment by supporting and accentuating relevant human visual intelligence dimensions. Acknowledging our research as a starting point, we invite further conceptual and empirical research in this important research domain.

[3] Research-in-progress proceeding at a conference

References

[1] Gartner, Gartner Outline the Top 10 Forces to Impact Outsourcing and IT Services Industry, 2010.

[2] B.H. Wixom, H.J. Watson, A.M. Reynolds, J.A. Hoffer, Continental Airlines Continues to Soar with Business Intelligence, Information Systems Management, 25 (2008) 102-112.

[3] D. Hannon, Kraft Foods' Recipe for Successful Business Intelligence, SAP, SAPinsider, 2012.

[4] Gartner, Flipping to Digital Leadership, 2015.

[5] S. Negash, Business Intelligence, Communications of AIS, 2004 (2004) 177-195.

[6] N.H. Lurie, C.H. Mason, Visual Representation: Implications for Decision Making, Journal of Marketing, 71 (2007) 160-177.

[7] D. Bacic, A. Fadlalla, Business Information Visualization: A Visual Intelligence-Based Framework, AMCIS 2013, Chicago, IL, 2013.

[8] F.H. Post, G.M. Nielson, G. Bonneau, Data Visualization: The State of The Art, Proceedings of the 4th Dagstuhl Seminar on Scientific Visualization, Kluwer Academic Publishers, Boston/Dordrecht/London, 2002.

[9] P. Zhang, Business Information Visualization: Guidance for Research and Practice, Encyclopedia of Microcomputers, 2001.

[10] S. Card, J. Mackinlay, B. Shneiderman, Readings in Information Visualization: Using Vision to Think, Morgan Kaufmann Publishers 1999.

[11] H. Purchase, N. Andrienko, T. Jankun-Kelly, M. Ward, Theoretical Foundations of Information Visualization, in: A. Kerren, J. Stasko, J.-D. Fekete, C. North (Eds.) Information Visualization, Springer Berlin / Heidelberg 2008, pp. 46-64.

[12] C. Chen, Top 10 unsolved information visualization problems, IEEE Computer Graphics and Applications, 25 (2005) 12-16.

[13] D.A. Keim, F. Mansmann, J. Schneidewind, H. Ziegler, Challenges in Visual Data Analysis,, Proceedings of Information Visualization (IV 2006), IEEE, 2006, pp. 9-16.

[14] J.J. Thomas, K.A. Cook, Illuminating the Path, IEEE CS Press, 2005.

[15] J.J. Thomas, J. Kielman, Challenges for visual analytics, Information Visualization, 8 (2009) 309-314.

[16] D.P. Tegarden, Business Information Visualization, Communications of AIS, Volume 1 (1999) 1-37.

[17] Gartner, Gartner Says Treat Business Intelligence Programmes as Cultural Transformation, not Just Another IT Project, 2010a.

[18] W.S. Cleveland, The elements of graphing data, Wadsworth, Monterey, CA, 1985.

[19] S. Kosslyn, Understanding charts and graphs, Applied Cognitive Psychology, 3 (1989) 185-225.

[20] E.R. Tufte, The Visual Display of Quantitative Information, Graphics Press, Cheshire, CT, 1983.

[21] E.R. Tufte, Envisioning information, Graphics Press, Cheshire, CT, 1990.

[22] J.C.R. Licklider, Man-Computer Symbiosis, IRE Transactions on Human Factors in Electronics, HFE-1 (1960) 4-11.

[23] Z.S. Zannetos, Toward Intelligent Management Information Systems, Industrial Managment Review, 9 (1968) 21-38.

[24] W.R. King, The Intelligent MIS-a Management Helper, Business Horizons, 16 (1973) 5.

[25] T.G. West, Forward into the past: a revival of old visual talents with computer visualization, SIGGRAPH Comput. Graph., 29 (1995) 14-19.

[26] G.H. Roid, Stanford-Binet Intelligence Scales, Fifth Edition: Technical Manual, Riverside Publishing, Itasca, IL, 2003.

[27] K.A. Becker, History of the Stanford-Binet Intelligence Scales:Content and Psychometrics, Stanford-Binet Intelligence Scales, Fifth Edition Assessment Service Bulletin Number 1, Riverside Publishing, Itasca, IL, 2003.

[28] K.S. McGrew, Cattell-Horn-Carroll (CHC) Definition Project, 2004.

[29] K.S. McGrew, CHC theory and the human cognitive abilities project: Standing on the shoulders of the giants of psychometric intelligence research, Intelligence, 37 (2009) 1-10.

[30] J.C. Cavanaugh, F. Blanchard-Fields, Adult development and aging, 5th ed., Wadsworth Publishing/Thomson Learning, Belmont, CA:, 2006.

[31] J.W. Tukey, Exploratory data analysis, Addison-Wesley, Reading, MA, 1977.

[32] E.R. Tufte, Visual Explanations: Images and Quantities, Evidence and Narrative, Graphics Press, Cheshire, CT, 1997.

[33] J. Baker, D.R. Jones, J. Burkman, Using Visual Representations of Data to Enhance Sensemaking in Data Exploration Tasks, Journal of the Association for Information Systems, 10 (2009) 533-559.

[34] J.D. Mackinlay, P. Hanrahan, C. Stolte, Show Me: Automatic Presentation for Visual Analysis, Visualization and Computer Graphics, IEEE Transactions on, 13 (2007) 1137-1144.

[35] S. Savovska, S. Loshkovska, Taxonomy of User Intention and Benefits of Visualization for Financial and Accounting Data Analysis, in: Trajkovik, Mishev (Eds.) ICT Innovations 2013, Springer2014, pp. 197-207.

[36] S. Mansmann, M. Scholl, Visual OLAP : a New Paradigm for Exploring Multidimensional Aggregates, Proceedings of the IADIS International Conference on Computer Graphics and Visualization 2008 (CGV2 008). IADIS, Amsterdam, 2008, pp. 59-66.

[37] R. Kosara, H. Hauser, D. Gresh, An Interaction View on Information Visualization,, EUROGRAPHICS 2003 (EG '03), 2003.

[38] Y. Ji Soo, K. Youn ah, J.T. Stasko, J.A. Jacko, Toward a Deeper Understanding of the Role of Interaction in Information Visualization, Visualization and Computer Graphics, IEEE Transactions on, 13 (2007) 1224-1231.

[39] Z. Liu, J.T. Stasko, Mental Models, Visual Reasoning and Interaction in Information Visualization: A Top-down Perspective, Visualization and Computer Graphics, IEEE Transactions on, 16 (2010) 999-1008.

[40] W. Dilla, D.J. Janvrin, R. Raschke, Interactive Data Visualization: New Directions for Accounting Information Systems Research, Journal of Information Systems, 24 (2010) 1-37.

[41] B.M. Wildemuth, The Effects of Domain Knowledge on Search Tactic Formulation, Journal of the American Society for Information Science & Technology, 55 (2004) 246-258.

[42] D.Z. Hambrick, R.W. Engle, Effects of Domain Knowledge, Working Memory Capacity, and Age on Cognitive Performance: An Investigation of the Knowledge-Is-Power Hypothesis, Cognitive Psychology, 44 (2002) 339-387.

[43] I. Benbasat, R.G. Schroeder, An Experimental Investigation of Some MIS Design Variables, MIS Quarterly, 1 (1977) 37-49.

[44] U. Fayyad, G. Piatetsky-Shapiro, P. Smyth, From data mining to knowledge discovery in databases, AI Magazine, v17 (1996) p37(18).

[45] J.M. Mackay, J.J. Elam, A Comparative Study of How Experts and Novices Use a Decision Aid to Solve Problems in Complex Knowledge Domains, Information Systems Research, 3 (1992) 150-172.

[46] J.-Y. Mao, I. Benbasat, The Use of Explanations in Knowledge-Based Systems: Cognitive Perspective and a Process-Tracing Analysis, Journal of Management Information Systems, 17 (2000) 153-179.

[47] A.P. Sinha, H. Zhao, Incorporating domain knowledge into data mining classifiers: An application in indirect lending, Decision Support Systems, 46 (2008) 287-299.

[48] E. Cardinaels, The interplay between cost accounting knowledge and presentation formats in cost-based decision-making, Accounting, Organizations and Society, 33 (2008) 582-602.

[49] D. Bacic, R. Appan, Impact of Domain Knowledge on Information Presentation Format Choice: A Cognitive Fit Perspective, AMCIS 2012 Proceedings, Seattle, WA, 2012.

[50] R. Hackathorn, The BI Watch: Real-Time to Real-Value, DM Review, 14 (2004) 24-43.

[51] Gartner, Magic Quadrant for Advanced Analytics Platforms, 2015.

[52] Saama, Saama Teams up With Tableau to Deliver Advanced Analytics to Insurance, High-Tech, CPG, Life Sciences and Healthcare Customers, 2015.

[53] D.F. Lohman, Spatial ability, Encyclopedia of intelligence, Macmillan, New York, 1994, pp. 1000-1007.

[54] Z. Huang, H. Chen, F. Guo, J.J. Xu, S. Wu, W.-H. Chen, Expertise visualization: An implementation and study based on cognitive fit theory, Decision Support Systems, 42 (2006) 1539-1557.

[55] W.N. Dilla, P.J. Steinbart, The effects of alternative supplementary display formats on balanced scorecard judgments, International Journal of Accounting Information Systems, 6 (2005) 159-176.

[56] F.B. Viegas, M. Wattenberg, F. van Ham, J. Kriss, M. McKeon, ManyEyes: a Site for Visualization at Internet Scale, Visualization and Computer Graphics, IEEE Transactions on, 13 (2007) 1121-1128.

[57] B. Ives, Graphical User Interfaces for Business Information Systems, MIS Quarterly, 6 (1982) 15-47.

[58] I. Benbasat, A.S. Dexter, P. Todd, An experimental program investigating color-enhanced and graphical information presentation: an integration of the findings, Communications of the ACM, 29 (1986) 1094-1105.

[59] I. Benbasat, A.S. Dexter, An Investigation of the Effectiveness of Color and Graphical Information Presentation Under Varying Time Constraints, MIS Quarterly, 10 (1986) 59-83.

[60] J. Heer, M. Bostock, V. Ogievetsky, A tour through the visualization zoo, Commun. ACM, 53 (2010) 59-67.

[61] I. Benbasat, A.S. Dexter, An Experimental Evaluation of Graphical and Color-Enhanced Information Presentation, Management Science, 31 (1985) 1348-1364.

[62] S.L. Jarvenpaa, G.W. Dickson, Graphics and managerial decision making: research-based guidelines, Communications of the ACM, 31 (1988) 764-774.

[63] T.M. Shaft, I. Vessey, The Role of Cognitive Fit in The Relationship Between Software Comprehension and Modification, MIS Quarterly, 30 (2006) 29-55.

[64] I. Vessey, Cognitive fit: A theory-based analysis of the graphs vs. tables literature, Decision Sciences, 22 (1991) 219-241.

[65] I. Vessey, D. Galletta, Cognitive Fit: An Empirical Study of Information Acquisition, Information Systems Research, 2 (1991) 63-84.

[66] A.S. Kelton, R.R. Pennington, B.M. Tuttle, The Effects of Information Presentation Format on Judgment and Decision Making: A Review of the Information Systems Research, Journal of Information Systems, 24 (2010) 79-105.

[67] R.B. Dull, D.P. Tegarden, A Comparison of Three Visual Representations of Complex Multidimensional Accounting Information, Journal of Information Systems, 13 (1999) 117.

[68] Z. Bin, S.A. Watts, Visualization of Network Concepts: The Impact of Working Memory Capacity Differences, Information Systems Research, 21 (2010) 327-344.

[69] B. Adipat, D. Zhang, L. Zhou, The Effects of Tree-View Based Presentation Adaptation on Mobile Web Browsing, MIS Quarterly, 35 (2011) 99-122.

[70] N.S. Umanath, I. Vessey, Multiattribute Data Presentation and Human Judgment: A Cognitive Fit Perspective, Decision Sciences, 25 (1994) 795-824.

[71] A.R. Dennis, T.A. Carte, Using Geographical Information Systems for Decision Making: Extending Cognitive Fit Theory to Map-Based Presentations, Information Systems Research, 9 (1998) 194-203.

[72] C. Frownfelter-Lohrke, The Effects of Differing Information Presentations of General Purpose Financial Statements on Users' Decisions, Journal of Information Systems, 12 (1998) 99-107.

[73] C. Speier, I. Vessey, J.S. Valacich, The Effects of Interruptions, Task Complexity, and Information Presentation on Computer-Supported Decision-Making Performance, Decision Sciences, 34 (2003) 771-797.

[74] C. Speier, The influence of information presentation formats on complex task decision-making performance, International Journal of Human - Computer Studies, 64 (2006) 1115-1131.

[75] A. Urbaczewski, M. Koivisto, The Importance of Cognitive Fit in Mobile Information Systems, Communications of AIS, 2008 (2008) 185-196.

[76] R. Agarwal, A.P. Sinha, M. Tanniru, Cognitive Fit in Requirements Modeling: A Study of Object and Process Methodologies, Journal of Management Information Systems, 13 (1996) 137-162.

[77] A.P. Sinha, I. Vessey, Cognitive fit: an empirical study of recursion and iteration, Software Engineering, IEEE Transactions on, 18 (1992) 368-379.

[78] K.-S. Suh, Y.E. Lee, The Effects of Virtual Reality on Consumer Learning: An Empirical Investigation, MIS Quarterly, 29 (2005) 673-697.

[79] P.A. Beckman, Concordance between task and interface rotational and translational control improves ground vehicle performance, Human Factors, 44 (2002) 644+.

[80] J. Gettinger, S.T. Koeszegi, M. Schoop, Shall we dance? — The effect of information presentations on negotiation processes and outcomes, Decision Support Systems, 53 (2012) 161-174.

[81] I.L. Huang, An Empirical Analysis of Students' Difficulties on Learning Conceptual Data Modeling, Academy of Information & Management Sciences Journal, 15 (2012) 73-85.

[82] M. Shen, M. Carswell, R. Santhanam, K. Bailey, Emergency management information systems: Could decision makers be supported in choosing display formats?, Decision Support Systems, 52 (2012) 318-330.

[83] J. Gettinger, E. Kiesling, C. Stummer, R. Vetschera, A comparison of representations for discrete multi-criteria decision problems, Decision Support Systems, 54 (2013) 976-985.

[84] A.S. Abrahams, R. Barkhi, Concept comparison engines: A new frontier of search, Decision Support Systems, 54 (2013) 904-918.

[85] R.C. Basole, M.A. Bellamy, Visual analysis of supply network risks: Insights from the electronics industry, Decision Support Systems, 67 (2014) 109-120.

[86] B.M. Tuttle, R. Kershaw, Information Presentation and Judgment Strategy from a Cognitive Fit Perspective, Journal of Information Systems, 12 (1998) 1.

[87] V. Khatri, I. Vessey, V. Ramesh, P. Clay, S.-J. Park, Understanding Conceptual Schemas: Exploring the Role of Application and IS Domain Knowledge, Information Systems Research, 17 (2006) 81-99.

[88] B.E. Mennecke, M.D. Crossland, B.L. Killingsworth, Is a Map More Than a Picture? The Role of SDSS Technology, Subject Characteristics, and Problem Complexity on Map Reading and Problem Solving, MIS Quarterly, 24 (2000) 601-629.

[89] C. Ware, Information Visualization: Perception for Design, Morgan Kaufmann, San Francisco, CA, 2000.

[90] N. Tractinsky, J. Meyer, Chartjunk or Goldgraph? Effects of Presentation Objectives and Content Desirability on Information Presentation, MIS Quarterly, 23 (1999) 397-420.

[91] C.J. Watson, R.W. Driver, The Influence of Computer Graphics on the Recall of Information, MIS Quarterly, 7 (1983) 45-53.

[92] N. Kumar, I. Benbasat, The Effect of Relationship Encoding, Task Type, and Complexity on Information Representation: An Empirical Evaluation of 2D And 3D Line Graphs, MIS Quarterly, 28 (2004) 255-281.

[93] J. Bertin, English Translation: Semiology of Graphics, University of Wisconsin Press, Madison, Winsconsin, 1983.

[94] S.M. Kosslyn, Understanding Charts and Graphs, Applied Cognitive Psychology, 3 (1989) 185-226.

[95] W.S. Cleveland, R. McGill, Graphical Perception: Theory, Experimentation, and Application to the Development of Graphical Methods, Journal of the American Statistical Association, 79 (1984) 531-554.

[96] S. Kosslyn, Elements of Graph Design, W.H. Freeman and Co.,, New York, NY, 1994.

[97] T. Ahokas, Information Visualization in a Business Decision Support System, Faculty of Science, Department of Computer Science, University of Helsinki, 2008.

[98] M.H. Ashcraft, Fundamentals of Cognition Addison-Wesley Educational Publishers, New York, 1998

[99] G.A. Miller, The magical number seven, plus or minus two: some limits on our capacity for processing information, Psychological Review, 63 (1956) 81-97.

[100] R.N. Shepard, L.A. Cooper, Mental Images and Their Transformations, The MIT Press, Cambridge, MA, 1982.

[101] S. Kosslyn, Image and Mind, Harvard University Press, Cambridge, MA, 1980.

[102] M. Wertheimer, Laws of Organization in Perceptual Forms, in: W.D. Ellis (Ed.) A Source Book of Gestalt Psychology, Routledge and Kegan Paul Ltd1938.

[103] J.Q. Chen, S.M. Lee, An exploratory cognitive DSS for strategic decision making, Decision Support Systems, 36 (2003) 147-160.

[104] R.W. Zmud, Supporting senior executive through decision support technologies: a review and directions for future research, in: H.G.S.E. E.R. McLean (Ed.) Decision Support Systems: A Decade in Perspective, Elsevier Science Publishers, North-Holland, Amsterdam, 1986.

[105] R.W. Schmell, N.S. Umanath, An experimental evaluation of the impact of data display format on recall performance, Communications of the ACM, 31 (1988) 562-570.

[106] A. Chandra, R. Krovi, Representational congruence and information retrieval: Towards an extended model of cognitive fit, Decision Support Systems, 25 (1999) 271-288.

[107] K.A. Ericsson, W. Kintsch, Long-Term Working Memory, Psychological Review, 102 (1995) 211-245.

[108] T.R. Ricks, J. Wiley, The influence of domain knowledge on the functional capacity of working memory, Journal of Memory and Language, 61 (2009) 519-537.

[109] M.G. Rhodes, D.P. McCabe, Expertise makes the world slow down: Judgements of duration are influenced by domain knowledge, Quarterly Journal of Experimental Psychology, 62 (2009) 2313-2319.

[110] R. Kosara, J. Mackinlay, Storytelling: The next step for visualization, Computer, DOI (2013) 44-50.

[111] M. Elias, M.-A. Aufaure, A. Bezerianos, Storytelling in Visual Analytics Tools for Business Intelligence, in: P. Kotzé, G. Marsden, G. Lindgaard, J. Wesson, M. Winckler (Eds.) Human-Computer Interaction – INTERACT 2013, Springer Berlin Heidelberg, 2013, pp. 280-297.

[112] W. Wojtkowski, W.G. Wojtkowski, Storytelling: its role in information visualization., European Systems Science Congress, 2002.

[113] I. McGregor, J.G. Holmes, How storytelling shapes memory and impressions of relationship events over time, Journal of Personality and Social Psychology, 76 (1999) 16.

[114] N. Gershon, W. Page, What storytelling can do for information visualization, Communications of the ACM, 44 (2001) 31-37.

[115] R. Shank, Tell Me a Story, Northwestern University Press, Evanston, 1990.

[116] N. Gershon, S.G. Eick, Visualization's new tack: making sense of information, IEEE Spectrum, 32 (1995) 38-40,42,44-47,55-56.

[117] J. Hullman, N. Diakopoulos, Visualization rhetoric: Framing effects in narrative visualization, Visualization and Computer Graphics, IEEE Transactions on, 17 (2011) 2231-2240.

[118] J. Hullman, S. Drucker, N.H. Riche, L. Bongshin, D. Fisher, E. Adar, A Deeper Understanding of Sequence in Narrative Visualization, Visualization and Computer Graphics, IEEE Transactions on, 19 (2013) 2406-2415.

[119] E. Segel, J. Heer, Narrative visualization: Telling stories with data, Visualization and Computer Graphics, IEEE Transactions on, 16 (2010) 1139-1148.

[120] K.-L. Ma, I. Liao, J. Frazier, H. Hauser, H.-N. Kostis, Scientific storytelling using visualization, Computer Graphics and Applications, IEEE, 32 (2012) 12-19.

[121] D.L. Goodhue, R.L. Thompson, Task-Technology Fit and Individual Performance, MIS Quarterly, 19 (1995) 213-236.

[122] E.J. Johnson, J.W. Payne, Effort and Accuracy In Choice, Management Science, 31 (1985) 395-414.

[123] J.B. Smelcer, E. Carmel, The Effectiveness of Different Representations for Managerial Problem Solving: Comparing Tables and Maps, Decision Sciences, 28 (1997) 391-420.

[124] V. Khatri, V. Iris, S. Ram, V. Ramesh, Cognitive Fit Between Conceptual Schemas and Internal Problem Representations: The Case of Geospatio-Temporal Conceptual Schema Comprehension, IEEE Transactions on Professional Communication, 49 (2006) 109-127.

[125] S.-Y. Hung, Expert versus novice use of the executive support systems: an empirical study, Information and Management, 40 (2003) 177-189.

[126] K.H. Lim, I. Benbasat, The Effect Of Multimedia on Perceived Equivocality and Perceived Usefulness of Information Systems, MIS Quarterly, 24 (2000) 449-471.

[127] J.W. Tukey, Some graphic and semigraphic displays, in: T.A. Bancroft (Ed.) Statistical papers in honor of George W. Snedecor, Iowa State University Press, Ames, 1972, pp. 293-316.

Dr. Dinko Bačić is an Assistant Professor of Computer Information Systems in the Department of Management and Information Sciences at Romain College of Business at the University of Southern Indiana. He holds an MBA degree in Finance from Miami University (Ohio) and a DBA degree in Information Systems from the Cleveland State University. Dr. Bačić's research is focused on theory-based empirical research with current interests in Information Visualization, decision making, cognitive effort, eye-tracking, Business Intelligence, and the impact of IS on firm performance. Dr. Bačić has over fifteen years of experience in Business Intelligence, Finance, and HR. He provided consulting services to firms in banking and clinical research industry.

Dr. Adam Fadlalla is a Professor of Information Systems in the Department of Accounting and Information Systems of Qatar University. He holds an MBA in Finance and Decision Sciences from Miami Ohio, an MSc in Computer Science and a PhD in Information Systems from the University of Cincinnati. Dr. Fadlalla's research spans both the conceptual and the applied aspects of Information Systems. His publications appeared in many journals, including Journal of Computers and Operations Research, Omega, Information & Management, Interfaces, Journal of the American Medical Informatics Association, Journal of Healthcare Quality, Government Information Quarterly, and Journal of American College of Surgeons, among others. His current research interests include the strategic use of information systems, predictive analytics and discovery of knowledge hidden in the ever increasing data accumulation, and modeling in general to improve the quality of organizational outcomes. Dr. Fadlalla provided consulting services to large international organizations.

Highlights

- Business Information Visualization terminology is consolidated
- Visual IQ framework is adopted to suggest the value of using five anchoring dimensions of human visual intelligence in identifying critical BIV elements.
- BIV elements aligned with five dimensions of visual IQ are identified and contextualized in decision making context
- Practice focused research gaps and opportunities are proposed